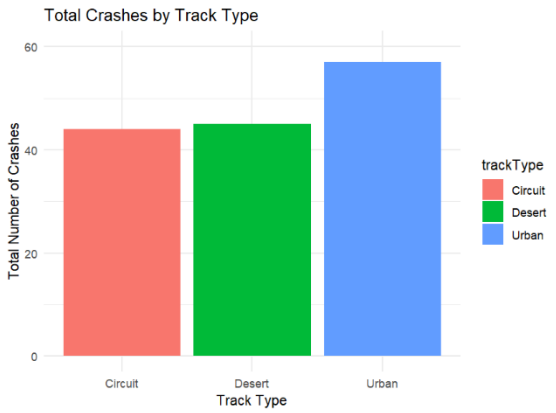
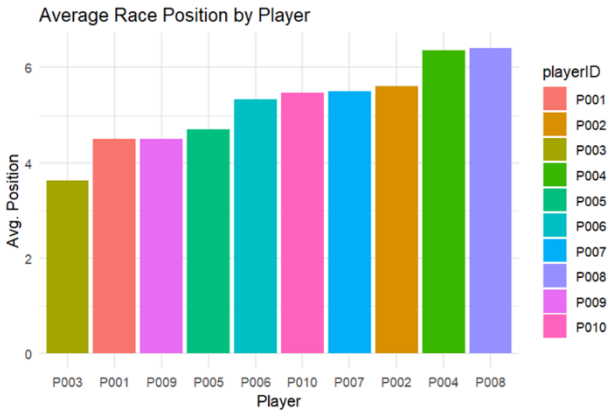
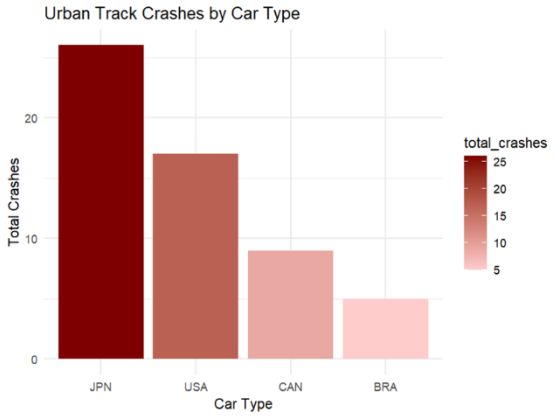
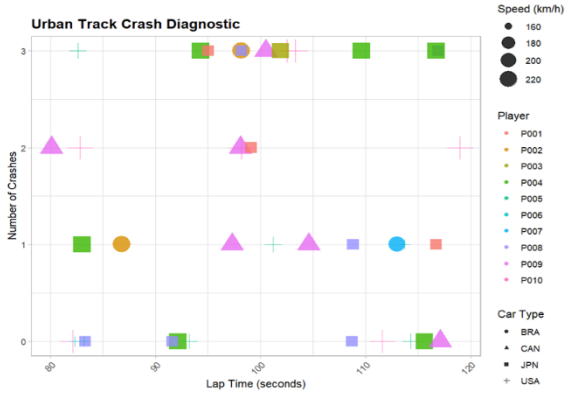
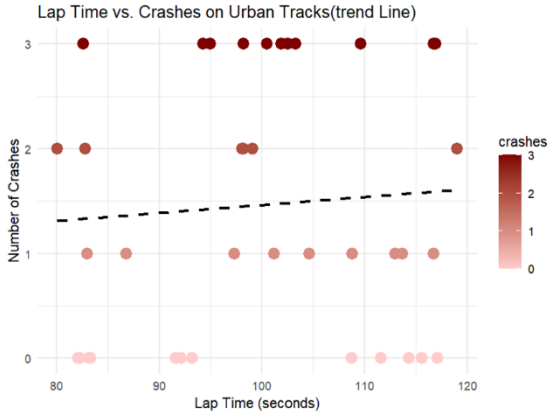
CAR RACING DASHBOARD

