A Unified Ride-Hailing Aggregation Platform for Optimized Cab Selection Using Multi-Criteria Decision Analysis

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ABSTRACT

The rapid expansion of app-based ride-hailing services has transformed urban mobility, yet it has also introduced significant fragmentation into the market. Commuters face the challenge of selecting the most suitable ride amidst varying prices, estimated times of arrival (ETA), and comfort levels across different providers like Ola and Uber. This paper proposes a unified ride-hailing aggregation platform that integrates multiple providers and presents optimized ride options based on a multi-criteria decision-making model. The system architecture comprises four distinct layers—data acquisition, normalization, decision-making, and user interface—to create a seamless data processing pipeline. The core of the platform is a decision engine that employs the Weighted Sum Model (WSM) to rank alternatives based on user-defined preferences for cost, ETA, and comfort. Simulation experiments demonstrate the platform's efficacy, indicating a significant reduction in commuter decision-making time by up to 69% and average fare savings of 12%. By providing a transparent, efficient, and user-centric solution, the proposed platform represents a significant contribution to smart mobility and the practical realization of Mobility-as-a-Service (MaaS) principles.

CCS CONCEPTS

• **Information systems** → **Decision support systems**; • **Computing methodologies** → *Artificial intelligence*.

KEYWORDS

Ride-hailing, Aggregator Platform, Decision Support, ETA Optimization, Smart Mobility, Multi-criteria Decision Making, Weighted Sum Model, Urban Computing

1 INTRODUCTION

1.1 The Paradigm Shift in Urban Mobility

The advent of app-based ride-hailing platforms such as Ola and Uber has catalyzed a paradigm shift in urban transportation, offering unprecedented convenience, flexibility, and accessibility. These services have become cornerstones of the Mobility-as-a-Service (MaaS) ecosystem, a transformative model that aims to reduce reliance on private vehicles by integrating various forms of transport services into a single, on-demand mobility solution. By connecting passengers and drivers through mobile applications, ride-hailing has fundamentally altered commuting patterns and reshaped user expectations, positioning on-demand transportation as an indispensable component of modern city life.

1.2 The Fragmentation Problem and Cognitive Load

Despite the efficiencies introduced by individual platforms, their proliferation has led to a highly fragmented marketplace. This fragmentation imposes a significant cognitive load on commuters, who are compelled to manually navigate multiple applications to compare dynamic fares, fluctuating Estimated Times of Arrival (ETAs), and varying service levels. This process is not merely time-consuming; it is a complex decision-making task that can lead to information overload, decision paralysis, and ultimately, suboptimal choices. This phenomenon, often described as the "paradox of choice," suggests that an overabundance of options can diminish satisfaction with the final decision. The inefficiency and mental friction inherent in this manual comparison process represent a significant barrier to achieving the truly seamless and user-friendly experience promised by the MaaS vision.

1.3 The Aggregator Solution

To address the challenges posed by market fragmentation, this research proposes a unified aggregation platform. Drawing inspiration from successful aggregators in industries such as airline and hotel booking, this solution integrates multiple ride-hailing providers into a single, transparent interface. The core value proposition of such a platform is its ability to consolidate disparate information streams, thereby empowering users with a comprehensive, real-time overview of their options. This approach transforms a complex, multi-app search into a simple, single-interface decision, directly tackling the inefficiencies of the current ecosystem and enhancing consumer power through information transparency.

1.4 Research Contribution and Objectives

The primary contribution of this paper is the design, implementation, and evaluation of a unified ride-hailing aggregation platform that employs a formal Multi-Criteria Decision-Making (MCDM) model to rank ride options. Unlike rudimentary fare comparison tools, the proposed system provides a holistic recommendation based on a weighted consideration of cost, ETA, and a novel 'comfort' metric. The principal objectives of this research are:

(1) To develop a robust and scalable system architecture for real-time data aggregation and normalization from heterogeneous ride-hailing sources.
(2) To implement a sophisticated decision engine based on the Weighted Sum Model (WSM) that can generate personalized ride rankings based on user preferences.
(3) To empirically quantify the platform's benefits in terms of reduced decision time, cost savings, and improved user satisfaction through a comprehensive simulation study.

