FACULTY OF PSYCHOLOGY
AND EDUCATIONAL SCIENCES

ERRORS ON THE RACETRACK

INVESTIGATING THE IMPACT OF ERRORS IN FORMULA ONE RACING

Word count: 11.487

Ayala Denul

Student number: 01802163

Supervisor: Prof. Dr. Wim Notebaert

A dissertation submitted to Ghent University in partial fulfilment of the requirements for the degree of Master of Science in Psychology (Theoretical and Experimental Psychology)

Academic year: 2022 - 2023

GHENT UNIVERSITY

Abstract

In sports, it is crucial to adapt to errors and negative outcomes. However, research on post-error behavior of athletes is limited. Furthermore, the handful of studies available mainly focus on basketball. In this thesis post-error behavior of athletes participating in the motorsport Formula One was examined by analyzing lap time data. Based on a general definition of errors as a mismatch between the expected outcome and actual outcome of one's actions, we operationalized errors as laps with a slower lap time than the preceding lap. Using this definition, we investigated how Formula One drivers adapt following errors and how this can be related to existing cognitive control theories. Due to differences between races, ten races were first analyzed separately. Next, the results from each race were entered into meta-analyses. The meta-analytical results revealed that following an error (i.e., a slower lap), drivers systematically speed up again on the next lap. In lab tasks, this has been described as post-error speeding or even post-error recklessness. In Formula One, this could suggest that drivers go full gas, and perhaps take more risks as they try to immediately compensate for the slower lap time. As far as we know, this is a first study on post-error behavior of Formula One drivers. The main contribution of this study is that it increases our understanding of the generalizability of results across sports. On top of this, we discuss the applied relevance of our research for the world of sports.

Nederlandstalige Samenvatting

In sport is het cruciaal dat men zich aanpast aan fouten en negatieve uitkomsten. Onderzoek naar het gedrag van sporters na fouten is echter beperkt. Bovendien focussen de handvol beschikbare studies zich voornamelijk op basketbal. In deze thesis is het gedrag na fouten van Formule 1-coureurs onderzocht door rondetijden te analyseren. Op basis van een algemene definitie van fouten als een mismatch tussen de verwachte uitkomst en de werkelijke uitkomst van iemands acties, operationaliseerden we fouten als ronden met een tragere rondetijd dan de voorgaande ronde. Aan de hand van deze definitie onderzochten we hoe Formule 1-coureurs zich aanpassen na fouten en hoe dit gerelateerd kan worden aan bestaande cognitieve controle-theorieën. Vanwege verschillen tussen races werden tien races eerst apart geanalyseerd. Vervolgens werden de resultaten van elke race in meta-analyses ingevoerd. Uit de meta-analytische resultaten bleek dat Formule 1-coureurs na een fout (d.w.z. na een langzamere ronde) systematisch weer sneller rijden in een volgende ronde. In de context van computer taken werd dit omschreven als 'post-error speeding' of zelfs 'post-error roekeloosheid'. In Formule 1 zou dit erop kunnen wijzen dat coureurs vol gas gaan, en misschien meer risico's nemen omdat ze proberen de tragere rondetijd onmiddellijk te compenseren. Voor zover bekend, is dit de eerste studie over het gedrag van Formule 1-coureurs na een fout. De belangrijkste bijdrage van deze studie is dat het ons inzicht in de generaliseerbaarheid van de resultaten over verschillende sporten vergroot. Daarnaast, bespreken we ook de toegepaste relevantie van ons onderzoek voor de sportwereld.

Acknowledgements

I would like to express my sincere gratitude to my promotor, prof. dr. Wim Notebaert, for all the interesting discussions, valuable insights and detailed feedback provided throughout the entire process of this dissertation. Not only did prof. Notebaert contribute greatly to this work, but he also sparked my interest in (sport) psychological research.

Further, I want to thank some very important people who have had a profound impact on me throughout my studies. Over the past five years, there were several moments when I was ‘unhappy’ as I felt challenged too little in my studies. However, these people guided me towards, and through, new challenges and opportunities and encouraged me to further develop my skills.

First, I owe an immeasurable amount of gratitude to my mom and dad for their unconditional support and love. They are my true role models, and I cannot thank them enough. I also want to thank my two brothers. While they may not realize it, they both taught me some invaluable lessons. My older brother, Thomas, not only shared his expertise in programming but also offered me a very different and unique way to look at the world and tackle problems. My younger brother, Matteo, has showed me the importance of passion and emotions in my work, for which I am very grateful. Together, these four people, my family, have taught me to always stay true to myself and be proud of myself.

Last, but certainly not least, I would like to convey a heartfelt thank you to my partner and best friend, Jonas Devloo. He has continuously encouraged me to explore my interests and passion for sport psychology, take on new challenges and set any self-doubt aside. Through all the stress and chaos, he has been my guiding light.

Table of Contents

Introduction 1

Post-Error Behavioral Adaptations 1

Post-Error Behavioral Adaptations in Sports 3

Formula One and Research on Formula One 5

Errors in Formula One 6

The Current Thesis 8

Materials and Methods 10

Datasets 10

Race Selection 10

Lap Time Analysis 13

Results 15

Discussion 23

Post-Error Behavioral Adaptations in Formula One 23

Advantages and Implications 25

Limitations and Future Directions 26

Conclusion 29

Data Availability Statement 29

References 30

Appendix A: Scatterplots Lap Time Data 35

Appendix B: Standard Deviations and Means of the ‘Difference in Lap Time with the Previous Lap’ and Performance Measures per Race 40

Introduction

Post-Error Behavioral Adaptations

Detection of and adaptation to errors and sub-optimal outcomes is vital for adaptive human behavior (Steinhauser & Kiesel, 2011). That is why post-error behavior has been a topic of interest in research for many years. One of the best documented post-error effects is post-error slowing. This effect entails slowing down of responses after an error compared to after a correct response (Danielmeier & Ullsperger, 2011; Schroder & Moser, 2014). Post-error slowing has long been interpreted in terms of adaptive cognitive control. Cognitive control is the ability to adapt behavior and information processing to task demands, context and goals (Larson et al., 2015; Notebaert et al., 2009). Identifying and responding to errors is considered a crucial aspect of cognitive control (Larson et al., 2015; Steinhauser & Kiesel, 2011). Cognitive control theories view post-error slowing as a strategic adaptation that results in more cautious behavior, leading to slower responses and increased accuracy following errors (Damaso et al., 2020; Notebaert et al., 2009; Williams et al., 2016).

While some studies indeed observe an increased accuracy following errors, providing supportive evidence for the cognitive control account (Danielmeier et al., 2011; Danielmeier & Ullsperger, 2011; Desmet et al., 2012; Van der Borght et al., 2016), other studies fail to observe a post-error accuracy increase (Danielmeier & Ullsperger, 2011; Hajcak & Simons, 2008; Notebaert et al., 2009; Notebaert & Verguts, 2011). Therefore, the cognitive control account has been challenged by other accounts trying to explain the dissociation between post-error slowing and post-error accuracy. These alternative accounts are often referred to as ‘non-strategic accounts’ or ‘maladaptive accounts’ as they do not consider post-error slowing to be a strategic adaptive effect. Instead, these accounts argue that errors and post-error processes will lead to impaired performance (Musco et al., 2023; Wessel, 2018). For instance, Notebaert et al. (2009) proposed the orienting account according to which slowing occurs after infrequent events because these capture the attention and slow down task-relevant processing, which will in turn negatively impact performance. This account thus argues that post-error slowing is often observed because errors are typically infrequent and therefore surprising. In line with this idea, Notebaert et al. (2009) observed post-error slowing when errors were infrequent, but observed post-correct slowing and post-error speeding when errors were frequent. They also found that, independent of the frequency of errors, participants made more errors following an error.

More recently, consensus models have been proposed in which the strategic and non-strategic accounts are integrated. For example, Wessel (2018) proposed the adaptive orienting account of error processing. In this model two stages are dissociated. First, a mismatch between expected and actual outcome activates an automatic cascade in which ongoing processes are interrupted and attention is oriented to the source of the mismatch. This stage is proposed to be triggered by any unexpected event, not only errors. However, for errors, the first stage is followed by a second controlled stage when sufficient time remains. In this stage, controlled processes are activated to retune to the task and increase caution. This two-stage model thus integrates the idea of non-strategic accounts that error-detection and its consequences will impair performance with the idea of strategic accounts that post-error processes will lead to improved performance (Wessel, 2018).

Despite these recent attempts to integrate strategic and non-strategic accounts on post-error behavioral adaptations, the theoretical debate continues. One aspect which has further fueled this debate, is the fact that several studies did not observe post-error slowing or even observed post-error speeding following infrequent errors. Compared to post-error slowing, post-error speeding is speeding up of responses after an error compared to after a correct response. In a study on sequential effects of a previous outcome on current performance, Williams et al. (2016) compared the performance of paid and unpaid participants using the ‘Buckets Game’. This task differs from typical forced-choice tasks as it is characterized by an explicit speed-accuracy trade-off and is relatively slow-paced. Therefore, it allows for more deliberate post-error adaptations. Williams et al. (2016) observed no post-error slowing when participants were paid and even observed post-error speeding when participants were unpaid. They interpreted their results in terms of participant motivation. According to the authors, unpaid participants were discouraged after errors and therefore become reckless which caused them to respond faster and less accurate. Further, when reanalyzing two memory experiments, Damaso et al. (2020) observed normal post-error slowing after errors caused by responding too fast and observed post-error speeding after errors due to poor evidence quality. Similarly, Steinhauser and Kiesel (2011) observed that participants slowed down after errors caused by themselves, but sped up after externally caused errors (e.g., an error due to a keyboard malfunction). Lastly, speeding following sub-optimal outcomes has also been observed in gambling tasks. For example, Verbruggen et al. (2017) observed that participants sped up following a gambled loss.

Since none of the previously explained accounts is able to account for this lack of post-error slowing, it has been proposed that the feeling of control over the outcome might determine whether post-error slowing or speeding occurs (Eben et al., 2023). Controllability, or better lack of controllability, indeed seems to characterize situations in which post-error speeding is observed. Based on these observations and their own research, Eben et al. (2023) proposed that people take the controllability of the outcome into account to adapt to errors in the most adaptive way. If people feel they have control over the outcome, the best option is to slow down and be more cautious which might yield better outcomes in the future. On the other hand, if they feel they have no control over the outcome, being more cautious will not work. The best alternative might then be to speed up to increase the number of successes in the same amount of time. So, depending on the controllability, either post-error slowing or post-error speeding is goal-directed and adaptive (Eben et al., 2023).

While the debate regarding the mechanisms underlying post-error behavioral adaptations continues in lab studies, it is also necessary to consider the applicability of these findings to real-world contexts. However, it is important to recognize that the definition of errors may differ depending on the context. In cognitive control literature, errors are typically defined as pressing an incorrect response button. This definition is not always applicable to real-world situations, which complicates extending the findings from lab studies to other contexts. Additionally, since contextual factors can influence and determine which post-error behavioral adaptations occur, the context might still create differences in post-error behavior even when similar (operational) definitions are used. Research should thus investigate post-error behavior in different real-world settings while clearly delineating what constitutes an error and acknowledging the specific context. By broadening the scope of research to real-world settings, our understanding of post-error behavior could improve significantly.

Post-Error Behavioral Adaptations in Sports

One context in which detecting, adapting to and learning from errors is especially crucial is in sports. Yet, the literature on post-error behavior of athletes is limited. A possible reason for this might be that it is not always easy to define errors in sport contexts and that an overarching (over different sports) conceptual definition might not even be possible. Therefore, we propose to use a more general definition of errors in which errors are defined as a mismatch between the expected outcome and actual outcome of one’s actions (Musco et al., 2023; Wessel et al., 2012). Using this definition, one can formulate an operational definition of errors based on the specific sport context.

Previously, Yu et al. (2021) investigated the behavioral adaptations of athletes following self-generated errors using a combined flanker/stop-signal task. They assessed whether post-error adjustments differ between athletes participating in open-skill sports, closed-skill sports and controls with a sedentary lifestyle. Yu et al. (2021) used a dichotomous typology of sports suggested by Schmidt and Wrisberg (2008). Based on the complexity, stability and predictability of the environment, Schmidt and Wrisberg (2008) differentiate between open- and closed-skill exercise. Closed-skill sports are characterized by little direct interaction with an opponent, a self-paced context and little adjustment due to unpredictability (Chueh et al., 2017; Schmidt & Wrisberg, 2008; Yu et al., 2021). Open-skill sports, on the other hand, are characterized by frequent dynamic interactions and a lot of unpredictability (Chueh et al., 2017; Schmidt & Wrisberg, 2008; Yu et al., 2021). This leads to uncertainty about which actions need to be prepared beforehand and therefore requires more flexibility. The results of Yu et al. (2021) revealed that both sport groups needed less time for successful post-error adjustment compared to the control group. Specifically, the authors only observed post-error slowing in the group of sedentary controls and there were no differences in post-error accuracy between the three groups. Moreover, they observed post-error speeding in the open-skill sport group. These results clearly contrast with previous studies showing longer post-error slowing and increased post-error accuracy in people with better fitness (Themanson & Hillman, 2006; Themanson et al., 2008). Yu et al. (2021) argue that this might be because the participants in these previous studies were not athletes with regular sport training, but rather just individuals with a higher physical activity compared to controls. So, Yu et al. (2021) concluded that athletes with regular sport training, especially those participating in open-skill sports, have a more efficient error processing compared to sedentary controls.

While Yu et al. (2021) assessed differences in post-error adaptations between athletes and non-athletes, it is difficult to generalize these conclusions to real-life sport performances. Besides studying the post-error behavior of athletes using computer tasks, it is also necessary to evaluate their post-error behavior during sport participation. More applied research on post-error behavioral adaptations in sports is mostly limited to analyses of real game data of basketball games. In basketball, players repeatedly make field goal attempts and free shots. The ball can either land in the basket or outside the basket. Given that errors are generally defined as deviations from one's goal (Musco et al., 2023; Wessel et al., 2012), this binary outcome structure allows to delineate an error from a correct action. Therefore, previous studies on the effect of a previous outcome on subsequent behavior and performance in sports have focused their analyses on basketball. Bocskocsky et al. (2014) concluded that basketball players are more cautious after misses and thus are less likely to attempt a difficult shot after a missed shot, while they are more likely to attempt a difficult shot following a hit. In line with this, the study of Neiman and Loewenstein (2011) revealed that basketball players significantly change their behavior on a three-point field goal (3-pointer) based on the outcome of the previous 3-pointer. More specifically, they attempt less 3-pointers after a missed 3-pointer compared to a made 3-pointer, the effect of multiple made or missed 3-pointers is cumulative and the effect of the outcome on a 3-pointer diminishes over time. However, the results of Rao (2010) indicated that basketball players do not change their behavior in response to any length of strings of misses or hits. It is necessary to note that the datasets and methods differed between the three studies, which might, in part, explain the different results. First, Rao (2010) included only one NBA (National Basketball Association) team in his analysis which resulted in only 4.522 shots being analyzed, Bocskocsky et al. (2014) included over 83.000 shots from a whole NBA season and Neiman and Loewenstein (2011) analyzed over 76.000 shots from both men's and women's basketball seasons. Second, the way the datasets were constructed also differed between the studies. Finally, the models and equations used to analyze the effect of a previous shot on the current shot were also different.

Besides the fact that the results of these three studies are inconsistent with each other, these studies also contrast with the post-error recklessness and speeding observed in athletes participating in open-skill sports (Williams et al., 2016; Yu et al., 2021). As basketball is considered an open-skill sport (Wang et al., 2013), one would expect post-error speeding or recklessness based on the research of Yu et al. (2021). Instead, post-error cautiousness or no response to errors was observed. This demonstrates that findings from lab studies cannot easily be generalized to real-life game data. Thus, to gain a good understanding of post-error adaptations during sport participation, it is necessary to study post-error behavior using data from real-life sport performances. On top of this, it is also necessary to consider different sports besides basketball. While the studies of Bocskocsky et al. (2014), Neiman and Loewenstein (2011) and Rao (2010) provide insight into how basketball players adapt following an error (i.e., a missed shot), it is difficult to generalize these findings to other sports. Generalization is complicated by similar reasons which complicate generalizing lab results to real-world settings. First, the operational definition of errors can differ across sports. This already complicates generalizing findings from one sport to another. Second, the context in which errors occur differs greatly across sports. In lab research, it has been demonstrated that the context might determine which post-error behavioral adaptations are goal-directed and adaptive. Similarly, it is possible that contextual differences between sports, lead to different post-error behavioral adaptations to be adaptive. While every competitive sport has the general goal to win, the exact manner to reach that goal indeed differs across sports. This highlights the need for further research on post-error behavioral adaptations in sports. Specifically, it is necessary to investigate the adaptations that occur in various sports while clearly delineating what constitutes an error in these sports. In order to address this gap in the literature, this thesis will examine post-error behavior in a different sport than basketball, namely in the motorsport Formula One (F1).

Formula One and Research on Formula One

Over the past few years, F1 has grown into a global phenomenon with millions of fans worldwide (van Leeuwen et al., 2017). This has resulted in a booming industry surrounding F1 (Aversa et al., 2015; Bell et al., 2016). Despite the popularity of the sport and the huge business surrounding it, the literature on F1 is relatively limited. The problem is not that there is no data available on F1 races. On the contrary, a lot of data is publicly available online due to fans dedicating websites to F1 results and due to the FIA's (Féderation Internationale de l'Automobile) freely accessible motorsport results and statistics database. Race data is not just informative for fans, F1 teams also make extensive use of both race data and data generated by their cars, making F1 a data-driven sport (Bell et al., 2016). During a race, large amounts of data are constantly transmitted to the team. The team uses this data together with more general race data before, during and after races for strategic purposes.

