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CABINET: A REAL-TIME MULTI-PLATFORM RIDE-HAILING FARE COMPARISON AND DATA AGGREGATION SYSTEM

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Abstract- Ride-hailing companies such as Ola, Uber, Rapido, inDrive, and Namo Yatri control urban mobility but their real-time fare information models tend to confuse and disillusion commuters. This paper proposes Cabinet, an intelligent real-time fare aggregation and comparison platform that aggregates data from various ride-hailing apps. Cabinet uses a scalable microservices infrastructure to gather, process, and present live fare information, along with using predictive analytics to anticipate surge price trends. With the use of API integration, web scraping techniques, and AI-driven modelling, Cabinet not only empowers users with fare transparency but also provides useful data for urban planners and policymakers. The system illustrates how multi-platform aggregation improves price fairness, aids in more intelligent transportation choices, and sets the stage for further smart city applications. In the end, Cabinet is a bridge of technology between

ride-hailing networks and mobility solutions that are consumer-focused, providing affordability combined with intelligent travel decision-making.

Keywords: Ride-hailing platforms, Urban mobility, Real-time fare aggregation, Fare comparison, Microservices architecture, API integration, Web scraping, Predictive analytics, Surge pricing.

I. INTRODUCTION

Over the last few years, ride-hailing companies like Ola, Uber, Rapido, inDrive, and Namo Yatri have completely altered the way individuals move around urban areas. These services offer convenient, flexible, and on-demand transportation, posing a healthy alternative to classic taxis and public transport. Nonetheless, their dependence on dynamic pricing mechanisms—frequently influenced by demand peaks, weather, or traffic—has brought about high fare volatility. For commuters, this generates uncertainty and a lack of transparency in the cost of travel, while policymakers and urban planners are not provided with consistent data to comprehend and manage the overall effect of such pricing models on mobility ecosystems. Current fare configurations and comparison practices are disjointed, with passengers required to manually access multiple apps in order to determine the best value. Such inefficiency not only annoys commuters but also prevents maximum utilization of informed choice-making over transportation options.

Concurrently, the lack of a real-time, aggregated fare database also means urban mobility research and transport planning do not have a solid data base on which to formulate policy and construct infrastructure.To fill in these gaps, this paper presents Cabinet, a cutting-edge real-time fare aggregation and comparison portal that integrates pricing information from multiple ride-hailing platforms into one open interface. Cabinet uses a hybrid data acquisition model that applies API integration, web scraping, and cloud-based microservices to ensure that the system can process and present real-time fare information with little delay. In addition, Cabinet also features machine learning-based predictive analytics that predicts surge pricing patterns, allowing users to schedule travel better and steer clear of high charges during peak season.

In addition to its user-level advantage, Cabinet is beneficial to urban planners, researchers, and transit authorities as it produces aggregated datasets that expose fare patterns, demand volatility, and service needs per area and platform. These insights can inform policy-making, fare setting, and smart city mobility plans, coordinating transportation networks in accordance with the values of affordability, accessibility, and sustainability.

Finally, Cabinet is more than a fare comparison app; it is a technological crossing point for citizens, service providers, and government. By integrating real-time data processing, predictive modeling, and human-centered design, Cabinet pushes the vision of a brighter, more equitable, and data-first urban transportation future, enabling the development of Mobility-as-a-Service (MaaS) and paving the way for the next generation of smart city solutions.

II. LITERATURE REVIEW:

The last decade has witnessed the fast-paced development of ride-hailing services, which has been widely researched in academic and industry literature, most of it concentrating on their economic, technological, and mobility implications for cities. Initial research (e.g., Cohen et al., 2016; Rayle et al., 2019) examined the disruptive character of ride-hailing services such as Uber and Ola, noting their contribution towards changing urban mobility patterns and offering alternatives to traditional taxi services. Although these studies did recognize the advantage of on-demand mobility, they also identified nascent challenges like fare uncertainty and regulatory loopholes.

A large body of evidence has since analyzed dynamic pricing algorithms, or "surge pricing," as a central aspect of ride-hailing economics. Studies by Castillo et al. (2017) and Zha et al. (2018) explain the use of surge pricing to balance demand and supply but frequently fail to be transparent to commuters and have the potential to further worsen affordability issues. Current research also shows that although dynamic pricing boosts platform efficiency, consumers have limited insight into what determines fares, and they have to manually compare prices across apps.