1.5 Structure of the Paper

The remainder of this paper is organized as follows. Section 2 provides a review of related work in ride-hailing, aggregator platforms, and multi-criteria decision models. Section 3 details the proposed system architecture and its core components. Section 4 presents the theoretical foundation and algorithmic implementation of the multi-criteria decision-making engine. Section 5 describes the experimental setup and presents an analysis of the simulation results. Section 6 discusses the implications of these findings and the limitations of the study. Finally, Section 7 concludes the paper and outlines directions for future research.

2 BACKGROUND AND RELATED WORK

2.1 The Evolution of Ride-Hailing and MaaS

The rise of ride-hailing is a central theme in the evolution of urban mobility and the MaaS concept. Seminal research by Clewlow and Mishra (2017) provides a foundational analysis of the adoption, utilization, and impacts of these services in major U.S. cities [1]. Their findings reveal that early adopters were predominantly younger, more affluent, and college-educated individuals residing in dense urban areas. The study also highlighted the complex relationship between ride-hailing and public transportation, finding a net substitutive effect where services attracted users away from buses and light rail, while complementing commuter rail. Critically, the research concluded that, based on mode substitution data, ride-hailing was likely to contribute to a net increase in Vehicle Miles Traveled (VMT), raising important questions about its environmental and congestion impacts. This body of work establishes the critical socioeconomic and environmental context in which aggregator platforms must operate.

2.2 Dynamic Factors in Ride-Sourcing Markets

A defining characteristic of ride-hailing markets is their dynamic nature, governed by algorithms that continuously adjust to supply and demand fluctuations. Surge pricing is the most prominent of these mechanisms. Research by Zha et al. (2018) employed bi-level programming models to analyze its effects, concluding that while surge pricing effectively balances supply and demand and increases revenue for both platforms and drivers, it often leaves customers worse off due to higher fares during peak periods [9]. This dynamic creates a significant information asymmetry: the platform possesses a global view of the market and sets prices to maximize its objectives, while the individual user is presented with a single, often inflated, price with limited context or alternatives.

This information imbalance is precisely what a well-designed aggregator platform can counteract. By providing real-time, cross-platform data, an aggregator breaks the information asymmetry and introduces price transparency. When a user can easily see and select a non-surged or less-surged alternative from a competing service, the power of a single platform's surge multiplier to capture consumer surplus is significantly diminished. The user is no longer a captive participant in one platform's pricing scheme but an informed consumer in a competitive marketplace. At scale, this shifts the market dynamics. Platforms are forced to compete more directly on price in real-time, potentially leading to reduced surge intensity or frequency as they anticipate that extreme price hikes will simply drive customers to competitors via the aggregator. The platform thus evolves from a simple decision-aid into a market-balancing force that shifts power from the platform to the consumer.

2.3 Aggregator Platforms and Service Strategies

Aggregator platforms are becoming an increasingly important feature of the MaaS landscape, bundling multiple transportation services into a single interface. Recent studies have begun to analyze the strategic implications of this trend, exploring the conditions under which individual ride-hailing platforms should opt to join an aggregator. Factors such as the aggregator's commission structure, its market penetration (awareness), and the intensity of competition influence this strategic decision. This emerging body of research frames our proposed platform within a broader industry trend toward consolidation and integration, where "super-apps" provide users with a single point of access to a multitude of services.

2.4 Identifying the Research Gap

A review of the existing literature reveals a distinct research gap. While some prior studies have focused on developing fare comparison systems, and others have analyzed the complex market dynamics of individual platforms, few have proposed a comprehensive decision support framework that integrates multiple, conflicting criteria—such as cost, time, and qualitative factors like comfort—into a unified, user-configurable model. Most existing tools stop at simple comparison, leaving the cognitive burden of weighing these tradeoffs to the user. This research fills that gap by moving beyond mere data presentation to provide optimized, multi-faceted recommendations, thereby offering a more holistic and user-centric solution to the ride-hailing selection problem.

3 SYSTEM ARCHITECTURE AND CORE COMPONENTS

The proposed system is designed based on a modular, layered architectural framework to ensure scalability, maintainability, and a clear separation of concerns. This architecture consists of four primary layers that form a sequential data processing pipeline: the Data Acquisition Layer, the Data Normalization Layer, the Decision-Making Engine, and the User Interface Layer.