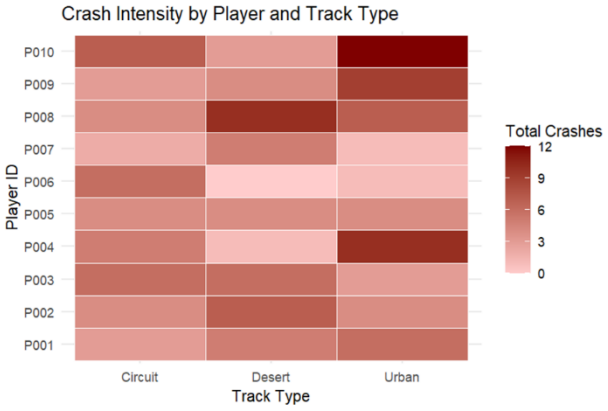












Created By Ali Muhammad- Tool used: R Language, Microsoft Excel

Portfolio Case Study Layout: *Urban Track Crash Analytics*

Urban Track Crash Analytics

A multi-dimensional analysis of player behavior, car dynamics, and track design

My name is Ali Muhammad, and I specialize in data storytelling, dashboard design, and performance analytics. This case study showcases my ability to simulate racing data, uncover crash patterns, and translate complex insights into accessible, visually compelling narratives.

Executive Summary

This case study explores crash dynamics on simulated racing tracks, with a focused lens on Urban environments. Using R and ggplot2, I analyzed player behavior, car performance, and track design to uncover patterns in crash frequency and race outcomes.

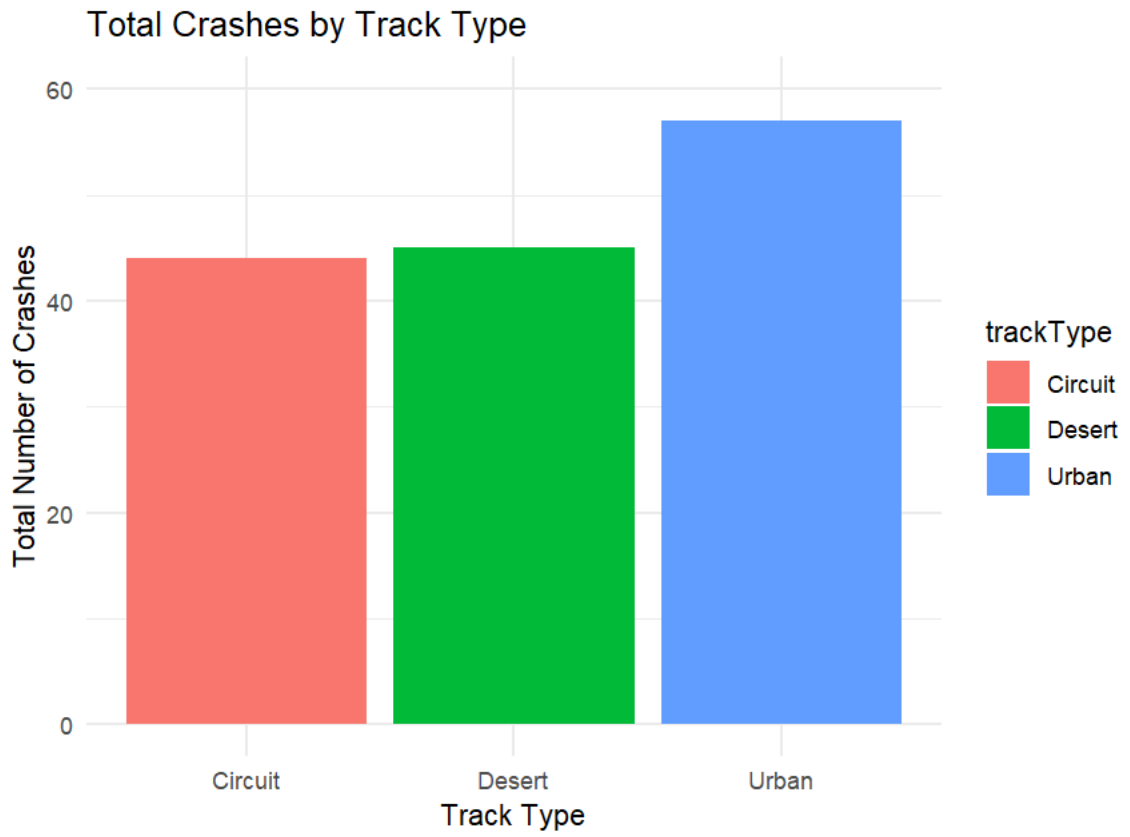
The dataset includes 10 players across 100 races, with variables such as lap time, speed, car type, and track type. Through multi-dimensional visualizations and diagnostic charts, I identified key risk factors and performance trends.

