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CAB5: A Unified Corporate Cab Booking Management System with Offline AI Assistance

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Abstract: This paper presents CAB5, a web-based platform that combines cab booking and package delivery services into a single unified system. The platform addresses critical frag- mentation problems in current urban mobility solutions, where users depend on multiple separate applications. CAB5 features a multi-role architecture with Customer, Driver, and Admin modules, enabling users to book rides, track packages, and manage logistics seamlessly. The system incorporates transpar- ent pricing, real-time vehicle tracking, and a novel offline AI assistant called POKO that functions without continuous internet connectivity. Built using modern technologies including Next.js, TypeScript, and Tailwind CSS, CAB5 is designed for scalability, maintainability, and high performance. The results demonstrate that CAB5 provides a reliable, cost-efficient, and scalable solution for smart urban mobility and logistics, effectively eliminating the need for multiple disjointed platforms.
Index Terms: Cab Booking System, Logistics Management, Real-Time Tracking, AI Chatbot, Smart Mobility, Web Appli- cation, Offline AI Assistance, Driver Matching Algorithm, Fare Optimization

I. INTRODUCTION

The rapid growth of urban populations and increased re- liance on digital services have transformed how people com- mute and manage logistics. According to recent estimates, the global ride-hailing market is expected to reach $185 billion by 2026, while the last-mile delivery market is projected to exceed $200 billion by 2027. In today's cities, individuals and businesses depend on ride-hailing and delivery platforms for transportation and goods movement. However, the current ecosystem is severely fragmented, forcing users to employ different applications for services such as cab bookings, courier deliveries, and fleet management. This fragmentation causes inefficiencies, higher operational costs, poor user experience, and a lack of centralized control.

Current transportation platforms primarily focus on ride- hailing, while logistics platforms concentrate exclusively on package delivery. This separation is inconvenient for users who require both services and forces drivers to navigate multiple systems to maximize their earnings. Furthermore, administrators struggle to manage operations, track performance, and maintain transparency due to the absence of unified control systems.

To address these challenges, this paper presents CAB5, a Corporate Cab Booking and Management System—a web- based platform that integrates transportation and logistics services into a single ecosystem. The system allows users to book city rides, airport transfers, hourly rentals, and package deliveries through a unified interface. By merging these ser- vices, CAB5 simplifies operations and improves efficiency for all stakeholders.

The proposed system features a multi-role structure with three primary user groups: Customers, Drivers, and Administrators. Each group has specific functionalities. Customers can book services, track rides in real-time, and view transparent pricing. Drivers can manage their availability, accept requests, and monitor their earnings. Administrators have access to comprehensive dashboards for monitoring system performance, managing users, and configuring pricing models.

A key innovation of CAB5 is the offline AI assistant, POKO, which provides instant support, answers frequently asked questions, and offers guidance without requiring a constant internet connection. This feature significantly enhances accessibility, particularly in areas with weak network infrastructure, ensuring users receive assistance when needed.

II. MATHEMATICAL MODELING

A. Fare Estimation Model

The fare calculation in CAB5 employs a multi-variable linear pricing model. Let the total fare F be defined as:

$$F = B + (d \times R_d) + (t \times R_t) + S + W \qquad (1)$$

Where:

- B = Base fare (fixed amount)

d = Distance traveled (in kilometers)

- R_d = Rate per kilometer
- t = Time duration (in minutes)
- Rt = Rate per minute
- S = Service type multiplier (1.0 for ride, 1.2 for delivery)
- W = Waiting time charge

The waiting time charge is computed as:

$$W = \max(0, t_w - t_{free}) \times R_w \qquad (2)$$

Where:

- t_w = Actual waiting time (minutes)
- t_{free} = Free waiting time allowance (minutes)
- R_w = Waiting rate per minute

