

# NVH Analysis Dashboard Report

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## Overview of Approach:

### 1. Data Source:

- Generated synthetic data to perform a real-world NVH condition test on several vehicle models and road surfaces.
- The data included noise levels (dB), vibration frequency (Hz), harshness scores, vehicle IDs, road surfaces, timestamps, and vehicle metadata.

### 2. Data Preparation:

- The data was cleaned and prepared using Power Query in Power BI.
- Deletion of duplicate rows and null value handling.
- Created speed bands (Low: 0-40 km/h, Medium: 40-80 km/h, High: 80+ km/h) and vehicle age categories.
- Merged datasets linking vehicle IDs to measurements and customer feedback.
- Comfort scores calculated from customer feedback (6-point scale).

### 3. Defining KPIs:

- Key metrics: Mean Noise (68.19 dB), Mean Vibration (101.06 Hz), Mean Harshness (5.88).
- Statistical measures included median and standard deviation calculated via DAX functions.
- Trends analyzed and compared across road surfaces, vehicle models, engine types, and speed bands.
- Correlation analysis between NVH metrics and customer comfort scores.

### 4. Dashboard Creation:

- A scorecard displaying key KPIs (mean, median, standard deviation) for each NVH metric was created.
- Line charts visualized NVH metric trends over time (2023-2024).
- Stacked bar charts displayed NVH performance by vehicle model and road surface.
- Slicers enabled dynamic filtering by vehicle model, engine type, road surface, and speed band.

## Charts Added in the Dashboard:

- Page 1 - Scorecard: 6 KPI Cards shows overall performance summary (Mean, Median, Standard Deviation for Noise, Vibration, Harshness).
- Page 2 - NVH Variability: Line Chart: Shows how monthly NVH changes over time (Jan 2023 - Dec 2024), Clustered Columns Chart: Compares NVH metrics at different speed bands (low, medium, high).
- Page 3 - NVH and Road Surface Analysis: 3 Stacked Bar Charts: Compares vibration, noise, and harshness across different Road Surfaces and vehicle models.
- Page 4 - NVH and Customer Comfort Analysis: 3 Line and Column Charts: Shows relationships between NVH metrics and customer comfort scores by Vehicle Models.

## Key Insights and Recommendations:

### 1. Harshness:

- Mean score: 5.88 (median: 6.20), with 32.3% exceeding 7.0 threshold.

- Gravel surfaces produce harshness of 7.55 vs 4.50 on concrete.
- Recommendation: Investigate suspension system and tire quality to reduce harshness. Optimize damping for rough surfaces and improve ride comfort.

## **2. Noise:**

- Mean noise level: 68.19 dB (median: 67.68 dB), with 31.9% exceeding 75 dB
- Standard deviation of 13.27 dB indicates high variability across conditions.
- Recommendation: Enhance sound insulation and investigate noise sources such as engine, exhaust, wind, and tire noise.

## **3. Vibration:**

- Mean vibration level: 101.06 Hz (median: 95.26 Hz).
- Gravel and cobblestone surfaces show 139.82 Hz vs 57.06 Hz on asphalt.
- Recommendation: Check for imbalances in wheels and engine mounts.

## **4. Trend Analysis:**

- Monthly trends show fluctuating NVH performance from Jan 2023 to Dec 2024, with harshness and vibration varying significantly.
- No significant improvement trend observed, indicating current performance has plateaued across all metrics.
- Recommendation: Establish continuous improvement targets with year-over-year goals (e.g., annual reduction in harshness).

## **5. Vehicle Performance:**

- Electric vehicles Achieved highest comfort (3.87) vs gasoline engines (3.45).
- Top models: Electric Bike G1, Hybrid Bike H1; Underperformers: Cruiser B2, Sport Bike C1.
- Recommendation: Benchmark top performers and accelerate electric/hybrid adoption. Conduct root cause analysis for underperforming models.

## **Assumptions and Limitations:**

### **Assumptions:**

- Simulated data reflects typical real-world NVH behavior.

### **Limitations:**

- Simulated data may miss real-world extreme cases.
- Analysis focused solely on noise, vibration, and harshness metrics, omitting external variables like tire condition or climate.
- Recommendations derive from generalized patterns in simulated data, potentially overlooking unique model specific performance characteristics.