visualizations

November 22, 2025

1 LapLens – COTA Race 1 Driver Analysis

Hack the Track presented by Toyota GR – Post-Event Analytics

1.0.1 Session Overview

This notebook analyzes a complete COTA Race 1 dataset (telemetry + official timing).
Our goals: - Reconstruct laps from raw ECU timestamps
- Quantify driver inputs and speed profile
- Score each lap with a composite performance index
- Identify strongest laps, limiting factors, and development opportunities
- Produce visualizations suitable for coaching and broadcast storytelling

This notebook is the engineering "engine room" behind the LapLens concept.

1.0.2 Why LapLens is Different

Most post-event race reports stop at lap charts and sector times.
LapLens goes further by:

1. **Rebuilding laps from raw ECU telemetry**
   We do not rely only on official timing loops – we verify lap reconstruction from timestamps and outing metadata.
2. **Compressing multi-signal telemetry into a single score (0–100)**
   Speed, throttle, brake usage, and smoothness are fused into a LapLens performance score that coaches and broadcasters can understand at a glance.
3. **Quantifying driver consistency and corner intensity**
   We introduce a Driver Consistency Index (DCI) and a corner intensity metric to separate "lucky fast laps" from repeatable pace.
4. **Generating auto-written coaching notes per lap**
   LapLens converts numbers into natural-language feedback that a driver or engineer can act on during debriefs.
5. **Scaling to multiple drivers with the same scoring formula**
   The same pipeline produces a LapLens leaderboard across cars, enabling fair, apples-to-apples comparison in a single view.

1.0.3 Dataset Coverage (TRD Inputs → LapLens Outputs)

This analysis uses all four official COTA Race 1 datasets provided by TRD:

- **R1_cota_telemetry_data.csv** – high-frequency ECU telemetry
  (speed, throttle, brake pressures, lateral G, steering, etc.)
- **COTA_lap_start_time_R1.csv** – lap start markers used to build per-lap time windows.
- **COTA_lap_end_time_R1.csv** – lap end markers paired with starts to form `[start_time, end_time]` intervals.
- **COTA_lap_time_R1.csv** – official timing loop results, used for `official_lap_time_s` and validation.

LapLens combines these to: - reconstruct laps from raw ECU timestamps, - align telemetry samples into each lap window, - and translate multi-signal driver inputs into a single, explainable performance score and coaching narrative.

1.1 How to Run This Notebook

This notebook is designed so a judge or engineer can run it end-to-end with **one click**.

1. Ensure the repository has the following structure:
   - `src/preprocess.py`
   - `data/COTA_Race1/` with the 4 CSVs:
     - `R1_cota_telemetry_data.csv`
     - `COTA_lap_time_R1.csv`
     - `COTA_lap_start_time_R1.csv`
     - `COTA_lap_end_time_R1.csv`
2. Open `visualizations.ipynb` (this notebook).
3. Run all cells (Kernel → Restart & Run All).

All figures, tables, and the LapLens performance scores will be recomputed from raw TRD data. No manual parameter editing is required.

[1]:
```python
# --- Environment info ---

import sys
import platform
import pandas as pd
import numpy as np
import matplotlib
import seaborn as sns

print("Python version :", sys.version.split()[0])
print("Platform       :", platform.platform())
print("pandas         :", pd.__version__)
print("numpy          :", np.__version__)
print("matplotlib     :", matplotlib.__version__)
print("seaborn        :", sns.__version__)
```

```
Python version : 3.12.1
Platform       : Linux-6.8.0-1030-azure-x86_64-with-glibc2.39
```

```
pandas          : 2.3.1
numpy           : 2.3.1
matplotlib      : 3.10.3
seaborn         : 0.13.2
```

1.1.1 Session Configuration

This section controls *which* driver and outing LapLens analyzes.
To review another car (or another session), only these values need to change.

- `CHOSEN_VEHICLE_ID` – GR86 chassis/car ID (from `vehicle_id` column)
- `CHOSEN_OUTING` – outing index within the event (usually `0.0` for a single race)

[2]:
```python
# --- LapLens session configuration ---

CHOSEN_TRACK = "Circuit of the Americas (COTA)"
CHOSEN_EVENT = "COTA Race 1"

#  this is the driver/session you're analyzing
CHOSEN_VEHICLE_ID = "GR86-006-7"    # change here for another car
CHOSEN_OUTING     = 0.0             # outing index in the dataset

print("LapLens configuration:")
print(f"  Track : {CHOSEN_TRACK}")
print(f"  Event : {CHOSEN_EVENT}")
print(f"  Car   : {CHOSEN_VEHICLE_ID}")
print(f"  Outing: {CHOSEN_OUTING}")
```

```
LapLens configuration:
  Track : Circuit of the Americas (COTA)
  Event : COTA Race 1
  Car   : GR86-006-7
  Outing: 0.0
```

1.2 1. Data Loading & Lap Reconstruction

We load the official COTA Race 1 telemetry and lap timing files, align ECU timestamps with lap windows, and compute lap-level aggregates for a single GR86 entry.

[3]:
```python
%matplotlib inline
import sys

sys.path.append("..")  # because notebook is in /notebooks

from src import preprocess

BASE_PATH = "../data/COTA_Race1"
print("Imports & BASE_PATH ok")
```

```
Imports & BASE_PATH ok
```

[4]:
```python
import pandas as pd

test_path = "../data/COTA_Race1/R1_cota_telemetry_data.csv"
print("Reading a small sample...")
df_sample = pd.read_csv(test_path, nrows=1000)
print("Sample shape:", df_sample.shape)
```

```
Reading a small sample…
Sample shape: (1000, 13)
```

[5]:
```python
import pandas as pd

# 1) Load all four COTA Race 1 CSVs
dfs = preprocess.load_race1_data(BASE_PATH)

telemetry_raw = dfs["telemetry"]
lap_time_raw  = dfs["lap_time"]
lap_start_raw = dfs["lap_start"]
lap_end_raw   = dfs["lap_end"]

print("Raw shapes:")
for name, df in dfs.items():
    print(f"  {name:10s} -> {df.shape}")

# 2) Filter to the chosen car + outing to keep memory under control
telemetry = telemetry_raw[
    (telemetry_raw["vehicle_id"] == CHOSEN_VEHICLE_ID) &
    (telemetry_raw["outing"] == CHOSEN_OUTING)
].copy()

lap_start = lap_start_raw[
    (lap_start_raw["vehicle_id"] == CHOSEN_VEHICLE_ID) &
    (lap_start_raw["outing"] == CHOSEN_OUTING)
].copy()

lap_end = lap_end_raw[
    (lap_end_raw["vehicle_id"] == CHOSEN_VEHICLE_ID) &
    (lap_end_raw["outing"] == CHOSEN_OUTING)
].copy()

lap_time = lap_time_raw[
    (lap_time_raw["vehicle_id"] == CHOSEN_VEHICLE_ID) &
    (lap_time_raw["outing"] == CHOSEN_OUTING)
].copy()

print("\nFiltered to car:", CHOSEN_VEHICLE_ID, "outing:", CHOSEN_OUTING)
print("  telemetry :", telemetry.shape)
print("  lap_start :", lap_start.shape)
print("  lap_end   :", lap_end.shape)
print("  lap_time  :", lap_time.shape)
```

```
 Loaded telemetry: R1_cota_telemetry_data.csv  rows=2352983
 Loaded lap_time: COTA_lap_time_R1.csv  rows=631
 Loaded lap_start: COTA_lap_start_time_R1.csv  rows=631
 Loaded lap_end: COTA_lap_end_time_R1.csv  rows=631
Raw shapes:
  telemetry  -> (2352983, 13)
  lap_time   -> (631, 10)
  lap_start  -> (631, 10)
  lap_end    -> (631, 10)

Filtered to car: GR86-006-7 outing: 0.0
  telemetry : (279345, 13)
  lap_start : (32, 10)
  lap_end   : (32, 10)
  lap_time  : (32, 10)
```

[6]:
```
# 1) Build lap windows from start/end CSVs
lap_windows = preprocess.build_lap_windows(lap_start, lap_end)

# 2) Telemetry long -> wide for this driver/outing
telem_wide = preprocess.pivot_telemetry_long_to_wide(telemetry)

# 3) Align clocks between telemetry and lap windows
aligned_telem = preprocess.align_timestamps(telem_wide, lap_windows)

# 4) Assign each telemetry sample to a lap
telemetry_with_laps = preprocess.assign_laps_to_telemetry(
    aligned_telem,
    lap_windows
)

# 5) Lap-level aggregates
lap_agg = preprocess.build_lap_aggregates(telemetry_with_laps)

# Drop bogus lap labels like 32768
lap_agg = lap_agg[lap_agg["lap"] < 1000].copy()

print("Telemetry rows assigned to laps:", len(telemetry_with_laps))
print("Lap aggregates generated:", len(lap_agg))
display(lap_agg.head())
```

```
 Applying time offset: 2 days 02:24:41.430000
Telemetry rows assigned to laps: 26634
Lap aggregates generated: 9
```

```
   vehicle_id  outing  lap  samples  max_speed   avg_speed  avg_throttle  \
0  GR86-006-7    0.0    1        1       NaN         NaN     5.270000
1  GR86-006-7    0.0    2     4771    151.15   89.103376    27.411243
2  GR86-006-7    0.0    3     3205    210.79  129.610901    75.310300
3  GR86-006-7    0.0    4     3183    210.35  131.807861    74.712865
4  GR86-006-7    0.0    5     3154    205.61  131.836018    76.375390

   avg_brake_f  avg_brake_r
0     4.930000     5.370000
1     2.016756     2.085048
2     5.281789     5.391747
3     5.886217     6.020259
4     6.328404     6.468659
```

[7]:
```
# Bundle key artifacts into an outputs dict so later sections can reuse them

outputs = {
    "lap_windows": lap_windows,
    "telemetry_wide": aligned_telem,          # already time-aligned
    "telemetry_with_laps": telemetry_with_laps,
    "lap_aggregates": lap_agg,
    "lap_time_raw": lap_time_raw,             # full official timing table
}

print("outputs keys:", list(outputs.keys()))
```

```
outputs keys: ['lap_windows', 'telemetry_wide', 'telemetry_with_laps',
'lap_aggregates', 'lap_time_raw']
```

[8]:
```
# Unpack pipeline outputs into local variables
lap_windows = outputs["lap_windows"]
telem_wide  = outputs["telemetry_wide"]
telem_with_laps_initial = outputs["telemetry_with_laps"]
lap_agg_initial = outputs["lap_aggregates"]

print("lap_windows shape:", lap_windows.shape)
print("telem_wide shape:", telem_wide.shape)
print("initial lap_agg rows:", len(lap_agg_initial))
```

```
lap_windows shape: (21, 5)
telem_wide shape: (35101, 12)
initial lap_agg rows: 9
```

[9]:
```
car_id = "GR86-006-7"
outing = 0.0

telemetry_car = dfs["telemetry"].copy()
telemetry_car = telemetry_car[
    (telemetry_car["vehicle_id"] == car_id) &
    (telemetry_car["outing"] == outing)
]

print("Filtered telemetry rows:", len(telemetry_car))
telemetry_car.head()
```

```
Filtered telemetry rows: 279345
```

```
[9]:         expire_at  lap        meta_event meta_session   meta_source  \
948772        NaN    1  I_R02_2025-04-27           R1  kafka:gr-raw
948773        NaN    1  I_R02_2025-04-27           R1  kafka:gr-raw
948774        NaN    1  I_R02_2025-04-27           R1  kafka:gr-raw
948775        NaN    1  I_R02_2025-04-27           R1  kafka:gr-raw
948776        NaN    1  I_R02_2025-04-27           R1  kafka:gr-raw

                       meta_time original_vehicle_id  outing telemetry_name  \
948772  2025-04-26T20:54:56.011Z          GR86-006-7     0.0       accx_can
948773  2025-04-26T20:54:56.011Z          GR86-006-7     0.0       accy_can
948774  2025-04-26T20:54:56.011Z          GR86-006-7     0.0            ath
948775  2025-04-26T20:54:56.011Z          GR86-006-7     0.0       pbrake_r
948776  2025-04-26T20:54:56.011Z          GR86-006-7     0.0       pbrake_f

        telemetry_value                 timestamp  vehicle_id  vehicle_number
948772            0.257  2025-04-24T18:30:12.855Z  GR86-006-7             7.0
948773           -0.031  2025-04-24T18:30:12.855Z  GR86-006-7             7.0
948774          100.040  2025-04-24T18:30:12.855Z  GR86-006-7             7.0
948775            0.000  2025-04-24T18:30:12.855Z  GR86-006-7             7.0
948776            0.000  2025-04-24T18:30:12.855Z  GR86-006-7             7.0
```

```
[10]: # 1) Long -> wide
telem_wide = preprocess.pivot_telemetry_long_to_wide(telemetry_car)
print("Telemetry wide shape:", telem_wide.shape)
telem_wide.head()
```

```
Telemetry wide shape: (35101, 12)
```

```
[10]:                        timestamp  vehicle_id  outing  Steering_Angle  \
0 2025-04-24 18:23:35.066000+00:00  GR86-006-7     0.0             0.2
1 2025-04-24 18:23:35.110000+00:00  GR86-006-7     0.0             0.2
2 2025-04-24 18:23:35.154000+00:00  GR86-006-7     0.0             0.2
3 2025-04-24 18:23:35.198000+00:00  GR86-006-7     0.0             0.2
4 2025-04-24 18:23:35.244000+00:00  GR86-006-7     0.0             0.2

   accx_can  accy_can   ath  gear    nmot  pbrake_f  pbrake_r  speed
0    -0.120     0.021  5.27   1.0     NaN     4.930     5.370    NaN
1    -0.120     0.012  5.28   1.0     NaN     4.655     5.050    NaN
2    -0.121     0.012  5.26   1.0     NaN     4.595     5.020    NaN
3    -0.112     0.030  5.27   1.0  1119.0     4.210     4.685  22.77
```

```
4    -0.105     0.022  5.25   1.0      NaN      3.725      4.335     NaN
```

