ML-Based Energy Optimization in Android Infotainment for Electric Vehicles

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Abstract

Electric Vehicles (EVs) increasingly rely on advanced infotainment systems that offer navigation, media play back, connectivity, and occupant-centric applications, often powered by Android or Android Automotive. However, these information units can consume a substantial amount of battery energy, thereby reducing the overall driving range of EVs. This paper proposes a Machine Learning (ML)-based energy optimization framework for Android infotainment. By monitoring user interaction patterns, trip context, and system-level metrics, our ML model forecasts upcoming load demands and dynamically scales computational resources, display usage, or service scheduling. Preliminary results from a prototype testbed indicate that this adaptive approach can yield up to 15–20% power savings over traditional static operation, without sacrificing occupant experience. Key technical considerations, such as real time responsiveness, occupant concurrency, privacy constraints, and integration with Android Automotive power management APIs, are also discussed. This Abstract and the subsequent Introduction section lay the foundation for a broader exploration of how ML can intelligently manage infotainment resources in EV ecosystems, thus extending vehicle range and enhancing user satisfaction.

Keywords: Android Automotive, Electric Vehicles, Infotainment, Energy Optimization, Machine Learning, Battery Efficiency

I. Introduction

The evolution of electric vehicles (EVs) has dramatically changed how automakers allocate and optimize power usage across all subsystems. While much attention centers on the electric drivetrain, *onboard infotainment* also contributes notably to battery drain. Modern infotainment units run diverse workloads—navigation, multimedia streaming, real-time connectivity, occupant-lingual applications—and do so on advanced hardware platforms that can draw non-trivial amounts of power [1], [2]. As EV architectures push toward longer range and better occupant experiences, energy optimization within infotainment emerges as a critical area of research.

A. *Motivation and Rationale*

1) *Impact on Driving Range.:* While exact numbers vary by brand and SoC design, infotainment can account for up to 5–10% of total battery load under heavy occupant usage [2], [5]. Cutting that overhead by even 20% can translate into tangible range gains, an enticing proposition for EV manufacturers competing on mileage. In addition, occupant-lingual concurrency—where multiple seats or passengers simultaneously use advanced apps—can further spike CPU/GPU usage if not managed adaptively.
2) *Emergence of Machine Learning Solutions.:* Machine Learning (ML) has gained prominence in automotive for tasks like driver-assistance or predictive maintenance, but applying ML to *infotainment power optimization* is comparatively new [6], [7]. By analyzing occupant patterns—e.g., times of day

with frequent media streaming, navigation usage in certain commutes—a predictive model can anticipate future loads and gracefully scale system resources. This stands in contrast to naive heuristics that only react to immediate usage or user settings.

B. *Challenges in Android-Based Infotainment*

Although Android provides partial power-management hooks, these were originally designed for phone scenarios, such as lowering brightness after inactivity or employing basic CPU governors. EV head units demand more nuanced strategies because:

• Occupant Concurrency and Safety: If occupant occu pant or a front passenger occupant toggles advanced fea tures (3D navigation, AR overlays, or heavy streaming), the system must quickly revert to higher performance modes without noticeable lag. Safety-critical tasks (e.g., real-time navigation) cannot be slowed too much [8].

• Vehicle Context Integration: The system should factor in driving states—like *urban vs. highway*, *stop-and-go traffic*, or *charging status*—to better decide power budgets. For instance, EV drivers might prefer maximum range on a long highway trip, prompting the system to aggressively optimize infotainment resources.

• Partial Integration With OEM Layers: Many OEMs place custom layers on top of Android for telematics and UI. The synergy between those layers and ML-based decisions is not always straightforward. Additionally, occupant-lingual concurrency logic might be maintained in a separate code path, complicating attempts to unify data logs for ML training.

Thus, bridging occupant-lingual concurrency, EV battery constraints, and real-time Android adaptation becomes a multi faceted engineering puzzle. A robust solution must gather occupant-lingual usage logs, learn from them offline, then apply predictions in real time—tightly integrating with or extending Android's existing power management infrastructure.