Key Findings:

- Urban tracks have the highest crash rate but also the best average race position
- Player P010 crashes most frequently, while P003 consistently ranks highest in performance
- Japanese car types show elevated crash counts on Urban tracks
- Speed and lap time influence crash frequency, but not always predictably
- Multi-variable diagnostics reveal risky combinations of player, car, and track

This project demonstrates my ability to simulate complex datasets, build accessible visual narratives, and translate raw data into actionable insights. It reflects my approach to data storytelling, dashboard design, and performance analysis—combining analytical rigor with audience-focused clarity.

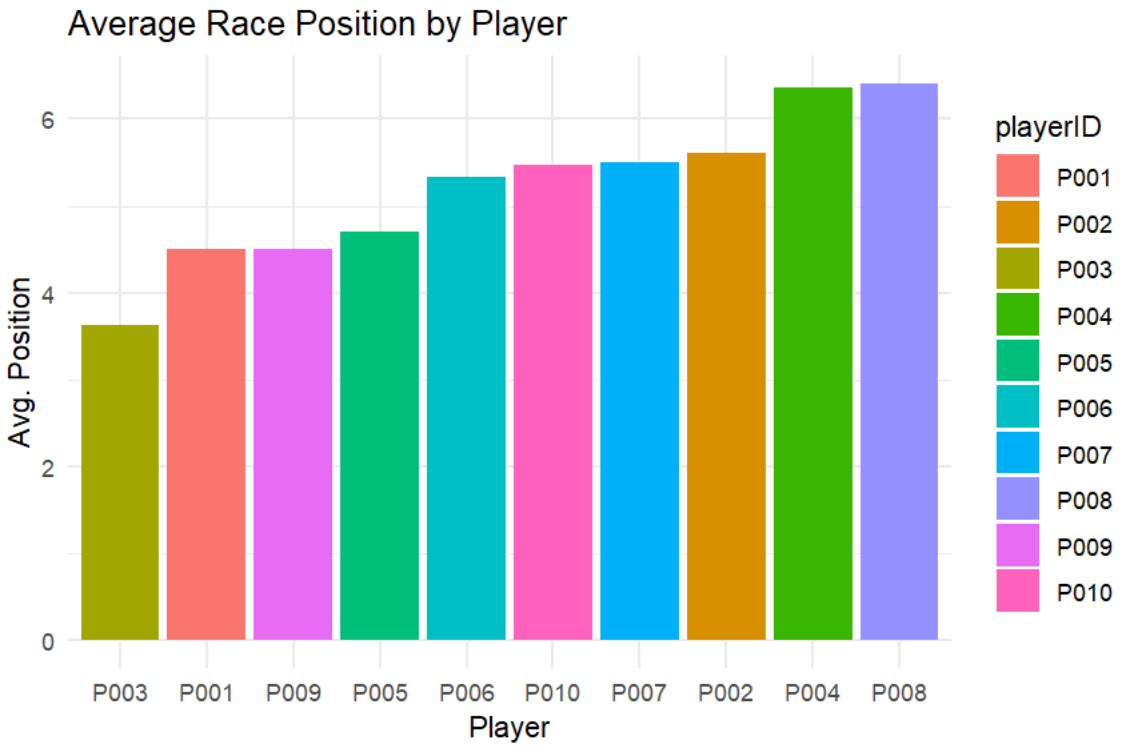
Track-Level Analysis



Insight: This chart compares the total number of crashes across Circuit, Desert, and Urban tracks. Urban tracks show the highest crash count, followed by Desert and Circuit.

Conclusion: Urban environments present the greatest safety challenge, likely due to tighter turns, unpredictable layouts, and visual complexity. This finding sets the foundation for deeper diagnostics into player behavior and car performance on Urban tracks.