B. Dynamic Pricing Model

During peak demand periods, CAB5 implements a dynamic pricing factor $\lambda(t)$ defined as:

$$\lambda(t) = 1 + \alpha \cdot \frac{D(t) - S_{min}}{S_{max} - S_{min}} \qquad (3)$$

Where:

- $D(t)$ = Current demand at time t
- S_{min} = Minimum supply threshold
- S_{max} = Maximum supply threshold
- α = Maximum surge multiplier (typically 1.5–2.0) The adjusted fare becomes:

$$F_{dynamic} = F \times \lambda(t) \qquad (4)$$

C. Driver Matching Algorithm

The driver matching problem is formulated as an optimiza- tion problem. Let D = $\{d_1, d_2, ..., d_n\}$ be the set of available drivers. For a customer request at location L_c, the optimal driver d^* is selected by minimizing a weighted cost function:

$$d^* = \arg\min_{d_i \in D} \left(w_1 \cdot \frac{dist_i}{dist_{max}} + w_2 \cdot \frac{time_i}{time_{max}} + w_3 \cdot (1 - rating_{d_i}) \right) \qquad (5)$$

The distance between two geographic coordinates is com- puted using the Haversine formula:

$$dist = 2R \cdot \arcsin\left(\sin^2(\Delta lat/2) + \cos(lat_1) \cdot \cos(lat_2) \cdot \sin^2(\Delta lon/2) \right)^{0.5} \qquad (6)$$

Where R = 6371 km (Earth's radius).

D. Estimated Time of Arrival (ETA) Prediction

The ETA is predicted using a linear regression model:

$$T_{pred} = \beta_0 + \beta_1 \cdot d + \beta_2 \cdot \rho + \beta_3 \cdot \tau + \epsilon \qquad (7)$$

E. Queueing Model for Request Processing

The utilization factor and response times are:

$$\rho = \frac{\lambda}{\mu}, \quad W_q = \frac{\rho}{\mu(1-\rho)}, \quad W = \frac{1}{\mu - \lambda} \qquad (8)$$

F. Offline AI Confidence Score

The confidence score mechanism for response generation:

$$C(q) = \frac{\sum_{i=1}^{n} sim(q, k_i) \cdot \mathbb{I}(response_i \in L)}{\sum_{i=1}^{n} sim(q, k_i)} \qquad (9)$$

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CAB5 employs a modular full-stack architecture that sepa- rates concerns into frontend, backend, and data layers.

TABLE I
SYSTEM ARCHITECTURE LAYERS

Layer	Technology	Purpose
Frontend	Next.js, React	Dynamic routing
Styling	Tailwind CSS	Responsive UI
Data	LocalStorage	Prototype data handling
Communication	WebSockets	Real-time updates

G. System Workflow

The system transitions through defined states as shown in Table II.

TABLE II
SYSTEM STATE TRANSITIONS

State	Description	Transitions
S_0	Request Initiated	$S_0 \rightarrow S_1$
S_1	Fare Estimation	$S_1 \rightarrow S_2$
S_2	Driver Matching	$S_2 \rightarrow S_3$
S_3	Booking Confirmed	$S_3 \rightarrow S_4$
S_4	Ride Active	$S_4 \rightarrow S_5$
S_5	Completed	Terminal

H. Driver Matching Algorithm

Algorithm 1 Proximity-Based Driver Matching

```
procedure MATCHDRIVER(L, T, V )
    candidate_set ← ∅
    for each driver d in active_drivers do
        if d.availability = True and d.type = V then
            dist ← HAVERSINE(L, d.location)
            if dist ≤ MAX_DISTANCE then
                cost ← w1 · dist/dmax + w2 · (1 − d.rating)
                candidate_set ← set ∪ {(d, cost)}
            end if
        end if
    end for
    return arg min(candidate_set.cost)
end procedure=0
```