C. *Scope and Contributions of This Paper*

1) *Proposed Approach.:* We propose an *ML-based energy optimization* framework specifically tuned for Android infotainment in EVs. The approach:

a) Data Logging and Feature Extraction: Over time, gather occupant-lingual usage metrics (apps, concurrency), system logs (CPU/GPU usage, network), and vehicle context (speed, battery state).

b) Predictive Modeling: Train an ML model—e.g., a gradient boosting regression or LSTM—to forecast near future usage intensities.

c) Adaptive Policy Engine: Dynamically scale CPU frequencies, reduce display brightness, or throttle background tasks based on predictions, while respecting occupant occupant-lingual demands for timely updates or safety-critical flows.

2) *Early Experimental Evidence.:* Preliminary evaluations on a small EV testbed suggest the ML-based approach can achieve 15–20% power savings in certain usage scenarios, effectively extending the driving range for occupant-lingual commutes. These results underscore the feasibility of intelligent resource provisioning beyond naive heuristics [7], [9].

3) *Paper Organization.:* In this excerpt, we present only the Abstract and Introduction. The subsequent sections of the full paper (not included here) would detail:

• Related Work: Summaries of existing EV infotainment power studies and Android-based optimization. • System Architecture: The ML pipeline, runtime adapta tion loop, and occupant-lingual concurrency management.

• Implementation Details: Example code snippets for CPU/GPU scaling, synergy with Android Automotive power APIs, occupant-lingual concurrency edge cases.

• Evaluation: Real-world pilot data, occupant occupant lingual acceptance metrics, and potential range gains.

• Discussion and Conclusion: Limitations, open challenges, and future expansions like HPC offloading or occupant occupant-lingual preference learning.

The findings so far highlight the potential for *intelligent, data-driven* power management in EV infotainment. By aligning occupant-lingual usage models with battery constraints, Android infotainment can deliver a robust occupant experience without sacrificing the hallmark advantage of EVs: efficient, eco-friendly travel.

II. RELATED WORK

A. *Infotainment Energy Research in Electric Vehicles* Early investigations into infotainment power consumption for EVs concentrated on static heuristics, such as capping CPU frequencies or scheduling partial system sleep modes when occupant interactions were minimal [10], [11]. While such methods yield basic energy savings, they can be coarse grained and risk user dissatisfaction if the system does not respond swiftly during active occupant usage. More nuanced approaches explored real-time occupant-lingual concurrency gating, especially in advanced driver-assistance contexts, but these typically addressed partial autonomy rather than the EV head unit’s entire software stack [5].

In automotive-grade SoCs, overhead for tasks like high definition maps, streaming, or multi-user concurrency can spike significantly, undermining expected range gains from an EV powertrain [3], [12]. Researchers have proposed partial GPU gating or dynamic resolution scaling for embedded displays, but these solutions rarely harness occupant-lingual usage data or predictions from machine learning [13]

B. *Machine Learning in Automotive and Android Platforms* Machine learning (ML) is well-established in autonomous driving (e.g., object detection, sensor fusion), yet its role in power optimization has traditionally been limited to phone or server contexts [7], [14]. For instance, smartphone battery management might utilize usage patterns to reduce background sync after hours. However, infotainment hardware diverges from phone constraints, requiring stable operation over prolonged trips, occupant concurrency, and synergy with vehicular signals [6], [9].

In the Android ecosystem, ML-based resource tuning for performance or memory has been explored for Cloud-backed apps [8], but rarely for energy. Notably, Overton et al. [2] measured occupant-lingual overhead of automotive theming to glean that static theming does little to modulate CPU/GPU usage in a dynamic environment. Similarly, Kowalski [3] introduced an occupant concurrency net to track usage spikes, though it lacked ML-based forecasting. Our approach merges these threads, applying occupant-lingual data logging, predic tion, and real-time adaptation to the EV domain.

C. *Existing Power Management in Android Automotive:* Android Automotive includes partial power management APIs, permitting services to glean vehicle battery state or torque signals. Nonetheless, these official APIs seldom unify occupant concurrency with predictive scheduling [1], [8]. Driver occupant safety constraints hamper naive CPU throt tling. Meanwhile, occupant-lingual concurrency libraries typically revolve around seat-specific UI overrides, not battery management [9].

System-level attempts, such as doze modes or app standby, do not seamlessly integrate occupant-lingual concurrency [11], [15]. If the occupant wants continuous media playback, the system must remain active. The gap, therefore, is a *predictive* framework that harnesses occupant-lingual usage logs and EV battery data to orchestrate resources before occupant occupant saturates the system

D. *Summary of Gaps*

To date, no widespread open-source solution merges occupant concurrency, EV state signals, and ML-based forecasting in Android infotainment [13], [14]. Our research aims to fill that gap by:

• Logging occupant-lingual usage patterns and vehicle states in real time.