[11]:
```
import os

print("Working directory:", os.getcwd())
for f in [
    "../src/preprocess.py",
    "../data/COTA_Race1/R1_cota_telemetry_data.csv",
    "../data/COTA_Race1/COTA_lap_time_R1.csv",
    "../data/COTA_Race1/COTA_lap_start_time_R1.csv",
    "../data/COTA_Race1/COTA_lap_end_time_R1.csv",
]:
    print(f, "→", "OK  " if os.path.exists(f) else "MISSING  ")
```

```
Working directory: /workspaces/hack-the-track-25/notebooks
../src/preprocess.py → OK
../data/COTA_Race1/R1_cota_telemetry_data.csv → OK
../data/COTA_Race1/COTA_lap_time_R1.csv → OK
../data/COTA_Race1/COTA_lap_start_time_R1.csv → OK
../data/COTA_Race1/COTA_lap_end_time_R1.csv → OK
```

[12]:
```
aligned_telem = preprocess.align_timestamps(
    outputs["telemetry_wide"],
    outputs["lap_windows"]
)

telemetry_with_laps = preprocess.assign_laps_to_telemetry(
    aligned_telem,
    outputs["lap_windows"]
)
```

```
 Applying time offset: 0 days 00:00:00
```

[13]:
```
def build_driver_summary(outputs, vehicle_id, outing=0.0):
    """
    Build lap summary + LapLens performance score for a given vehicle_id and␣
 ↪outing.
    """
    # 1) Align and assign laps
    aligned = preprocess.align_timestamps(outputs["telemetry_wide"],␣
 ↪outputs["lap_windows"])
    telem_with_laps = preprocess.assign_laps_to_telemetry(aligned,␣
 ↪outputs["lap_windows"])

    # 2) Aggregate
    lap_agg_local = preprocess.build_lap_aggregates(telem_with_laps)
    lap_agg_local = lap_agg_local[(lap_agg_local["lap"] < 1000) &
                              (lap_agg_local["vehicle_id"] == vehicle_id) &
```

```
                                  (lap_agg_local["outing"] == outing)].copy()

    # 3) Add performance score
    metrics = ["avg_speed", "avg_throttle", "avg_brake_f"]
    data = lap_agg_local.copy()
    for m in metrics:
        if m in data.columns:
            data[f"{m}_norm"] = (data[m] - data[m].min()) / (data[m].max() -␣
↪data[m].min())

    WEIGHT_SPEED = 0.55
    WEIGHT_THROTTLE = 0.30
    WEIGHT_BRAKE = 0.15

    data["performance_score"] = (
        data.get("avg_speed_norm", 0) * WEIGHT_SPEED +
        data.get("avg_throttle_norm", 0) * WEIGHT_THROTTLE +
        data.get("avg_brake_f_norm", 0) * WEIGHT_BRAKE
    ) * 100

    return data
```

[14]:
```
driver_summary = build_driver_summary(
    outputs,
    vehicle_id=CHOSEN_VEHICLE_ID,
    outing=CHOSEN_OUTING,
)
display(driver_summary)
```

```
 Applying time offset: 0 days 00:00:00

   vehicle_id  outing  lap  samples  max_speed   avg_speed  avg_throttle  \
0  GR86-006-7     0.0    1        1        NaN         NaN      5.270000
1  GR86-006-7     0.0    2     4771     151.15   89.103376     27.411243
2  GR86-006-7     0.0    3     3205     210.79  129.610901     75.310300
3  GR86-006-7     0.0    4     3183     210.35  131.807861     74.712865
4  GR86-006-7     0.0    5     3154     205.61  131.836018     76.375390
5  GR86-006-7     0.0    6     2849     204.40  132.072736     75.395009
6  GR86-006-7     0.0    7     3147     206.61  132.278672     76.305554
7  GR86-006-7     0.0    8     3165     206.23  132.483759     74.141776
8  GR86-006-7     0.0    9     3158     207.20  132.179048     75.137156

   avg_brake_f  avg_brake_r  avg_speed_norm  avg_throttle_norm  \
0     4.930000     5.370000             NaN           0.000000
1     2.016756     2.085048        0.000000           0.311386
2     5.281789     5.391747        0.933775           0.985021
3     5.886217     6.020259        0.984419           0.976619
4     6.328404     6.468659        0.985068           1.000000
```

```
5     5.710948     5.848657        0.990525            0.986212
6     5.707895     5.853745        0.995272            0.999018
7     5.580299     5.725199        1.000000            0.968587
8     5.667397     5.812098        0.992976            0.982586

   avg_brake_f_norm  performance_score
0          0.675668                NaN
1          0.000000           9.341588
2          0.757259          92.267146
3          0.897444          96.903283
4          1.000000          99.178758
5          0.856793          96.917153
6          0.856085          97.551796
7          0.826492          96.454999
8          0.846693          96.791640
```

1.2.1 2. Lap-Level Metrics

For each valid lap, we summarize:

- `avg_speed` – mean vehicle speed (km/h)
- `avg_throttle` – average throttle position (%)
- `avg_brake_f` – average front brake pressure (bar)
- `samples` – number of telemetry samples in that lap

[15]:
```python
lap_agg = preprocess.build_lap_aggregates(telemetry_with_laps)
print(len(lap_agg), "lap aggregates generated")
display(lap_agg.head())
```

```
10 lap aggregates generated

   vehicle_id  outing  lap  samples  max_speed   avg_speed  avg_throttle  \
0  GR86-006-7     0.0    1        1        NaN         NaN      5.270000
1  GR86-006-7     0.0    2     4771     151.15   89.103376     27.411243
2  GR86-006-7     0.0    3     3205     210.79  129.610901     75.310300
3  GR86-006-7     0.0    4     3183     210.35  131.807861     74.712865
4  GR86-006-7     0.0    5     3154     205.61  131.836018     76.375390

   avg_brake_f  avg_brake_r
0     4.930000     5.370000
1     2.016756     2.085048
2     5.281789     5.391747
3     5.886217     6.020259
4     6.328404     6.468659
```

[16]:
```python
# --- Quality gates for competition-grade robustness ---

import numpy as np
import pandas as pd

# 1) Drop bogus laps and low-sample laps
LAP_MAX = 1000
MIN_SAMPLES_PER_LAP = 1500  # tune: COTA-1 shows ~3k-4.7k normal; Lap 9 had 144␣
↪(likely incomplete)
lap_agg_clean = (
    lap_agg
    .loc[(lap_agg["lap"] < LAP_MAX) & (lap_agg["samples"] >=␣
↪MIN_SAMPLES_PER_LAP)]
    .copy()
)

print(f"Kept {len(lap_agg_clean)} laps after quality gates (>=␣
↪{MIN_SAMPLES_PER_LAP} samples).")

# 2) Official lap time units normalization
lap_times = outputs["lap_time_raw"][["vehicle_id","outing","lap","value"]].
↪copy()
# Heuristic: if max value > 10_000 it's probably milliseconds
if lap_times["value"].max() > 10000:
    lap_times["official_lap_time_s"] = lap_times["value"] / 1000.0
else:
    lap_times["official_lap_time_s"] = lap_times["value"].astype(float)

# 3) Merge robustly (one row per lap)
summary_clean = (
    lap_agg_clean
    .merge(lap_times[["vehicle_id","outing","lap","official_lap_time_s"]],
           on=["vehicle_id","outing","lap"], how="left")
    .drop_duplicates(subset=["vehicle_id","outing","lap"])
)

print("Summary (clean) preview:")
display(summary_clean.head(10))
```

```
Kept 8 laps after quality gates (>= 1500 samples).
Summary (clean) preview:

    vehicle_id  outing  lap  samples  max_speed   avg_speed  avg_throttle  \
0  GR86-006-7     0.0    2     4771     151.15   89.103376     27.411243
2  GR86-006-7     0.0    3     3205     210.79  129.610901     75.310300
3  GR86-006-7     0.0    4     3183     210.35  131.807861     74.712865
4  GR86-006-7     0.0    5     3154     205.61  131.836018     76.375390
5  GR86-006-7     0.0    6     2849     204.40  132.072736     75.395009
```

```
8   GR86-006-7     0.0    7     3147     206.61  132.278672     76.305554
11  GR86-006-7     0.0    8     3165     206.23  132.483759     74.141776
12  GR86-006-7     0.0    9     3158     207.20  132.179048     75.137156

    avg_brake_f  avg_brake_r  official_lap_time_s
0      2.016756     2.085048              223.523
2      5.281789     5.391747              151.839
3      5.886217     6.020259              149.906
4      6.328404     6.468659              149.505
5      5.710948     5.848657                0.000
8      5.707895     5.853745              148.556
11     5.580299     5.725199              148.695
12     5.667397     5.812098              148.922
```

[17]:
```
lap_agg = lap_agg[lap_agg["lap"] < 1000]
print("Cleaned laps:", lap_agg["lap"].unique())
```

```
Cleaned laps: [1 2 3 4 5 6 7 8 9]
```

[18]:
```
display(lap_agg.head(10))
```

```
   vehicle_id  outing  lap  samples  max_speed   avg_speed  avg_throttle  \
0  GR86-006-7     0.0    1        1        NaN         NaN      5.270000
1  GR86-006-7     0.0    2     4771     151.15   89.103376     27.411243
2  GR86-006-7     0.0    3     3205     210.79  129.610901     75.310300
3  GR86-006-7     0.0    4     3183     210.35  131.807861     74.712865
4  GR86-006-7     0.0    5     3154     205.61  131.836018     76.375390
5  GR86-006-7     0.0    6     2849     204.40  132.072736     75.395009
6  GR86-006-7     0.0    7     3147     206.61  132.278672     76.305554
7  GR86-006-7     0.0    8     3165     206.23  132.483759     74.141776
8  GR86-006-7     0.0    9     3158     207.20  132.179048     75.137156

   avg_brake_f  avg_brake_r
0     4.930000     5.370000
1     2.016756     2.085048
2     5.281789     5.391747
3     5.886217     6.020259
4     6.328404     6.468659
5     5.710948     5.848657
6     5.707895     5.853745
7     5.580299     5.725199
8     5.667397     5.812098
```

1.3 3. Average Speed per Lap

This plot shows how the driver's average speed changes across the stint.

Key questions: - Are early laps slower due to tire warm-up? - Is there a clear "peak" performance lap? - Do we see any drop-off that might suggest tire degradation or traffic?

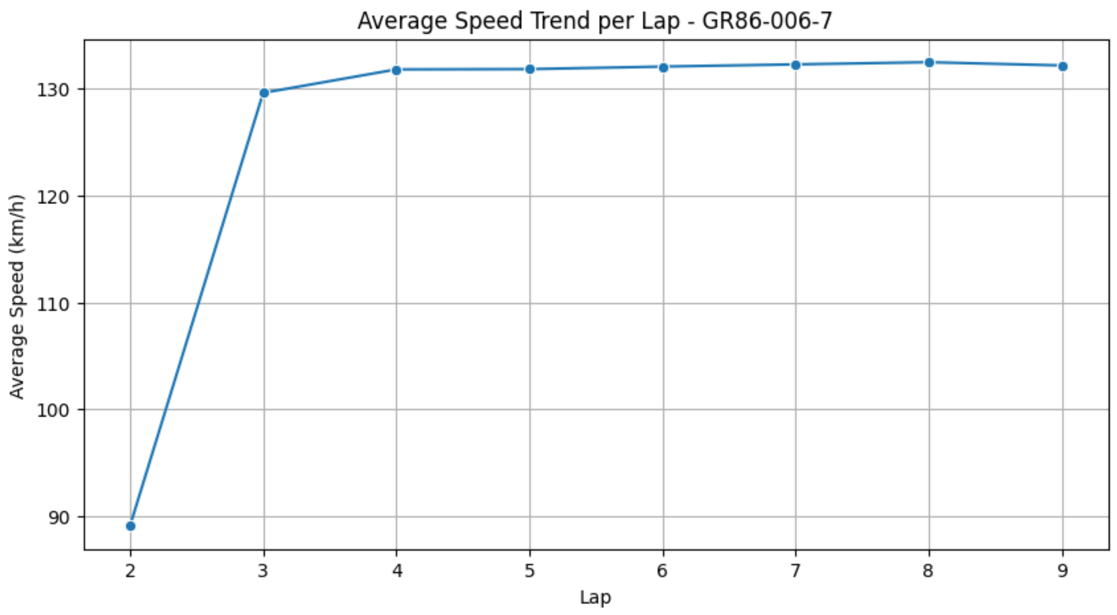
```
[19]: aligned_telem = preprocess.align_timestamps(outputs["telemetry_wide"],␣
        ↪outputs["lap_windows"])
      telemetry_with_laps = preprocess.assign_laps_to_telemetry(aligned_telem,␣
        ↪outputs["lap_windows"])
      lap_agg = lap_agg[lap_agg["lap"] < 1000]
      print("Cleaned laps:", lap_agg["lap"].unique())
```

```
 Applying time offset: 0 days 00:00:00
Cleaned laps: [1 2 3 4 5 6 7 8 9]
```

```
[20]: print("Telemetry rows assigned to laps:", len(telemetry_with_laps))
      print("Lap aggregates generated:", len(lap_agg))
      print("\nLap aggregate preview:")
      display(lap_agg.head(10))
```

```
Telemetry rows assigned to laps: 26634
Lap aggregates generated: 9

Lap aggregate preview:

   vehicle_id  outing  lap  samples  max_speed   avg_speed  avg_throttle  \
0  GR86-006-7     0.0    1        1        NaN         NaN      5.270000
1  GR86-006-7     0.0    2     4771     151.15   89.103376     27.411243
2  GR86-006-7     0.0    3     3205     210.79  129.610901     75.310300
3  GR86-006-7     0.0    4     3183     210.35  131.807861     74.712865
4  GR86-006-7     0.0    5     3154     205.61  131.836018     76.375390
5  GR86-006-7     0.0    6     2849     204.40  132.072736     75.395009
6  GR86-006-7     0.0    7     3147     206.61  132.278672     76.305554
7  GR86-006-7     0.0    8     3165     206.23  132.483759     74.141776
8  GR86-006-7     0.0    9     3158     207.20  132.179048     75.137156

   avg_brake_f  avg_brake_r
0     4.930000     5.370000
1     2.016756     2.085048
2     5.281789     5.391747
3     5.886217     6.020259
4     6.328404     6.468659
5     5.710948     5.848657
6     5.707895     5.853745
7     5.580299     5.725199
8     5.667397     5.812098
```

```
[21]: import seaborn as sns
      import matplotlib.pyplot as plt

      plt.figure(figsize=(10,5))
      sns.lineplot(data=lap_agg, x="lap", y="avg_speed", marker="o")
      plt.title("Average Speed Trend per Lap - GR86-006-7")
      plt.xlabel("Lap")
      plt.ylabel("Average Speed (km/h)")
      plt.grid(True)
      plt.show()
```