The limited existing studies on F1 are mostly from an engineering, technological or economical perspective and do not focus on the behavior of the drivers. There are many analyses on the car design, with most studies focusing on the aerodynamics of F1 cars and how to improve this. Every piece of the car and its effect on the aerodynamic performance has been studied in detail (Axerio-Cilies, 2012; Azmi et al., 2017; Patil et al., 2014; Prat, 2018; Rind & Hu, 2007). There are also studies on the evolution and impact of technological developments in the world of F1 (Jenkins, 2010; Jenkins & Floyd, 2001). The last domain with a relatively large body of literature on F1 is the economic domain. For example, Aversa et al. (2015) investigated the business model of F1 firms and their impact on firm performance and Henderson et al. (2010) investigated the impact of the Singapore Grand Prix on tourism.

However, in addition to the car, F1 drivers are also an essential part of the sport. Therefore, studying the drivers and their behavior, next to analyzing and improving the cars, can also help to improve performance. One reason for the limited research on F1 drivers is the fact that, for a long time, racecar drivers were not considered athletes (Potkanowicz & Mendel, 2013). Due to this stereotype, only a handful of studies have focused on racecar drivers before. For example, Baur et al. (2006) and van Leeuwen et al. (2017) compared the motor and driving skills of racecar drivers and non-racing drivers, and Bernardi et al. (2014) compared their brain activity. While all three authors focus on racecar drivers, only Bernardi et al. (2014) included some F1 drivers in their sample. The other studies included racecar drivers competing in other competitions. A few studies have also tried to answer the question ‘Which F1 driver is the best of all time?’ (Bell et al., 2016; Eichenberger & Stadelmann, 2009; Phillips, 2014). It is clear that research on racecar drivers is scarce, with most studies examining physiological differences or general driving performance. Furthermore, only some of these studies included F1 drivers in their sample. So, while F1 drivers play a crucial role in the sport, research on their behavior is lacking.

Errors in Formula One

F1 is an exceptionally demanding sport, not just physically, but also mentally and cognitively (Klarica, 2001; Potkanowicz & Mendel, 2013). Due to the demanding nature of the sport, everyone involved needs to perform their job with the highest precision. It is imperative to avoid mistakes, as any mistake can have profound consequences including serious damage, injuries or death. The fact that in F1 any mistake can have huge repercussions becomes clear by looking at the high number of crashes, serious injuries and deaths. In total 52 drivers lost their lives in accidents during F1 events. Most fatalities occurred in the 50’s, 60’s and 70’s. Since then, safety has improved dramatically due to various safety protocols being adopted by the FIA (Potter, 2011). Due to these safety improvements only one driver died in F1 since 1994. The safety measures thus reduced the risk of deaths and serious injuries, but there is still a high crash rate. In 2018 there were 31 incidents in 21 races, in 2019 27 incidents in 21 races and in 2020 there were 26 incidents in 17 races (UKGamblingSites, 2022). Furthermore, research by Potter (2011) indicates that from 1950 to 1996 F1 drivers exhibit partially offsetting behavior in response to safety improvements. Specifically, a decrease in the probability of a casualty given an accident by 1%, increased the accident rate by 0.53%. Drivers responded even stronger to changes in the risk of death. When the probability of death given an accident decreased by 1%, the accident rate increased by 1.3%. So, increased safety reduces the risk of casualties and deaths given an accident, but seems to lead to more reckless behavior of the drivers. Lastly, despite all safety devices and protocols, crashes can still have serious consequences for drivers and teams. First, crashes can cause physical injuries or psychological distress to the drivers involved (Guest et al., 2016; Minoyama & Tsuchida, 2004). Second, on the side of the team, crashes can come with a big price tag due to material damage.

On top of this continuous stress due to the ever-present risk of crashes, injuries and death, there is a huge pressure to perform optimally all the time in order to score as many points as possible. The sport comprises two Championships: the Driver Championship and Constructor Championship. The goal is to win the Constructor Championship as team and win the Driver Championship as individual driver. Both championships are won by accumulating the highest number of points over all races of a season. Points are awarded based on the finishing position of the drivers in each race. Due to the non-forgiving and precise nature of F1, any minor mistake during the race could mean the difference between winning or losing (crucial points). So, everyone needs to put in their best performance every single race as there is absolutely no room for errors, not even for minor errors with non-life-threatening consequences. As F1 reporter Will Buxton said in the fourth season of the Netflix series ‘Drive to Survive’, “In the race, there’s no margin for error. No room for mistakes” (Gay-Rees et al., 2022).

Mistakes are of course inevitable when it comes to humans, F1 not being an exception. However, as far as we know, no research has looked yet at the post-error behavior of F1 drivers. As mentioned earlier, to investigate post-error behavior in a sport, it is important to define beforehand what constitutes an error and a correct action. Importantly, we cannot consider mistakes which lead to an inability to continue the race (e.g., a crash) as there is no post-error behavior to analyze. Investigating the impact of a crash on the performance in the next race would be possible but we decided against this because of the long interval between two races. Therefore, we will consider only specific in-race mistakes and correct actions. In each race, the goal is to finish as fast as possible trough driving the fastest laps. Given that errors are generally defined as a mismatch between the expected outcome and actual outcome of one’s actions (Musco et al., 2023; Wessel et al., 2012), the speed goal allows to distinguish ‘errors’ from ‘correct actions’. To investigate the effect of errors on the drivers, we will focus on lap times. We will use the time set on a previous lap as expectation for the time on the next lap. A slower lap than the preceding lap could then be considered erroneous, even when we are agnostic about the reason for the slower lap time. To avoid that slower laps are the consequence of incidents, only races without incidents will be selected. However, slower laps can still be caused by various factors, for example, by a driving error, by a lapse of attention or by traffic. This means that sometimes the driver might feel responsible for the slow down error, but other times not. We are aware that in lab tasks, one would typically distinguish these situations (e.g., Eben et al. (2023)). However, in this study, this distinction is not possible with the available data.

The Current Thesis

In this thesis we will study the post-error behavior of F1 drivers using data which is publicly available online. Our operational definition of driver-errors allows us to investigate the behavior of a driver following errors. Interestingly, this operational definition also allows us to consider the gravity of the error (i.e., how much slower a lap is than the preceding lap) as the deviation from the expectation is treated as a continuous measure. Additionally, we will take driver performance into account and explore the interaction between performance during the race (e.g., number positions gained or lost) and post-error behavioral adaptations. On the basis of adaptive accounts of error processing, we predict that drivers who adapt more after errors, will drive a better race. Lastly, we will explore whether error commission itself is correlated with performance by investigating the standard deviations and means of the difference in lap time with the preceding lap.

Due to limited and inconsistent research on post-error behavior in sports, it is difficult to formulate a hypothesis for our main research question based on previous research. Using a computer task, Yu et al. (2021) demonstrated that athletes with regular sport training showed no post-error slowing compared to controls. Furthermore, they even observed post-error speeding in the open-skill sport group. A difficult question is whether F1 should be considered an open- or closed-skill sport. When focusing only on F1 races, one could consider these open as there are frequent dynamic interactions and the drivers are faced with a lot of unpredictability. So, based on this study, we would expect post-error speeding. However, based on more applied research in the field of basketball, post-error cautiousness or no response to errors could be expected. Bocskocsky et al. (2014) and Neiman and Loewenstein (2011) both observed that basketball players are more cautious following misses and more reckless following made shots. However, Rao (2010) concluded that basketball players do not change their behavior in response to misses or hits. Since basketball and F1 are very different sports which place different demands on the athletes involved, it is unsure whether the effects found in basketball will generalize to F1. Lastly, it could also be important to consider the controllability over the outcome. More general lab research on post-error adjustment namely suggests that the feeling of control over the outcome might determine whether post-error slowing or speeding occurs

(Eben et al., 2023). However, as mentioned earlier, the reason for the slower lap time is unsure and cannot be derived from the available dataset. Therefore, it is not possible to build a clear hypothesis based on the controllability drivers experience to have over the outcome and errors.

It is clear that the results of previous studies are inconsistent, making it difficult to formulate a clear hypothesis for our main research question. We will explore what adaptations take place in the context of F1 and how these relate to previous studies. By expanding the scope of post-error research in sports beyond basketball, we aim to determine how generalizable the results are to other sports. This might in turn inform on the influence of contextual differences between sports on post-error adaptations. Furthermore, this study also has applied relevance for the world of sports, in particular for F1. Since performance and error monitoring are highly important in sports, a better understanding of post-error behavior could potentially inform on how to improve performance, train athletes or even select athletes.

Materials and Methods

Datasets

Data on the fastest lap times, races and drivers was retrieved from Ergast Developer API (http://ergast.com/mrd/). The database of Ergast Developer API includes racing data of F1 races since 1950 and can be used for non-commercial purposes. The database was downloaded in April 2022. All our analysis were performed using data from the Ergast Developer API datasets. From their database, four datafiles were used in the analyses: a file including results from the races (results.csv), a file on pit stops during the races (pit_stops.csv), a file including the lap times set in the races (lap_times.csv) and a file with information on the drivers (drivers.csv).

To select the races and to check the data of Ergast Developer API, the FIA's F1 archives were first consulted. These archives include timing information, visual lap charts and additional race information such as information on incidents. Additionally, for the race selection we also consulted online available lap charts, race reports and online available lists of red flags, yellow flags and safety car deployments. Table 1 provides an overview of all additional information sources consulted to check the Ergast Developer API data or select the races.

Information on driver performance during a race was retrieved from Ergast Developer API. Information on driver performance anno 2023 was retrieved from the FIA's archives website and the official F1 website. The data from both information sources was retrieved in April 2023 and combined into one dataset. The general performance datafile is made availble on the OSF (see Data Availability Statement).

Table 1

List of Additional Information Sources Used to Check the Data or Select Races.

Link	**Information Source**
https://www.fia.com/f1-archives	FIA's F1 archive
https://davidor.github.io/formula1-lap-charts/#/	Lap charts
https://www.formula1.com/	F1 official website
https://f1.fandom.com/wiki/Red-flagged_races	Red flagged races
https://en.wikipedia.org/wiki/List_of_red-flagged_Formula_One_races	Red flagged races
https://f1.fandom.com/wiki/Safety_Car#List_of_Safety_Car_deployments	Safety car deployments

Race Selection

For the lap time analysis, ten grands prix (GP) from 2016 to 2021 were selected. These races were selected based on the absence of red flags, yellow flags, (virtual) safety cars and collisions or incidents involving two or more cars during the race. We chose to exclude races in which any of these events occurred as the occurrence of these events could compromise the lap times set in the race. The selection was made using lap charts and technical reports available on the FIA’s F1 archives websites and using online lists of red-flagged races and safety car deployments. In case of doubt, full race reports which are available on the F1 official website were consulted. In eight out of the ten races one or more drivers retired or had technical issues. However, these drivers did not hinder any of the other drivers as this would have resulted in an intervention by the stewards (e.g., a red flag or safety car). Therefore, these races were still included but the drivers who encountered issues during the race were excluded from the analyses. Table 2 provides an overview of the races analyzed and total number of drivers included and excluded in the analyses. Table 3 provides an extensive overview of all the drivers who participated in each race and which drivers were removed from the analyses, and why.

Table 2

Overview of the Analyzed Races.

Race	**Number of drivers included**	**Number of drivers removed**
2016 Japanese GP	22	0
2017 Abu Dhabi GP	17	3
2018 Russian GP	18	2
2019 Hungarian GP	18	2
2020 Hungarian GP	19	1
2020 70th Anniversary GP	19	1
2020 Spanish GP	19	1
2021 Monaco GP	18	2
2021 French GP	20	0
2021 Dutch GP	17	3

Table 3

Extensive Overview of the Drivers who Participated in Each Race.

Surname	First name	2016 Japanese GP	2017 Abu Dhabi GP	2018 Russian GP	2019 Hungarian GP	2020 Hungarian GP	2020 70th Anniv. GP	2020 Spanish GP	2021 Monaco GP	2021 French GP	2021 Dutch GP	Total
Albon	Alexander				X	X	X	X				4
Alonso	Fernando	X	X	X					X	X	X	6
Bottas	Valtteri	X	X	X	X (D)	X	X	X	X (R)	X	X	8
Button	Jenson	X										1
Ericsson	Marcus	X	X	X								3
Gasly	Pierre		X	X (R)	X	X (R)	X	X	X	X	X	7
Giovinazzi	Antonio				X	X	X	X	X	X	X	7
Grosjean	Romain	X	X	X	X (R)	X	X	X				6
Gutiérrez	Esteban	X										1
Hamilton	Lewis	X	X	X	X	X	X	X	X	X	X	10
Hartley	Brendon		X	X (R)								1
Hülkenberg	Nico	X	X	X	X		X					5
Kubica	Robert				X						X	2
Kvyat	Daniil	X			X	X	X	X				5
Latifi	Nicholas					X	X	X	X	X	X	6
Leclerc	Charles			X	X	X	X	X (R)	X (DNS)	X	X	6
Magnussen	Kevin	X	X (R)	X	X	X	X (R)	X				5
Massa	Felipe	X	X									2
Mazepin	Nikita								X	X	X (R)	2
Nasr	Felipe	X										1
Norris	Lando				X	X	X	X	X	X	X	7
Ocon	Esteban	X	X	X		X	X	X	X	X	X	9
Palmer	Jolyon	X										1
Pérez	Sergio	X	X	X	X	X		X	X	X	X	9
Räikkönen	Kimi	X	X	X	X	X	X	X	X	X		9
Ricciardo	Daniel	X	X (R)	X	X	X	X	X	X	X	X	9
Rosberg	Nico	X										1
Russell	George				X	X	X	X	X	X	X (R)	6
Sainz	Carlos	X	X (C)	X	X	X	X	X	X	X	X	9
Schumacher	Mick								X	X	X	3
Sirotkin	Sergey			X								1
Stroll	Lance		X	X	X	X	X	X	X	X	X	9
Tsunoda	Yuki								X	X	X (R)	2
Vandoorne	Stoffel		X	X								2
Verstappen	Max	X	X	X	X	X	X	X	X	X	X	10
Vettel	Sebastian	X	X	X	X	X	X	X	X	X	X	10
Wehrlein	Pascal	X	X									2

Note. If a driver was excluded from the analysis, the reason for exclusion is indicated: retirement (R), collision involving only 1 car (C), did not start (DNS), damage without retirement (D).

Lap Time Analysis

To investigate how drivers adapt following an error, lap times of the selected races were analyzed. Differences between circuits hindered analyzing the races together as these differences impact lap times. Therefore, in a first step, each race was analyzed separately. Next, the results of these separate analyses were entered into meta-analyses.

First, the lap time data of each race was preprocessed. For each driver, the first and last lap and the lap before and after a pit stop were removed. For the remaining laps, two difference scores were calculated. First, the difference in lap time with the preceding lap was calculated, which was used as indicator of errors vs. correct actions. A positive difference indicated a slower lap than the preceding lap, while a negative difference indicated a faster lap than the preceding lap. Second, the difference with the following lap was calculated which was used to investigate adaptation. A positive difference indicated that, on the next lap, the driver slowed down, while a negative difference indicated that the driver sped up. Importantly, we took into account the fact that we removed the laps before and after a pit stop as the difference scores were only calculated for consecutive laps.

After preprocessing the data, two univariate linear regression models were fitted. In each model the difference in lap time with the preceding lap was the independent variable (Difference 1) and the difference in lap time with the following lap the dependent variable. Further, the sign of the independent variable was taken into account (i.e., whether it was a positive or negative difference) to allow for a direct comparison of the effect following errors and correct actions (Sign). In both models, a different measure of performance was taken into account to explore whether the effects differ depending on performance of the driver. In model 1, the change in positions between start and finish of each driver was entered as measure of performance (Position Change). In model 2, the finishing position of each driver was entered as measure of performance (Finishing Position). An example of a race analysis script (including the preprocessing steps) is made available on the OSF (see Data Availability Statement).

In order to generalize across different races, the relevant regression coefficients of the two univariate linear regression models obtained for each race were entered into a meta-analysis. The relevant regression coefficients are: one for the effect following a negative difference with the preceding lap, one for the difference in effect following a positive difference with the preceding lap compared to a negative difference, one for the interaction effect with performance for negative differences with the preceding lap and one for the difference in interaction effect with performance for positive differences with the preceding lap compared to negative differences. The other regression coefficients were not further analyzed as these were not relevant for our research question. As there are four relevant regression coefficients in each model, eight meta-analyses were performed in total. Significance was inferred based on the 95% confidence intervals. For each coefficient, a random-effect model was used as high heterogeneity between races was expected due to differences in the driver population, circuits and years. The heterogeneity could further be assessed using the Cochran's Q test for heterogeneity. The meta-analysis script and datafiles are available on the OSF (see Data Availability Statement).

The main analyses were followed up by a closer investigation of the standard deviations and means of the difference in lap time with the preceding lap (i.e., the deviation from the expectation) of each driver in each race. The mean indicates one's average deviation from the expectation and the standard deviation indicates how widely spread these deviations are from one's mean deviation. Specifically, potential correlations with performance measures were explored to investigate whether error commission itself is correlated with performance. Two types of performance measures were included, namely variables reflecting performance in the specific race and variables reflecting performance anno 2023. The variables reflecting in-race performance are starting position, finishing position and difference in positions between start and finish. Further, finishing position and difference in position corrected for retired drivers were also included. Specifically, these measures were corrected for all drivers behind a retiring driver. Meaning that when one driver retired, the finishing position of every driver behind him was corrected by one since this position gain could have been due to the retirement only. The variables reflecting performance anno 2023 are number of races started, number of championships won, number of race wins, number of podiums, number of career points and number of career points per started race by April 2023.