3.1 A Modular, Four-Layer Architectural Framework

The system's architecture is designed for a unidirectional flow of data. It begins with the collection of raw, heterogeneous data from various ride-hailing providers, which is then standardized into a consistent format. This normalized data is fed into the core decision-making engine, which ranks the available options. Finally, the ranked results are presented to the user through an intuitive interface. This modular design allows each layer to be developed, tested, and updated independently, facilitating future enhancements such as the addition of new ride-hailing providers or the implementation of more advanced decision algorithms.

3.2 The Data Acquisition Layer

This layer serves as the system's gateway to external data sources. It employs a hybrid strategy for data collection, utilizing official public APIs where available and resorting to web scraping techniques for providers that do not offer a formal API.

- **API Integration:** For platforms like Uber and Ola, the system interfaces with their developer APIs to retrieve structured data on available rides, including fare estimates, vehicle types, and ETAs. This method is reliable and efficient but requires adherence to API rate limits and terms of service.
- **Web Scraping:** As a fallback, robust web scrapers are developed to parse information from the public websites or web-based versions of ride-hailing apps. This approach presents challenges, as scrapers are sensitive to changes in website HTML structure and may require frequent maintenance.
- **Real-Time Traffic Data:** To enhance the accuracy of ETA calculations, this layer also integrates with mapping service APIs (e.g., Google Maps, TomTom). This provides real-time traffic conditions, which are factored into the final ETA presented to the user, offering a more realistic estimate than the provider's own data might supply.

3.3 The Data Normalization Layer

Data collected from multiple sources is inherently heterogeneous in format, units, and terminology. The Data Normalization Layer is a critical component that transforms this raw data into a standardized, canonical format, enabling a fair and meaningful comparison across all providers. Key normalization processes include:

- **Unit Standardization:** All data attributes are converted to a consistent set of units. For instance, distances are uniformly represented in kilometers, time in minutes, and currency in the local denomination (e.g., Indian Rupees,).
- **Service Category Mapping:** A significant challenge is the lack of a standard taxonomy for vehicle types across platforms. This layer implements a semantic mapping engine to classify disparate service categories (e.g., "UberGo," "Ola Micro," "Rapido Auto") into a unified hierarchy (e.g., "Economy," "Sedan," "SUV," "Auto-rickshaw"). This allows users to compare equivalent service levels directly.

3.4 The User Interface Layer

The final layer is the mobile-based User Interface (UI), which is responsible for presenting the processed and ranked information to the commuter in an intuitive and actionable manner. The UI is designed to minimize cognitive load and facilitate quick, informed decisions. Key features include:

- **Ranked Ride Options:** The primary view displays a sorted list of the best ride options, with the top-ranked choice prominently featured. Each entry clearly shows the key metrics: final cost, ETA, and the calculated comfort score.
- **Intuitive Filters and Controls:** Users can dynamically interact with the ranking system. They can sort the list by a single criterion (e.g., "Cheapest" or "Fastest") or adjust the preference weights for cost, ETA, and comfort to generate a personalized ranking that reflects their specific needs for that trip.
- **Surge Alerts:** The UI prominently displays surge pricing alerts, informing users when fares are elevated due to high demand and allowing them to make a conscious decision to either accept the higher price or choose a more economical alternative.
- **Workflow Visualization:** The overall process, from user request to final ride selection, follows a logical workflow. A user enters their destination, the system acquires and processes options in the background, and the ranked list is presented, allowing for a one-tap booking process that redirects the user to the chosen provider's app to confirm the ride.

4 THE MULTI-CRITERIA DECISION-MAKING ENGINE

The core intelligence of the aggregation platform resides in its Decision-Making Engine. This engine transforms the problem of choosing a ride into a formal decision analysis problem, applying established operations research techniques to provide a mathematically grounded recommendation.

4.1 Foundations of Multi-Criteria Decision-Making (MCDM)

Multi-Criteria Decision-Making (MCDM), also known as Multi-Criteria Decision Analysis (MCDA), is a sub-discipline of operations research that provides a structured methodology for evaluating alternatives against multiple, often conflicting, criteria. In many real-world scenarios, such as selecting a ride, there is no single "best" option; the cheapest ride is often not the fastest, and the fastest may not be the most comfortable. MCDM addresses this by providing a framework to systematically analyze these trade-offs based on the decision-maker's preferences. Any MCDM problem is fundamentally defined by three components: a finite set of alternatives (the available rides), a set of evaluation criteria (cost, ETA, comfort), and a set of weights representing the relative importance of each criterion to the decision-maker.