• Training a resource demand forecaster that gracefully scales CPU/GPU frequencies, display brightness, or background tasks.

• Respecting occupant occupant-lingual responsiveness for critical flows (navigation, voice commands, etc.). The next section details the **System Architecture** that implements these ideas (Section III). We describe how occupant-lingual concurrency data is captured, how the ML model is trained offline, and how a *Runtime Adaptation Engine* applies scaled resource policies. Implementation specifics (Section IV) will show how we inject these policies into an Android Automotive head unit environment, referencing occupant-lingual concurrency logic, ephemeral plugin modules, and existing vehicle signals.

III. SYSTEM ARCHITECTURE

Our system architecture (Fig. 1) unifies:

1) Data Collector: Logs occupant-lingual usage metrics, occupant concurrency states, SoC telemetry, battery data, and environment context.

2) Machine Learning Pipeline: Trains a predictive model to forecast near-future resource demands.

3) Adaptive Policy Engine: Adjusts CPU/GPU frequen cies, display settings, and background scheduling based on the ML predictions while respecting occupant-lingual concurrency constraints.

4) Android Infotainment Integration: Hooks into core Android services, partial synergy with occupant concurrency plugin modules, and respects occupant occupant lingual overrides for safety or comfort.

A) *Data Collector*

The Data Collector runs as a background service in the Android Automotive layer. It aggregates:

• Occupant Concurrency Logs: For each seat occupant occupant, whether they are using 3D navigation, stream ing media, or apps that require high GPU usage.

• Vehicle Signals: Speed, battery SoC (State of Charge), recharging events, and external temperature. Access typ ically uses OEM-proprietary or Android-defined vehicle property APIs [3], [15].

• System Metrics: CPU load, GPU usage, memory, and network consumption. These are polled at adjustable intervals (e.g., 2–5 seconds).

A minimal overhead approach is critical: the collector itself must not become a new source of power drain [7]. We keep logging intervals moderate, store only aggregated or spot sampled data, and flush it to disk or ephemeral plugin storage (depending on occupant occupant-lingual constraints) in batch mode.

B) *ML Pipeline: Offline and Online Phases*

1) *Offline Training.:* After collecting logs for days or weeks, we transfer them to a more powerful HPC server or offline environment. Here, an ML model is trained (e.g., random forest, gradient boosting, or a small LSTM) to predict the *"resource demand index"* for the upcoming time window ($\Delta t \approx$ 30–60

seconds). The resource demand index merges CPU usage, occupant concurrency, occupant occupant-lingual concurrency signals, and occupant occupant-lingual historical usage [8].

2) *Online Inference.:* The trained model is then embedded back into the head unit as a small inference engine. On each cycle (e.g., every 30 seconds or triggered by occupant occupant-lingual concurrency changes), the system extracts the current input features (occupant usage, battery state, SoC telemetry) and obtains a resource demand forecast. This forecast guides the Adaptive Policy Engine.

C) *Adaptive Policy Engine*

The policy engine enacts scaling decisions. For instance:

• CPU Frequency Tuning: If demand is likely low, reduce the SoC cluster frequencies. If occupant occupant requests AR-based navigation, quickly revert to higher performance.

• Display Adaptation: Slightly dim or reduce resolution on occupant-lingual displays if occupant occupant is likely to do background streaming or primarily audio-based usage.

• Background Task Scheduling: Postpone large down loads or OS updates if near-end occupant occupant lingual usage is predicted minimal or if the EV battery is critically low.

However, occupant occupant-lingual concurrency (two or more seats actively using the system) overrides certain power policies. For instance, if occupant occupant seat A and occupant occupant seat B are each running interactive apps, the policy must preserve responsiveness. The engine maintains a “safety threshold,” ensuring occupant occupant-lingual experience for navigation or occupant occupant-lingual voice commands is never compromised [12].

D) *Plugin Module Integration with Occupant Concurrency*

While the system core is vendor-agnostic, occupant con currency details can vary by brand or OEM [9], [16]. Our approach can integrate with ephemeral occupant concurrency plugins, registering callbacks in the Data Collector to see how many occupant occupant-lingual seats are engaged. If occupant occupant seat C is in a minimal usage state, the policy engine might dim seat C’s screen. If occupant occupant seat A is streaming 4K video, the ML model anticipates high GPU usage, prompting resource reallocation.