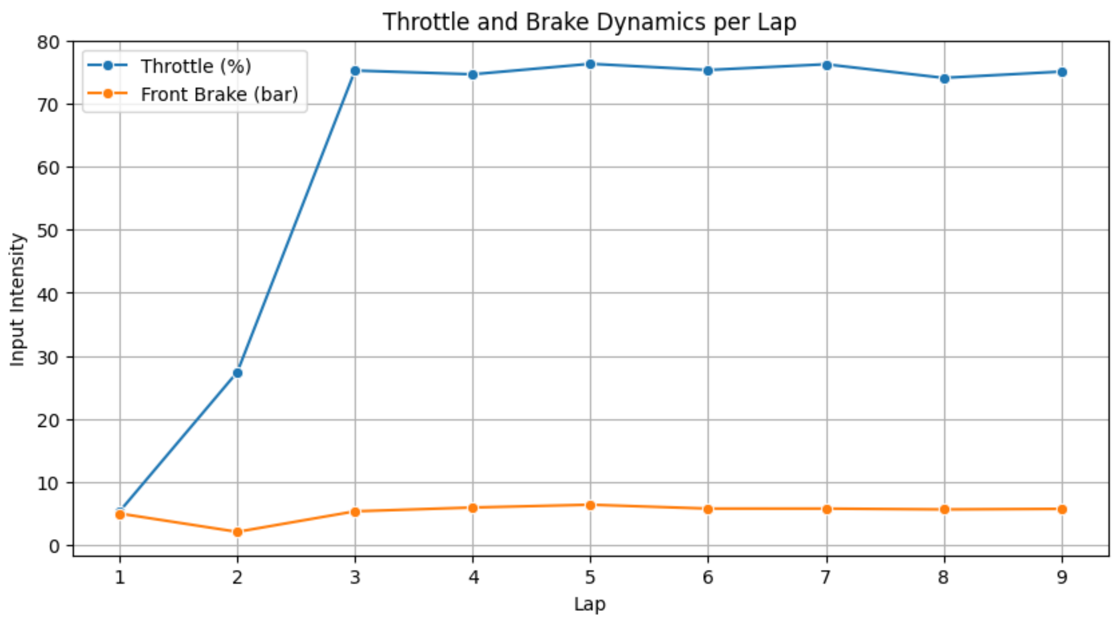


1.4 4. Driver Inputs per Lap (Throttle & Brake)

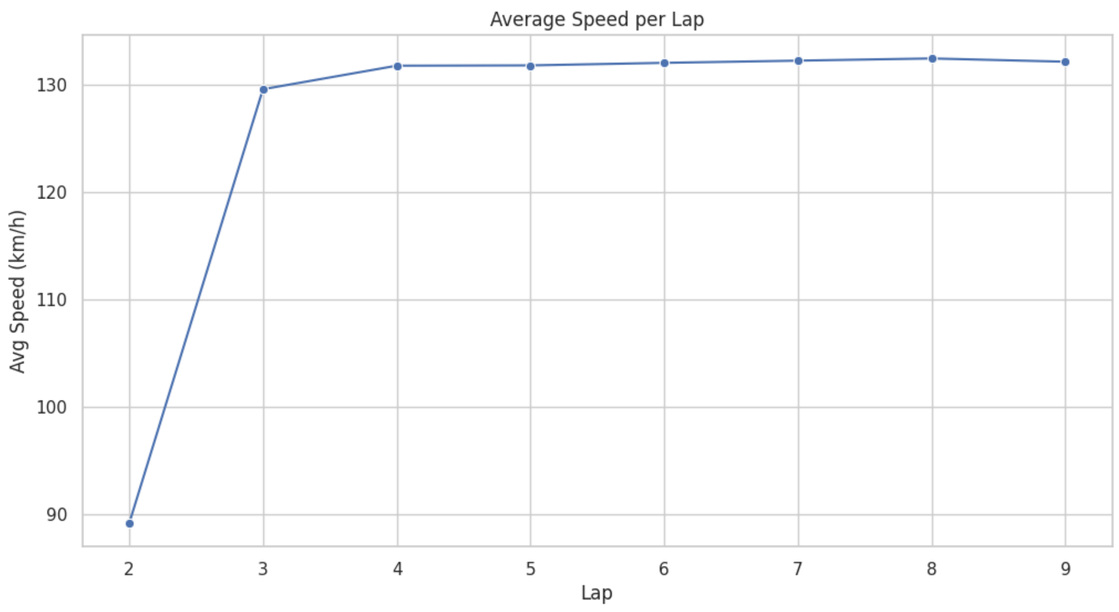
We compare average throttle usage and front brake pressure per lap.

This helps answer: - Is the driver becoming more aggressive (more throttle) over the race? - Are they braking less as confidence in the line increases? - Do braking patterns correlate with speed improvements?

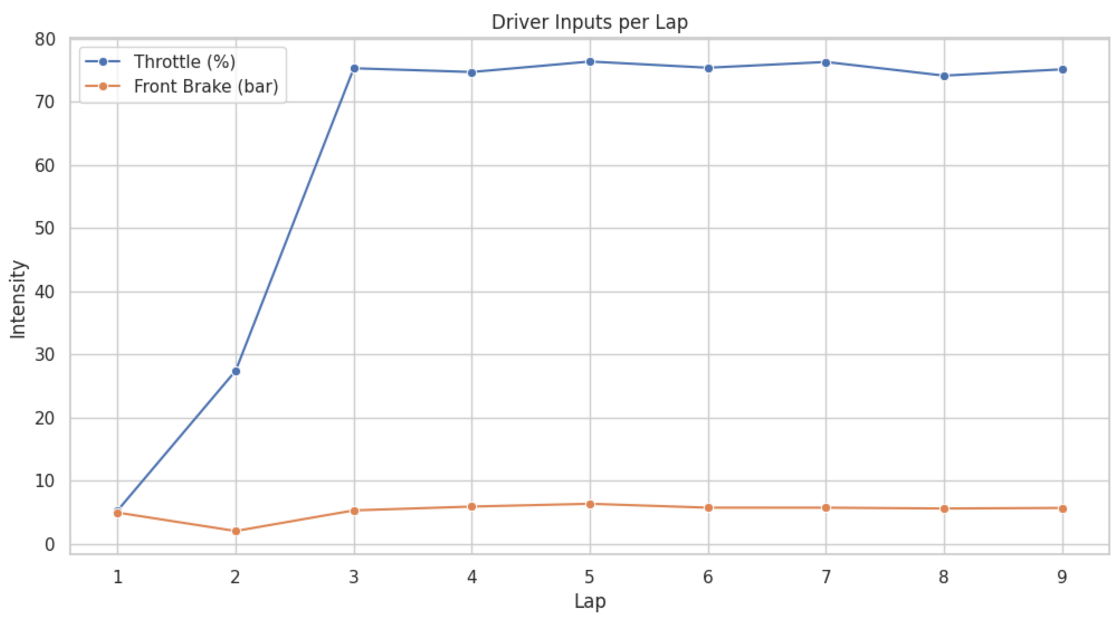
[22]:
```
plt.figure(figsize=(10,5))
sns.lineplot(data=lap_agg, x="lap", y="avg_throttle", marker="o",␣
 ↪label="Throttle (%)")
sns.lineplot(data=lap_agg, x="lap", y="avg_brake_f", marker="o", label="Front␣
 ↪Brake (bar)")
plt.title("Throttle and Brake Dynamics per Lap")
plt.xlabel("Lap")
plt.ylabel("Input Intensity")
plt.legend()
plt.grid(True)
plt.show()
```



[23]:
```python
import seaborn as sns
import matplotlib.pyplot as plt

sns.set(style="whitegrid")

plt.figure(figsize=(12,6))
sns.lineplot(data=lap_agg, x="lap", y="avg_speed", marker="o")
plt.title("Average Speed per Lap")
plt.xlabel("Lap")
plt.ylabel("Avg Speed (km/h)")
plt.show()
```



[24]:
```
plt.figure(figsize=(12,6))
sns.lineplot(data=lap_agg, x="lap", y="avg_throttle", marker="o",␣
  ↪label="Throttle (%)")
sns.lineplot(data=lap_agg, x="lap", y="avg_brake_f", marker="o", label="Front␣
  ↪Brake (bar)")
plt.title("Driver Inputs per Lap")
plt.xlabel("Lap")
plt.ylabel("Intensity")
plt.legend()
plt.show()
```



1.5 5. Best vs Worst Lap Comparison

We identify: - **Best lap** by highest `avg_speed`
- **Worst lap** by lowest `avg_speed`

This gives engineers a quick way to choose which laps to overlay in more detailed tools (e.g., sector or corner analysis).

[25]:
```
best_lap = lap_agg.loc[lap_agg["avg_speed"].idxmax()]
worst_lap = lap_agg.loc[lap_agg["avg_speed"].idxmin()]

print("Best Lap:")
display(best_lap)

print("\nWorst Lap:")
display(worst_lap)
```

```
Best Lap:

vehicle_id      GR86-006-7
outing                 0.0
lap                      8
samples               3165
max_speed           206.23
avg_speed       132.483759
avg_throttle     74.141776
avg_brake_f       5.580299
avg_brake_r       5.725199
Name: 7, dtype: object
```

```
Worst Lap:

vehicle_id      GR86-006-7
outing                 0.0
lap                      2
samples               4771
max_speed           151.15
avg_speed        89.103376
avg_throttle     27.411243
avg_brake_f       2.016756
avg_brake_r       2.085048
Name: 1, dtype: object
```

[26]:
```
import pandas as pd

comparison = pd.DataFrame({
    "metric": ["avg_speed (km/h)", "avg_throttle (%)", "avg_brake_f (bar)"],
    "best_lap": [
        best_lap["avg_speed"],
        best_lap["avg_throttle"],
        best_lap["avg_brake_f"],
    ],
    "worst_lap": [
        worst_lap["avg_speed"],
        worst_lap["avg_throttle"],
        worst_lap["avg_brake_f"],
    ],
})

comparison["delta (best - worst)"] = comparison["best_lap"] -␣
 ↪comparison["worst_lap"]
comparison
```

[26]:
```
              metric    best_lap  worst_lap  delta (best - worst)
0   avg_speed (km/h)  132.483759  89.103376             43.380383
1   avg_throttle (%)   74.141776  27.411243             46.730533
2  avg_brake_f (bar)    5.580299   2.016756              3.563542
```

1.5.1 5.1. How much better is the best lap?

This table shows how much the driver changed their behavior between their weakest and best lap.

- Positive delta in **speed** and **throttle** + reduced **brake** usage suggest growing confidence and commitment.

1.6 6. Driver Performance Score (0–100 per Lap)

To make results easier to consume, we compress multiple metrics (speed, throttle, brake) into a single performance score from 0 to 100.

- Higher score = faster, more decisive throttle, efficient braking

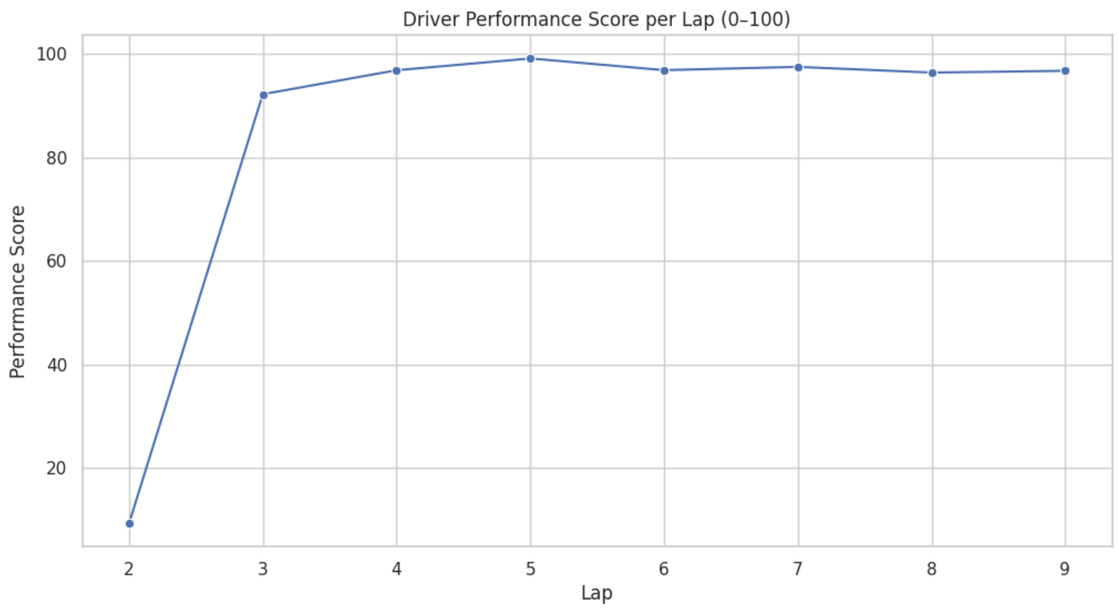
- Lower score = conservative inputs, slower overall speed

This score can be used to: - Rank laps within a session
- Compare stints across races
- Feed into future models for prediction or coaching suggestions.