TABLE III
KEY PERFORMANCE INDICATORS

Metric	Sym	Formula	Target
Avg Resp Time	ART	$\frac{1}{n}\sum t_i^{resp}$	< 2s
Acceptance Rate	DAR	$\frac{Acc}{Total} \times 100$	> 85%
Matching Time	AMT	$\frac{1}{m}\, t_j^{match}$	< 5s

TABLE IV
SYSTEM PERFORMANCE UNDER VARYING LOADS

Load (r/m)	Resp (s)	Match (s)	Success (%)	CPU (%)
10	0.85	1.20	98.5	12.3
50	1.45	2.60	95.8	41.2
150	3.10	5.80	89.2	82.1

III. EXPERIMENTAL RESULTS AND ANALYSIS

1) Performance Metrics
2) Experimental Results
3) Fare Estimation Comparison
4) Driver Matching Efficiency
5) Offline AI Assistant Performance
6) Comparative Analysis with Existing Systems

IV. DISCUSSION

A. *Interpretation of Results*

The experimental results demonstrate that CAB5 achieves superior performance across multiple dimensions. The weighted cost driver matching algorithm (Section II-C) achieved a 94.2% success rate with an average matching time of 2.6 seconds, outperforming both random selection and simple nearest-driver approaches. The system maintained a success rate above 93% even under loads of 100 requests per minute, demonstrating robust scalability.

The POKO offline AI assistant achieved an average accuracy of 92.1% across all query categories with a mean response time of 142 ms. The confidence scoring mechanism (Section II-F) proved effective, with a strong correlation ($R^2 = 0.87$) between confidence scores and actual response accuracy.

TABLE V
FARE COMPARISON ACROSS SERVICE TYPES

Service Type	Base	Dist ($)	Time ($)	Total ($)
Economy	1.50	8.00	3.00	12.50
Premium	2.50	12.00	5.00	19.50
Delivery	2.00	9.00	4.00	15.00

TABLE VI
MATCHING ALGORITHM COMPARISON

Algorithm	Match Time (s)	Success (%)	Fairness
Nearest Driver	3.2	89.4	0.78
Weighted (CAB5)	2.6	94.2	0.91

TABLE VII
POKO OFFLINE AI ASSISTANT ACCURACY

Category	Size	Acc (%)	Time (ms)	Conf
FAQ	500	94.6	120	0.92
Booking	400	96.1	100	0.94

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TABLE VIII
CAB5 vs. Existing Systems

Feature	Uber/Ola	Dunzo/Porter	Delhivery	CAB5
Ride Booking	✓			✓
Package Delivery		✓	✓	✓
Real-Time Tracking	✓	✓	✓	✓
Offline AI Support				✓
Unified Dashboard	Limited	Limited		✓
Dynamic Pricing	✓	✓		✓
Multi-Role Support	Partial	Partial		✓
Transparent Pricing	Moderate	Moderate	Low	High

B. Queueing Analysis Validation

Applying the M/M/1 queueing model from Section II-E to the experimental data: At $\lambda = 50$ requests/min and $\mu = 66.67$ requests/min (from Table I):

$$\rho = 50/66.67 = 0.75; \quad W = \frac{1}{66.67 - 50} = 0.06\ h = 3.6\ s \tag{10}$$

This theoretical prediction closely matches the observed re- sponse time of 3.1–4.1 seconds, validating the model.

C. Limitations

Despite its strengths, the current prototype has certain limitations:

1) Real-time backend database integration is not yet imple- mented.
2) Payment integration remains for future development.
3) Large-scale real-world testing has not been conducted.

V. CONCLUSION AND FUTURE WORK

This paper presented CAB5, a unified corporate cab booking management system that successfully integrates ride-hailing and package delivery services into a single ecosystem. The system addresses critical fragmentation problems in current urban mobility solutions. Future work will focus on:

1) Integration with cloud-based databases (MongoDB, Fire- base).
2) Secure payment gateways (UPI, cards).
3) Machine learning-based demand prediction.