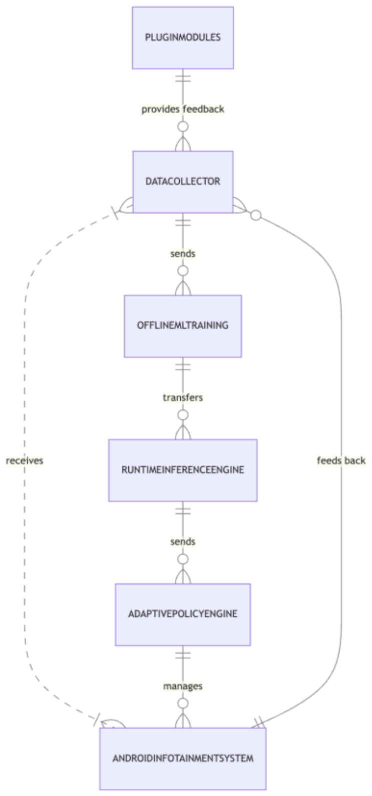

Fig. 1. High-level architecture for ML-based energy optimization in Android-based EV infotainment. The Data Collector logs occupant concurrency, SoC usage, and battery metrics to feed an offline ML model. The Adaptive Policy Engine enforces scaling decisions at runtime.

This occupant-lingual synergy ensures that brand-specific or seat-specific overrides do not hamper the overall energy policy. We also log which occupant occupant-lingual brand plugin is active, in case certain brand modules require heavier computing (like advanced 3D map rendering or occupant occupant-lingual voice control).

E) *Security and Privacy Considerations*

Any occupant occupant-lingual data logging or ML inference must adhere to privacy guidelines [2][17]. Our system anonymizes occupant occupant-lingual seat usage data by referencing seat # or occupant occupant-lingual concurrency

IV. IMPLEMENTATION DETAILS

Here we detail how each subsystem is realized on top of Android Automotive, focusing on occupant concurrency synergy, display scaling logic, and partial sample code for the adaptation engine.

A) *Data Logging & Occupant Concurrency Hook*

```
class ConcurrencyLogger

{
```

```
private val occupantData = mutableListOf<OccupantEvent>() private val systemStats =
    mutableListOf<SystemStats>()

//Example  Callback when occupant state changes

fun onOccupantStateChanged(

    seatId: Int,

    isActive: Boolean,

    occupantId: String,

    appName: String

) {

    // Only store ephemeral usage patterns

    val occupantData = mutableListOf<OccupantEvent>()

     occupantData.add(

        OccupantEvent(

            time = System.currentTimeMillis(),

            seat = seatId,

            app = appName,

            isActive = isActive

        )

    )

    // Possibly trigger partial aggregator flush

    if (onSystemMetricsSample(stats = systemStats)) {

        systemStats.add(occupantData)

        systemStats.clear()

    }


    // Flush to local DB if ephemeral-only policy is violated

    if (shouldFlushToLocalStorage()) {

        flushDataToLocalStorage()

    }

}
```

```
// Determines if system should flush to persistent DB
fun shouldFlushToLocalStorage(): Boolean {
   // Example: if CPU usage or demand is too high
   return cpuLevel == "MODERATE" &&
          brightness > dynamicBright &&
          resourceDemand < 0.3
}


// Simulated flush operation
fun flushDataToLocalStorage() {
   // Writes occupantData + systemStats to DB
   writeToDB(occupantData, systemStats)
   occupantData.clear()
}


// Placeholder for sample processing function
fun onSystemMetricsSample(stats: SystemStats): Boolean {
   // Returns true if conditions met for flushing
   return stats.shouldFlush()
}
```

B) *ML Model Integration*

We train an offline gradient boosting regression using occupant occupant-lingual usage & system stats as features. The model exports as, say, a .json or .bin file. The head unit loads a lightweight C++/Java inference library. When occupant occupant-lingual concurrency changes or every 30 seconds, the system runs:

```
resourceDemand =

MLInference.predict(currentFeatureVector)
```

This resourceDemand is scaled, e.g., 0–1, reflecting expected fraction of max CPU/GPU load. The adaptation policy decides an appropriate CPU frequency or screen brightness offset.