First, the standard deviation and mean was calculated separately for each driver. Next, correlation coefficients were calculated between the standard deviations and performance measures and between the means and the performance measures. Since only ten races were included, no statistical tests could be performed as there were too little datapoints. We thus provide a description of the correlation patterns that arose in our dataset. A correlation between the mean difference in lap time with the preceding lap and performance, would suggest that high or low performing drivers tend to have a higher or lower average deviation from their preceding lap time. Similarly, a correlation between the standard deviation of the difference in lap time with the preceding lap and performance, would suggest that high or low performing drivers tend to have a more or less variable deviation from one's mean deviation from their preceding lap time. The datafile and script of these exploratory analyses are available on the OSF (see Data Availability Statement).

Results

Heterogeneity across the ten races was evaluated by calculating the Cochran's Q statistic for the eight meta-analyses (Table 4). The results showed that significant heterogeneity was present in seven of the eight meta-analyses. The only exception was the third meta-analysis, which did not show significant heterogeneity at the 0.05 level of significance. Nonetheless, we chose to use random effects models for the meta-analyses given the differences in driver population, circuits and years. The lack of significant heterogeneity in the third meta-analysis does not rule out the use of a random effects model as there could still be non-significant heterogeneity. Furthermore, the other regression coefficients obtained from the same regression model did show significant heterogeneity.

Table 4

Overview of Cochrane's Q Statistics and Tests of Heterogeneity for the Eight Meta-Analyses.

Regression model	**Regression coefficient**	**Cochran's Q statistic**	**Degrees of freedom**	**P-value**
Model 1	Difference 1	54.76	9.00	< 0.0001
	Difference 1 * Sign	38.61	9.00	< 0.0001
	Difference 1 * Position Change	11.61	9.00	0.2362
	Difference 1 * Sign * Position Change	31.02	9.00	0.0003
Model 2	Difference 1	43.03	9.00	< 0.0001
	Difference 1 * Sign	38.24	9.00	< 0.0001
	Difference 1 * Finishing Position	28.93	9.00	0.0007
	Difference 1 * Sign * Finishing Position	27.55	9.00	0.0011

Table 5 reports the means and standard deviations of the independent and dependent variable for each race. The total number of datapoints analyzed in each race is also reported. In total 9855 laps over all ten races were included in the lap time analyses. The number of laps analyzed in each race varied between 789 and 1260. The mean difference in lap time with the previous lap ranges from -121.7ms to 45.6ms (Mean x) and the standard deviation from 652.3ms to 1146.8ms (SD x). The mean difference in lap time with the following lap ranges from -73.5ms to 60.9ms (Mean y) and the standard deviation from 654.7ms to 1062.8ms (SD y). Scatterplots of the lap time data are reported in Appendix A.

Table 5

Overview of the Means and Standard Deviations and Number of Observations per Analyzed Race.

Race	**Mean x (ms)**	**SD x (ms)**	**Mean y (ms)**	**SD y (ms)**	**Number of laps**
2016 Japanese GP	45.6	738.5	60.9	739.4	953
2017 Abu Dhabi GP	-58.8	889	-32.2	883.8	801
2018 Russian GP	-58.4	945.6	-32.1	938.8	811
2019 Hungarian GP	-23.5	804.6	-6.7	814.5	1105
2020 Hungarian GP	-121.7	1146.8	-73.5	1062.8	1110
2020 70th Anniversary GP	-36.9	652.3	-23.6	654.7	789
2020 Spanish GP	-9.2	745	6.2	741.6	1060
2021 Monaco GP	-51.6	960.8	-33.6	955.5	1260
2021 French GP	-30.8	789.4	-8.6	779.5	905
2021 Dutch GP	8.3	900.9	18.2	899.6	1061

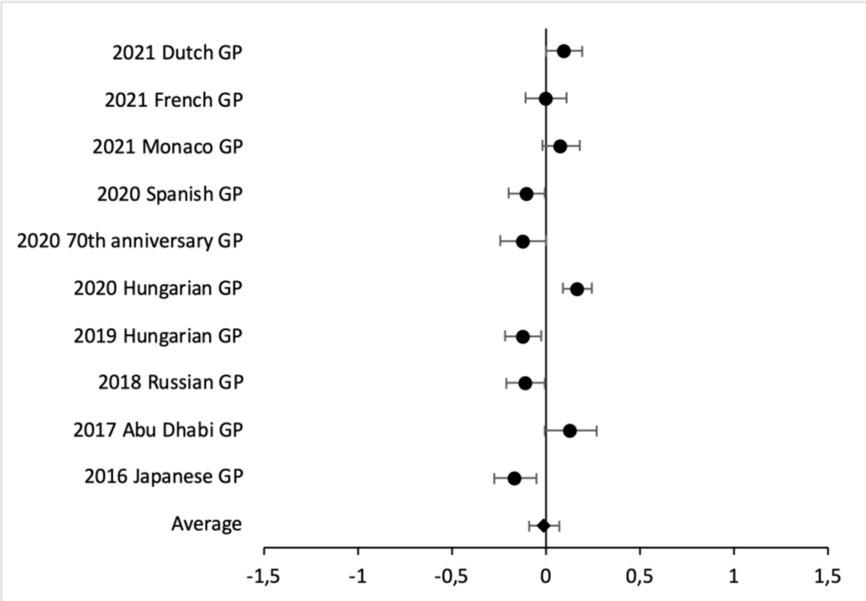
Note. This table provides an overview of the mean and standard deviation of the difference in lap time with the previous lap (x) and difference in lap time with the following lap (y) for each analyzed race. The number of laps per analyzed race is also reported.

Figure 1 provides an overview of the results of the meta-analyses on the four relevant regression coefficients of model 1. Model 1 fitted the effect of the difference in lap time with the previous lap on the difference in lap time with the following lap, taking into account the sign of independent variable and the change in positions of each driver. Panel A and B of Figure 1 indicate that the effect of a difference in lap time with the previous lap on the difference in lap time with the following lap, is significantly different depending on the sign of the difference in lap time with the previous lap and that this effect is significant for positive differences only (i.e., when a driver drove a slower lap compared to the previous lap). More specifically, the results indicate that, over all races, when a lap was faster than the lap before, there was no significant adaptation on the following lap. Further, the meta-analytical results indicate there is a significant negative effect when a driver set a slower lap time compared to the lap before. Panel C and D of Figure 1 indicate that there is no significant interaction effect between a difference with the previous lap and the change in positions, neither for positive nor for negative differences.

Figure 1

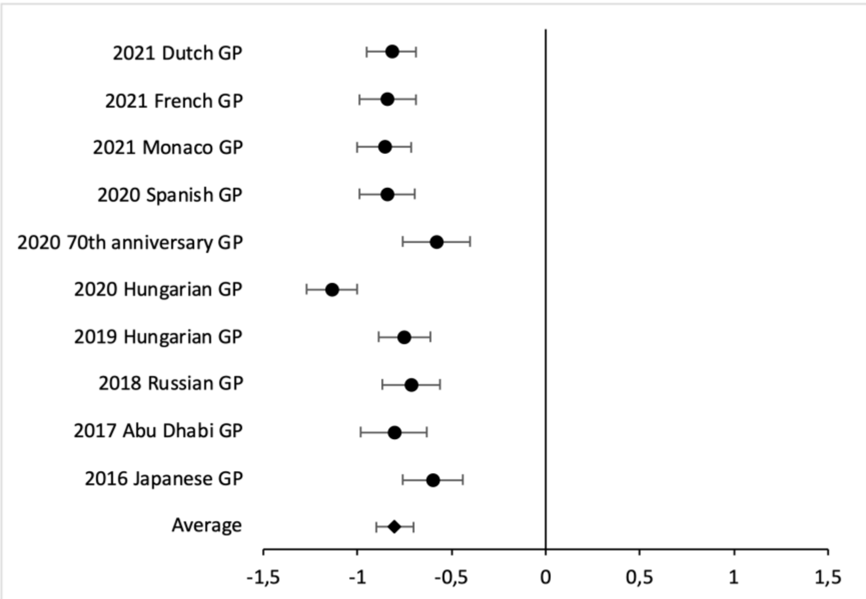
Results of the Meta-Analyses of the Relevant Regression Coefficients of Model 1.

1A. Difference 1



0.10 [0.00, 0.19]
0.00 [-0.11, 0.11]
0.08 [-0.02, 0.18]
-0.10 [-0.20, -0.01]
-0.12 [-0.24, 0.00]
0.17 [0.09, 0.25]
-0.12 [-0.21, -0.02]
-0.11 [-0.21, -0.01]
0.13 [-0.01, 0.27]
-0.16 [-0.27, -0.05]
-0.01 [-0.09, 0.07]

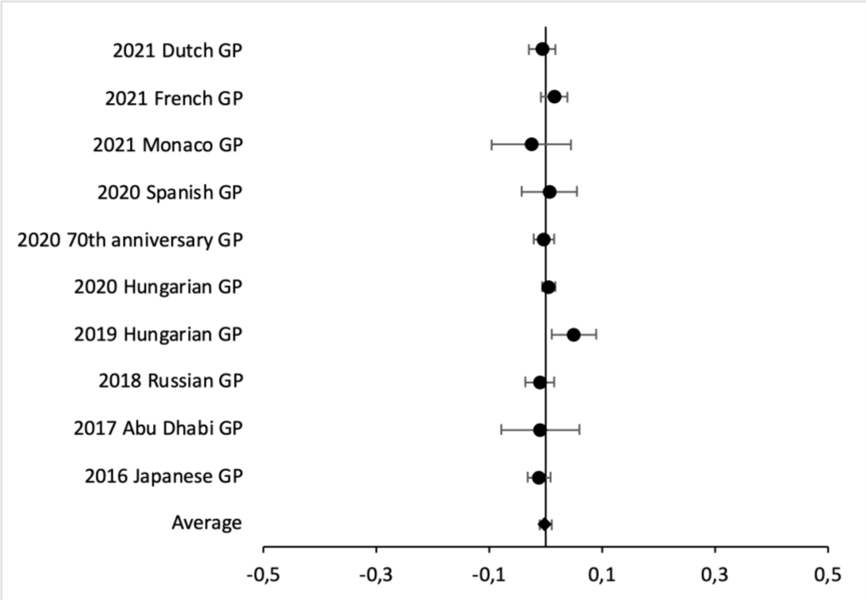
1B. Difference 1 * Sign



-0.82 [-0.95, -0.69]
-0.84 [-0.99, -0.69]
-0.86 [-1.00, -0.71]
-0.84 [-0.99, -0.70]
-0.58 [-0.76, -0.40]
-1.14 [-1.27, -1.00]
-0.75 [-0.89, -0.62]
-0.72 [-0.87, -0.56]
-0.81 [-0.98, -0.63]
-0.60 [-0.76, -0.44]
-0.80 [-0.90, -0.70]

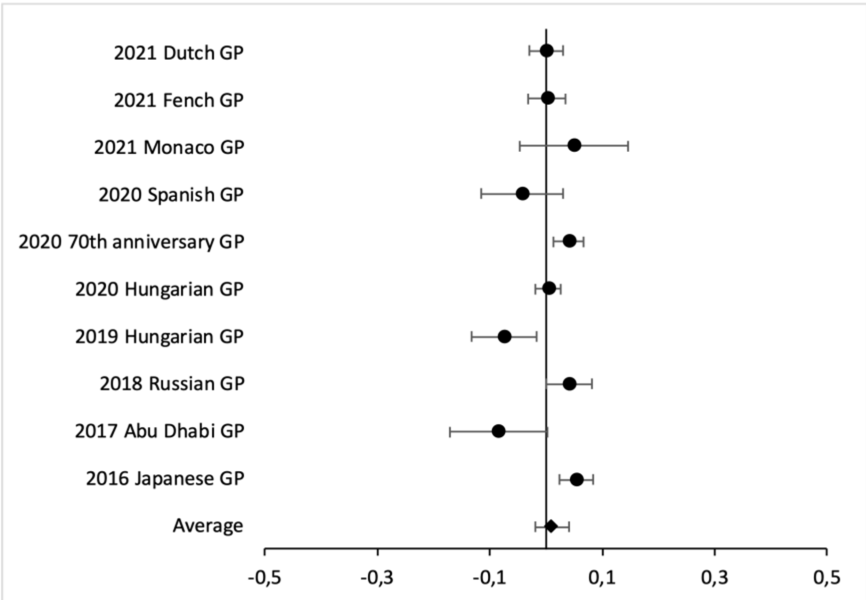
Figure 1 (continued)

1C. Difference 1 * Position Change



-0.01 [-0.03, 0.02]
0.02 [-0.01, 0.04]
-0.03 [-0.10, 0.04]
0.01 [-0.04, 0.06]
0.00 [-0.02, 0.02]
0.01 [-0.01, 0.02]
0.05 [0.01, 0.09]
-0.01 [-0.04, 0.01]
-0.01 [-0.08, 0.06]
-0.01 [-0.03, 0.01]
0.00 [-0.01, 0.01]

1D. Difference 1 * Sign * Position Change



0.00 [-0.03, 0.03]
0.00 [-0.03, 0.04]
0.05 [-0.05, 0.15]
-0.04 [-0.12, 0.03]
0.04 [0.01, 0.07]
0.00 [-0.02, 0.03]
-0.07 [-0.13, -0.02]
0.04 [0.00, 0.08]
-0.08 [-0.17, 0.00]
0.05 [0.02, 0.08]
0.01 [-0.02, 0.03]

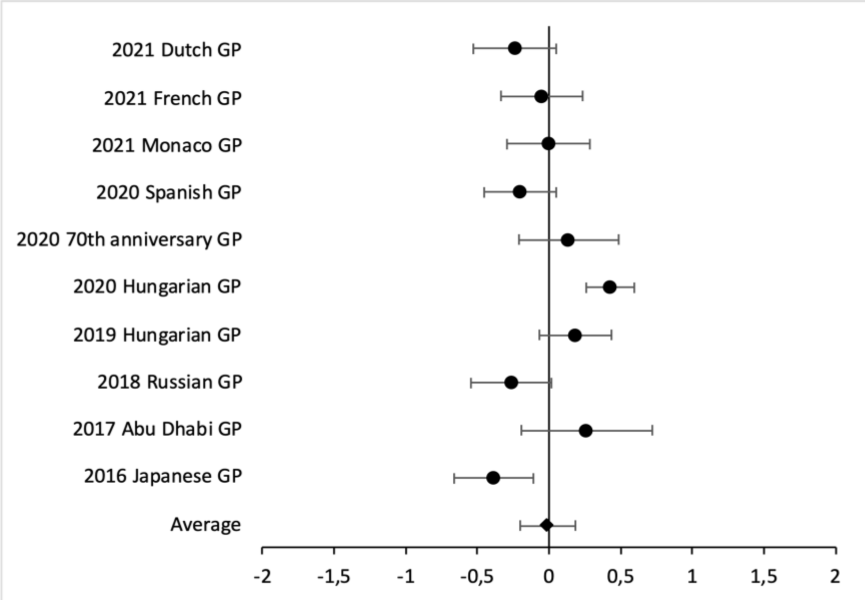
Note. Model 1 fitted the effect of the difference in lap time with the previous lap (Difference 1) on the difference in lap time with the following lap, taking into account the sign of independent variable (Sign) and the change in positions of each driver (Position Change). Panel A shows the effect for negative differences (faster lap), panel B shows the difference in effect for positive differences (slower lap) compared to negative differences, panel C shows the interaction effect with performance for negative differences and panel D shows the difference in interaction effect with performance for positive differences compared to negative differences.

Figure 2 provides an overview of the results of the meta-analyses on the four relevant regression coefficients of model 2. Model 2 fitted the effect of the difference in lap time with the previous lap on the difference in lap time with the following lap, taking into account the sign of independent variable and the finishing position of each driver. Panel A and B of Figure 2 indicate that, similar to model 1, the effect of a difference in lap time with the previous lap on the difference in lap time with the following lap, is significantly different depending on the sign of the difference in lap time with the previous lap and that this effect is significant for positive differences only (i.e., when a driver drove a slower lap compared to the previous lap). Specifically, the results indicate that, over all races, when a lap was faster than the previous lap, there was no significant difference between the lap and the next lap. So, in line with model 1, the meta-analytical results indicate that there is no significant adaptation following a faster lap. Further, the results indicate that there is a significant negative effect when a driver set a slower lap time compared to the lap before. The estimates of the effects differ slightly due to the inclusion of a different performance measure in each model. However, the meta-analytical effects are highly similar. Panel C and D of Figure 2 indicate that there is no significant interaction effect between a difference with the previous lap and the finishing position of a driver, neither for positive nor for negative differences

Figure 2

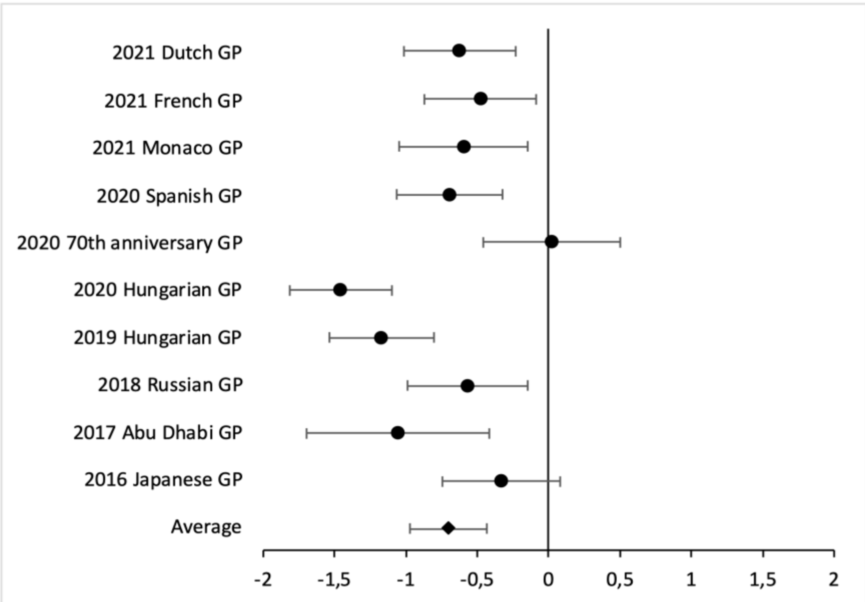
Results of the Meta-Analyses of the Relevant Regression Coefficients of Model 2.