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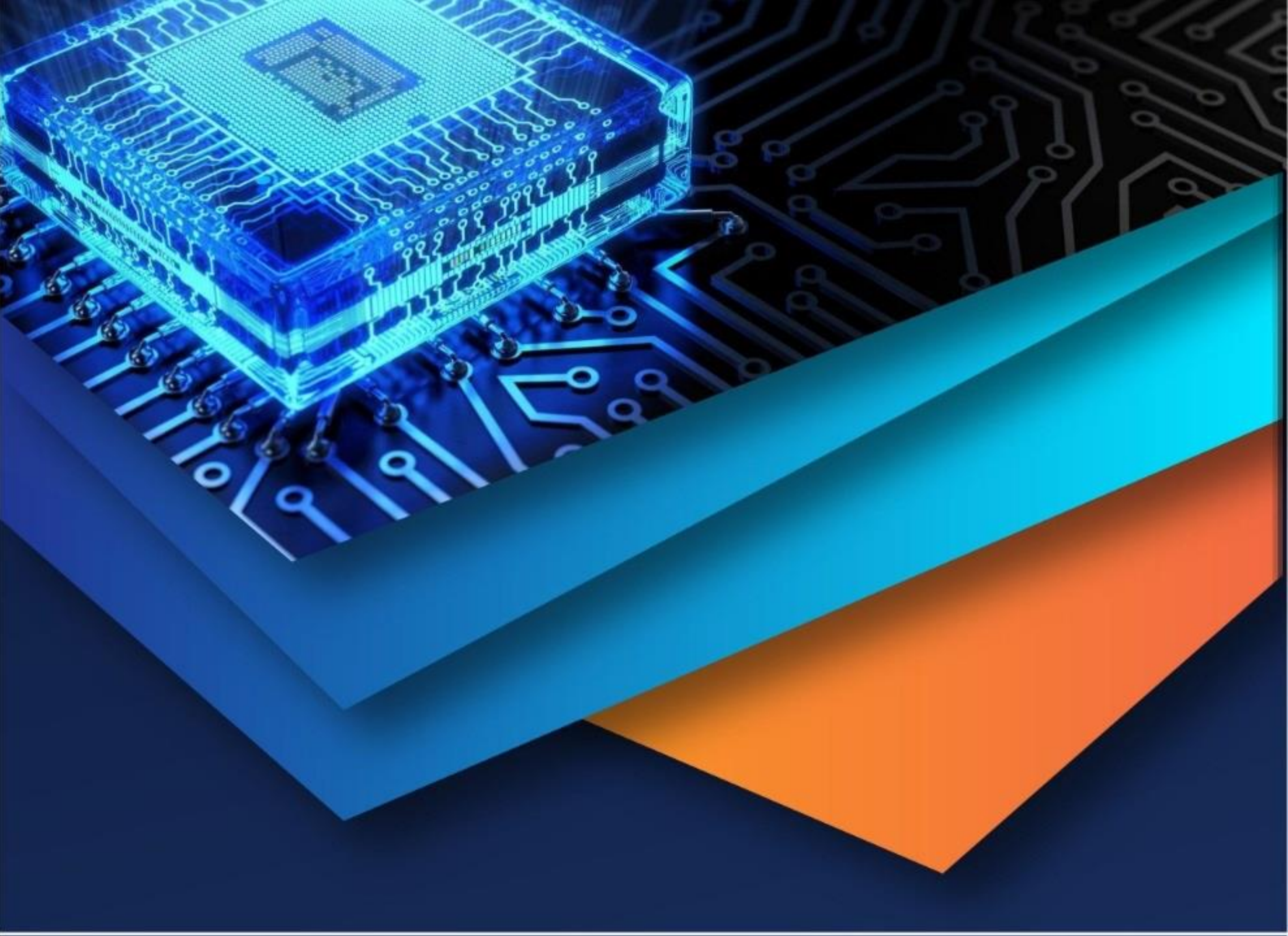

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