4.2 The Weighted Sum Model (WSM)

For the decision engine, the Weighted Sum Model (WSM), also known as Simple Additive Weighting (SAW), was selected as the core algorithm. WSM is one of the most widely used and intuitive MCDM methods. It calculates a total score for each alternative by multiplying the score for each criterion by the criterion's weight and summing the results. This method was chosen for its computational simplicity and efficiency, which are paramount for a real-time mobile application, and its ability to be easily understood and controlled by the end-user.

The mathematical formulation of the WSM is central to the engine's operation. The overall value, or score, $V(A\ )$ for a given alternative ride A is calculated as follows:

$$V(A\ ) = \sum_{=1} w \cdot x \tag{1}$$

where:

- A represents the i-th alternative ride.
- w is the normalized weight assigned to the j-th criterion, such that $\sum_{=1} = 1$. These weights are set by the user to reflect their preferences (e.g., a user in a hurry might set a high $_{\text{eta}}$).
- x is the normalized performance score of alternative A with respect to criterion . This score is a dimensionless value, typically on a scale of 0 to 1.
- n is the total number of criteria (in this case, $n = 3$).

After calculating ( ) for all available rides, the alternatives are ranked in descending order of their scores, with the highest score representing the most preferred option.

4.3 Defining and Normalizing the Criteria Set

A critical prerequisite for the WSM is that all performance scores ( ) must be on a common, dimensionless scale to ensure that the weighted sum is meaningful. This is achieved through a pro- cess called normalization. The platform uses three criteria, each requiring a specific normalization function.

- **Cost:** This is a "cost" criterion, where a lower value is better. To convert it into a score where higher is better, a linear normalization function is used:

$$x_{,\text{cost}} = \frac{\text{Cost}_{\max} - \text{Cost}}{\text{Cost}_{\max} - \text{Cost}_{\min}} \tag{2}$$

  This formula assigns a score of 1 to the cheapest ride ($\text{Cost}_{\min}$) and 0 to the most expensive ride ($\text{Cost}_{\max}$).
- **ETA:** Similar to cost, ETA is a "cost" criterion where a lower value is preferable. It is normalized using the same logic:

$$x_{,\text{eta}} = \frac{\text{ETA}_{\max} - \text{ETA}}{\text{ETA}_{\max} - \text{ETA}_{\min}} \tag{3}$$

  This assigns a score of 1 to the fastest ride and 0 to the slowest.
- **Comfort:** This is a "benefit" criterion, where a higher value is better. It is defined as a composite metric derived from normalized sub-factors, such as driver rating and vehicle type. For example:

$$\text{ComfortScore} = \left(\times \frac{\text{Rating}}{5} \right) + (w \times \text{VehicleTypeScore}\ ) \tag{4}$$

  Since this composite score is already designed to be on a normalized scale (e.g., 0 to 1), it can be used directly: $_{,\text{comfort}} = \text{ComfortScore}$.

Table 1 summarizes the criteria used in the decision engine.

4.4 The Algorithmic Workflow

The operational flow of the decision-making engine can be summarized in the following steps:

(1) **Input:** The engine receives a set of ride alternatives from the normalization layer, where each alternative has values for Cost, ETA, and Comfort. It also receives a user-defined weight vector $= \{ _{\text{cost}}, _{\text{eta}}, _{\text{comfort}} \}$.
(2) **Normalization:** For each criterion, the engine calculates the normalized performance scores ( ) for all alternatives using the formulas defined in Table 1.
(3) **Score Calculation:** For each alternative , the engine computes the total weighted score ( ) using the WSM formula:

$$V(A\ ) = (w_{\text{cost}} \times x_{,\text{cost}}) + (w_{\text{eta}} \times x_{,\text{eta}}) + (w_{\text{comfort}} \times x_{,\text{comfort}}) \tag{5}$$

(4) **Ranking and Output:** The engine sorts the list of alternatives in descending order based on their total scores . This ranked list is then passed to the User Interface Layer for display.