2A. Difference 1



-0.24 [-0.53, 0.05]
-0.05 [-0.33, 0.23]
0.00 [-0.29, 0.29]
-0.20 [-0.45, 0.05]
0.14 [-0.21, 0.48]
0.43 [0.26, 0.60]
0.19 [-0.06, 0.44]
-0.26 [-0.54, 0.02]
0.26 [-0.20, 0.72]
-0.38 [-0.66, -0.11]
-0.01 [-0.20, 0.18]

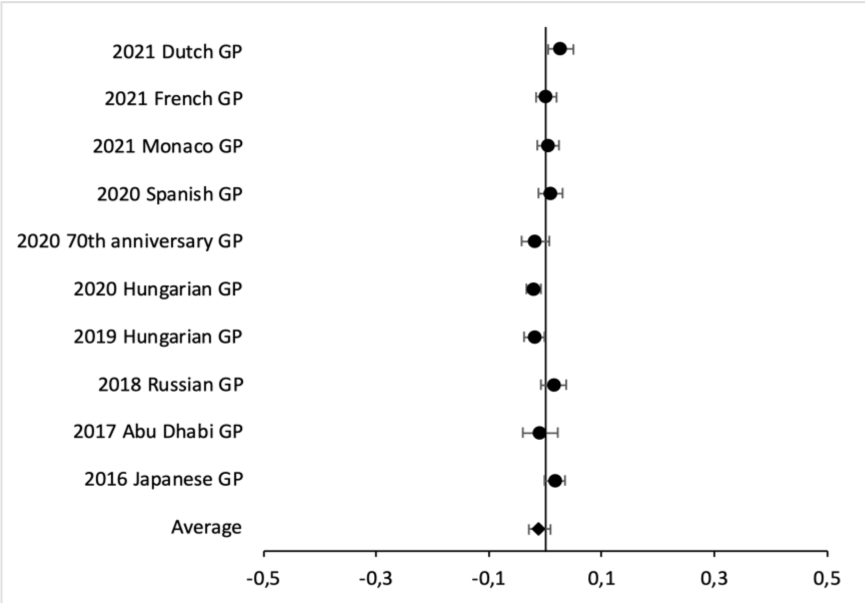
2B. Difference 1 * Sign



-0.62 [-1.02, -0.23]
-0.48 [-0.87, -0.08]
-0.60 [-1.05, -0.15]
-0.69 [-1.06, -0.33]
0.02 [-0.46, 0.50]
-1.46 [-1.81, -1.10]
-1.17 [-1.54, -0.81]
-0.57 [-0.99, -0.15]
-1.05 [-1.69, -0.41]
-0.33 [-0.75, 0.08]
-0.70 [-0.97, -0.43]

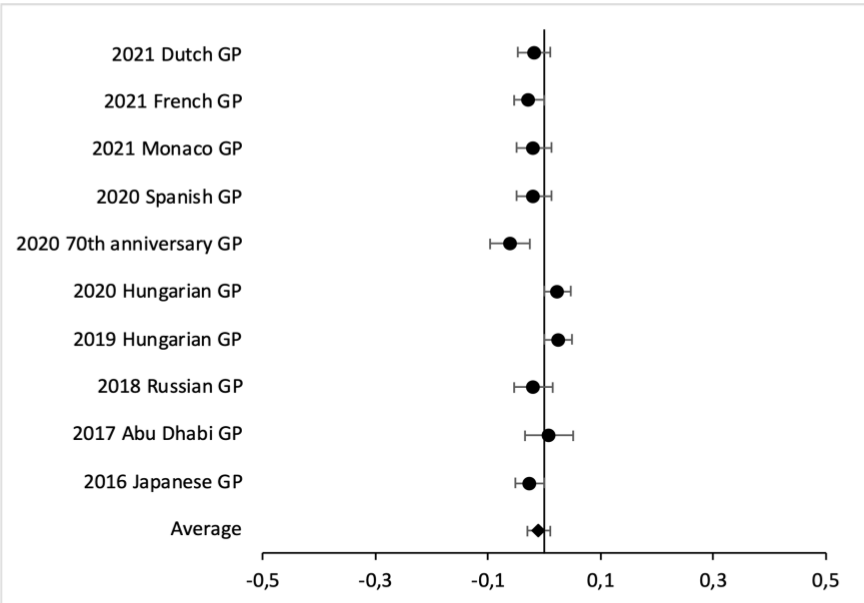
Figure 2 (continued)

2C. Difference 1 * Finishing position



0.03 [0.00, 0.05]
0.00 [-0.02, 0.02]
0.00 [-0.01, 0.02]
0.01 [-0.01, 0.03]
-0.02 [-0.04, 0.01]
-0.02 [-0.03, -0.01]
-0.02 [-0.04, 0.00]
0.02 [-0.01, 0.04]
-0.01 [-0.04, 0.02]
0.02 [0.00, 0.03]
-0.01 [-0.03, 0.00]

2D. Difference 1 * Sign * Finishing Position



-0.02 [-0.05, 0.01]
-0.03 [-0.05, 0.00]
-0.02 [-0.05, 0.01]
-0.02 [-0.05, 0.01]
-0.06 [-0.10, -0.03]
0.02 [0.00, 0.05]
0.02 [0.00, 0.05]
-0.02 [-0.05, 0.01]
0.01 [-0.03, 0.05]
-0.03 [-0.05, 0.00]
-0.01 [-0.03, 0.00]

Note. Model 2 fitted the effect of the difference in lap time with the previous lap (Difference 1) on the difference in lap time with the following lap, taking into account the sign of independent variable (Sign) and the finishing position of each driver (Finishing Position). Panel A shows the effect for negative differences (faster lap), panel B shows the difference in effect for positive differences (slower lap) compared to negative differences, panel C shows the interaction effect with performance for negative differences and panel D shows the difference in interaction effect with performance for positive differences compared to negative differences.

Finally, we explored potential correlations between performance measures and the standard deviation and the mean of the difference in lap time with the preceding lap of each driver in each race. Table 6 provides an overview of the correlation coefficients. An extensive overview of the standard deviations, means and performance measures per race per driver is provided in Appendix B.

Interestingly, the standard deviations seemed to be moderately correlated with performance in a specific race, performance in the season and performance anno 2023. The means were not to slightly correlated with performance. In each race, racers whose standard deviations were smaller had a better starting position and a better finishing position. Furthermore, when looking at the difference in positions between start and finish, racers whose standard deviations were smaller gained more places or lost less places. This pattern became even stronger when correcting for retired drivers. When focusing on performance anno 2023, similar patterns arose. Racers whose standard deviations were smaller, started in more races, won more races, were on more podiums, won more championships and won more career points by April 2023. These correlations were not due to experience only, as the number of career points per race was also higher for these racers. Importantly, these correlations are exploratory in nature as no statistical test was performed.

Table 6

Correlations Between Performance Measures and Drivers' Standard Deviation (SD) or Mean of the Difference in Lap Time with the Preceding Lap.

Variable	Correlation with SD	Correlation with Mean
Starting Pos.	0,37	-0,06
Finishing Pos.	0,57	0,01
Pos. Difference	-0,28	-0,11
Finishing Pos. Corrected	0,54	0,02
Pos. Difference Corrected	-0,31	-0,09
# R	-0,22	0,05
# C	-0,24	0,11
# W	-0,26	0,12
# P	-0,27	0,12
Career Points	-0,30	0,11
Points / R	-0,37	0,10

Note. Variables reflecting performance in a race: starting position (Starting Pos.), finishing position (Finishing Pos.), difference in positions (Pos. Difference), finishing position corrected for retired drivers (Finishing Pos. Corrected) and difference in positions corrected for retired drivers (Pos. Difference Corrected). Variables reflecting performance by April 2023: number of races started (# R), number of championships won (# C), number of race wins (# W), number of podiums (# P), number of career points (Career Points) and number of career points per started race (Points / R).

Discussion

Post-Error Behavioral Adaptations in Formula One

The objective of this thesis was to study post-error behavior in F1 racing. We analyzed lap time data from ten incident-free races between 2016 and 2021 to investigate how F1 drivers adapt following errors. Based on a general definition of errors as a mismatch between expected and actual outcome (Musco et al., 2023; Wessel et al., 2012), we formulated an operational definition of driver-errors. In our analyses, we considered the time set on the previous lap the expectation for the next lap. Consequently, a slower lap than the preceding one could be considered erroneous, as the general goal is to drive as fast as possible. The results of our meta-analyses revealed no significant adaptation following a lap on which drivers accelerated (i.e., a correct action), while faster lap times were observed following a lap on which drivers slowed down (i.e., an error). This indicates that when drivers set a slower lap compared to the lap before, they speed up again on the next lap. However, they do not show any adaptation when they set a faster lap compared to the lap before. Given our operational definition of driver-errors, these findings are in line with the concept of post-error speeding which is defined as speeding up after an error compared to after a correct response.

In lab tasks, post-error speeding has also been referred to as post-error recklessness (Williams et al., 2016). In line with this, we propose that the observed post-error speeding in F1 racing may indicate that drivers take more risks and become more reckless in an attempt to immediately compensate for a slower lap. Previous research suggests that recklessness and thrill-seeking tendencies may indeed characterize racecar drivers. A previous study examining the impact of increased safety on driver behavior found that improved safety measures resulted in drivers exhibiting more reckless behavior, partially offsetting the safety improvements (Potter, 2011). Additionally, the trait sensation-seeking has been shown to correlate with the participation in dangerous sports and fast and reckless driving (Zuckerman, 2015). Sensation-seeking is defined as "the need for varied, novel, and complex sensations and experiences and the willingness to take physical and social risks for the sake of such experiences" (Zuckerman, 1979, p. 10). Thrill-seeking, a subcategory of sensation-seeking, has also been found to predict involvement in motorsports (Yıldırım-Yenier et al., 2016). In this study, motorsport involvement was a categorical variable with three levels, namely not involved, spectator or driver. Higher thrill-seeking scores were related to higher levels of involvement (Yıldırım-Yenier et al., 2016). Although a detailed investigation of recklessness in F1 drivers specifically is lacking, these studies suggest that F1 drivers respond to external changes with heightened recklessness, and that sensation- and thrill-seeking are predict participation in motorsports and reckless driving. Therefore, we argue that the observed post-error speeding pattern in our study could also be labeled post-error recklessness, as a reckless attitude may underlie this behavior.

While our primary objective was to investigate post-error behavior in F1 racing, our findings also have implications for the phenomenon known as the 'Hot Hand'. In contrast to post-error behavior, the Hot Hand is a phenomenon related to success and refers to a greater chance of future success following a previous successful outcome (Williams et al., 2016). Whether or not the Hot Hand is a fallacy, has already been extensively debated in the field of basketball (Bocskocsky et al., 2014; Gilovich et al., 1985; Neiman & Loewenstein, 2011; Rao, 2010). However, similar to the literature on post-error behavior, research in other sports is necessary to enhance the applicability and generalizability of the findings. Our study demonstrates that, following a lap on which drivers sped up, they do not significantly speed up more or slow down again on the subsequent lap. An interesting avenue for future research could involve examining the beliefs of F1 fans and racecar drivers regarding this phenomenon. This would complement research on the Hot Hand effect in basketball, in which both behavior and beliefs regarding the hot hand effect are investigated (Gilovich et al., 1985).

We also tested the interaction effect between lap time difference scores and driver performance. We hypothesized an interaction between post-error adaptations and performance, as adaptive accounts of error processing posit that post-error processes are engaged to improve performance (Musco et al., 2023; Wessel, 2018). Given that there are many different aspects of driver performance, we considered two different performance measures: the finishing position in a race and change in positions between start and finish in a race. The results revealed no significant interaction with neither performance measures. A possible reason for the lack of interaction effect is the fact that F1 is the pinnacle of motorsport. F1 represents the highest class of international formula racing, which includes any open-wheeled single-seater motorsport. To compete in F1 as a racecar driver requires many years of dedication, hard work and outstanding performance in lower motorsport classes. Due to this selection, performance effects might be small. Another reason for the lack of interaction with performance could be the distant and indirect nature of the performance measures used, which are influenced by multiple factors beyond just post-error adaptations.

While post-error adaptations were not found to be related with performance, a further exploration of the difference scores revealed another driver factor that may be related to performance. By using a difference score between current and previous lap time as indicator of errors vs. correct actions, we were able to investigate the means and standard deviations of these difference scores. The mean indicated one's average deviation from the expected lap time and the standard deviation indicated how widely spread these deviations are from one's mean deviation. Calculating the standard deviation per driver revealed that better performance is correlated with a smaller standard deviation. This correlation was observed not only for in race performance, but also for performance two to seven years later (i.e., performance by April 2023). In contrast, the means of the difference score showed little or no correlation with the performance measures. A lower standard deviation indicates that the difference scores are closer to the mean difference score of the driver. This implies that drivers who exhibit more consistent deviations from their previous lap times tend to perform better, regardless of their mean difference from their previous lap time. So, instead of the post-error and post-correct behavioral adaptations, the consistency of the deviations from the preceding lap time seems to be correlated with performance. The correlation between the standard deviations of the difference scores and performance could also explain why no significant interaction effect between the post-error behavioral adaptations and performance was observed. It is important to note that these analyses were exploratory in nature, as the limited dataset prevented testing these correlations. Therefore, future research could aim to further investigate and evaluate the significance of these correlations. It would be particularly interesting to determine whether this deviation-consistency factor is a stable factor which predicts future performance, as these findings would have practical implications for F1 teams and academies in driver selection and training.

Advantages and Implications

Previous research on post-error behavior during real-life sport performances has predominantly focused on basketball. We have argued that research in other sports is necessary to increase our scientific understanding of post-error behavior in sports and to determine to what extent these effects generalize across sports. In line with this, our study investigated the post-error behavior of F1 drivers. Given that F1 races can be considered an open-skill sport, our results confirm the results of Yu et al. (2021) who showed post-error speeding in a group of athletes participating in open-skill sports using a computer task. However, both our results and those of Yu et al. (2021) contrast with previous research on post-error behavior in basketball, another open-skill sport (Wang et al., 2013). Studies in basketball have shown either post-error cautiousness or no response to errors (Bocskocsky et al., 2014; Neiman & Loewenstein, 2011; Rao, 2010). We identify two possible reasons for these contrasting results. First, the (operational) definition of errors differs across lab studies and different sports, making it difficult to generalize findings across these different settings. Second, while every competitive sport has the general goal to win, the exact manner to reach that goal differs greatly across sports. As a consequence, the most goal-directed and adaptive way to adapt to errors might differ across sports. It is thus possible that, similar to lab studies, (contextual) differences between sports create differences in post-error behavior across sports.

Future research on post-error processes in sports could help to disentangle which factors or dimensions determine which post-error behavioral adaptations will occur in a sport. It is possible that a dichotomous typology of sports as open- or closed-skill is unable to fully capture the differences between sports. A close investigation of the definitions of open- and closed- skill sports reveals that two important dimensions, which distinguish between sports, are intertwined. Closed-skill sports are defined as sports that are characterized by little direct interaction with an opponent, a self-paced context and little adjustment due to unpredictability. Open-skill sports are characterized by frequent dynamic interactions, an externally-paced context and a lot of unpredictability, which leads to more uncertainty and requires more flexibility (Chueh et al., 2017; Schmidt & Wrisberg, 2008; Yu et al., 2021). Within these definitions, the concepts of ‘interactivity’ and ‘agency’ are combined and assumed to be connected. However, the level of interactivity and agency in sports can vary independently of each other. Firstly, sports differ in their degree of interactivity, ranging from individual sports to interactive team-sports. On top of this, within team-sports, one can distinguish between inter- and intra-team interactions. Secondly, sports also vary in the athletes’ sense of agency, which refers to the feeling of control over one’s own actions and their consequences in the external world (Haggard, 2017; Moore, 2016). This dimension is closely related to the concept of ‘controllability’ which has been proposed to determine post-error adaptations in lab-based tasks (Eben et al., 2023). Therefore, rather than a dichotomous typology of sports, a multidimensional typology of sports might be more useful to understand the differences in post-error adaptations across sports. However, the dimensions suggested above are based primarily on the definitions of open- and closed-skill sports. To gain a good understanding of which dimensions indeed differentiate sports in terms of post-error adaptations, further research in various other sports is needed. This will contribute to a more comprehensive understanding of the factors influencing and determining post-error behavior in different sport contexts.