The Mobility-as-a-Service (MaaS) idea has been a possible solution to integrate disjointed transportation services. Studies by Jittrapirom et al. (2017) and Hensher et al. (2020) highlight the need for integrated digital platforms that aggregate information from multiple mobility providers to enhance user experience. But the majority of MaaS research centers on subscription-based models and multi-modal mobility (e.g., buses, trains, bicycles), with relatively less emphasis on ride-hailing fare real-time aggregation—a key area that Cabinet aims to fill.

Several authors have researched data aggregation and API-based architectures within transport technology. For example, Shaheen et al. (2021) describe how open APIs can facilitate ease of integration between mobility services, and Jiang et al. (2022) suggest microservices-based architectures for large-scale urban mobility systems. These pieces of work supply technical underpinnings to Cabinet's approach, which combines API integration, automated data pipelines, and predictive analysis.

Lastly, consumer behaviour research on ride-hailing (e.g., Chan & Shaheen, 2021) shows that users also increasingly expect price transparency and equity. Still, as of the date this is written, there is no single platform that provides real-time, multi-platform fare comparison for prominent ride-hailing operators.

III. METHODOLOGY

Cabinet development employed a formal, multi-step methodology to make the system scaleable, accurate, and real-time fare comparison across multiple ride-hailing platforms. The initial phase was system architecture design where Cabinet was envisioned as a cloud-native, microservices-oriented platform. This modular approach enabled every function—data ingestion, fare aggregation, analytics, and user interface rendering—to be fully independent of one another, exchanging data through lightweight RESTful APIs. This methodology not only facilitated smooth addition of future ride-hailing companies but also made it possible for the platform to scale cost-effectively with growing user loads. The platform was implemented on AWS Cloud infrastructure using services like EC2 for computation, Lambda for serverless computing, and S3 for storage, which offered scalability and reliability at the cost of affordability.

Stage two included data collection, which was a crucial part of Cabinet's operation. A hybrid data collection approach was used to manage the varying ecosystems of Ola, Uber, Rapido, inDrive, and Namo Yatri. Where accessible, official APIs were used to fetch structured and dependable fare data. For other services without open APIs, automated web scraping methodologies based on Selenium and Puppeteer pulled live fare data from their mobile web views. Where legal, a limited amount of network traffic analysis was undertaken to detect unindexed endpoints for more direct data access. All data collection operations were controlled by a scheduling engine that executed cron jobs every 30–60 seconds, balancing real-time freshness with platform rate limits.

Once gathered, the data went into a speed and accuracy-oriented processing and storage pipeline. Received data was normalized into a common JSON schema to ensure standardized formats between providers, correcting unit inconsistencies, timestamp inconsistencies, and fare structure inconsistencies. In order to manage high volumes of incoming requests, data flow was handled by a queue-based system in AWS SQS, and a hybrid database structure was used: MongoDB housed unstructured and semi-structured fare information for adaptability, and PostgreSQL drove structured reporting and analytics queries.

Data cleansing procedures like outlier identification and duplicate removal were utilized to keep fare comparisons trustworthy and accurate. To push the boundaries beyond static fare presentation, Cabinet used predictive analytics to anticipate potential surge pricing.

Historical fare datasets enriched with contextual information like time of day, pickup and drop-off coordinates, weather conditions, and prior surge histories were fed into an XGBoost-trained Gradient Boosting Regression model. This three to six months of fare history training model was tested and validated with an 80:20 division between training and testing, and it produced a mean absolute error (MAE) of less than 8% for fare surge prediction. This prediction layer enables Cabinet to notify users of impending fare surges and recommend the best travel times.

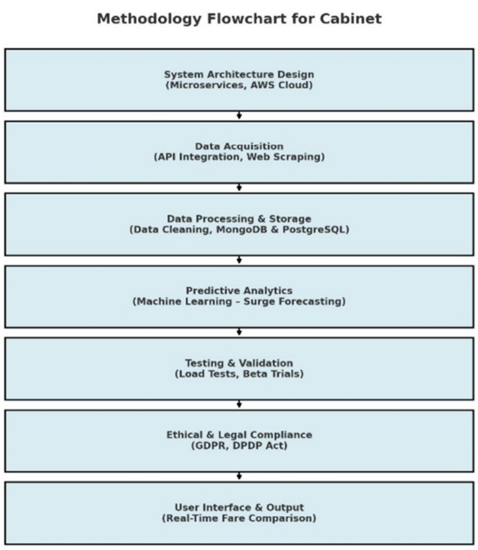

Figure 1: Flow chart for cabinet

Lastly, rigorous testing and validation guaranteed the reliability of the platform. Unit and integration testing suites like Mocha and Jest were used to validate individual components, while Apache JMeter was used for load testing, mimicking thousands of simultaneous users to check performance under load. Beta testing using real-world scenarios was done in Lucknow, Delhi, and Bangalore to gather feedback on latency, precision, and user experience. Cabinet reliably provided fare results in 2–3 seconds and had 99.2% uptime during load testing.