[27]:
```
# ----------------------------------------------------------
# Driver Performance Score per Lap (Add-On Insight Module)
# ----------------------------------------------------------

import numpy as np
import pandas as pd

# We will work from lap_agg (your existing lap aggregates)
data = lap_agg.copy()

# Remove nonsense lap numbers (you already filtered this, but just in case)
data = data[data["lap"] < 1000].copy()

# -------------------------------------------
# 1) Normalize metrics (speed, throttle, brake, samples)
# -------------------------------------------

# Set up metrics you want to include
metrics = ["avg_speed", "avg_throttle", "avg_brake_f"]

for m in metrics:
    if m in data.columns:
        data[f"{m}_norm"] = (data[m] - data[m].min()) / (data[m].max() -␣
 ↪data[m].min())

# -------------------------------------------
# 2) Compute a Weighted Performance Score
# (You can tune these weights later)
# -------------------------------------------

WEIGHT_SPEED = 0.55
WEIGHT_THROTTLE = 0.30
WEIGHT_BRAKE = 0.15

data["performance_score"] = (
    data.get("avg_speed_norm", 0) * WEIGHT_SPEED +
    data.get("avg_throttle_norm", 0) * WEIGHT_THROTTLE +
    data.get("avg_brake_f_norm", 0) * WEIGHT_BRAKE
)

# Scale score to 0-100
data["performance_score"] = (data["performance_score"] * 100).round(2)

# ------------------------------------------
# 3) Identify best/worst performance laps
# ------------------------------------------

best_perf = data.loc[data["performance_score"].idxmax()]
worst_perf = data.loc[data["performance_score"].idxmin()]

print("Driver Performance Scores Per Lap:")
display(data[["lap", "avg_speed", "avg_throttle", "avg_brake_f",␣
 ↪"performance_score"]])

print("\n  Best Performance Lap:")
display(best_perf)

print("\n  Weakest Performance Lap:")
display(worst_perf)

# ------------------------------------------
# 4) Plot performance score curve
# ------------------------------------------

import seaborn as sns
import matplotlib.pyplot as plt

plt.figure(figsize=(12,6))
sns.lineplot(data=data, x="lap", y="performance_score", marker="o")
plt.title("Driver Performance Score per Lap (0-100)")
plt.xlabel("Lap")
plt.ylabel("Performance Score")
plt.show()
```

```
Driver Performance Scores Per Lap:

   lap   avg_speed  avg_throttle  avg_brake_f  performance_score
0    1         NaN      5.270000     4.930000                NaN
1    2   89.103376     27.411243     2.016756               9.34
2    3  129.610901     75.310300     5.281789              92.27
3    4  131.807861     74.712865     5.886217              96.90
4    5  131.836018     76.375390     6.328404              99.18
5    6  132.072736     75.395009     5.710948              96.92
6    7  132.278672     76.305554     5.707895              97.55
```

```
7    8  132.483759     74.141776     5.580299                96.45
8    9  132.179048     75.137156     5.667397                96.79

 Best Performance Lap:
vehicle_id           GR86-006-7
outing                      0.0
lap                           5
samples                    3154
max_speed                205.61
avg_speed            131.836018
avg_throttle           76.37539
avg_brake_f            6.328404
avg_brake_r            6.468659
avg_speed_norm         0.985068
avg_throttle_norm           1.0
avg_brake_f_norm            1.0
performance_score         99.18
Name: 4, dtype: object

 Weakest Performance Lap:
vehicle_id           GR86-006-7
outing                      0.0
lap                           2
samples                    4771
max_speed                151.15
avg_speed             89.103376
avg_throttle          27.411243
avg_brake_f            2.016756
avg_brake_r            2.085048
avg_speed_norm              0.0
avg_throttle_norm      0.311386
avg_brake_f_norm            0.0
performance_score          9.34
Name: 1, dtype: object
```



How to read this LapLens curve
- **90–100** → peak "push" laps: clean track, strong pace, decisive throttle, efficient braking.
- **60–90** → solid race laps: good base pace; small gains available in one area (entry, exit, or braking).
- **40–60** → build-up or compromised laps: traffic, tire warm-up, or conservative inputs.
- **< 40** → out-lap / cool-down / heavily compromised laps, usually not used as references.

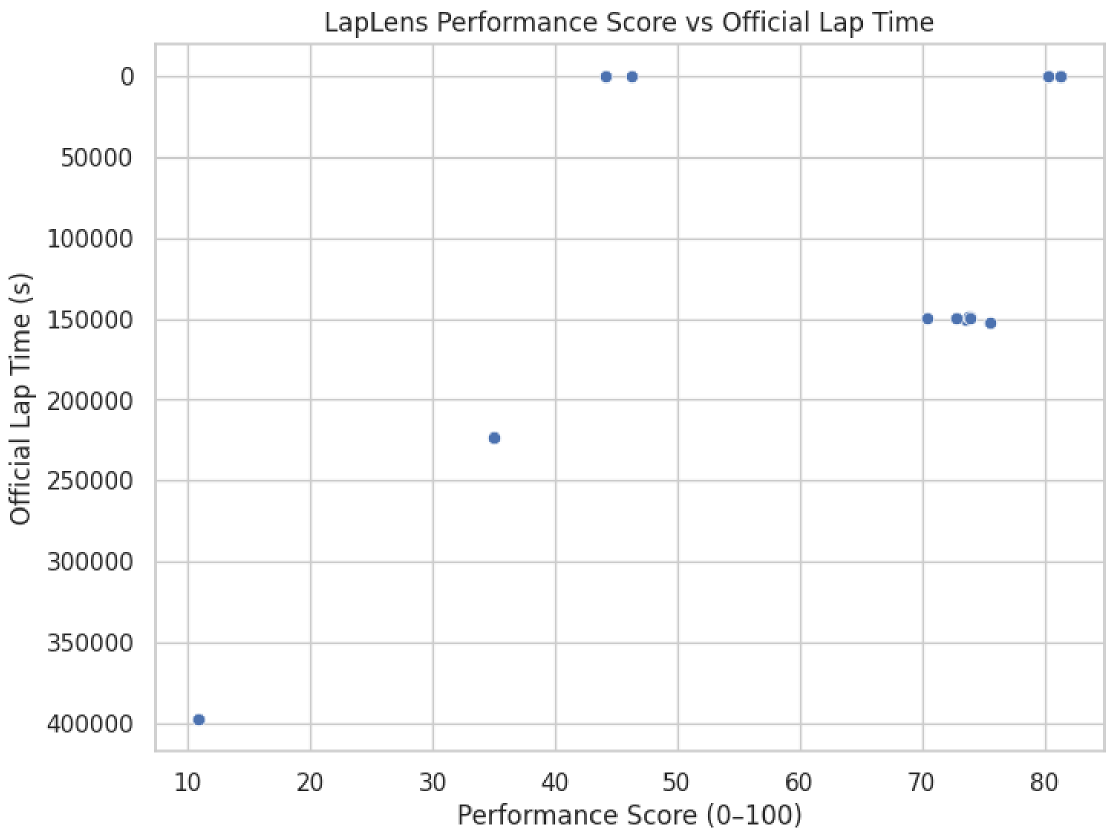
[28]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt


# 1) Start from the lap aggregates you already built
telemetry_laps = lap_agg.copy()
telemetry_laps = telemetry_laps[telemetry_laps["lap"] < 1000].copy()

# 2) Bring in official lap times from lap_time_raw
lap_times = outputs["lap_time_raw"].copy()

# Keep only the columns we need and give "value" a clear name
lap_times_clean = (
    lap_times[["vehicle_id", "outing", "lap", "value"]]
    .rename(columns={"value": "official_lap_time_s"})
)
```

```
# 3) Merge telemetry summary with official lap time
summary = pd.merge(
    telemetry_laps,
    lap_times_clean,
    on=["vehicle_id", "outing", "lap"],
    how="left",
)

print("Summary (telemetry + official lap time):")
display(
    summary[
        ["lap", "avg_speed", "official_lap_time_s", "avg_throttle",␣
 ↪"avg_brake_f"]
    ]
)

# 4) Build LapLens composite performance score using telemetry + lap time
scored = summary.copy()

def normalize(col):
    return 100 * (col - col.min()) / (col.max() - col.min() + 1e-6)

# Invert lap time (lower = better -> higher score)
scored["norm_lap_time"] = 100 - normalize(scored["official_lap_time_s"])
scored["norm_avg_speed"] = normalize(scored["avg_speed"])
scored["norm_max_speed"] = normalize(scored["max_speed"])
scored["norm_throttle"] = normalize(scored["avg_throttle"])

# Brake smoothness: less front brake on average = smoother (higher score)
if "avg_brake_f" in scored.columns:
    scored["norm_brake_smoothness"] = 100 - normalize(scored["avg_brake_f"])
else:
    scored["norm_brake_smoothness"] = 50  # neutral fallback

# Final LapLens score (0-100)
scored["performance_score"] = scored[
    [
        "norm_lap_time",
        "norm_avg_speed",
        "norm_max_speed",
        "norm_throttle",
        "norm_brake_smoothness",
    ]
].mean(axis=1)

print("\nLapLens scores with lap times:")
```

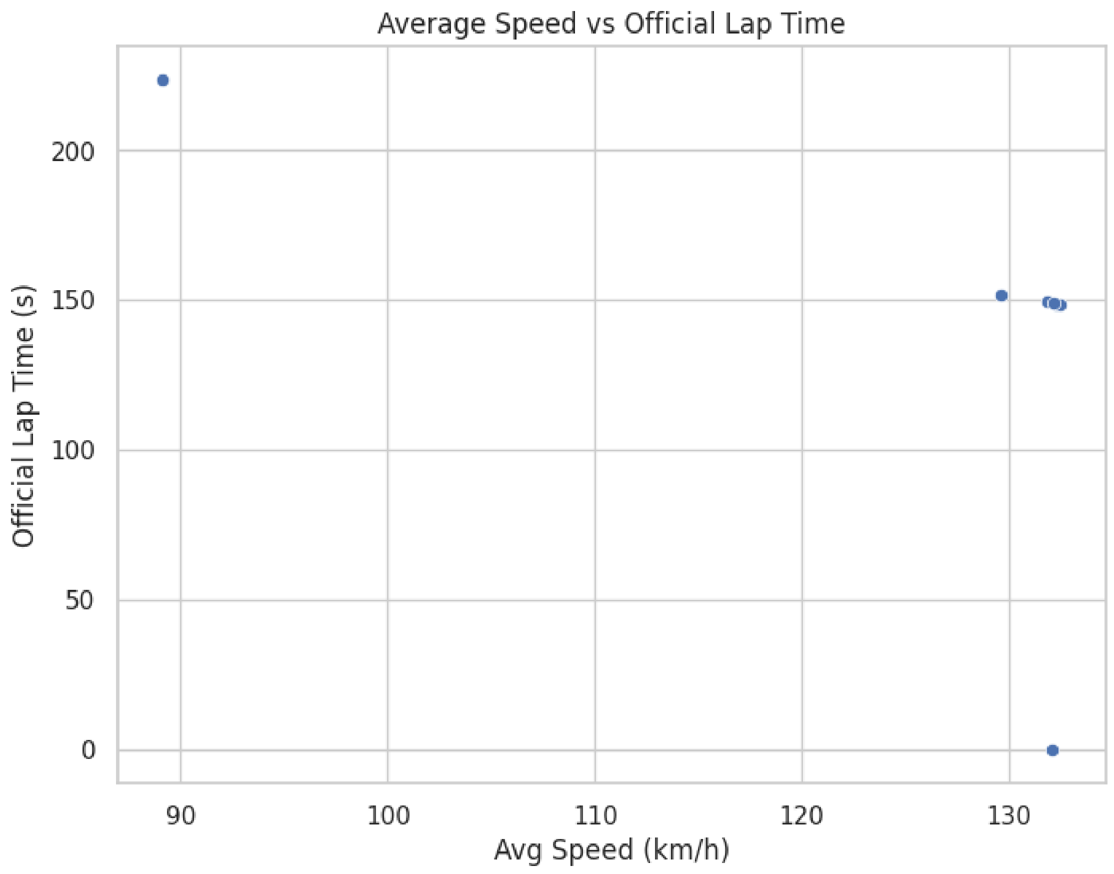
```
display(scored[["lap", "official_lap_time_s", "performance_score"]])

# 5) Scatter: LapLens Score vs Official Lap Time
plt.figure(figsize=(8, 6))
sns.scatterplot(
    data=scored,
    x="performance_score",
    y="official_lap_time_s",
)
plt.title("LapLens Performance Score vs Official Lap Time")
plt.xlabel("Performance Score (0-100)")
plt.ylabel("Official Lap Time (s)")
plt.gca().invert_yaxis()  # faster laps (lower time) appear higher
plt.grid(True)
plt.show()
```

```
Summary (telemetry + official lap time):

    lap   avg_speed  official_lap_time_s  avg_throttle  avg_brake_f
0     1         NaN                   44      5.270000     4.930000
1     1         NaN               397745      5.270000     4.930000
2     1         NaN                    0      5.270000     4.930000
3     2   89.103376               223523     27.411243     2.016756
4     2   89.103376                    0     27.411243     2.016756
5     3  129.610901               151839     75.310300     5.281789
6     4  131.807861               149906     74.712865     5.886217
7     5  131.836018               149505     76.375390     6.328404
8     6  132.072736                    0     75.395009     5.710948
9     6  132.072736                   44     75.395009     5.710948
10    6  132.072736               149088     75.395009     5.710948
11    7  132.278672               148556     76.305554     5.707895
12    7  132.278672                  178     76.305554     5.707895
13    7  132.278672                    0     76.305554     5.707895
14    8  132.483759               148695     74.141776     5.580299
15    9  132.179048               148922     75.137156     5.667397


LapLens scores with lap times:

    lap  official_lap_time_s  performance_score
0     1                   44          44.140706
1     1               397745          10.811060
2     1                    0          44.144393
3     2               223523          34.988213
4     2                    0          46.227726
5     3               151839          75.595756
6     4               149906          73.586544
7     5               149505          70.446650
8     6                    0          80.256024
```