The main advantage of this study is the use of meta-analyses to analyze the results across the ten different F1 races from 2016 to 2021. This approach is particularly valuable as it allowed us to account for differences between races which can impact lap times, such as length of the circuits. By pooling data across the different races, we were able to obtain a more precise estimate of the overall effect across the ten races which improves the accuracy and reliability of our findings. Lastly, our meta-analytical approach increases the generalizability of our findings as races from different years with a different driving population and driven on different circuits were included in the analyses. Overall, the use of meta-analyses in our study offers valuable advantages by providing a comprehensive analysis across multiple races, accounting for race differences, and increasing the generalizability of the findings to other F1 races.

Limitations and Future Directions

The main limitation of this study is the definition of errors vs. correct actions. Due to the complex nature of F1 racing, identifying and categorizing errors proved to be complicated. Based on a general definition of errors as deviations from the expected outcome (Musco et al., 2023; Wessel et al., 2012), we operationalized driver-errors as laps with a slower lap time than the preceding lap. Our operational definition focused on lap times specifically due to the availability of precise lap time data. However, we do not exclude the possibility that other errors are present or more relevant in the sport. For example, several mistakes and errors are defined in the FIA's Sporting Regulations. When suspected incidents or breaches of these regulations occur, the FIA stewards investigate them and impose sanctions and penalties on the drivers or teams who made a mistake. We chose to not investigate the effect of these regulatory mistakes, as these often come with a punishment for the drivers. The post-error behavioral effects could therefore also reflect effects by the penalty. Nevertheless, we acknowledge that our operational definition of errors is just one possible way of defining errors in the context of F1 racing. Other errors may exist and be relevant to investigate in this sport.

There were several methodological challenges which required specific data-processing steps and decisions. First, several information sources were used to select the races as each separate source was incomplete. This approach could have resulted in certain races that meet the predetermined criteria to be overlooked. Secondly, all racecar drivers who experienced any issues during a race were completely excluded from the analysis of that race, even if they did drive some laps. This decision was made to mitigate the impact of, for example, mechanical or technical issues. However, other researchers could choose to still include these drivers in the analysis. Thirdly, due to differences between races, a decision was made to analyze each race separately and enter the regression coefficients obtained in these analyses into meta-analyses. Alternatively, other methods, such as normalizing the lap time data, could have been used to address these differences.

There are also several challenges related to the interpretation of the results due to the inherent complexity of F1 racing. Firstly, it could be argued that the fast laps following a slow lap merely reflect regression to the mean. However, on the basis of regression to the mean, one would also expect a slow lap following fast laps, which was not observed. Therefore, we argue that it is unlikely that the results are due to regression to the mean. Nevertheless, it should be acknowledged that our analyses do not completely rule out the possibility that the findings reflect an influence of other factors. While we considered a slower lap than the preceding lap erroneous, we are agnostic about the reason for the slower lap. The slower lap could have been caused by a variety of factors such as a driving errors, traffic, tire management or weather conditions. It is possible that these factors slowed down the drivers on one lap, which they then compensated on the following lap. One way to potentially investigate this alternative explanation would be to include these potential confounding factors in the linear regression models. Unfortunately, we were unable to incorporate these factors in our analyses, as the available dataset did not include information on factors such as weather conditions or traffic.

Interpretation wise, it is also possible to argue that the correlations between the standard deviations of the difference scores and performance measures are due to 'traffic', with higher-performing drivers experiencing less ‘traffic’ as they start more in front which allows them to deviate more consistently from their preceding laps. However, this statement relies on the assumption that ‘traffic’ is related to the starting position. So, while this may hold true for the correlation with starting position, it is important to note that other performance measures are also correlated with the standard deviations. One of these correlations potentially contradicts the traffic-statement, namely the correlation between the standard deviations and position change between start and finish of a race. Drivers with a smaller standard deviation, lost less or gained more positions throughout a race. If a driver gained more positions, it means they have overtaken more cars, which could also be seen as encountering traffic. So, while we are agnostic about the significance and reason for the observed correlations, we argue that attributing these correlations to the influence of traffic is also premature. As previously mentioned, more research is necessary to investigate the significance and understand the reason and predictive ability of these correlations.

Our research question can also be approached using different types of F1 data. Firstly, instead of using online data, one could use data collected by F1 teams themselves as these data are more extensive compared to online available data. For example, we were only able to investigate lap time data. However, F1 racing teams not only collect timing information on a lap basis, but also per (mini-) sector. As (mini-) sectors are smaller than laps, (mini-) sector analyses could uncover more instantaneous adaptations. Another option could be to use simulation data to investigate the post-error behavior of racecar drivers. F1 simulators recreate F1 cars in a virtual environment and are primarily used to train drivers and to learn more about the car in order to set them up as best as possible to optimize performance. Similar to F1 racing data, analyzing the simulation data could provide valuable insights into the behavior of the drivers. The main advantage of using F1 simulation data over racing data is that the data is cleaner, since many confounding factors are excluded in these simulations. Simulation data could therefore also be used to rule out that our findings reflect an influence of other factors, such as traffic, tire management or weather conditions. Additionally, with simulation data, adaptations following errors which normally prevent drivers to continue racing, such as crashes, can also be investigated. By exploring these different data types, researchers can gain a more comprehensive understanding of post-error behavior in F1 racing and uncover insights that may not be revealed from analyzing lap times alone. However, obtaining these different types of data would require a collaboration with F1 teams.

All suggestions and analyses above focused solely on racecar drivers. However, in addition to the drivers, F1 pit stop teams play a crucial role as well during an F1 race. Pit stop times can significantly impact a driver’s race performance, making it important to understand the adaptations that occur following bad vs. good pit stops. Analyzing these adaptations using racing data is challenging due to the limited number of pit stops during a race and the fact that they are spread by multiple laps. Therefore, a more useful approach might be to investigate the adaptations following a pit stop during pit stop practices. During these practices, multiple pit stops can be performed more closely to each other, providing more suitable data for the analyses of post-error behavioral adaptations. Knowledge on how pit stop teams adapt, can help to improve pit stop trainings and provide insights into pit stop strategies, which ultimately can help to enhance overall race performance.

Conclusion

The present study used online available data on lap times set in F1 races from 2016 to 2021 to investigate the post-error behavioral adaptations of F1 drivers. The meta-analytical results revealed a negative effect following errors, meaning that when drivers slowed down on a lap, they speed up again on the next lap. No significant meta-analytical adaptation was observed following a lap on which drivers sped up. Additionally, the results revealed that there was no significant interaction between these effects and performance in a race. However, further exploration of the standard deviations of the difference in lap time with a preceding lap, revealed that smaller standard deviations are correlated with better performance in a race, as well as better performance two to seven years later. This research adds to the limited research on post-error processes in sports by investigating data from real-life sport performances in a different sport than basketball. We highlighted the difference between the results in both sports and concluded that research in various other sports is needed to identify which contextual factors or dimensions determine the adaptations that take place in a sport. Studies in sports might in turn inform general research on post-error behavior, where theoretical discussions persist. Furthermore, research on errors in sports has applied relevance as it can provide valuable insight for the world of sports on how to enhance performance and select or train athletes. In conclusion, this study sheds light on the post-error behavioral adaptations of F1 drivers and emphasizes the need for research across various sports in order to determine the factors and dimensions that shape adaptive behavior in sports and to provide actionable insights for the world of sports.

Data Availability Statement

The race results, pit stop, lap time and driver information datafiles were retrieved from https://ergast.com/mrd/. The remaining datafiles and R-scripts can be found on https://osf.io/g6qn5/?view_only=7c53aa2dbf7b48cab86deaf01906516b.

References

Aversa, P., Furnari, S., & Haefliger, S. (2015). Business model configurations and performance: A qualitative comparative analysis in Formula One racing, 2005–2013. *Industrial and Corporate Change*, *24*(3), 655-676. https://doi.org/10.1093/icc/dtv012

Axerio-Cilies, J. (2012). *Predicting Formula 1 tire aerodynamics: sensitivities, uncertainties and optimization*. Stanford University.

Azmi, A., Sapit, A., Mohammed, A., Razali, M., Sadikin, A., & Nordin, N. (2017). Study on airflow characteristics of rear wing of F1 car. IOP Conference Series: Materials Science and Engineering,

Baur, H., Müller, S., Hirschmüller, A., Huber, G., & Mayer, F. (2006). Reactivity, stability, and strength performance capacity in motor sports. *British journal of sports medicine*, *40*(11), 906-910; discussion 911. https://doi.org/10.1136/bjsm.2006.025783

Bell, A., Smith, J., Sabel, C. E., & Jones, K. (2016). Formula for success: Multilevel modelling of Formula One Driver and Constructor performance, 1950–2014. *Journal of Quantitative Analysis in Sports*, *12*(2), 99-112. https://doi.org/doi:10.1515/jqas-2015-0050

Bernardi, G., Cecchetti, L., Handjaras, G., Sani, L., Gaglianese, A., Ceccarelli, R., Franzoni, F., Galetta, F., Santoro, G., Goebel, R., Ricciardi, E., & Pietrini, P. (2014). It's not all in your car: functional and structural correlates of exceptional driving skills in professional racers. *Frontiers in human neuroscience*, *8*, 888. https://doi.org/10.3389/fnhum.2014.00888

Bocskocsky, A., Ezekowitz, J., & Stein, C. (2014). The Hot Hand : A New Approach to an Old Fallacy.

Chueh, T. Y., Huang, C. J., Hsieh, S. S., Chen, K. F., Chang, Y. K., & Hung, T. M. (2017). Sports training enhances visuo-spatial cognition regardless of open-closed typology. *PeerJ*, *5*, e3336. https://doi.org/10.7717/peerj.3336

Damaso, K., Williams, P., & Heathcote, A. (2020). Evidence for different types of errors being associated with different types of post-error changes. *Psychonomic bulletin & review*, *27*(3), 435-440. https://doi.org/10.3758/s13423-019-01675-w

Danielmeier, C., Eichele, T., Forstmann, B. U., Tittgemeyer, M., & Ullsperger, M. (2011). Posterior medial frontal cortex activity predicts post-error adaptations in task-related visual and motor areas. *The Journal of neuroscience : the official journal of the Society for Neuroscience*, *31*(5), 1780-1789. https://doi.org/10.1523/JNEUROSCI.4299-10.2011

Danielmeier, C., & Ullsperger, M. (2011). Post-Error Adjustments. *Frontiers in Psychology*, *2*, 233. https://doi.org/10.3389/fpsyg.2011.00233

Desmet, C., Imbo, I., De Brauwer, J., Brass, M., Fias, W., & Notebaert, W. (2012). Error adaptation in mental arithmetic. *Quarterly journal of experimental psychology (2006)*, *65*(6), 1059-1067. https://doi.org/10.1080/17470218.2011.648943

Eben, C., Vermeylen, L., Chen, Z., Notebaert, W., Ivanchei, I., & Verbruggen, F. (2023). When Response Selection Becomes Gambling: Post-error Slowing and Speeding in Self-paced Colour Discrimination Tasks. *Collabra: Psychology*, *9*(1), 73052. https://doi.org/10.1525/collabra.73052

Eichenberger, R., & Stadelmann, D. (2009). Who Is The Best Formula 1 Driver? An Economic Approach to Evaluating Talent. *Economic Analysis and Policy*, *39*(3), 389-406. https://doi.org/10.1016/S0313-5926(09)50035-5

Gay-Rees, J., Martin, P., & Todd, S. (2022, 11 March 2022). Gloves Are Iff (Season 4, Episode 9). *Formula 1: Drive to Survive*. Netflix.

Gilovich, T., Vallone, R., & Tversky, A. (1985). The hot hand in basketball: On the misperception of random sequences. *Cognitive Psychology*, *17*(3), 295-314. https://doi.org/10.1016/0010-0285(85)90010-6

Guest, R., Tran, Y., Gopinath, B., Cameron, I. D., & Craig, A. (2016). Psychological distress following a motor vehicle crash: A systematic review of preventative interventions. *Injury*, *47*(11), 2415-2423. https://doi.org/10.1016/j.injury.2016.09.006

Haggard, P. (2017). Sense of agency in the human brain. *Nature Reviews Neuroscience*, *18*(4), 196-207. https://doi.org/10.1038/nrn.2017.14

Hajcak, G., & Simons, R. F. (2008). Oops!.. I did it again: An ERP and behavioral study of double-errors. *Brain and cognition*, *68*(1), 15-21. https://doi.org/10.1016/j.bandc.2008.02.118

Henderson, J. C., Foo, K., Lim, H., & Yip, S. (2010). Sports events and tourism: The Singapore formula one grand prix. *International Journal of Event and Festival Management*.

Jenkins, M. (2010). Technological discontinuities and competitive advantage: A historical perspective on Formula 1 motor racing 1950–2006. *Journal of Management Studies*, *47*(5), 884-910.

Jenkins, M., & Floyd, S. (2001). Trajectories in the evolution of technology: A multi-level study of competition in Formula 1 racing. *Organization studies*, *22*(6), 945-969.

Klarica, A. J. (2001). Performance in motor sports. *British journal of sports medicine*, *35*(5), 290-291. https://doi.org/10.1136/bjsm.35.5.290

Larson, M. J., LeCheminant, J. D., Carbine, K., Hill, K. R., Christenson, E., Masterson, T., & LeCheminant, R. (2015). Slow walking on a treadmill desk does not negatively affect executive abilities: an examination of cognitive control, conflict adaptation, response inhibition, and post-error slowing. *Frontiers in Psychology*, *6*. https://doi.org/10.3389/fpsyg.2015.00723

Minoyama, O., & Tsuchida, H. (2004). Injuries in professional motor car racing drivers at a racing circuit between 1996 and 2000. *British journal of sports medicine*, *38*(5), 613-616. https://doi.org/10.1136/bjsm.2003.007674

Moore, J. W. (2016). What Is the Sense of Agency and Why Does it Matter? [Review]. *Frontiers in Psychology*, *7*. https://doi.org/10.3389/fpsyg.2016.01272

Musco, M. A., Zazzera, E., Paulesu, E., & Sacheli, L. M. (2023). Error observation as a window on performance monitoring in social contexts? A systematic review. *Neuroscience & Biobehavioral Reviews*, *147*, 105077. https://doi.org/10.1016/j.neubiorev.2023.105077

Neiman, T., & Loewenstein, Y. (2011). Reinforcement learning in professional basketball players. *Nature communications*, *2*, 569. https://doi.org/10.1038/ncomms1580

Notebaert, W., Houtman, F., Opstal, F. V., Gevers, W., Fias, W., & Verguts, T. (2009). Post-error slowing: an orienting account. *Cognition*, *111*(2), 275-279. https://doi.org/10.1016/j.cognition.2009.02.002

Notebaert, W., & Verguts, T. (2011). Conflict and error adaptation in the Simon task. *Acta Psychologica*, *136*(2), 212-216. https://doi.org/10.1016/j.actpsy.2010.05.006

Patil, A., Kshirsagar, S., & Parge, T. (2014). Study of front wing of formula one car using computational fluid dynamics. *International Journal of Mechanical Engineering and Robotics Research*, *3*(4), 282.

Phillips, A. J. K. (2014). Uncovering Formula One driver performances from 1950 to 2013 by adjusting for team and competition effects. *Journal of Quantitative Analysis in Sports*, *10*(2), 261-278. https://doi.org/10.1515/jqas-2013-0031

Potkanowicz, E. S., & Mendel, R. W. (2013). The case for driver science in motorsport: a review and recommendations. *Sports medicine (Auckland, N.Z.)*, *43*(7), 565-574. https://doi.org/10.1007/s40279-013-0040-2

Potter, J. M. (2011). Estimating the Offsetting Effects of Driver Behavior in Response to Safety Regulation: The Case of Formula One Racing. *Journal of Quantitative Analysis in Sports*, *7*(3). https://doi.org/10.2202/1559-0410.1276

Prat, L. I. (2018). *Study of the aerodynamics of the Formula 1 rear wheels* Universitat Politècnica de Catalunya].

Rao, J. (2010). Experts' Perceptions of Autocorrelation: The Hot Hand Fallacy Among Professional Basketball Players.

Rind, E., & Hu, Z. W. (2007). Aerodynamics of F1 car side mirror.

Schmidt, R. A., & Wrisberg, C. A. (2008). *Motor learning and performance: A situation-based learning approach*. Human kinetics.