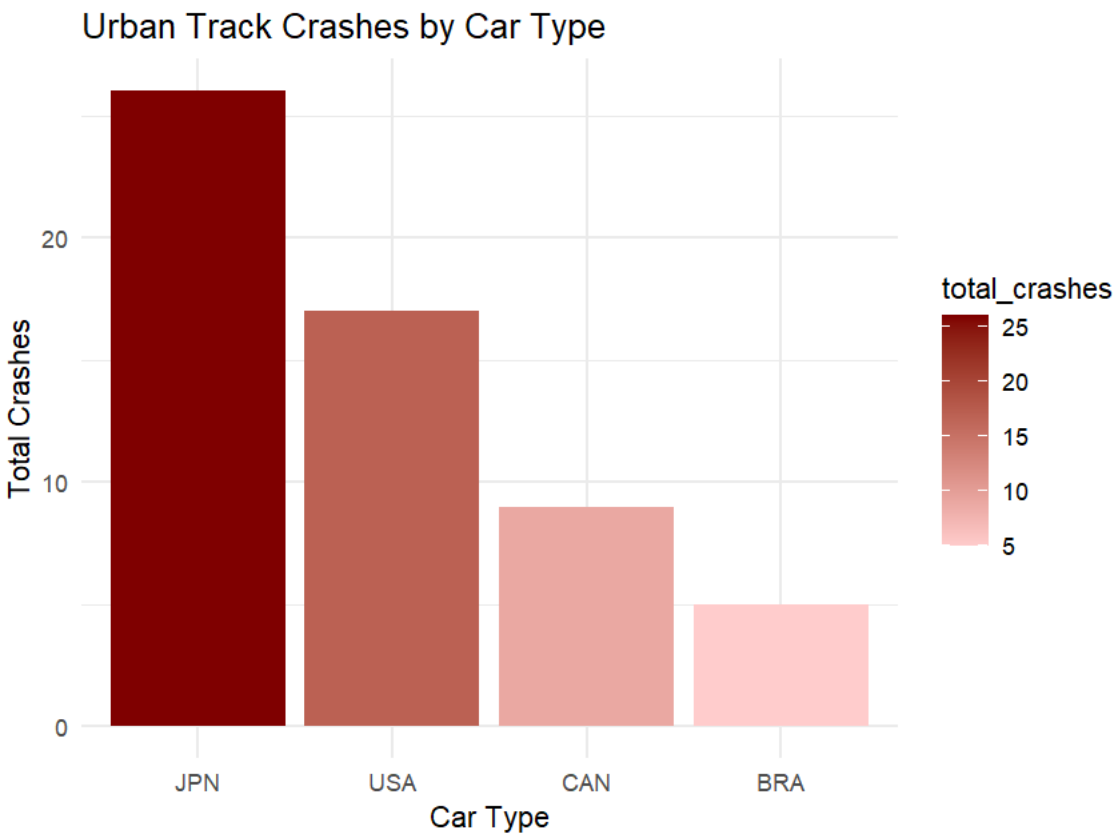
Player-Level Analysis



Insight: This chart ranks players by their average race position across all track types. Player P003 consistently finishes near the top (avg. position ~2), while P008 ranks lowest (~6.5), indicating weaker performance.

Conclusion: P003 demonstrates strong racing strategy and control, making them the most consistent performer. P008 may require support in car selection, track familiarity, or driving tactics. This analysis helps identify top performers and those needing improvement—essential for coaching, matchmaking, or game balancing.