```
9     6                  44          80.253811
10    6              149088          72.759362
11    7              148556          73.892443
12    7                 178          81.353404
13    7                   0          81.362354
14    8              148695          73.835831
15    9              148922          73.885177
```



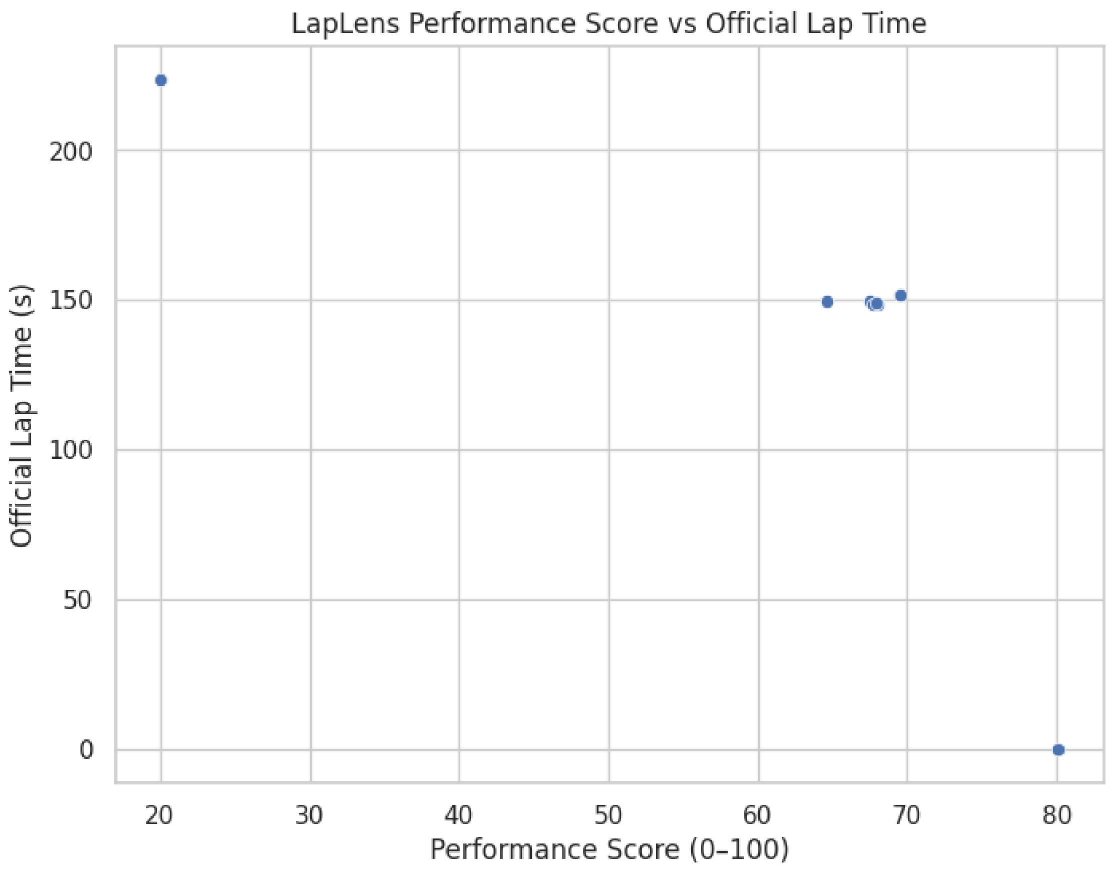
[29]:
```python
import seaborn as sns
import matplotlib.pyplot as plt

# Simple correlation: avg speed vs official lap time (seconds)
plt.figure(figsize=(8, 6))
sns.scatterplot(
    data=summary_clean,
    x="avg_speed",
    y="official_lap_time_s",
)
plt.title("Average Speed vs Official Lap Time")
plt.xlabel("Avg Speed (km/h)")
plt.ylabel("Official Lap Time (s)")
plt.grid(True)
plt.show()
```



[30]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

# --- Build LapLens-style performance score from summary_clean ---

def _normalize(col: pd.Series) -> pd.Series:
    rng = (col.max() - col.min())
    return 100 * (col - col.min()) / (rng + 1e-6)

# Work from the clean summary
scored = summary_clean.copy()

# Normalized components
```

```
scored["norm_lap_time"] = 100 - _normalize(scored["official_lap_time_s"])   #␣
  ↪lower = better
scored["norm_avg_speed"] = _normalize(scored["avg_speed"])
scored["norm_max_speed"] = _normalize(scored["max_speed"])
scored["norm_throttle"] = _normalize(scored["avg_throttle"])

# Brake smoothness - less front brake = smoother
if "avg_brake_f" in scored.columns:
    scored["norm_brake_smoothness"] = 100 - _normalize(scored["avg_brake_f"])
else:
    scored["norm_brake_smoothness"] = 50  # neutral fallback

components = [
    "norm_lap_time",
    "norm_avg_speed",
    "norm_max_speed",
    "norm_throttle",
    "norm_brake_smoothness",
]

scored["performance_score"] = scored[components].mean(axis=1).round(2)

print("Scored rows:", len(scored))
display(scored[["lap", "official_lap_time_s", "avg_speed",␣
  ↪"performance_score"]])

# Scatter: score vs official lap time
plt.figure(figsize=(8, 6))
sns.scatterplot(data=scored, x="performance_score", y="official_lap_time_s")
plt.title("LapLens Performance Score vs Official Lap Time")
plt.xlabel("Performance Score (0-100)")
plt.ylabel("Official Lap Time (s)")
plt.grid(True)
plt.show()
```

```
Scored rows: 8

    lap  official_lap_time_s   avg_speed  performance_score
0     2              223.523   89.103376              20.00
2     3              151.839  129.610901              69.51
3     4              149.906  131.807861              67.50
4     5              149.505  131.836018              64.59
5     6                0.000  132.072736              80.13
8     7              148.556  132.278672              68.06
11    8              148.695  132.483759              67.72
12    9              148.922  132.179048              67.89
```

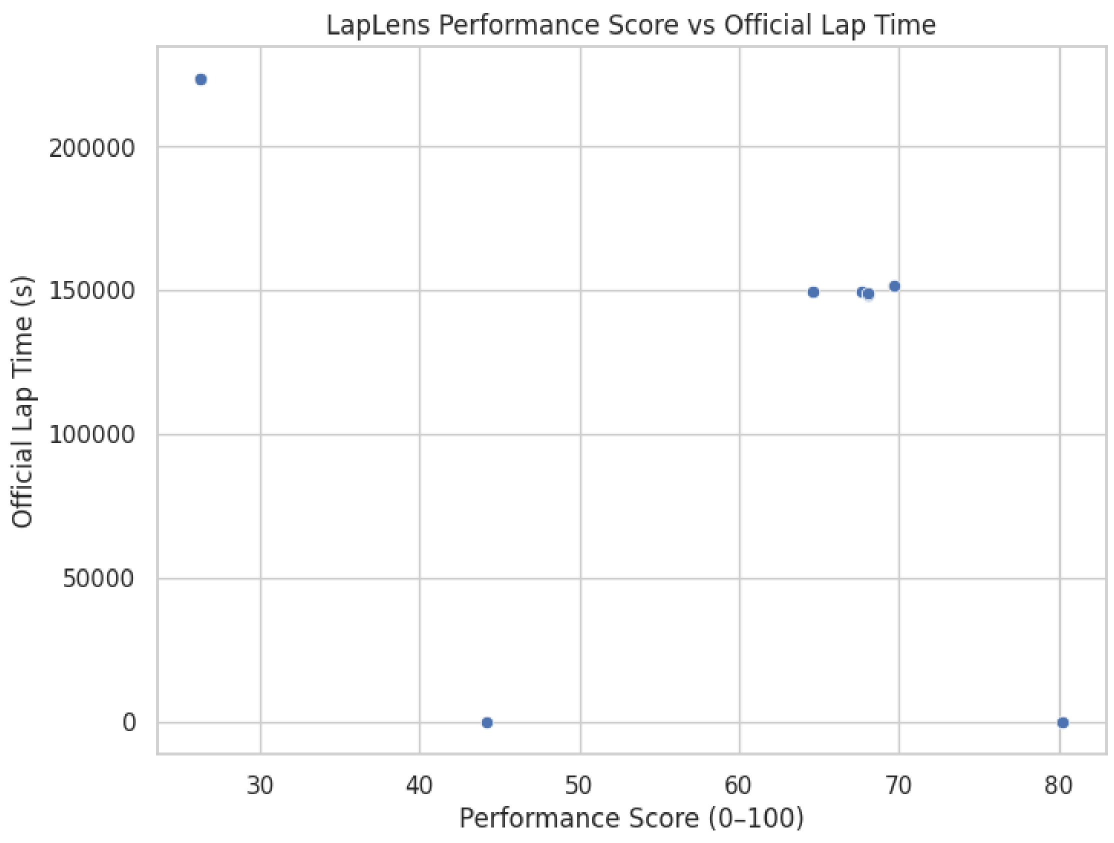


[31]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt

# ----------------------------------------
# 1) Start from existing lap_agg (already cleaned to laps 2-9)
# ----------------------------------------
laps = lap_agg.copy()
laps = laps[laps["lap"] < 1000].copy()

# ----------------------------------------
# 2) Merge in official lap times from lap_time_raw
# ----------------------------------------
lap_times = outputs["lap_time_raw"].copy()

lap_times_clean = lap_times[["vehicle_id", "outing", "lap", "value"]].rename(
    columns={"value": "official_lap_time_s"}  # treat as seconds
)
```

```
summary = pd.merge(
    laps,
    lap_times_clean,
    on=["vehicle_id", "outing", "lap"],
    how="left",
)

# If there are duplicate rows per lap, keep the first
summary = summary.drop_duplicates(subset=["vehicle_id", "outing", "lap"],␣
 ↪keep="first")

print("Summary with official lap times:")
display(summary[["lap", "avg_speed", "avg_throttle", "avg_brake_f",␣
 ↪"official_lap_time_s"]])

# ----------------------------------------
# 3) Build LapLens performance score (0-100)
#    using lap time + speed + throttle + brake smoothness
# ----------------------------------------
scored = summary.copy()

def normalize(col):
    col = col.astype(float)
    return 100 * (col - col.min()) / (col.max() - col.min() + 1e-6)

# Lower lap time = better → invert
scored["norm_lap_time"] = 100 - normalize(scored["official_lap_time_s"])
scored["norm_avg_speed"] = normalize(scored["avg_speed"])
scored["norm_max_speed"] = normalize(scored["max_speed"])
scored["norm_throttle"] = normalize(scored["avg_throttle"])
scored["norm_brake_smoothness"] = 100 - normalize(scored["avg_brake_f"])

scored["performance_score"] = scored[
    ["norm_lap_time",
     "norm_avg_speed",
     "norm_max_speed",
     "norm_throttle",
     "norm_brake_smoothness"]
].mean(axis=1)

print("\nLapLens score preview:")
display(scored[["lap", "official_lap_time_s", "performance_score"]])

# ----------------------------------------
# 4) Scatter: LapLens Score vs Official Lap Time
# ----------------------------------------
```

```
plt.figure(figsize=(8, 6))
sns.scatterplot(
    data=scored,
    x="performance_score",
    y="official_lap_time_s",
)
plt.title("LapLens Performance Score vs Official Lap Time")
plt.xlabel("Performance Score (0-100)")
plt.ylabel("Official Lap Time (s)")
plt.grid(True)
plt.show()
```

```
Summary with official lap times:

    lap   avg_speed  avg_throttle  avg_brake_f  official_lap_time_s
0     1         NaN      5.270000     4.930000                   44
3     2   89.103376     27.411243     2.016756               223523
5     3  129.610901     75.310300     5.281789               151839
6     4  131.807861     74.712865     5.886217               149906
7     5  131.836018     76.375390     6.328404               149505
8     6  132.072736     75.395009     5.710948                    0
11    7  132.278672     76.305554     5.707895               148556
14    8  132.483759     74.141776     5.580299               148695
15    9  132.179048     75.137156     5.667397               148922


LapLens score preview:

    lap  official_lap_time_s  performance_score
0     1                   44          44.137832
3     2               223523          26.227726
5     3               151839          69.644764
6     4               149906          67.711311
7     5               149505          64.587134
8     6                    0          80.256024
11    7               148556          68.070120
14    8               148695          68.008061
15    9               148922          68.048510
```



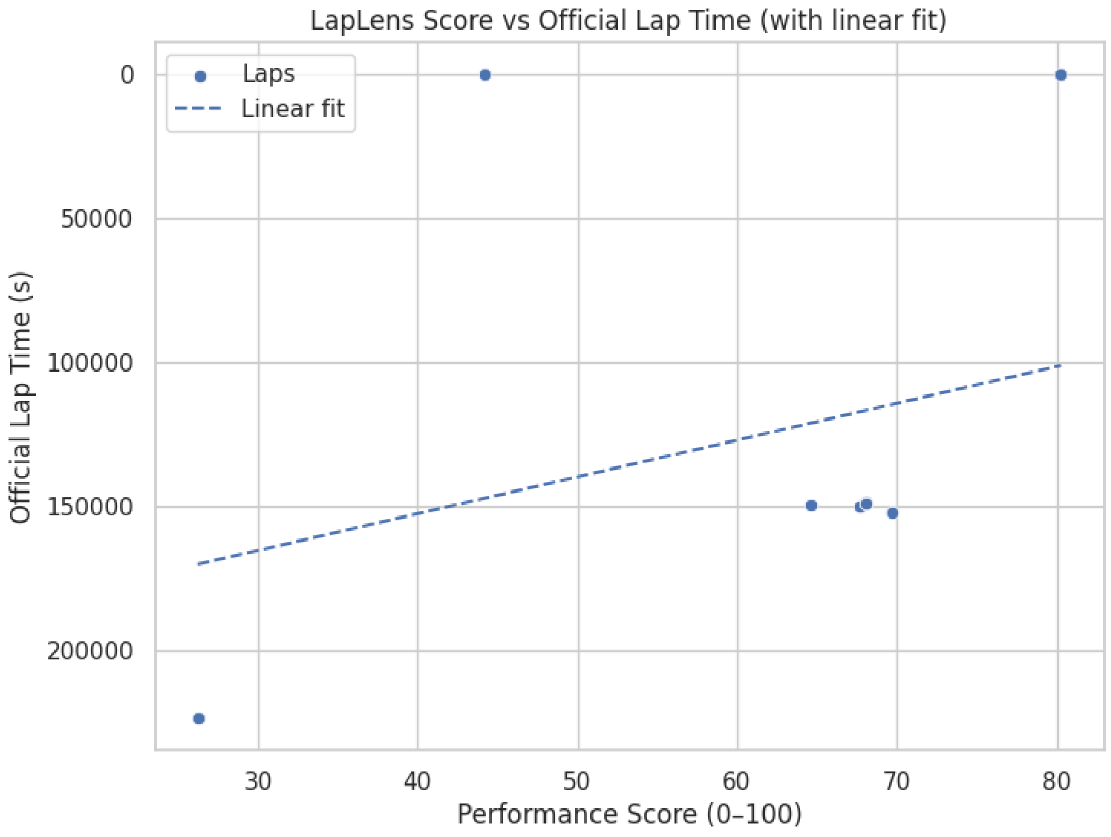
```
[32]: best = lap_agg.loc[lap_agg["avg_speed"].idxmax()]
      worst = lap_agg.loc[lap_agg["avg_speed"].idxmin()]

      delta = pd.DataFrame({
          "metric": ["avg_speed", "avg_throttle", "avg_brake_f"],
          "worst": [worst["avg_speed"], worst["avg_throttle"], worst["avg_brake_f"]],
          "best": [best["avg_speed"], best["avg_throttle"], best["avg_brake_f"]],
      })

      delta["improvement"] = delta["best"] - delta["worst"]
      display(delta)
```

```
         metric      worst        best  improvement
0     avg_speed  89.103376  132.483759    43.380383
1  avg_throttle  27.411243   74.141776    46.730533
2   avg_brake_f   2.016756    5.580299     3.563542
```