Schroder, H., & Moser, J. (2014). Improving the study of error monitoring with consideration of behavioral performance measures. *Frontiers in human neuroscience*, *8*, 178. https://doi.org/10.3389/fnhum.2014.00178

Steinhauser, M., & Kiesel, A. (2011). Performance monitoring and the causal attribution of errors. *Cognitive, affective & behavioral neuroscience*, *11*(3), 309-320. https://doi.org/10.3758/s13415-011-0033-2

Themanson, J. R., & Hillman, C. H. (2006). Cardiorespiratory fitness and acute aerobic exercise effects on neuroelectric and behavioral measures of action monitoring. *Neuroscience*, *141*(2), 757-767. https://doi.org/10.1016/j.neuroscience.2006.04.004

Themanson, J. R., Pontifex, M. B., & Hillman, C. H. (2008). Fitness and action monitoring: evidence for improved cognitive flexibility in young adults. *Neuroscience*, *157*(2), 319-328. https://doi.org/10.1016/j.neuroscience.2008.09.014

UKGamblingSites. (2022, 10 march 2022). *How Often Do F1 Drivers Crash?* Retrieved 18 march 2022 from https://www.ukgamblingsites.com/sports-betting/f1/how-often-do-f1-drivers-crash/

Van der Borght, L., Desmet, C., & Notebaert, W. (2016). Strategy Changes After Errors Improve Performance [Original Research]. *Frontiers in Psychology*, *6*. https://doi.org/10.3389/fpsyg.2015.02051

van Leeuwen, P. M., de Groot, S., Happee, R., & de Winter, J. C. F. (2017). Differences between racing and non-racing drivers: A simulator study using eye-tracking. *PloS one*, *12*(11), e0186871. https://doi.org/10.1371/journal.pone.0186871

Verbruggen, F., Chambers, C. D., Lawrence, N. S., & McLaren, I. P. L. (2017). Winning and losing: Effects on impulsive action. *Journal of Experimental Psychology: Human Perception and Performance*, *43*(1), 147-168. https://doi.org/10.1037/xhp0000284

Wang, C.-H., Chang, C.-C., Liang, Y.-M., Shih, C.-M., Chiu, W.-S., Tseng, P., Hung, D. L., Tzeng, O. J. L., Muggleton, N. G., & Juan, C.-H. (2013). Open vs. Closed Skill Sports and the Modulation of Inhibitory Control. *PloS one*, *8*(2), e55773. https://doi.org/10.1371/journal.pone.0055773

Wessel, J. R. (2018). An adaptive orienting theory of error processing. *Psychophysiology*, *55*(3), e13041. https://doi.org/10.1111/psyp.13041

Wessel, J. R., Danielmeier, C., Morton, J. B., & Ullsperger, M. (2012). Surprise and Error: Common Neuronal Architecture for the Processing of Errors and Novelty. *The Journal of Neuroscience*, *32*(22), 7528. https://doi.org/10.1523/JNEUROSCI.6352-11.2012

Williams, P., Heathcote, A., Nesbitt, K., & Eidels, A. (2016). Post-error recklessness and the hot hand. *Judgment and Decision Making*, *11*, 174-184.

Yıldırım-Yenier, Z., Vingilis, E., Wiesenthal, D. L., Mann, R. E., & Seeley, J. (2016). Relationships between thrill seeking, speeding attitudes, and driving violations among a sample of motorsports spectators and drivers. *Accident Analysis & Prevention*, *86*, 16-22. https://doi.org/10.1016/j.aap.2015.09.014

Yu, C. C., Muggleton, N. G., Chen, C. Y., Ko, C. H., & Liu, S. (2021). The comparisons of inhibitory control and post-error behaviors between different types of athletes and physically inactive adults. *PloS one*, *16*(8), e0256272. https://doi.org/10.1371/journal.pone.0256272

Zuckerman, M. (2015). Sensation Seeking: Behavioral Expressions and Biosocial Bases. In J. D. Wright (Ed.), *International Encyclopedia of the Social & Behavioral Sciences (Second Edition)* (pp. 607-614). Elsevier. https://doi.org/10.1016/B978-0-08-097086-8.25036-8

Zuckerman, M. S. (1979). Sensation Seeking : Beyond the Optimal Level of Arousal.

Appendix A: Scatterplots Lap Time Data

Figure A1

Scatterplots of the Lap Time Difference Scores for the 2016 Japanese GP.

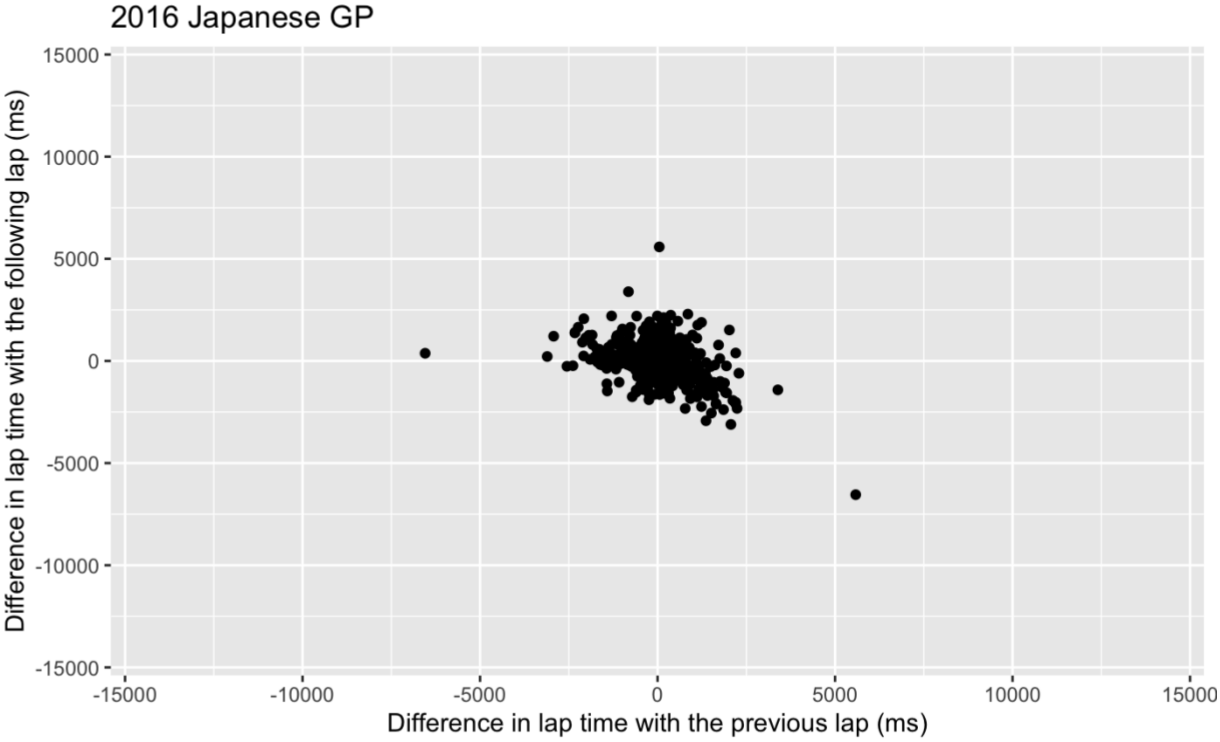


Figure A2

Scatterplots of the Lap Time Difference Scores for the 2017 Abu Dhabi GP.

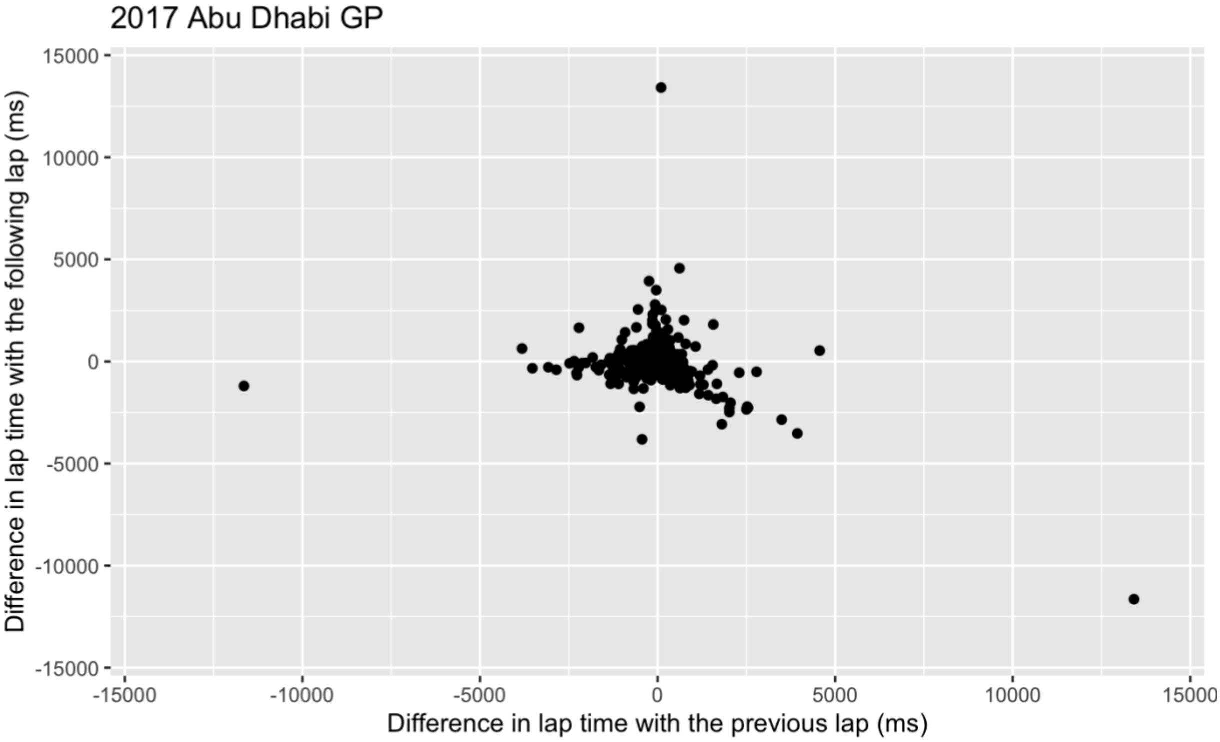


Figure A3

Scatterplots of the Lap Time Difference Scores for the 2018 Russian GP.

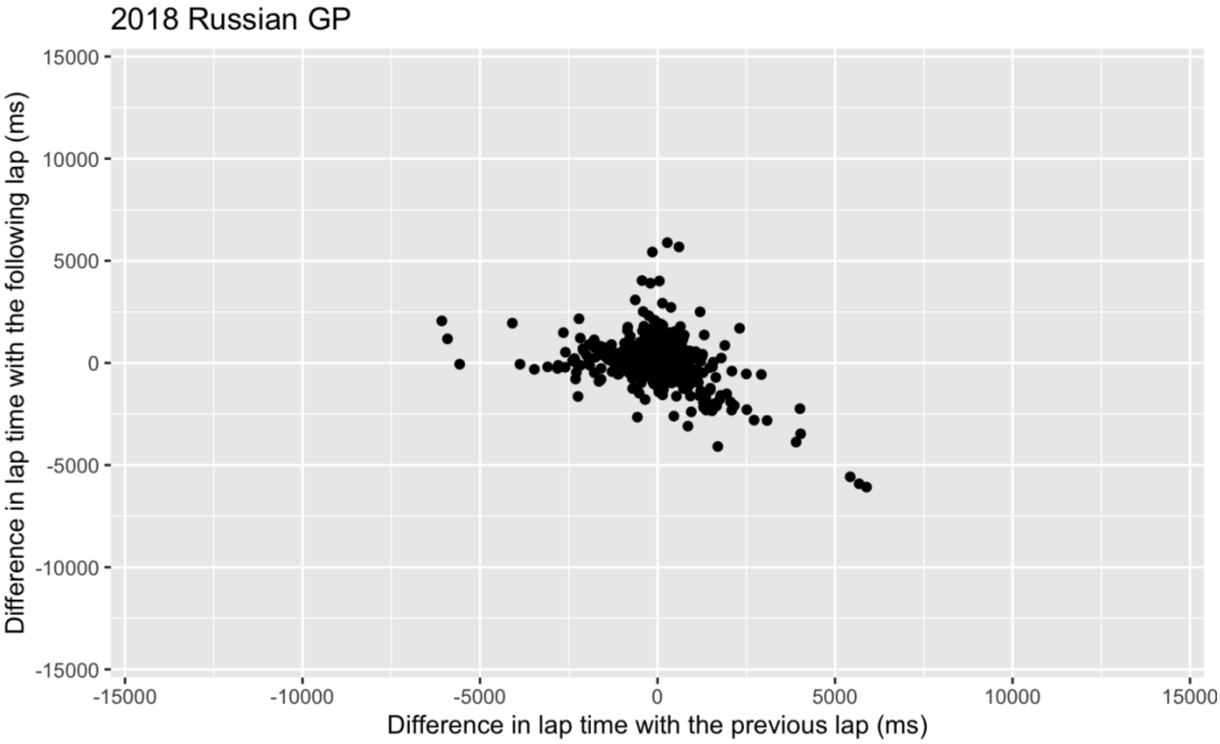


Figure A4

Scatterplots of the Lap Time Difference Scores for the 2019 Hungarian GP.

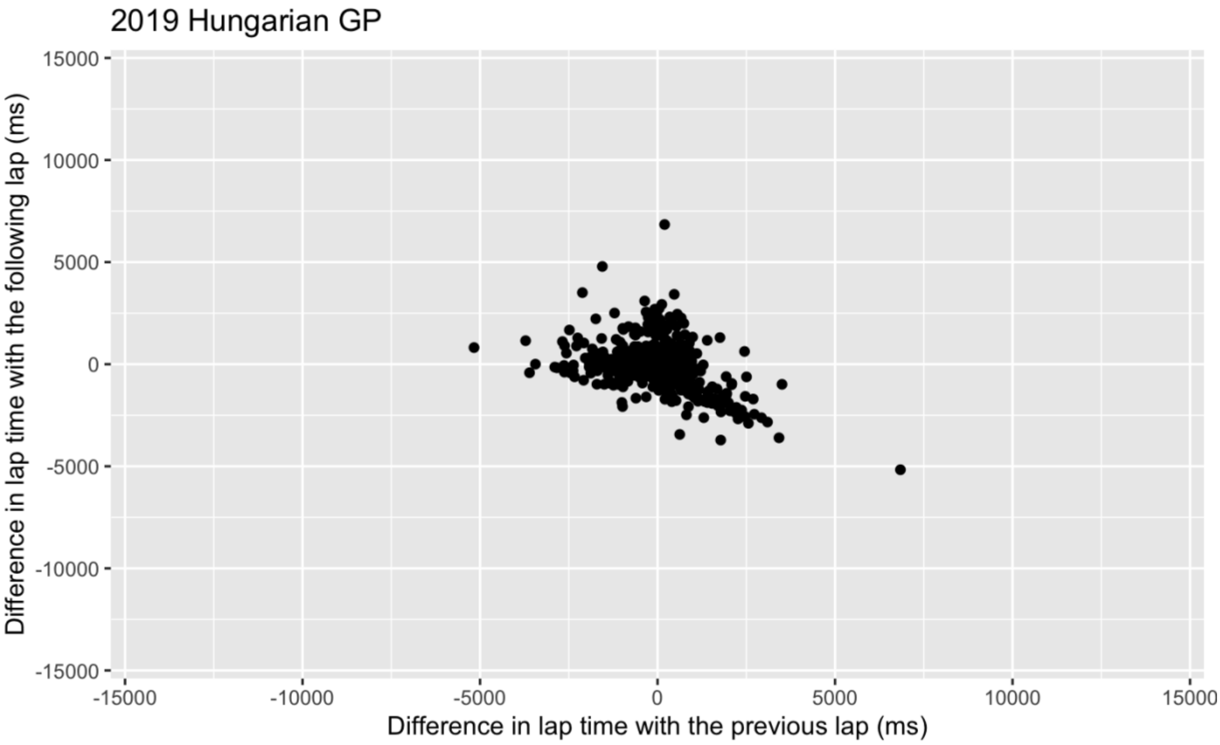


Figure A5

Scatterplots of the Lap Time Difference Scores for the 2020 Hungarian GP.

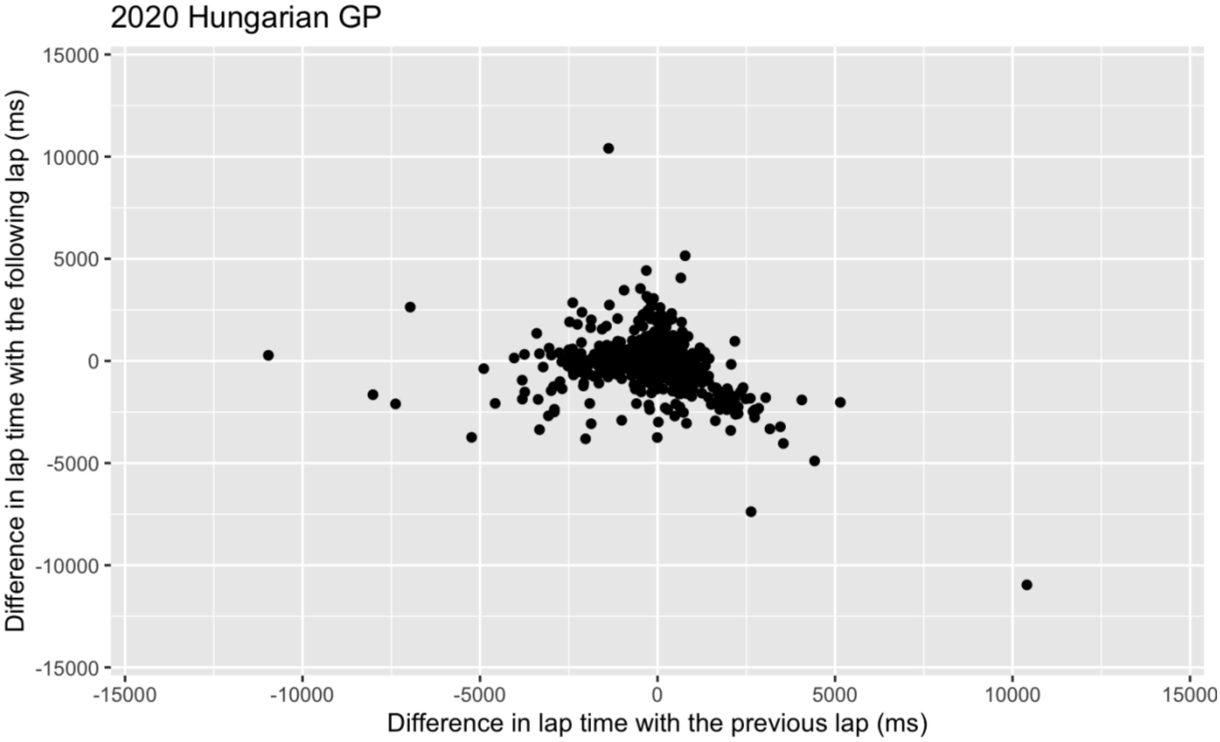


Figure A6

Scatterplots of the Lap Time Difference Scores for the 2020 70th Anniversary GP.