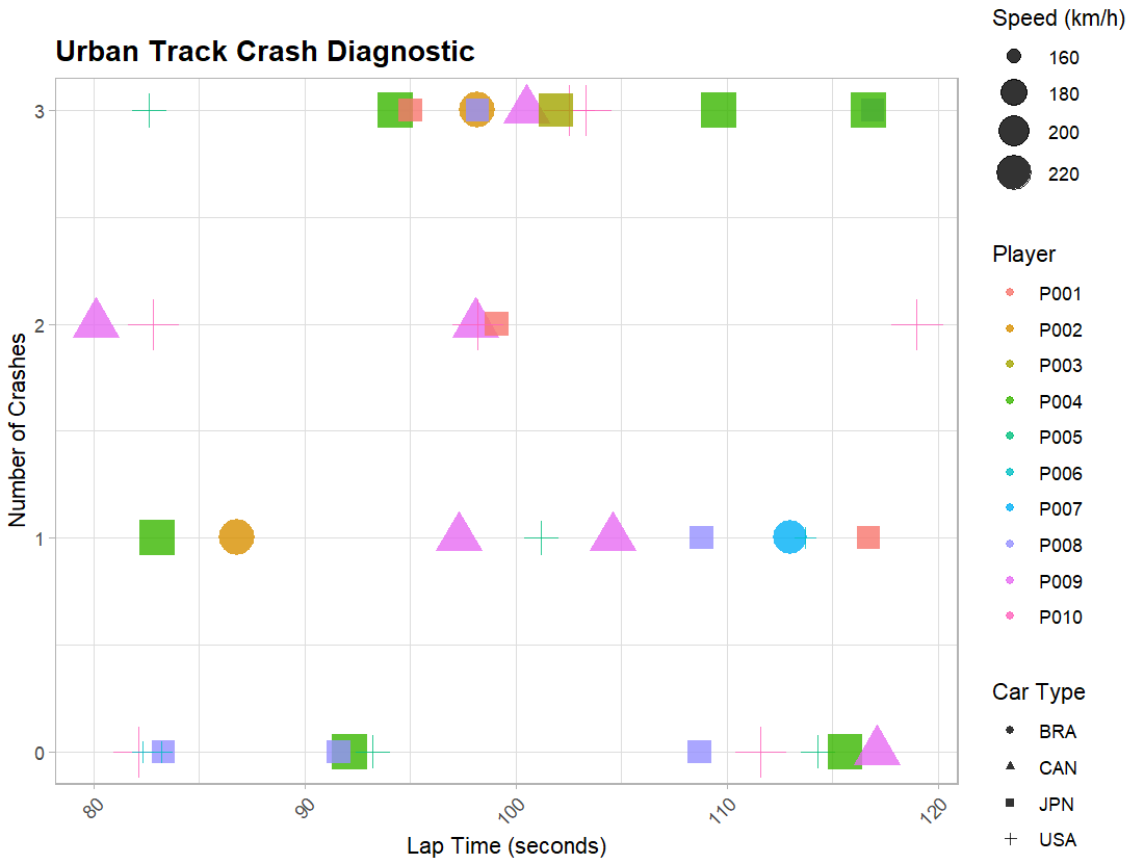
Urban Track Crash Rate by Player



Insight: This chart compares crash totals on Urban tracks across four car types: Japan (JPN), USA, Canada (CAN), and Brazil (BRA). Japanese cars show the highest crash count (~25), followed by USA (~17), Canada (~10), and Brazil (~5).

Conclusion: Car type significantly influences crash frequency. Japanese models may offer higher speed or sensitivity, making them harder to control on Urban tracks. This insight supports tuning recommendations, car balancing strategies, or targeted driver training based on vehicle origin.