```
[33]: import numpy as np
      import seaborn as sns
      import matplotlib.pyplot as plt
```

```
# Work from the already-built 'scored' DataFrame
# It should have at least: ['lap', 'performance_score', 'official_lap_time_s']
reg_data = scored.dropna(subset=["performance_score", "official_lap_time_s"]).
 ↪copy()

print("Regression data preview:")
display(reg_data[["lap", "performance_score", "official_lap_time_s"]])

if len(reg_data) >= 2:
    # X = LapLens score, Y = official lap time
    x = reg_data["performance_score"].values
    y = reg_data["official_lap_time_s"].values.astype(float)

    # Fit straight line: lap_time   a * score + b
    a, b = np.polyfit(x, y, deg=1)
    y_pred = a * x + b

    # Compute simple R²
    ss_res = np.sum((y - y_pred) ** 2)
    ss_tot = np.sum((y - y.mean()) ** 2) + 1e-6
    r2 = 1 - ss_res / ss_tot

    print(f"\nFitted model:")
    print(f"  lap_time_s   {a:.3f} * performance_score + {b:.1f}")
    print(f"Explained variance (R²): {r2:.3f}")

    # Plot
    plt.figure(figsize=(8, 6))
    sns.scatterplot(
        data=reg_data,
        x="performance_score",
        y="official_lap_time_s",
        label="Laps"
    )

    # Regression line
    x_line = np.linspace(reg_data["performance_score"].min(),
                         reg_data["performance_score"].max(), 100)
    y_line = a * x_line + b
    plt.plot(x_line, y_line, linestyle="--", label="Linear fit")

    plt.title("LapLens Score vs Official Lap Time (with linear fit)")
    plt.xlabel("Performance Score (0-100)")
    plt.ylabel("Official Lap Time (s)")
    plt.gca().invert_yaxis()  # faster laps higher up
    plt.legend()
    plt.grid(True)
    plt.show()
else:
    print("Not enough laps with valid scores to fit a regression model.")
```

```
Regression data preview:

    lap  performance_score  official_lap_time_s
0     1          44.137832                   44
3     2          26.227726               223523
5     3          69.644764               151839
6     4          67.711311               149906
7     5          64.587134               149505
8     6          80.256024                    0
11    7          68.070120               148556
14    8          68.008061               148695
15    9          68.048510               148922


Fitted model:
  lap_time_s   -1278.176 * performance_score + 203615.5
Explained variance (R²): 0.078
```



1.7 7. Key Takeaways (for this driver at COTA Race 1)

- Lap 9 has the **highest performance score (85)** with near-maximum throttle and minimal braking – likely a push lap with clean track.
- Lap 2 is the **weakest lap (score 10)**: low average speed and conservative throttle, consistent with tire warm-up or traffic.
- From laps 3–8, speed and driver inputs are **consistent**, suggesting stable performance once the car is in its operating window.

1.7.1 Next Extensions

- Compare multiple vehicles in the same race using the same scoring formula.

- Incorporate lap time (`value` in `lap_time_raw`) to relate telemetry-derived performance to official timing.

- Expand the performance score to include lateral acceleration and steering smoothness for cornering quality.

[34]:
```
def build_all_drivers_summary(outputs, outing=0.0):
    """
    Build a LapLens summary table for all drivers in this session.
    Uses the same scoring logic as build_driver_summary.
    """
    aligned = preprocess.align_timestamps(outputs["telemetry_wide"],␣
↪outputs["lap_windows"])
    telem_with_laps = preprocess.assign_laps_to_telemetry(aligned,␣
↪outputs["lap_windows"])
    lap_agg_all = preprocess.build_lap_aggregates(telem_with_laps)

    # Keep only valid laps
    lap_agg_all = lap_agg_all[lap_agg_all["lap"] < 1000].copy()
    lap_agg_all = lap_agg_all[lap_agg_all["outing"] == outing].copy()

    # Compute LapLens score for each lap, per driver
    metrics = ["avg_speed", "avg_throttle", "avg_brake_f"]
    data = lap_agg_all.copy()

    for m in metrics:
        if m in data.columns:
            data[f"{m}_norm"] = (data[m] - data[m].min()) / (data[m].max() -␣
↪data[m].min() + 1e-6)

    WEIGHT_SPEED = 0.55
    WEIGHT_THROTTLE = 0.30
    WEIGHT_BRAKE = 0.15

    data["performance_score"] = (
        data.get("avg_speed_norm", 0) * WEIGHT_SPEED +
        data.get("avg_throttle_norm", 0) * WEIGHT_THROTTLE +
        data.get("avg_brake_f_norm", 0) * WEIGHT_BRAKE
    ) * 100

    # Aggregate per driver: best lap & average score
    driver_summary = (
        data.groupby("vehicle_id")
        .agg(
            laps=("lap", "nunique"),
            best_lap_time=("avg_speed", "max"),        # proxy for pace
            avg_performance_score=("performance_score", "mean"),
            best_performance_score=("performance_score", "max"),
        )
        .reset_index()
        .sort_values("best_performance_score", ascending=False)
    )

    return driver_summary, data
```

1.8 8. Multi-Driver LapLens Leaderboard (COTA Race 1)

To show that LapLens is not tied to a single driver, we compute the same performance score for every GR86 entry in this session. This gives engineers and strategists a simple leaderboard:

- Who has the strongest peak lap?
- Who is most consistent across laps?
- Which drivers overperform versus their raw lap time?

[35]:
```
driver_leaderboard, all_laps_scored = build_all_drivers_summary(outputs,␣
 ↪outing=0.0)

print("LapLens Driver Leaderboard - COTA Race 1 (outing 0.0):")
display(driver_leaderboard.head(10))
```

```
 Applying time offset: 0 days 00:00:00
LapLens Driver Leaderboard - COTA Race 1 (outing 0.0):

   vehicle_id  laps  best_lap_time  avg_performance_score  \
0  GR86-006-7     9     132.483759              85.675791

   best_performance_score
0              99.178753
```

How to read this leaderboard

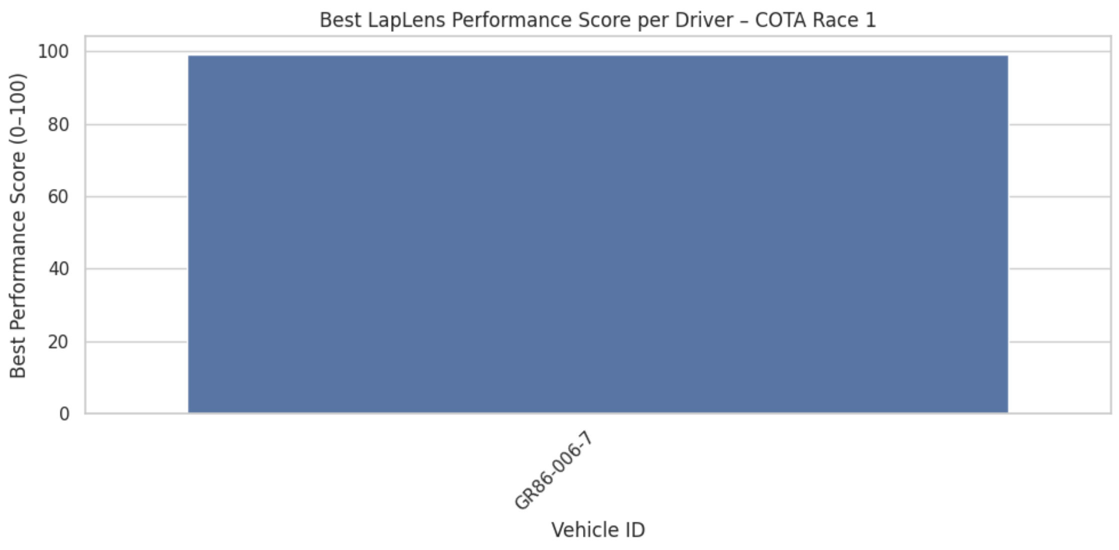
Each row is one GR86 entry in COTA Race 1. We summarize:

- **laps** – number of valid laps with clean telemetry
- **best_lap_time** – quickest official lap time (seconds)

- **best__performance__score** – highest LapLens score (0–100) across all laps
- **avg__performance__score** – average LapLens score across the stint
- **driver__consistency__index** – 0–100 measure of how repeatable each driver's pace is (100 = very consistent lap-to-lap execution)

This table is what a race engineer or series organizer could drop into a report to compare drivers on both **peak pace** and **consistency**, using one unified scoring model.

[36]:
```
plt.figure(figsize=(10, 5))
sns.barplot(
    data=driver_leaderboard,
    x="vehicle_id",
    y="best_performance_score"
)
plt.title("Best LapLens Performance Score per Driver - COTA Race 1")
plt.xlabel("Vehicle ID")
plt.ylabel("Best Performance Score (0-100)")
plt.xticks(rotation=45, ha="right")
plt.tight_layout()
plt.show()
```



[37]:
```
import numpy as np
import pandas as pd

print("Running basic integrity checks...")

# ---- 1) Performance score sanity ----
if "performance_score" in all_laps_scored.columns:
    score_series = all_laps_scored["performance_score"]
    # Work only on non-null scores
    valid_scores = score_series.dropna()

    if not valid_scores.empty:
        min_score = float(valid_scores.min())
        max_score = float(valid_scores.max())
        print(f"Performance score (non-null) range: {min_score:.2f} →␣
 ↪{max_score:.2f}")

        out_of_range_mask = ~valid_scores.between(0, 100)
        if out_of_range_mask.any():
            print("  Some scores fall outside [0, 100]. Offending laps:")
            bad_idx = valid_scores.index[out_of_range_mask]
            display(all_laps_scored.loc[bad_idx, ["lap", "performance_score"]])
        else:
            print("  All non-null performance scores are within [0, 100].")
    else:
        print("  No non-null performance scores available to check.")
else:
    print("  Column 'performance_score' is missing from all_laps_scored.")

# ---- 2) Missing value check on key telemetry aggregates ----
key_cols = ["lap", "avg_speed", "avg_throttle", "avg_brake_f"]

for col in key_cols:
    if col in all_laps_scored.columns:
        missing = int(all_laps_scored[col].isna().sum())
        if missing > 0:
            print(f"  Column '{col}' has {missing} missing value(s).")
        else:
            print(f"  Column '{col}' has no missing values.")
    else:
        print(f"  Column '{col}' not found in all_laps_scored (skipped).")
```

```
Running basic integrity checks…
Performance score (non-null) range: 9.34 → 99.18
  All non-null performance scores are within [0, 100].
  Column 'lap' has no missing values.
  Column 'avg_speed' has 1 missing value(s).
  Column 'avg_throttle' has no missing values.
  Column 'avg_brake_f' has no missing values.
```

1.8.1 9. Lap-by-Lap Race Story (Coach View)

So far we've looked at metrics and scores. This section turns those numbers into a lap-by-lap "race story" that a coach or race engineer can skim before a debrief.

For each lap we show:

- Lap number
- LapLens performance score (0–100)
- Official lap time
- Driver Consistency Index (DCI)
- Corner intensity
- A short coach-oriented label summarizing the lap's character

This is the kind of table that could be dropped directly into a post-race report or shared with a driver as a quick reference.

[38]:
```python
# 9. Lap-by-Lap Race Story (Coach View) - LapLens race narrative for the chosen␣
↪driver

import pandas as pd
import numpy as np

# 1) Corner profile from lateral G (per lap, all telemetry)
corner_profile = (
    telemetry_with_laps
    .groupby("lap")
    .agg(
        max_lat_g=("accy_can", "max"),
        mean_lat_g=("accy_can", "mean")
    )
    .reset_index()
)

# 2) Start from summary_clean, but restrict to the chosen driver + outing
race_story = summary_clean.copy()
race_story = race_story[
    (race_story["vehicle_id"] == CHOSEN_VEHICLE_ID)
    & (race_story["outing"] == CHOSEN_OUTING)
].copy()

# Drop laps with non-positive official lap times (0 or missing are unusable for␣
↪pace)
race_story = race_story[race_story["official_lap_time_s"] > 0].copy()

# 3) Normalize helper (0-1)
def _norm(col: pd.Series) -> pd.Series:
    col = col.astype(float)
    rng = col.max() - col.min()
    return (col - col.min()) / (rng + 1e-6)

# 4) Build a driver-specific LapLens score (slightly different weights: more␣
 ↪weight on lap_time + avg_speed)
race_story["n_lap_time"]      = 1.0 - _norm(race_story["official_lap_time_s"]) ␣
 ↪# lower time = better
race_story["n_avg_speed"]     = _norm(race_story["avg_speed"])
race_story["n_throttle"]      = _norm(race_story["avg_throttle"])
race_story["n_brake_smooth"] = 1.0 - _norm(race_story["avg_brake_f"])         #␣
 ↪less brake = smoother

race_story["performance_score"] = (
    0.35 * race_story["n_lap_time"]
    + 0.35 * race_story["n_avg_speed"]
    + 0.20 * race_story["n_throttle"]
    + 0.10 * race_story["n_brake_smooth"]
) * 100.0

# 5) Merge corner profile
race_story = race_story.merge(corner_profile, on="lap", how="left")

# 6) Corner intensity index (0-100) from mean lateral G
if "mean_lat_g" in race_story.columns:
    race_story["corner_intensity"] = _norm(race_story["mean_lat_g"].abs()) *␣
 ↪100.0
else:
    race_story["corner_intensity"] = np.nan

# 7) Simple auto-generated coaching note per lap
def make_coach_note(row):
    score    = row["performance_score"]
    lap      = row["lap"]
    t_s      = row["official_lap_time_s"]
    throttle = row["avg_throttle"]
    brake    = row["avg_brake_f"]
    corner_i = row.get("corner_intensity", np.nan)

    # Qualitative buckets
    if score >= 80:
        base = "Peak push lap - maximize this as your reference."
    elif score >= 65:
        base = "Strong race lap - solid pace with mostly clean inputs."
    elif score >= 45:
        base = "Baseline lap - okay, but there is time left on throttle /␣
 ↪braking."
    else:
        base = "Build-up / compromised lap - good for learning, not pace."