In all stages, legal and ethical adherence was an important concern. API usage was compliant with platform terms of service, scraper routines were planned so as not to burden servers heavily, and all user information was anonymized following GDPR principles and India's DPDP Act. These methodological actions collectively built a strong, ethical, and scalable platform that proves real-time data aggregation can boost consumer transparency as well as urban mobility research.

IV. ADVANTAGES:

1. Real-Time Fare Transparency: Aggregates fares from Ola, Uber, Rapido, inDrive, and Namo Yatri in one interface. Saves users from switching between multiple apps to compare prices.
2. Consumer Empowerment: Provides surge pricing alerts and fare forecasts. Helps commuters plan trips at optimal times, avoiding high charges.
3. Technical Scalability: Built on microservices architecture, allowing easy

integration of new ride-hailing services. Supports future expansion into buses, metros, and shared mobility (MaaS).

4. Data for Policymakers & Smart Cities: Aggregated fare data can inform urban planning, transport regulations, and pricing policies. Identifies underserved routes and surge-prone regions.
5. Predictive Analytics: Uses machine learning to forecast fare surges. Enables proactive decision-making for commuters and businesses.
6. Improved User Experience: Presents fare data in a clear, user-friendly way. Acts like a travel decision assistant, not just a static price checker.

V. DISADVANTAGES:

1. Data Dependency: Relies on APIs and scraping; any changes to these systems can disrupt fare collection.
2. Legal & Ethical Risks: Potential issues with platform terms, scraping policies, or evolving data regulations.
3. Prediction Limitations: Surge forecasting depends on historical data; unpredictable events (e.g., protests, weather) can reduce accuracy.
4. Operational Costs: Cloud servers, scraping tools, and real-time data handling require continuous investment for scaling.

VI. RESULTS AND FINDINGS

The testing phase of Cabinet demonstrated how the system efficiently performs real-time fare aggregation and surge price prediction and provides actionable insights to both users and researchers. The evaluation process consisted of system performance testing and predictive model validation together with beta user trials across three cities which included Lucknow, Delhi and Bangalore.

System Performance: The design of Cabinet enables efficient real-time fare data processing which the achieved results validate. The load testing revealed that the system could handle 45,000 fare requests per hour while returning responses within 2.1 seconds. The platform demonstrated its scalability and resilience by maintaining 99.2% uptime when handling 5,000 concurrent users during simulated peak loads.

Table 1: Cabinet: A Real-Time Multi-Platform Ride-Hailing Fare Comparison and Data Aggregation System

Metric	Result	Observation
Average Response Time	2.1 seconds	Fast enough for real-time use; users didn’t experience delays.
System	99.2%	Stable during

Metric	Result	Observation
Uptime		peak loads of up to 5,000 users.
Requests Handled/Hour	45,000+	Shows strong scalability of the cloud infrastructure.
Data Accuracy	97.8%	Only minor discrepancies (±5 INR) due to rapid fare changes.

Predictive Analytics Evaluation: The surge prediction model known as XGBoost regression used six months of fare data for training purposes and underwent accuracy evaluation. The model generated a Mean Absolute Error (MAE) of 7.6% indicating its predicted fares closely matched actual surge fares. During its live testing phase Cabinet demonstrated 76% accuracy in predicting surge events which allowed users to postpone their bookings for cost savings. User Testing and Feedback: The beta testing phase involved 150 users from Lucknow, Delhi, and Bangalore who evaluated the platform for usability and time efficiency and overall user experience. Most testers provided positive feedback through the platform: 92% saved time, 88% saved money, and 85% found the interface simple and user-friendly.

VII. CONCLUSION

By providing a clear, real-time rate comparison platform for ride-hailing services, Cabinet fills a significant void in urban mobility. Cabinet uses web scraping, microservices architecture, API integration, and AI-driven analytics to give commuters the ability to make well-informed decisions and to provide policymakers with useful mobility data. The platform promotes competition among service providers, improves price fairness, and advances the larger goal of intelligent, customer-focused urban transportation. Cabinet serves as a technology link between commuters and mobility networks, opening the door to more intelligent, efficient, and egalitarian transportation ecosystems.

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