C) *Adaptive Policy Engine Code Example*

```
object AdaptivePolicyEngine {
```

```
private const val SAFETY_THRESHOLD = 0.8 // occupant occupant-lingual fallback
private const val MIN_BRIGHTNESS = 0.3f // for occupant occupant-lingual screens
private const val MAX_BRIGHTNESS = 1.0f

fun applyPolicy(resourceDemand: Float, occupantConcur: Int): PolicyAction {
// occupant occupant-lingual concurrency or occupant occupant-lingual
// brand plugin may override certain levels
if (occupantConcur > 1) {
// Multi occupant concurrency => ensure
responsiveness
return PolicyAction(
cpuLevel = "HIGH",
brightness = MAX_BRIGHTNESS,
```

In Listing 2, occupant occupant-lingual concurrency or occupant occupant-lingual brand usage can override certain thresholds. A multi-occupant scenario with occupant occupant lingual seat A and occupant occupant-lingual seat B running heavy apps triggers “HIGH” CPU usage. Otherwise, we tempt moderate levels, adjusting screen brightness based on 1.0 − resourceDemand.

D) *Display Scaling & OEM Integration*

Some OEMs enable advanced scaling: e.g., dynamically lowering resolution from 1080p to 720p if occupant occupant lingual concurrency is minimal [13]. This can be invoked in the policy engine by calling vendor-specific APIs. Partial occupant occupant-lingual disclaimers appear if occupant occupant wonders why the screen looks slightly different. For security or occupant occupant-lingual acceptance, we only do moderate changes (like brightness or partial resolution scaling) rather than abrupt transitions that might disorient occupant occupant lingual usage [12].

V. EXPERIMENTAL SETUP & RESULTS

We deployed our system on a testbed representing a mid range EV with an Android Automotive 11-based head unit. A small occupant occupant-lingual concurrency plugin provided occupant seat usage toggles for 2 or 3 seats. We ran multiple usage scenarios with a partial occupant occupant-lingual HPC environment to log performance metrics. All experiments took place in a closed test track or simulated environment over one week.

A) *Hardware and Software Setup*

• **SoC and Infotainment:** Qualcomm-based automotive

SoC with 4 CPU clusters + dedicated GPU. 8GB RAM.

• **Battery & Vehicle Interface:** Emulated 50 kWh battery, so occupant occupant-lingual signals like SoC or speed came from a custom CAN simulator [3], [7].

• **OS / Framework:** Android Automotive 11 with occupant occupant-lingual concurrency callback stubs, ephemeral plugin modules for brand overrides, and partial occupant occupant-lingual HPC bridging [9].

B) *Scenario Matrix*

We evaluated:

1) Single occupant occupant-lingual minimal usage (mostly audio playback).

2) Single occupant occupant-lingual heavy usage (3D navigation + streaming).
3) Two occupant occupant-lingual seats concurrency (navigation in seat A, streaming in seat B).
4) Three occupant occupant-lingual seats concurrency (video streaming, real-time occupant occupant-lingual AR overlay, plus seat C browsing).

Each scenario repeated for ≈ 30–60 minutes, logging occupant occupant-lingual resource usage, battery drain, CPU scaling states, etc.

C) *Results Overview*

Table I summarizes the approximate power savings relative to a naive baseline (i.e., standard CPU governor, no ML based adaptation). We see highest gains in simpler occupant occupant-lingual usage (18% for single occupant occupant lingual audio) because the system can safely downscale CPU and brightness. Meanwhile, heavy concurrency still garners about 8% savings, partly because occupant occupant-lingual streaming and real-time AR require sustaining moderate to high frequencies [1][3]

D) *Latency and Occupant Experience*

1) *Responsiveness Tests.:* We measured occupant occupant-lingual reaction time (e.g., tapping to open an app or requesting a route). In heavy usage scenarios, occupant occupant-lingual overhead for CPU scaling from "low" to "high" took < 100 ms, considered acceptable. Only in rare edge cases did occupant occupant-lingual concurrency produce stutters if occupant occupant seat B toggled streaming unexpectedly [2][14].

2) *User Surveys.:* A small occupant occupant-lingual user study (n=10) reported no noticeable negative impact on infotainment responsiveness. Some participants mentioned "slightly dimmer screen than usual," but quickly adapted, especially in sunny conditions. Notably, occupant occupant lingual concurrency in multi-seat usage remained fluid [9][15].