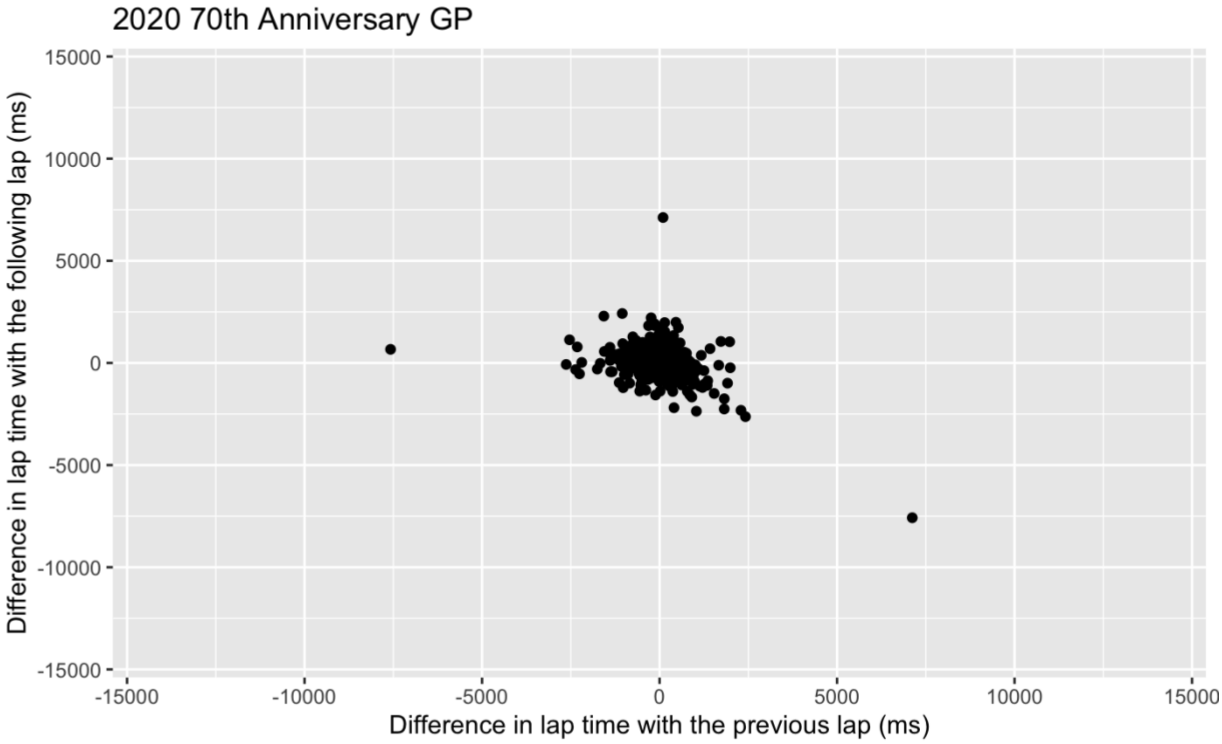


Figure A7

Scatterplots of the Lap Time Difference Scores for the 2020 Spanish GP.

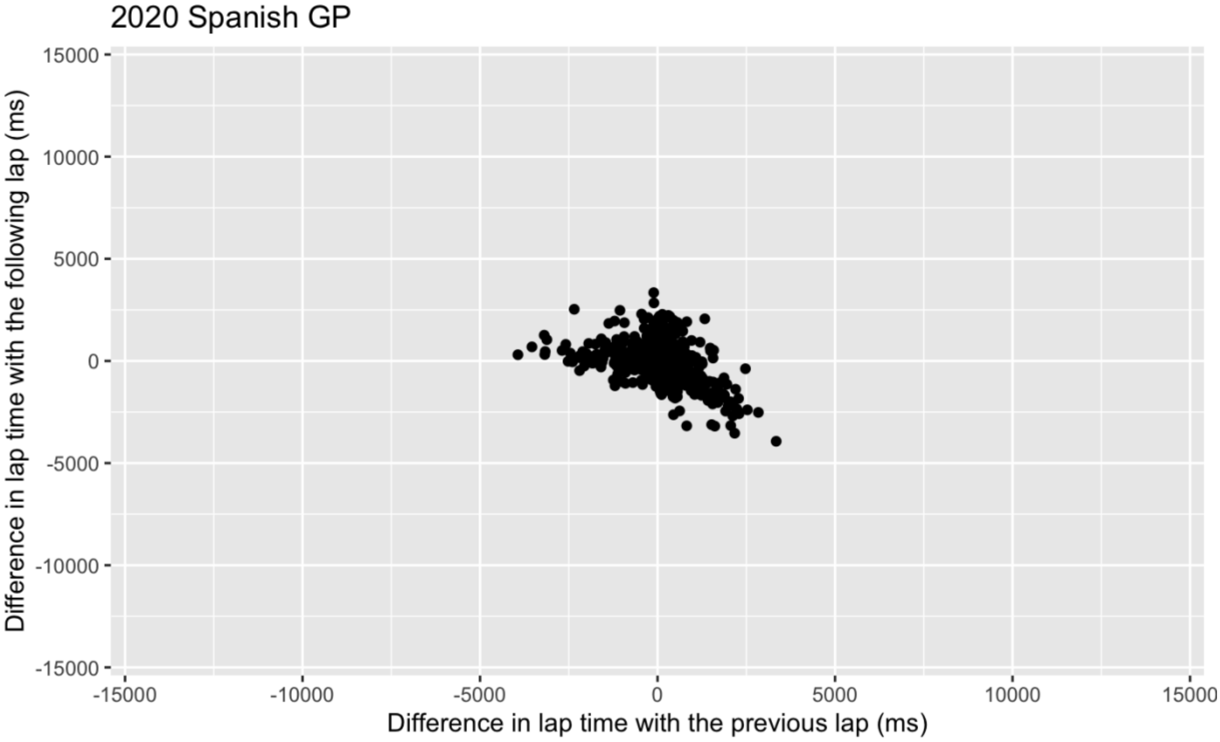


Figure A8

Scatterplots of the Lap Time Difference Scores for the 2021 Monaco GP.

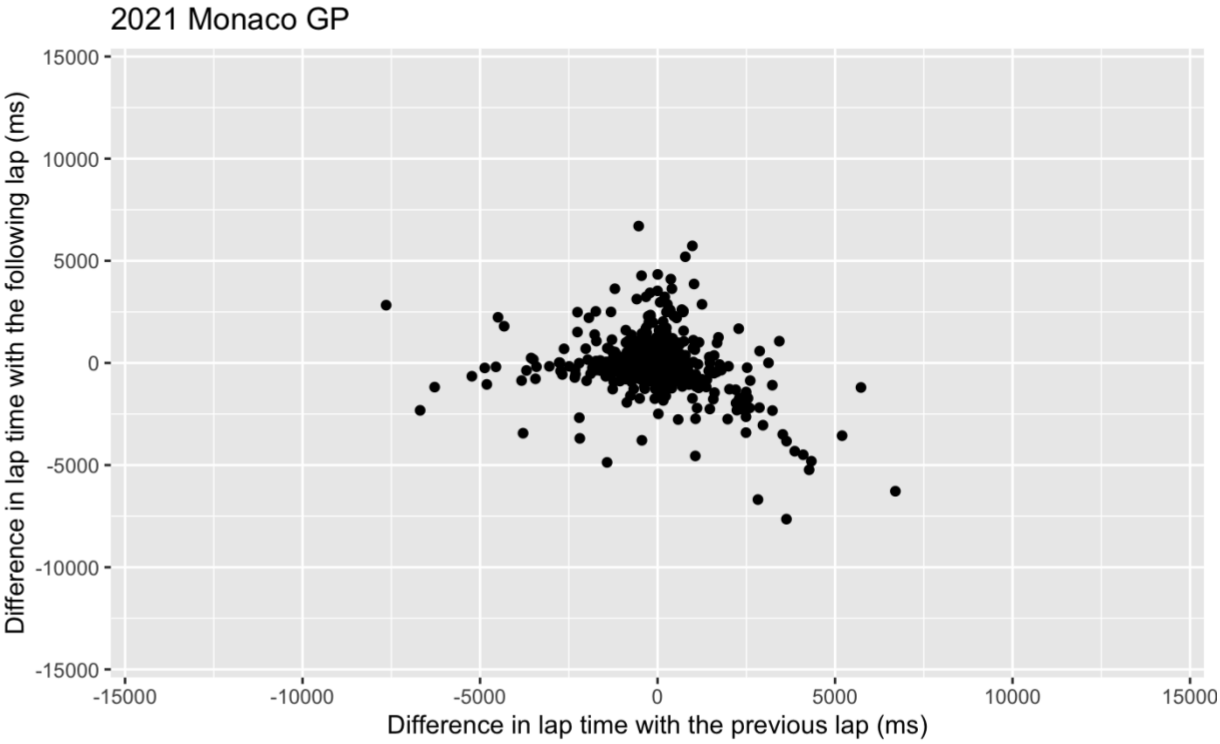


Figure A9

Scatterplots of the Lap Time Difference Scores for the 2021 French GP.

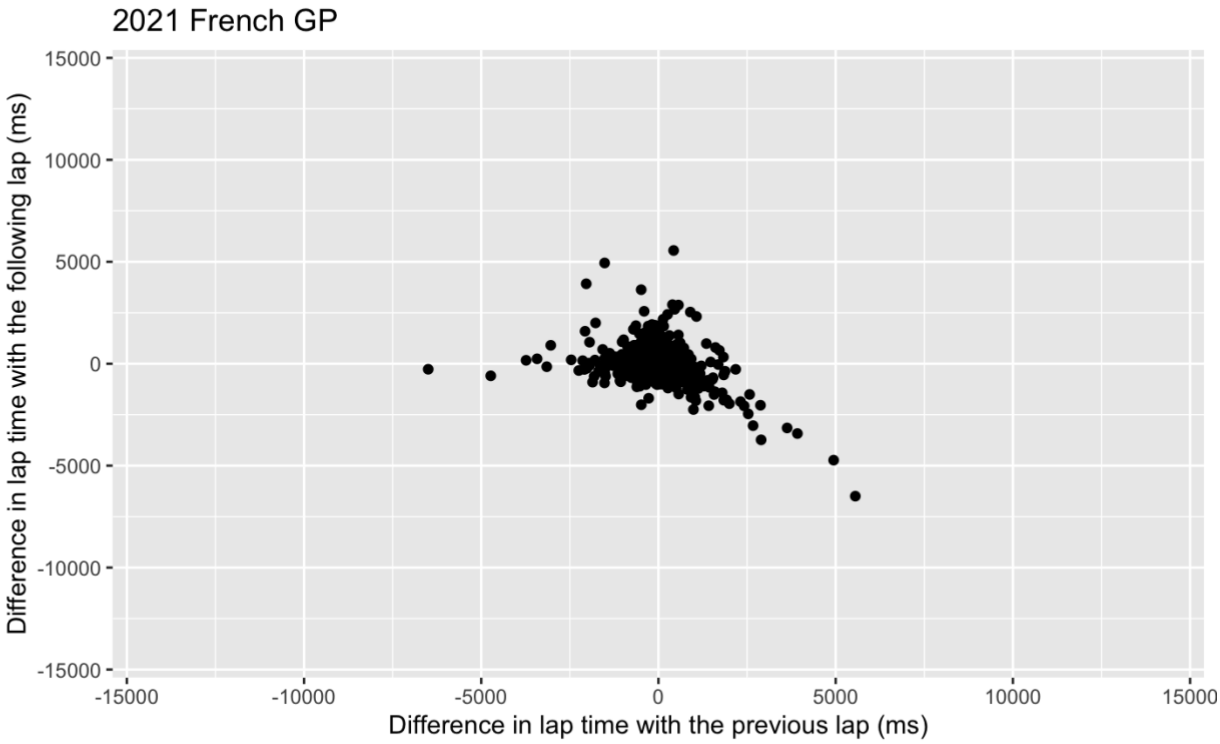
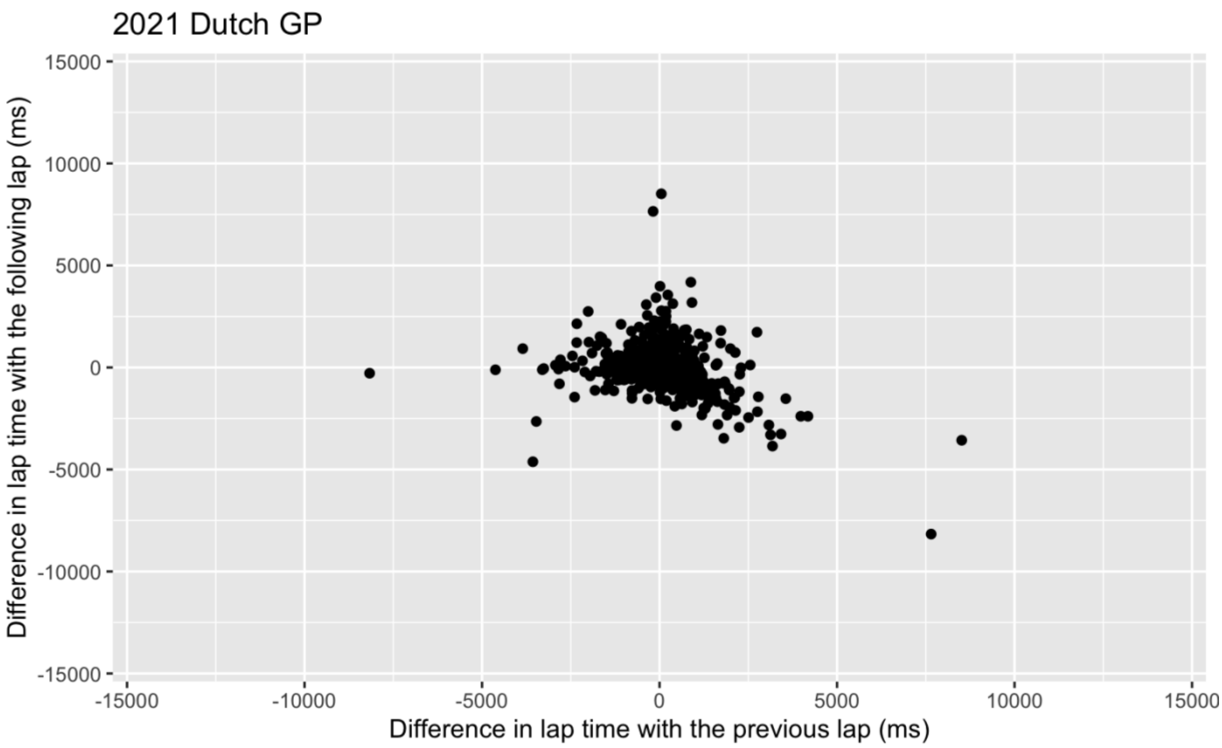


Figure A10

Scatterplots of the Lap Time Difference Scores for the 2021 Dutch GP.



Appendix B: Standard Deviations and Means of the 'Difference in Lap Time with the Previous Lap' and Performance Measures per Race

Table B1

Overview of the Standard Deviation (SD), Mean and Performance Measures of Each Driver in the 2016 Japanese GP.

Surname	SD (ms)	Mean (ms)	Starting Pos.	Finishing Pos.	Pos. Difference	# R	# C	# W	# P	Career Points	# Points / R
Bottas	323,18	0,76	11	10	1	204	0	10	67	1791	8,78
Verstappen	387,62	67,98	3	2	1	167	2	37	81	2104,5	12,6
Vettel	403,55	142,86	6	4	2	299	4	53	122	3098	10,36
Rosberg	404,84	73,21	1	1	0	206	1*	23	57	1594,5	7,74
Hamilton	449,91	49,95	2	3	-1	314	7	103	192	4453,5	14,18
Ricciardo	452,13	52,51	4	6	-2	232	0	8	32	1311	5,65
Massa	467,20	38,50	12	9	3	269	0	11	41	1167	4,34
Grosjean	614,76	105,77	7	11	-4	179	0	0	10	391	2,18
Button	619,67	59,29	22	18	4	306	1	15	50	1235	4,04
Pérez	653,98	45,33	5	7	-2	239	0	6	29	1288	5,39
Ericsson	667,41	0,49	18	15	3	97	0	0	0	18	0,19
Hülkenberg	677,50	21,00	9	8	1	179	0	0	10	391	2,18
Magnussen	741,41	14,51	17	14	3	145	0	0	1	184	1,27
Alonso	814,82	52,67	15	16	-1	359	2	32	101	2121	5,91
Palmer	828,58	-1,93	16	12	4	35	0	0	0	9	0,26
Kvyat	829,55	37,83	13	13	0	110	0	0	3	202	1,84
Ocon	845,48	63,62	20	21	-1	115	0	1	2	368	3,2
Räikkönen	850,61	57,60	8	5	3	349	1	21	103	1873	5,37
Wehrlein	870,93	92,36	21	22	-1	39	0	0	0	6	0,15
Nasr	909,52	-32,98	19	19	0	39	0	0	0	29	0,74
Sainz	1027,22	-4,05	14	17	-3	166	0	1	15	816,5	4,92
Gutiérrez	1539,99	80,88	10	20	-10	59	0	0	0	6	0,1

Note. Ordered from small to large SDs

Table B2

Overview of the Standard Deviation (SD), Mean and Performance Measures of Each Driver in the 2017 Abu Dhabi GP.