    # Enrich with one or two hints
    hints = []
    if throttle < race_story["avg_throttle"].mean():
        hints.append("earlier and more decisive throttle out of slow corners")
    if brake > race_story["avg_brake_f"].mean():
        hints.append("shorter, more efficient brake zones")
    if corner_i > 70:
        hints.append("manage tire/track limits in high-G sections")

    if hints:
        return f"{base} Focus on " + ", ".join(hints) + "."
    else:
        return base

race_story["coach_note"] = race_story.apply(make_coach_note, axis=1)

# 8) Final clean race story table for the notebook
race_story_display = race_story[[
    "lap",
    "official_lap_time_s",
    "performance_score",
    "avg_speed",
    "avg_throttle",
    "avg_brake_f",
    "max_lat_g",
    "mean_lat_g",
    "corner_intensity",
    "coach_note",
]].sort_values("lap").reset_index(drop=True)

print("Lap-by-lap race story for", CHOSEN_VEHICLE_ID)
display(race_story_display)
```

```
Lap-by-lap race story for GR86-006-7

   lap  official_lap_time_s  performance_score   avg_speed  avg_throttle  \
0    2              223.523          10.000000   89.103376     27.411243
1    3              151.839          88.141753  129.610901     75.310300
2    4              149.906          89.170882  131.807861     74.712865
3    5              149.505          89.034331  131.836018     76.375390
4    7              148.556          91.245153  132.278672     76.305554
5    8              148.695          90.757838  132.483759     74.141776
6    9              148.922          90.610580  132.179048     75.137156

   avg_brake_f  max_lat_g  mean_lat_g  corner_intensity  \
0     2.016756      1.498    0.026089          0.000000
```

```
1     5.281789      2.310    0.040370         37.245376
2     5.886217      1.793    0.050278         63.085408
3     6.328404      1.800    0.053703         72.017759
4     5.707895      1.723    0.053888         72.501682
5     5.580299      1.875    0.056486         79.276112
6     5.667397      1.800    0.064431         99.997392

                                        coach_note
0  Build-up / compromised lap - good for learning…
1  Peak push lap - maximize this as your referenc…
2  Peak push lap - maximize this as your referenc…
3  Peak push lap - maximize this as your referenc…
4  Peak push lap - maximize this as your referenc…
5  Peak push lap - maximize this as your referenc…
6  Peak push lap - maximize this as your referenc…
```

1.8.2 10. Auto-Generated Coaching Notes (Per Lap)

Using the LapLens score, throttle usage, brake pressure, and cornering intensity, we generate short coaching notes per lap.

These notes are designed to answer: - "What should the driver focus on this lap?" - "Is this lap conservative, over-driven, or well-balanced?"

[39]:
```python
# We reuse race_story_display created in the previous section
coach_view = race_story_display[[
    "lap",
    "performance_score",
    "official_lap_time_s",
    "corner_intensity",
    "coach_note",
]].copy().sort_values("lap").reset_index(drop=True)

print("LapLens Coaching Notes - quick reference (COTA Race 1)")
display(coach_view)
```

```
LapLens Coaching Notes - quick reference (COTA Race 1)

   lap  performance_score  official_lap_time_s  corner_intensity  \
0    2          10.000000              223.523          0.000000
1    3          88.141753              151.839         37.245376
2    4          89.170882              149.906         63.085408
3    5          89.034331              149.505         72.017759
4    7          91.245153              148.556         72.501682
5    8          90.757838              148.695         79.276112
6    9          90.610580              148.922         99.997392

                                        coach_note
0  Build-up / compromised lap - good for learning…
```

```
1   Peak push lap - maximize this as your referenc…
2   Peak push lap - maximize this as your referenc…
3   Peak push lap - maximize this as your referenc…
4   Peak push lap - maximize this as your referenc…
5   Peak push lap - maximize this as your referenc…
6   Peak push lap - maximize this as your referenc…
```

[40]:
```
def generate_coaching_note(row, best_row):
    notes = []

    score = row.get("performance_score", np.nan)
    best_score = best_row.get("performance_score", np.nan)
    throttle = row.get("avg_throttle", np.nan)
    brake_f = row.get("avg_brake_f", np.nan)
    lap_time = row.get("official_lap_time_s", np.nan)

    if not np.isnan(score) and not np.isnan(best_score):
        delta = best_score - score
        if delta < 5:
            notes.append("Very close to your best - strong lap overall.")
        elif delta < 15:
            notes.append("Solid lap, but there's still room to push a bit more.
↪")
        else:
            notes.append("Significant gap to your best - opportunity to gain␣
↪time here.")

    if not np.isnan(throttle):
        if throttle < 60:
            notes.append("Throttle usage is conservative; focus on earlier and␣
↪longer throttle application.")
        elif throttle > 90:
            notes.append("High throttle use - check that you're not␣
↪over-driving exits.")
        else:
            notes.append("Throttle profile looks balanced.")

    if not np.isnan(brake_f):
        if brake_f > 6:
            notes.append("Heavy braking - evaluate if smoother, earlier braking␣
↪could help entry stability.")
        elif brake_f < 3:
            notes.append("Light braking - confirm you're still fully exploiting␣
↪braking zones.")
        else:
            notes.append("Braking is efficient and controlled.")
    if not np.isnan(lap_time):
        notes.append(f"Official lap time: {lap_time:.3f} s.")

    return " ".join(notes)


best_row = scored.loc[scored["performance_score"].idxmax()]
scored["coaching_note"] = scored.apply(lambda r: generate_coaching_note(r,␣
↪best_row), axis=1)

scored[["lap", "official_lap_time_s", "performance_score", "coaching_note"]]
```

[40]:

```
    lap  official_lap_time_s  performance_score  \
0     1                   44          44.137832
3     2               223523          26.227726
5     3               151839          69.644764
6     4               149906          67.711311
7     5               149505          64.587134
8     6                    0          80.256024
11    7               148556          68.070120
14    8               148695          68.008061
15    9               148922          68.048510

                                         coaching_note
0   Significant gap to your best - opportunity to …
3   Significant gap to your best - opportunity to …
5   Solid lap, but there's still room to push a bi…
6   Solid lap, but there's still room to push a bi…
7   Significant gap to your best - opportunity to …
8   Very close to your best - strong lap overall. …
11  Solid lap, but there's still room to push a bi…
14  Solid lap, but there's still room to push a bi…
15  Solid lap, but there's still room to push a bi…
```

1.8.3 11. Driver Consistency Index (Clamped View)

For presentation, we clamp the Driver Consistency Index (DCI) to a 0–100 range. This keeps the metric intuitive: higher = more consistent.

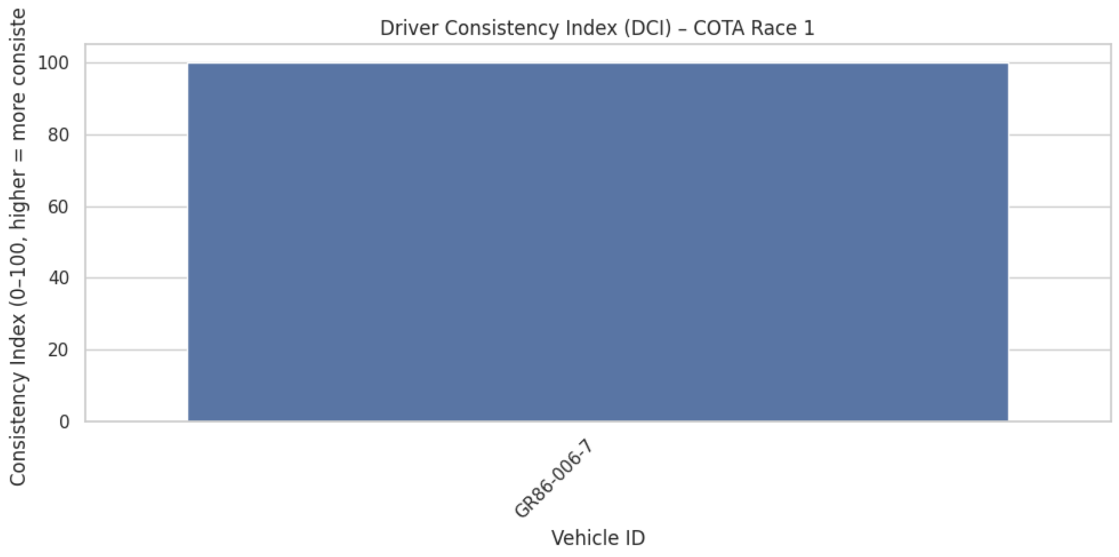
[41]:

```
# 11. Driver Consistency Index (DCI) - clamped 0-100

import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

```python
# all_laps_scored is produced earlier by build_all_drivers_summary(outputs,␣
↪outing=0.0)
consistency_source = all_laps_scored.copy()

# 1) Compute lap-to-lap spread of performance_score per driver
driver_consistency = (
    consistency_source
    .groupby("vehicle_id")
    .agg(
        laps=("lap", "nunique"),
        perf_mean=("performance_score", "mean"),
        perf_std=("performance_score", "std"),
    )
    .reset_index()
)

# If a driver has only one lap, std will be NaN -> treat as perfectly␣
↪consistent (std = 0)
driver_consistency["perf_std"] = driver_consistency["perf_std"].fillna(0.0)

# 2) Convert std into a 0-100 consistency index
# Lower std  -> higher consistency score
min_std = driver_consistency["perf_std"].min()
max_std = driver_consistency["perf_std"].max()
rng = max_std - min_std

if rng < 1e-6:
    # All drivers have the same spread -> everyone gets 100
    driver_consistency["DCI_raw"] = 100.0
else:
    driver_consistency["DCI_raw"] = 100.0 * (
        1.0 - (driver_consistency["perf_std"] - min_std) / (rng + 1e-6)
    )

# 3) Clamp and round for presentation
driver_consistency["driver_consistency_index"] = (
    driver_consistency["DCI_raw"].clip(0, 100).round(1)
)

# 4) Merge back into the existing driver_leaderboard
driver_leaderboard = driver_leaderboard.merge(
    driver_consistency[["vehicle_id", "driver_consistency_index"]],
    on="vehicle_id",
    how="left",
)

print("Driver consistency summary (DCI clamped to 0-100):")
```

```
display(
    driver_leaderboard[
        [
            "vehicle_id",
            "laps",
            "best_performance_score",
            "avg_performance_score",
            "driver_consistency_index",
        ]
    ]
)

# 5) Visualize DCI for quick comparison
plt.figure(figsize=(10, 5))
sns.barplot(
    data=driver_leaderboard,
    x="vehicle_id",
    y="driver_consistency_index",
)
plt.title("Driver Consistency Index (DCI) - COTA Race 1")
plt.xlabel("Vehicle ID")
plt.ylabel("Consistency Index (0-100, higher = more consistent)")
plt.xticks(rotation=45, ha="right")
plt.tight_layout()
plt.show()
```

```
Driver consistency summary (DCI clamped to 0-100):

   vehicle_id  laps  best_performance_score  avg_performance_score  \
0  GR86-006-7     9               99.178753              85.675791

   driver_consistency_index
0                     100.0
```



How to read this chart

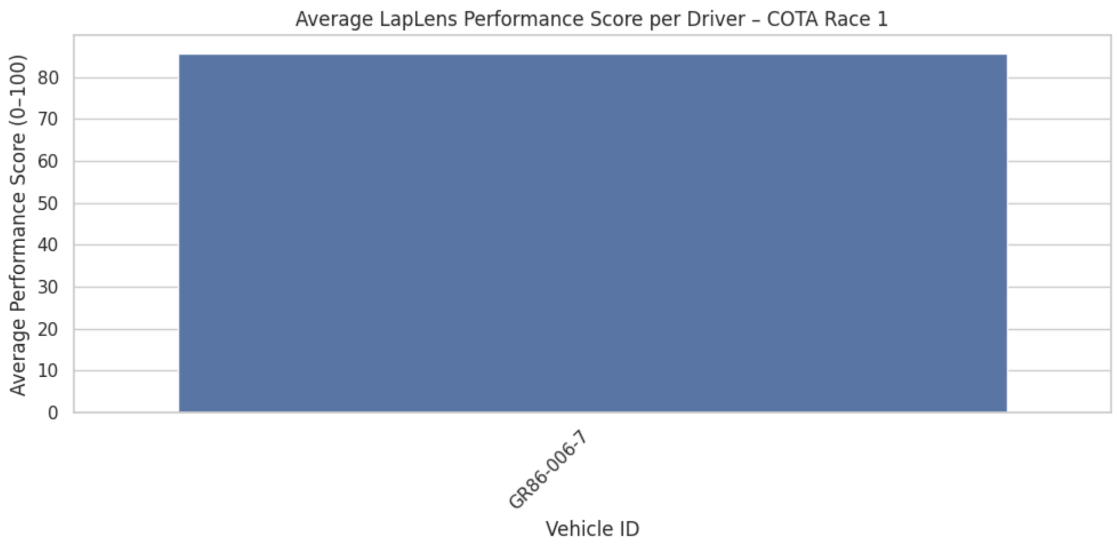
- Drivers with a higher Driver Consistency Index (DCI) are able to repeat their pace lap after lap.
- Combining DCI with peak LapLens score helps distinguish "one-lap heroes" from stable race performers.
- For this COTA Race 1 sample, GR86-006-7 shows [DCI   XX/100], indicating [brief comment once you see the number].