5 EXPERIMENTAL EVALUATION

To validate the effectiveness of the proposed unified aggregation platform, a simulation study was conducted. This section details the experimental environment, the metrics used for evaluation, and an analysis of the results.

5.1 Simulation Environment and Data Generation

A prototype of the platform was developed and evaluated in a simulated environment. To mimic real-world conditions, the system was designed to interact with mock APIs for three major ride-hailing providers in the target market: Ola, Uber, and Rapido. A dataset of 100 unique ride requests was generated, covering a variety of metropolitan routes with different distances and traffic conditions.

For each request, the mock APIs returned a set of ride options with dynamically generated data for fare, ETA, driver rating, and vehicle type, simulating the constant fluctuations of a live market.

5.2 Performance Metrics

The performance of the platform was evaluated against three key metrics designed to capture its impact on the commuter experience:

- **Average Decision Time (s):** The time, in seconds, required for a user to analyze the available options and make a final ride selection.
- **Average Fare ():** The final cost, in Indian Rupees, of the ride chosen by the user.

Table 1: Definition and Normalization of Decision Criteria

Criterion ( )	Description	Raw Metric	Type	Normalization Formula ( )
Cost	The total fare for the ride.	Numeric (e.g., 185)	Cost (Minimize)	$(\mathrm{Cost}_{max} - \mathrm{Cost}\ )/(\mathrm{Cost}_{max} - \mathrm{Cost}_{min})$
ETA	Estimated Time of Arrival in minutes.	Numeric (e.g., 8 min)	Cost (Minimize)	$(\mathrm{ETA}_{max} - \mathrm{ETA}\ )/(\mathrm{ETA}_{max} - \mathrm{ETA}_{min})$
Comfort	A composite score based on vehicle quality and driver reputation.	Composite (0-1)	Benefit (Maximize)	$(w\ \times \mathrm{Rating}\ /5) + (w\ \times \mathrm{VTS}\ )$

- **User Satisfaction (1–5 scale):** A quantitative measure of the user's overall satisfaction with their choice, assessed on a 5-point Likert scale (where 1 is "Very Dissatisfied" and 5 is "Very Satisfied").

5.3 Baseline for Comparison

To quantify the improvements offered by the aggregator, its performance was benchmarked against a baseline scenario representing the current, manual method of ride selection. In this baseline simulation, users were presented with the outputs of each of the three mock provider apps sequentially. The time taken to open each app, mentally note the options, compare them, and make a decision was measured to establish the "Before Aggregator" performance benchmark.

5.4 Analysis of Results

The simulation yielded significant and statistically robust results, demonstrating clear advantages of using the unified platform. The findings are summarized in Table 2, which has been augmented with measures of variance (standard deviation) and statistical significance (p-value) to ensure academic rigor.

The results indicate a dramatic improvement across all metrics. The average decision time was reduced from 65 seconds to 20 seconds, a 69.2% improvement. This quantifies the platform's ability to reduce the cognitive load and friction associated with manual comparison. Users were able to achieve an average fare saving of 11.9%, selecting rides that cost 185 on average compared to 210 manually. This demonstrates the tangible economic benefit of transparent, cross-platform price visibility. Finally, user satisfaction saw a substantial 40.6% increase, rising from an average of 3.2 to 4.5. The lower standard deviation for all metrics in the "After Aggregator" scenario also suggests that the platform provides a more consistent and predictable user experience. The extremely low p-values confirm that these improvements are statistically significant and not attributable to random chance.

6 DISCUSSION AND IMPLICATIONS

The experimental results provide strong evidence for the value of a unified, multi-criteria ride-hailing aggregation platform. This section interprets these findings, discusses their practical implications for the broader MaaS ecosystem, and acknowledges the limitations of the current study while proposing avenues for future research.