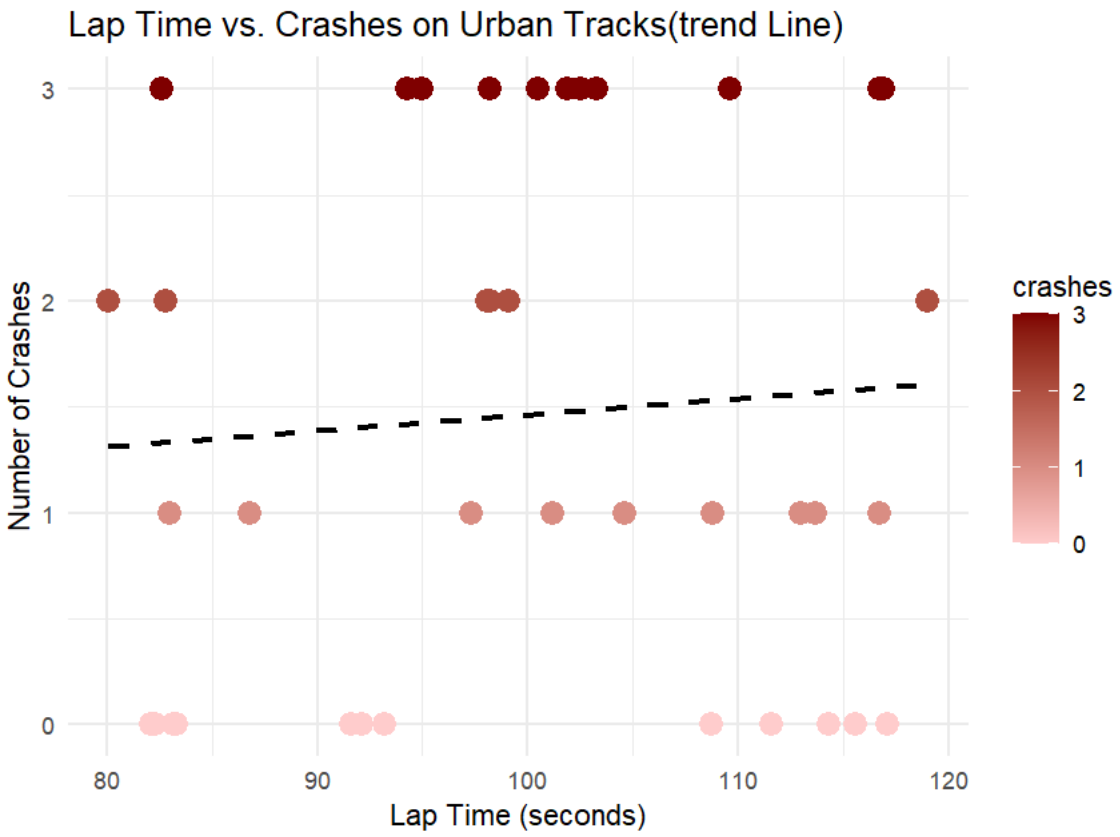
Multi-Variable Diagnostics



Insight: This scatter plot maps lap time against crash count, with each point representing a unique combination of player and car type. Color indicates player ID, shape represents car type, and size reflects speed. The chart reveals clusters of high-crash events around lap times of 90–110 seconds, with certain players and car types appearing more frequently in risky zones.

Conclusion: Crash risk on Urban tracks is influenced by a complex interplay of lap time, speed, player behavior, and car dynamics. Players using specific car types at higher speeds tend to experience more crashes, especially within a critical lap time window. This diagnostic visualization helps identify high-risk combinations and supports targeted tuning, driver coaching, or track redesign.