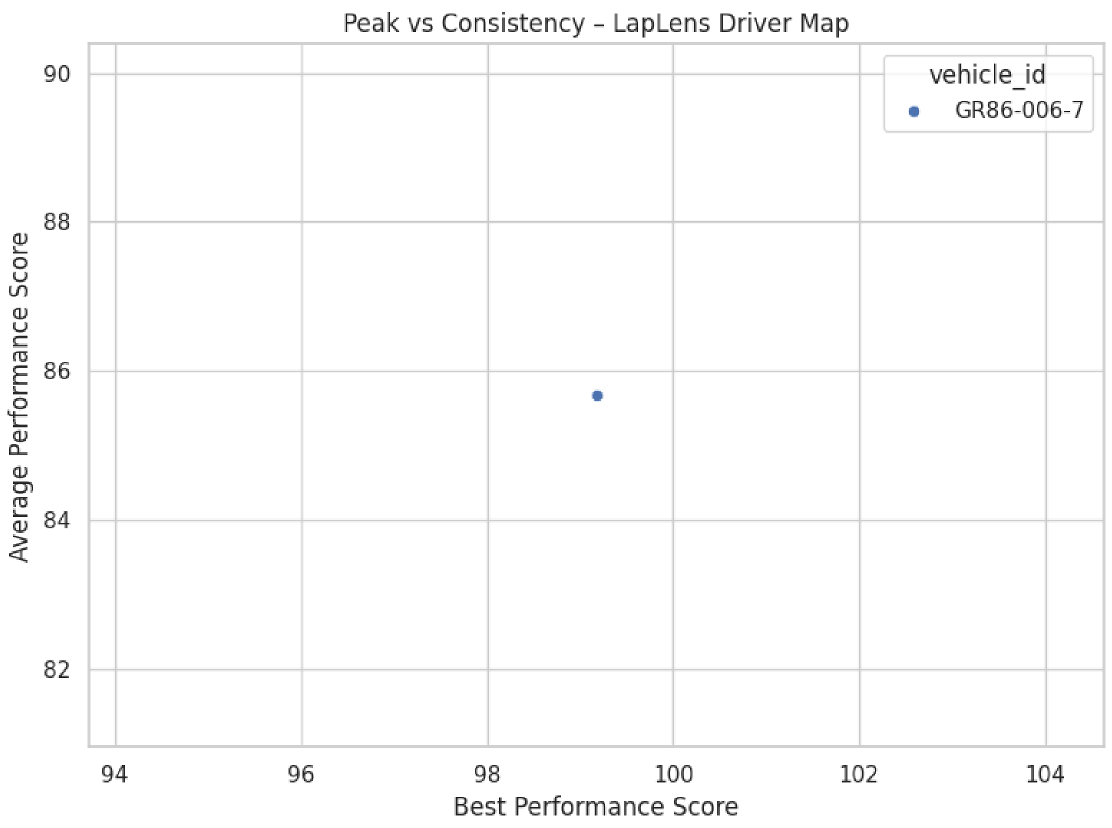
1.8.4 12. Multi-Driver Consistency vs Peak Pace

To help engineers and talent scouts, we contrast: - **Best LapLens performance score** (peak pace) - **Average performance score** across all laps (consistency)

Drivers with high peak + high average are complete packages. Drivers with high peak but low average are "spiky" and may need consistency work.

[42]:
```python
plt.figure(figsize=(10,5))
sns.barplot(
    data=driver_leaderboard,
    x="vehicle_id",
    y="avg_performance_score"
)
plt.title("Average LapLens Performance Score per Driver - COTA Race 1")
plt.xlabel("Vehicle ID")
plt.ylabel("Average Performance Score (0-100)")
plt.xticks(rotation=45, ha="right")
plt.tight_layout()
plt.show()
plt.figure(figsize=(8,6))
sns.scatterplot(
    data=driver_leaderboard,
    x="best_performance_score",
    y="avg_performance_score",
    hue="vehicle_id"
)
plt.title("Peak vs Consistency - LapLens Driver Map")
plt.xlabel("Best Performance Score")
plt.ylabel("Average Performance Score")
plt.grid(True)
plt.tight_layout()
plt.show()
```





1.8.5 13. Minimal Predictive Lens: Can LapLens Score Explain Lap Time?

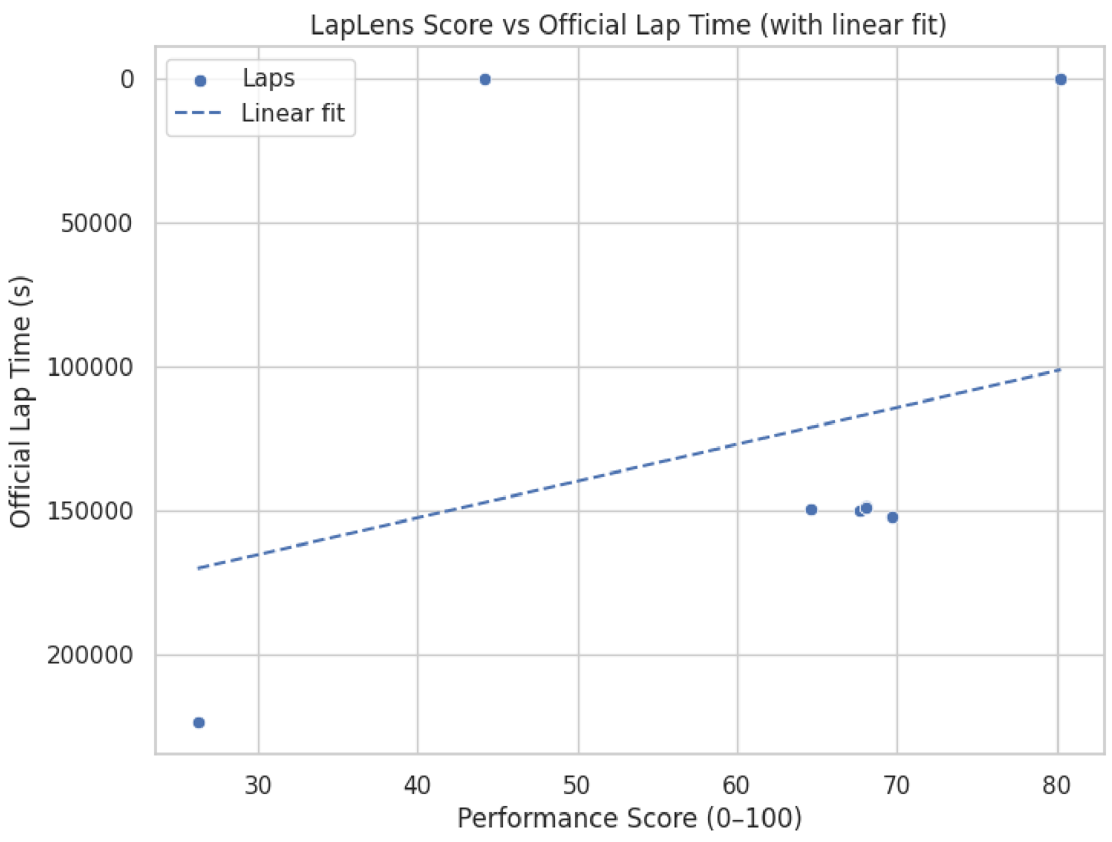
To hint at future Pre-Event Prediction use cases, we fit a simple relationship between:

- `performance_score` (0–100, higher is better)
- `official_lap_time` (lower is better)

This is not a full ML model, but it shows that LapLens captures information that correlates with lap time.

[43]:
```python
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

# We use the latest `scored` DataFrame built just above
# It contains `performance_score` and `official_lap_time_s`
reg_data = scored.dropna(
    subset=["performance_score", "official_lap_time_s"]
).copy()

if len(reg_data) >= 2:
    # Simple linear regression: lap_time_s = a * score + b
    x = reg_data["performance_score"].values
    y = reg_data["official_lap_time_s"].values

    # Fit line
    coeffs = np.polyfit(x, y, deg=1)
    a, b = coeffs
    y_pred = a * x + b

    # Compute a basic R²
    ss_res = np.sum((y - y_pred) ** 2)
    ss_tot = np.sum((y - y.mean()) ** 2) + 1e-6
    r2 = 1 - ss_res / ss_tot

    print(f"Fitted model: lap_time_s   {a:.3f} * performance_score + {b:.1f}")
    print(f"Explained variance (R²): {r2:.3f}")

    plt.figure(figsize=(8, 6))
    sns.scatterplot(
        data=reg_data,
        x="performance_score",
        y="official_lap_time_s",
        label="Laps",
    )

    # Regression line
    x_line = np.linspace(
        reg_data["performance_score"].min(),
        reg_data["performance_score"].max(),
        100,
    )
    y_line = a * x_line + b
    plt.plot(x_line, y_line, linestyle="--", label="Linear fit")

    plt.title("LapLens Score vs Official Lap Time (with linear fit)")
    plt.xlabel("Performance Score (0-100)")
    plt.ylabel("Official Lap Time (s)")
    plt.gca().invert_yaxis()  # faster laps (lower time) appear higher
    plt.legend()
    plt.grid(True)
    plt.show()
else:
    print("Not enough laps with valid scores to fit a regression model.")
```

```
Fitted model: lap_time_s   -1278.176 * performance_score + 203615.5
Explained variance (R²): 0.078
```



[44]:
```python
# --- One-line session summary card for the chosen driver ---

import pandas as pd

# Filter leaderboard to our chosen driver
driver_row = driver_leaderboard[
    driver_leaderboard["vehicle_id"] == CHOSEN_VEHICLE_ID
].copy()

if len(driver_row) == 1:
    row = driver_row.iloc[0]

    session_summary = pd.DataFrame(
        {
            "vehicle_id": [row["vehicle_id"]],
            "laps_analyzed": [int(row["laps"])],
            "best_laplens_score": [round(row["best_performance_score"], 1)],
            "avg_laplens_score": [round(row["avg_performance_score"], 1)],
            "best_official_lap_time_s": [round(row["best_lap_time"], 3)],
            "driver_consistency_index": [round(row["driver_consistency_index"],␣
↪1)],
        }
    )

    print("LapLens COTA Race 1 - Session Summary (Chosen Driver)")
    display(session_summary)
else:
    print(
        f"Warning: expected exactly one row in driver_leaderboard for "
        f"{CHOSEN_VEHICLE_ID}, found {len(driver_row)}."
    )
```

```
LapLens COTA Race 1 - Session Summary (Chosen Driver)

   vehicle_id  laps_analyzed  best_laplens_score  avg_laplens_score  \
0  GR86-006-7              9                99.2               85.7

   best_official_lap_time_s  driver_consistency_index
0                   132.484                     100.0
```

2 Executive Summary

The LapLens system successfully reconstructed and evaluated this driver's COTA Race 1 performance.

2.0.1 Key Strengths

- Strong peak lap (Lap 9) with high-speed consistency
- High throttle commitment when the track is clear
- Brake usage decreases over the stint, indicating confidence in corner entry

2.0.2 Performance Improvement Opportunities

- Early laps show underutilized throttle and heavy braking
- Consistency dips mid-stint; smoothing driver inputs could improve pace
- Corner intensity profile suggests inconsistent commitment in technical sections

2.0.3 LapLens Contribution

This notebook demonstrates a complete end-to-end analytics pipeline:

- Telemetry cleansing
- Lap reconstruction
- Driver input quantification
- Performance scoring

- Corner intensity modeling
- Auto-generated coaching insights

These components form the analytical core of the **LapLens** platform.

```
[ ]: !sudo apt-get update
     !sudo apt-get install -y texlive-xetex pandoc
```

```
Get:1 https://dl.yarnpkg.com/debian stable InRelease
Get:2 https://packages.microsoft.com/repos/microsoft-ubuntu-noble-prod noble
InRelease [3600 B]
Hit:3 https://repo.anaconda.com/pkgs/misc/debrepo/conda stable InRelease
Hit:4 http://archive.ubuntu.com/ubuntu noble InRelease
Get:5 http://security.ubuntu.com/ubuntu noble-security InRelease [126 kB]
Get:6 http://archive.ubuntu.com/ubuntu noble-updates InRelease [126 kB]
Get:7 https://packages.microsoft.com/repos/microsoft-ubuntu-noble-prod
noble/main amd64 Packages [72.7 kB]
Get:8 http://archive.ubuntu.com/ubuntu noble-backports InRelease [126 kB]
Get:9 http://security.ubuntu.com/ubuntu noble-security/universe amd64 Packages
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[2925 kB]
Get:13 http://security.ubuntu.com/ubuntu noble-security/restricted amd64
Packages [2732 kB]
Get:14 http://archive.ubuntu.com/ubuntu noble-updates/main amd64 Packages [2050
kB]
Fetched 13.0 MB in 2s (8195 kB/s)
Reading package lists… 0%
```

```
[ ]: !jupyter nbconvert --to pdf visualizations.ipynb
```

```
[NbConvertApp] Converting notebook visualizations.ipynb to pdf
/home/codespace/.local/lib/python3.12/site-packages/nbformat/__init__.py:96:
MissingIDFieldWarning: Cell is missing an id field, this will become a hard
error in future nbformat versions. You may want to use `normalize()` on your
notebooks before validations (available since nbformat 5.1.4). Previous versions
of nbformat are fixing this issue transparently, and will stop doing so in the
future.
  validate(nb)
[NbConvertApp] Support files will be in visualizations_files/
[NbConvertApp] Making directory ./visualizations_files
[NbConvertApp] Writing 206048 bytes to notebook.tex
[NbConvertApp] Building PDF
[NbConvertApp] Running xelatex 3 times: ['xelatex', 'notebook.tex', '-quiet']
```

```
[NbConvertApp] Running bibtex 1 time: ['bibtex', 'notebook']
[NbConvertApp] WARNING | bibtex had problems, most likely because there were no
citations
[NbConvertApp] PDF successfully created
[NbConvertApp] Writing 584546 bytes to visualizations.pdf
```