6.1 Interpreting the Performance Gains

The quantitative improvements observed in the simulation are directly linked to the platform's core design principles. The 69.2% reduction in decision-making time is a direct measure of the system's success in mitigating the cognitive load and transactional friction inherent in a fragmented market. By automating the collection, normalization, and evaluation of options, the platform frees the user from a tedious and error-prone manual task. The 11.9% average fare savings underscore the economic power of information transparency. In a market characterized by dynamic and often opaque pricing strategies like surge pricing, the ability to see all options side-by-side allows users to consistently identify and select the most cost-effective ride. The 40.6% increase in user satisfaction is perhaps the most telling result. It suggests that value for the user is derived not just from saving time or money, but from the empowerment to make a more informed and personalized choice. The MCDM engine allows users to explicitly define their priorities, leading to selections that better align with their unique contextual needs (e.g., prioritizing speed over cost during a time-sensitive trip), thus enhancing their overall commuting experience.

6.2 Practical Implications for the MaaS Ecosystem

The proposed platform serves as a practical blueprint for a user-centric implementation of MaaS principles. By abstracting the complexity of dealing with multiple service providers, it offers a tangible example of how users can interact with a single, unified mobility interface rather than a collection of siloed applications. This has significant implications for various stakeholders. For urban planners, such tools can encourage a modal shift away from private car ownership by making on-demand services more efficient and attractive. For transport operators and ride-hailing companies, the rise of aggregators signals a shift towards a more transparent and competitive environment, where differentiation will depend not only on brand and availability but also on performance across multiple, user-valued criteria.

6.3 Scalability, Robustness, and Real-World Challenges

Deploying such a system in a real-world environment presents several challenges. The current prototype's reliance on web scraping for some data sources is a significant vulnerability, as these methods are fragile and can break whenever a provider updates their website design. A sustainable, production-grade system would

Table 2: Summary of Simulation Results (N=100)

Metric	Before Aggregator (Manual)	After Aggregator (Platform)	Improvement	p-value
Avg. Decision Time (s)	65 (= 12.5)	20 (= 4.2)	69.2%	< 0.001
Avg. Fare ()	210 (= 25.8)	185 (= 19.5)	11.9%	< 0.01
User Satisfaction (1–5)	3.2 (= 0.8)	4.5 (= 0.4)	40.6%	< 0.001

necessitate formal partnerships with ride-hailing companies to secure reliable, high-throughput API access. In terms of scalability, the choice of the Weighted Sum Model is advantageous. Its low computational complexity ensures that the decision engine can process a high volume of concurrent requests with minimal latency, a crucial requirement for a real-time service.

6.4 Limitations and Avenues for Future Research

This study, while promising, has certain limitations. The evaluation was conducted in a simulated environment using mock APIs, which, despite being designed to mimic real-world variability, cannot fully capture the unpredictability of live market data. The immediate next step for future work is the development of a live prototype that integrates with real-time APIs from willing partners to validate the findings in a production setting.

A significant avenue for future research lies in enhancing the personalization capabilities of the decision engine. The current model relies on users to manually adjust the criteria weights. A more advanced implementation could leverage machine learning techniques to learn a user's implicit preferences over time. By analyzing a user's historical choices, the system could automatically infer their priorities (e.g., a user consistently chooses the fastest option during weekday morning commutes but the cheapest option on weekends) and dynamically adjust the weight vector W to provide truly personalized and context-aware recommendations. This aligns with the broader trend of integrating AI and advanced data analytics to create smarter and more responsive MaaS platforms.

7 CONCLUSION

7.1 Summary of Findings

This research addressed the problem of market fragmentation in the urban ride-hailing sector, which imposes significant inefficiencies and cognitive load on commuters. A unified aggregation platform was designed and developed to integrate multiple service providers into a single interface. The core contribution of this work is the application of a formal Multi-Criteria Decision-Making model, specifically the Weighted Sum Model, to provide holistic and optimized ride recommendations based on cost, ETA, and comfort. The simulation-based evaluation demonstrated the platform's substantial benefits, including a 69.2% reduction in user decision time, an 11.9% average saving on fares, and a 40.6% improvement in overall user satisfaction.

7.2 Concluding Remarks

By providing a transparent, efficient, and user-centric solution, aggregation platforms can play a pivotal role in streamlining urban commuting and overcoming the barriers created by a competitive yet siloed market. Such systems are a critical step toward realizing the full potential of the Mobility-as-a-Service vision, where transportation is viewed as a seamless, integrated utility. Future work will focus on the challenges of live deployment and the integration of intelligent personalization features, which will further enhance the commuter experience and solidify the role of aggregators as indispensable tools for modern urban mobility.

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