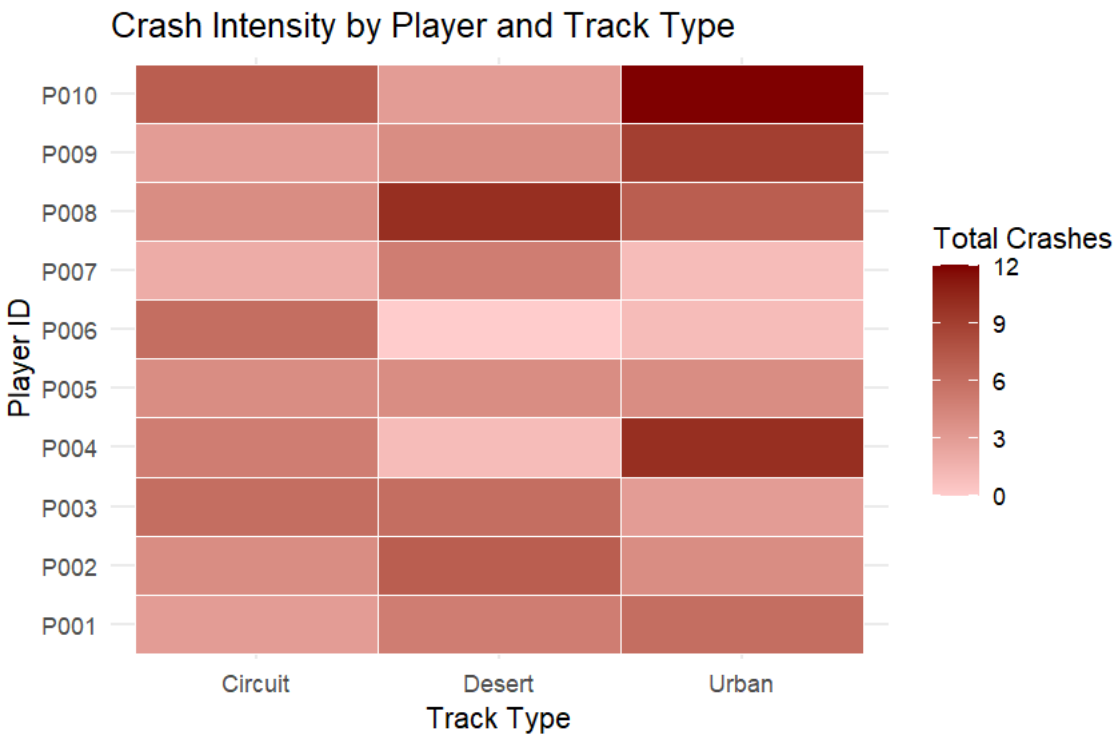
Lap Time vs. Crashes with Trend Line



Insight: This scatter plot visualizes the relationship between lap time and crash count on Urban tracks. Each point represents a lap, color-coded by crash intensity. The dashed trend line reveals a slight upward slope, suggesting a potential correlation between longer lap times and higher crash frequency.

Conclusion: Drivers who take longer to complete laps may be more prone to crashing—possibly due to poor control, fatigue, or inefficient driving strategies. While the correlation is modest, this trend supports further investigation into pacing, player skill, and track complexity. The chart adds predictive value to your crash diagnostics and strengthens the case for targeted coaching or layout adjustments.

Heatmap Overview



Insight: This heatmap visualizes crash intensity across three track types—Circuit, Desert, and Urban—for each player. Darker shades indicate higher crash counts. Player P010 shows the highest crash intensity on Urban tracks, while others like P007 and P003 maintain relatively low crash levels across all environments.

Conclusion: Crash frequency is not evenly distributed. Urban tracks consistently trigger more crashes, especially for players like P009 and P010. This visualization helps identify which players struggle on which track types, guiding targeted coaching, car selection, or track redesign. It also reinforces the need for adaptive difficulty and personalized feedback in gameplay environments.

Final Takeaways

🔍 Summary of Insights

- Urban tracks are the most crash-prone but also yield the best race outcomes
- Player behavior, car type, and lap timing all influence crash risk
- Multi-variable diagnostics reveal hidden patterns in performance and safety
- Heatmaps and trend lines help pinpoint high-risk combinations and outliers

🧭 Strategic Recommendations

- Prioritize driver training for players with high crash intensity
- Consider tuning car types (especially JPN models) for better control on Urban tracks
- Use diagnostic visuals to guide track redesign and adaptive difficulty settings
- Integrate predictive modeling to anticipate crash risk based on lap time and speed

💼 Skills Demonstrated

This case study showcases my ability to:

- Simulate and validate complex datasets
- Build multi-layered visual diagnostics using R and ggplot2
- Translate raw data into actionable insights
- Design accessible, audience-focused dashboards
- Communicate findings with clarity, strategy, and visual impact

About Me

I'm a data storyteller and dashboard designer with a passion for turning raw numbers into meaningful narratives. With an MA in Urdu and a strong foundation in analytical tools like R, Power BI, and Tableau, I blend technical precision with creative strategy. My work spans gaming analytics, financial systems, and accessibility-focused design—always tailored to audience impact and clarity.

I thrive on solving complex problems through simulation, visualization, and stakeholder engagement. Whether I'm mapping crash diagnostics in racing games or building vendor-ledger automation, my approach is methodical, empathetic, and audience-first. I'm committed to learning, iterating, and crafting visuals that speak louder than words.

Skills Used in This Project

- **Data Wrangling:** Simulated and cleaned multi-variable race data using R
- **Visualization:** Built diagnostic charts, heatmaps, and trend lines with ggplot2
- **Storytelling:** Translated technical insights into accessible, strategic narratives
- **Design Thinking:** Prioritized clarity, accessibility, and audience experience
- **Troubleshooting:** Resolved syntax, sampling, and layout issues during development