Surname	SD (ms)	Mean (ms)	Starting Pos.	Finishing Pos.	Pos. Difference	# R	# C	# W	# P	Career Points	# Points / R
Vettel	242,83	-68,60	3	3	0	299	4	53	122	3098	10,36
Hülkenberg	251,57	-77,42	7	6	1	179	0	0	10	391	2,18
Räikkönen	284,35	-35,08	5	4	1	349	1	21	103	1873	5,37
Hamilton	288,83	-0,56	2	2	0	314	7*	103	192	4453,5	14,18
Pérez	335,63	-56,44	8	7	1	239	0	6	29	1288	5,39
Bottas	354,65	-55,29	1	1	0	204	0	10	67	1791	8,78
Ocon	376,76	-47,65	9	8	1	115	0	1	2	368	3,2
Verstappen	439,72	-50,27	6	5	1	167	2	37	81	2104,5	12,6
Alonso	741,36	-51,09	11	9	2	359	2	32	101	2121	5,91
Ericsson	775,95	-174,23	19	17	2	97	0	0	0	18	0,19
Wehrlein	789,07	-79,40	18	14	4	39	0	0	0	6	0,15
Massa	823,00	-70,64	10	10	0	269	0	11	41	1167	4,34
Hartley	848,86	-64,77	20	15	5	25	0	0	0	4	0,16
Stroll	867,26	84,46	15	18	-3	126	0	0	3	221	1,75
Grosjean	888,39	-88,74	16	11	5	179	0	0	10	391	2,18
Vandoorne	902,40	-77,51	13	12	1	41	0	0	0	26	0,63
Gasly	2719,58	-69,19	17	16	1	112	0	1	2	336	3

Note. Ordered from small to large SDs

Table B3

Overview of the Standard Deviation (SD), Mean and Performance Measures of Each Driver in the 2018 Russian GP.

Surname	SD (ms)	Mean (ms)	Starting Pos.	Finishing Pos.	Pos. Difference	# R	# C	# W	# P	Career Points	# Points / R
Leclerc	397,94	-46,54	7	7	0	106	0	5	25	896	8,45
Räikkönen	418,96	-30,85	4	4	0	349	1	21	103	1873	5,37
Verstappen	477,92	-87,59	19	5	14	167	2	37	81	2104,5	12,6
Hamilton	526,35	-89,74	2	1	1	314	7*	103	192	4453,5	14,18
Ericsson	580,24	-27,10	10	13	-3	97	0	0	0	18	0,19
Alonso	689,89	-54,31	16	14	2	359	2	32	101	2121	5,91
Bottas	751,27	-91,04	1	2	-1	204	0	10	67	1791	8,78
Vettel	761,98	-59,93	3	3	0	299	4	53	122	3098	10,36
Ricciardo	778,14	-60,20	18	6	12	232	0	8	32	1311	5,65
Magnussen	815,46	-102,80	5	8	-3	145	0	0	1	184	1,27
Stroll	871,42	3,96	14	15	-1	126	0	0	3	221	1,75
Ocon	976,01	-64,78	6	9	-3	115	0	1	2	368	3,2
Pérez	1101,62	-113,87	8	10	-2	239	0	6	29	1288	5,39
Sirotkin	1146,70	35,18	13	18	-5	21	0	0	0	1	0,05
Sainz	1329,74	-57,93	11	17	-6	166	0	1	15	816,5	4,92
Vandoorne	1389,95	-11,95	15	16	-1	41	0	0	0	26	0,63
Grosjean	1491,66	-89,44	9	11	-2	179	0	0	10	391	2,18
Hülkenberg	1509,25	-95,71	12	12	0	179	0	0	10	391	2,18

Note. Ordered from small to large SDs

Table B4

Overview of the Standard Deviation (SD), Mean and Performance Measures of Each Driver in the 2019 Hungarian GP.

Surname	SD (ms)	Mean (ms)	Starting Pos.	Finishing Pos.	Pos. Difference	# R	# C	# W	# P	Career Points	# Points / R
Gasly	392,00	-38,87	6	6	0	112	0	1	2	336	3
Vettel	437,20	21,59	5	3	2	299	4	53	122	3098	10,36
Verstappen	480,96	14,50	1	2	-1	167	2	37	81	2104,5	12,6
Sainz	525,66	-33,19	8	5	3	166	0	1	15	816,5	4,92
Hamilton	531,95	33,92	3	1	2	314	7*	103	192	4453,5	14,18
Leclerc	539,90	51,71	4	4	0	106	0	5	25	896	8,45
Räikkönen	639,32	-43,73	10	7	3	349	1	21	103	1873	5,37
Hülkenberg	639,86	-31,13	11	12	-1	179	0	0	10	391	2,18
Kvyat	714,70	-48,20	13	15	-2	110	0	0	3	202	1,84
Magnussen	759,58	-82,90	14	13	1	145	0	0	1	184	1,27
Norris	784,52	-51,74	7	9	-2	86	0	0	6	438	5,09
Ricciardo	838,95	-64,32	20	14	6	232	0	8	32	1311	5,65
Stroll	912,50	3,19	18	17	1	126	0	0	3	221	1,75
Albon	915,27	-62,95	12	10	2	63	0	0	2	202	3,21
Pérez	960,96	-27,06	16	11	5	239	0	6	29	1288	5,39
Russell	1108,91	-17,44	15	16	-1	86	0	1	9	322	3,74
Giovinazzi	1124,68	-8,80	17	18	-1	62	0	0	0	21	0,34
Kubica	1461,05	-34,38	19	19	0	99	0	1	12	274	2,77

Note. Ordered from small to large SDs

Table B5

Overview of the Standard Deviation (SD), Mean and Performance Measures of Each Driver in the 2020 Hungarian GP.

Surname	SD (ms)	Mean (ms)	Starting Pos.	Finishing Pos.	Pos. Difference	# R	# C	# W	# P	Career Points	# Points / R
Verstappen	401,90	-3,92	8	2	6	167	2	37	81	2104,5	12,6
Stroll	638,40	-108,44	4	4	0	126	0	0	3	221	1,75
Hamilton	651,25	-107,60	2	1	1	314	7*	103	192	4453,5	14,18
Giovinazzi	684,80	23,39	18	17	1	62	0	0	0	21	0,34
Albon	742,53	-168,20	14	5	9	63	0	0	2	202	3,21
Norris	833,84	-31,14	9	13	-4	86	0	0	6	438	5,09
Ricciardo	857,26	-88,25	12	8	4	232	0	8	32	1311	5,65
Vettel	920,44	-94,20	6	6	0	299	4	53	122	3098	10,36
Bottas	952,27	-170,69	3	3	0	204	0	10	67	1791	8,78
Kvyat	989,19	-184,72	17	12	5	110	0	0	3	202	1,84
Ocon	1021,11	-79,98	15	14	1	115	0	1	2	368	3,2
Russell	1034,72	-32,07	13	18	-5	86	0	1	9	322	3,74
Räikkönen	1039,32	-114,97	19	15	4	349	1	21	103	1873	5,37
Magnussen	1131,57	-265,71	1	10	-9	145	0	0	1	184	1,27
Sainz	1142,65	-177,22	10	9	1	166	0	1	15	816,5	4,92
Leclerc	1241,73	-162,45	7	11	-4	106	0	5	25	896	8,45
Pérez	1304,14	-198,47	5	7	-2	239	0	6	29	1288	5,39
Grosjean	1670,37	-233,11	1	16	-15	179	0	0	10	391	2,18
Latifi	2914,96	-79,23	16	19	-3	61	0	0	0	9	0,15

Note. Ordered from small to large SDs

Table B6

Overview of the Standard Deviation (SD), Mean and Performance Measures of Each Driver in the 2020 70th Anniversary GP.

Surname	SD (ms)	Mean (ms)	Starting Pos.	Finishing Pos.	Pos. Difference	# R	# C	# W	# P	Career Points	# Points / R
Verstappen	237,85	-80,62	4	1	3	167	2	37	81	2104,5	12,6
Sainz	332,29	-51,07	12	13	-1	166	0	1	15	816,5	4,92
Vettel	333,64	-69,14	11	12	-1	299	4	53	122	3098	10,36
Stroll	350,60	-28,52	6	6	0	126	0	0	3	221	1,75
Kvyat	355,38	-74,55	16	10	6	110	0	0	3	202	1,84
Hülkenberg	365,49	-31,10	3	7	-4	179	0	0	10	391	2,18
Norris	424,80	-91,62	10	9	1	86	0	0	6	438	5,09
Leclerc	442,63	14,78	8	4	4	106	0	5	25	896	8,45
Gasly	448,59	-76,90	7	11	-4	112	0	1	2	336	3
Ocon	467,42	-96,42	14	8	6	115	0	1	2	368	3,2
Hamilton	515,67	62,17	2	2	0	314	7*	103	192	4453,5	14,18
Bottas	557,78	44,50	1	3	-2	204	0	10	67	1791	8,78
Albon	605,43	-49,93	9	5	4	63	0	0	2	202	3,21
Russell	620,26	6,55	15	18	-3	86	0	1	9	322	3,74
Giovinazzi	732,79	-33,15	19	17	2	62	0	0	0	21	0,34
Grosjean	761,52	-50,61	13	16	-3	179	0	0	10	391	2,18
Latifi	801,75	-36,71	18	19	-1	61	0	0	0	9	0,15
Räikkönen	911,85	-48,82	20	15	5	349	1	21	103	1873	5,37
Ricciardo	1770,95	-0,08	5	14	-9	232	0	8	32	1311	5,65

Note. Ordered from small to large SDs

Table B7

Overview of the Standard Deviation (SD), Mean and Performance Measures of Each Driver in the 2020 Spanish GP.

Surname	SD (ms)	Mean (ms)	Starting Pos.	Finishing Pos.	Pos. Difference	# R	# C	# W	# P	Career Points	# Points / R
Verstappen	399,23	-2,05	3	2	1	167	2	37	81	2104,5	12,6
Hamilton	417,19	-39,71	1	1	0	314	7*	103	192	4453,5	14,18
Bottas	421,25	14,96	2	3	-1	204	0	10	67	1791	8,78
Stroll	538,27	17,55	5	4	1	126	0	0	3	221	1,75
Latifi	594,30	29,61	19	18	1	61	0	0	0	9	0,15
Ocon	628,33	-83,34	15	13	2	115	0	1	2	368	3,2
Pérez	637,94	12,90	4	5	-1	239	0	6	29	1288	5,39
Russell	651,12	33,53	18	17	1	86	0	1	9	322	3,74
Kvyat	699,76	43,69	12	12	0	110	0	0	3	202	1,84
Sainz	710,42	-41,24	7	6	1	166	0	1	15	816,5	4,92
Magnussen	768,16	-32,72	16	15	1	145	0	0	1	184	1,27
Vettel	784,74	-12,55	11	7	4	299	4	53	122	3098	10,36
Grosjean	787,31	26,87	17	19	-2	179	0	0	10	391	2,18
Albon	800,19	4,16	6	8	-2	63	0	0	2	202	3,21
Gasly	847,78	-1,16	10	9	1	112	0	1	2	336	3
Norris	858,11	-64,71	8	10	-2	86	0	0	6	438	5,09
Giovinazzi	917,20	20,58	20	16	4	62	0	0	0	21	0,34
Ricciardo	1065,16	-111,29	13	11	2	232	0	8	32	1311	5,65
Räikkönen	1186,65	21,85	14	14	0	349	1	21	103	1873	5,37

Note. Ordered from small to large SDs

Table B8

Overview of the Standard Deviation (SD), Mean and Performance Measures of Each Driver in the 2021 Monaco GP.

Surname	SD (ms)	Mean (ms)	Starting Pos.	Finishing Pos.	Pos. Difference	# R	# C	# W	# P	Career Points	# Points / R
Verstappen	370,42	-25,58	1	1	0	167	2*	37	81	2104,5	12,6
Sainz	391,39	-7,58	3	2	1	166	0	1	15	816,5	4,92
Vettel	409,59	-44,44	7	5	2	299	4	53	122	3098	10,36
Norris	420,13	-23,83	4	3	1	86	0	0	6	438	5,09
Gasly	494,03	-74,27	5	6	-1	112	0	1	2	336	3
Pérez	511,08	-84,62	8	4	4	239	0	6	29	1288	5,39
Giovinazzi	583,48	0,70	9	10	-1	62	0	0	0	21	0,34
Hamilton	613,80	-60,78	6	7	-1	314	7	103	192	4453,5	14,18
Stroll	743,27	-72,71	12	8	4	126	0	0	3	221	1,75
Ocon	805,96	-46,80	10	9	1	115	0	1	2	368	3,2
Latifi	885,46	-14,10	17	15	2	61	0	0	0	9	0,15
Alonso	907,20	-23,33	16	13	3	359	2	32	101	2121	5,91
Tsunoda	979,66	-50,66	15	16	-1	46	0	0	0	46	1
Ricciardo	1174,74	-30,74	11	12	-1	232	0	8	32	1311	5,65
Räikkönen	1194,30	-82,74	13	11	2	349	1	21	103	1873	5,37
Russell	1414,30	-63,51	14	14	0	86	0	1	9	322	3,74
Mazepin	1700,56	-63,76	18	17	1	21	0	0	0	0	0
Schumacher	1918,05	-163,74	19	18	1	43	0	0	0	12	0,28

Note. Ordered from small to large SDs

Table B9

Overview of the Standard Deviation (SD), Mean and Performance Measures of Each Driver in the 2021 French GP.

Surname	SD (ms)	Mean (ms)	Starting Pos.	Finishing Pos.	Pos. Difference	# R	# C	# W	# P	Career Points	# Points / R
Hamilton	419,61	3,74	3	2	1	314	7	103	192	4453,5	14,18
Stroll	434,33	-76,15	20	10	10	126	0	0	3	221	1,75
Verstappen	440,69	8,63	2	1	1	167	2*	37	81	2104,5	12,6
Gasly	440,90	-13,28	7	7	0	112	0	1	2	336	3
Ricciardo	522,19	-30,26	11	6	5	232	0	8	32	1311	5,65
Pérez	615,40	-33,76	5	3	2	239	0	6	29	1288	5,39
Mazepin	631,33	-36,76	19	20	-1	21	0	0	0	0	0
Giovinazzi	636,44	-24,13	14	15	-1	62	0	0	0	21	0,34
Russell	638,46	-73,11	15	12	3	86	0	1	9	322	3,74
Norris	683,42	-84,74	9	5	4	86	0	0	6	438	5,09
Sainz	743,77	1,63	6	11	-5	166	0	1	15	816,5	4,92
Bottas	754,44	8,98	4	4	0	204	0	10	67	1791	8,78
Latifi	757,99	-100,67	17	18	-1	61	0	0	0	9	0,15
Ocon	782,48	-17,69	12	14	-2	115	0	1	2	368	3,2
Alonso	804,14	-50,11	10	8	2	359	2	32	101	2121	5,91
Vettel	826,98	-82,33	13	9	4	299	4	53	122	3098	10,36
Tsunoda	841,67	-19,09	1	13	-12	46	0	0	0	46	1
Räikkönen	1003,25	4,78	18	17	1	349	1	21	103	1873	5,37
Leclerc	1100,73	57,10	8	16	-8	106	0	5	25	896	8,45
Schumacher	1847,68	-51,02	16	19	-3	43	0	0	0	12	0,28

Note. Ordered from small to large SDs

Table B10

Overview of the Standard Deviation (SD), Mean and Performance Measures of Each Driver in the 2021 Dutch GP.

Surname	SD (ms)	Mean (ms)	Starting Pos.	Finishing Pos.	Pos. Difference	# R	# C	# W	# P	Career Points	# Points / R
Gasly	430,43	12,42	5	4	1	112	0	1	2	336	3
Verstappen	454,95	10,98	2	1	1	167	2*	37	81	2104,5	12,6
Leclerc	474,09	-5,50	6	5	1	106	0	5	25	896	8,45
Ricciardo	573,16	-38,58	11	11	0	232	0	8	32	1311	5,65
Bottas	584,11	35,84	4	3	1	204	0	10	67	1791	8,78
Ocon	602,35	-4,17	9	9	0	115	0	1	2	368	3,2
Hamilton	612,93	47,45	3	2	1	314	7	103	192	4453,5	14,18
Alonso	623,77	-33,30	10	6	4	359	2	32	101	2121	5,91
Sainz	710,84	-20,11	7	7	0	166	0	1	15	816,5	4,92
Giovinazzi	769,22	-36,07	8	14	-6	62	0	0	0	21	0,34
Norris	810,40	-38,38	14	10	4	86	0	0	6	438	5,09
Stroll	896,47	-1,63	13	12	1	126	0	0	3	221	1,75
Kubica	905,34	37,63	17	15	2	99	0	1	12	274	2,77
Pérez	958,28	109,90	1	8	-7	239	0	6	29	1288	5,39
Latifi	1059,03	62,73	1	16	-15	61	0	0	0	9	0,15
Vettel	1634,90	-31,40	16	13	3	299	4	53	122	3098	10,36
Schumacher	1938,75	39,66	18	18	0	43	0	0	0	12	0,28

Note. Ordered from small to large SDs