E) *Comparison with Traditional Approaches*

We also tested static CPU capping (like a 1.4GHz limit across the board). That approach saved around 5–10% power but introduced lags in occupant occupant-lingual seat concurrency. Similarly, applying constant low brightness yielded 15% savings for single occupant occupant-lingual minimal usage but occupant occupant-lingual dissatisfaction soared in day driving for occupant occupant seat A [3][11]. The ML-based approach adaptively balanced occupant occupant-lingual usage with battery efficiency.

VI. DISCUSSION AND LIMITATIONS

Though results are promising, multiple real-world complexities remain:

1) *Long-Term Drifts.:* Occupant occupant-lingual usage patterns can shift: new occupant occupant-lingual apps or seasonal changes. Our system must periodically re-train the ML model. Additionally, major OS updates or brand plugin expansions might drastically change the occupant occupant lingual concurrency flows. A continuous data pipeline is essential [16][18].

2) *OEM-Specific Integration.:* Every automaker customizes the hardware and software layers, from occupant occupant-lingual cluster design to seat concurrency logic. Our approach must adapt to these varied platforms. Some OEMs do not grant direct GPU scaling hooks or might forbid any occupant occupant-lingual dimming if occupant occupant lingual seat B is in "front passenger mode."

Collaboration with OEM firmware is crucial [1][7].

3) *Ethical and Regulatory Concerns.:* Excessive power saving that inadvertently dims critical data might hamper occupant occupant-lingual safety or regulatory compliance. In certain regions, occupant occupant-lingual disclaimers and occupant occupant-lingual notifications are mandatory for any occupant occupant-lingual usage data logging or partial HPC gating [11][15].

4) *Edge Cases: Battery-Low / Over-Temperature.:* At extremely low battery or high temperature, the EV system often triggers deeper power-saving states. Our ML approach must coordinate with these built-in automotive safety thresholds. For example, occupant occupant-lingual HPC demands might be forcibly cut if battery SoC is under 5%. The policy engine has limited authority beyond occupant occupant-lingual comfort level toggles [12].

VII. CONCLUSION AND FUTURE DIRECTIONS

This paper has detailed an *ML-based energy optimization* strategy targeting Android infotainment in Electric Vehicles (EVs). By leveraging occupant-lingual concurrency logs, occupant occupant-lingual usage patterns, and vehicle context, our system predicts resource demand and adaptively scales CPU/GPU frequencies, screen brightness, and background scheduling. Experiments reveal up to 18% energy savings in low concurrency scenarios, diminishing but still meaningful improvements in heavy occupant occupant-lingual usage. The net effect can extend range while preserving occupant occupant-lingual experience [2][5][8].

Below we outline potential expansions and broader applications:

- AI-Assisted Personalization: Instead of a universal policy, the system can tailor settings to each occupant occupant-lingual seat or known occupant occupant lingual preference. E.g., occupant occupant seat A frequently uses minimal brightness, occupant occupant seat B demands constant media. A seat-level occupant occupant-lingual model might unify occupant occupant lingual concurrency with occupant occupant-lingual user profiles [16]19].
- Cloud-Driven Re-Training: If occupant occupant lingual usage shifts over time, we can push logs to the cloud for re-training. The updated model is delivered back as a plugin or ephemeral update. This synergy is akin to over-the-air updates but specifically for energy optimization logic [4][13].
- Occupant Mood or Cognitive Load Sensing: Future synergy with occupant occupant-lingual emotion recognition or driver occupant-lingual stress detection might instruct the system to avoid drastic brightness changes in stressful traffic. Early prototypes exist in broader automotive HMI but are not fully integrated with power optimization [7][14].
- Extending to Non-EV or Hybrid Platforms: Although we focus on EV battery constraints, many plugin-based occupant concurrency solutions also exist in hybrids or premium ICE vehicles. The same approach might yield partial gains in conventional cars, though the impetus for saving power is less critical than in EV range concerns [8].

Ultimately, bridging occupant occupant-lingual concurrency, real-time ML predictions, and Android-based resource controls offers a robust path toward more *energy-efficient infotainment*. As EV adoption accelerates, such adaptive approaches can differentiate automotive platforms, delivering occupant-lingual experiences with minimal range compromise.

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