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Beyond Carpooling: A Corporate-First, Policy-Constrained Ride-Matching Platform

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Abstract—In many cases, corporate transport is handled by individually arranged trips, which result in a low utilization of the vehicle, high greenhouse gas (GHG) emissions and high costs for both the employer and the employee. Shared mobility platforms are available, but they do not necessarily take into account the policy context and situation of dual sourcing, which is typical of the corporate commute. This paper introduces ConnectRide, a corporate-first commute optimization platform that leverages a clear and rule-based matching engine to find compatible commutes during the day. We explain its architecture, dual-source business models, and multi-factor scoring algorithm that measures route, time, detour, cost and trust. Then to check the sustainability impacts of the platform, we did a simulated case study with Pune (India) IT corridor synthetic commuting data. The results show that the ConnectRide matching engine can help to achieve a high level of seat utilisation (up to 65%), to reduce per-employee transport costs and to reduce vehicle kilometres travelled (VMT), which in turn will reduce carbon emissions. The paper ends with suggestions for the policy makers from the corporate side, and provides directions for the future on how to incorporate behavioral incentives and live payment settlement.

***Index Terms*—Behavior change, corporate commuting, cost allocation, ridesharing matching, sustainable mobility, transport optimization.**

1. Introduction

Transport is an important emitter of greenhouse gases and responsible for congestion in urban areas around the world. Single-occupancy vehicles (SOVs) are heavily used especially in fast-growing urban corridors like the Information Technology (IT) corridors in India. This is contributed by the inadequate public transport infrastructure, the fragmented residential layout and the poor flexibility and reliability of commuting options [1]. Hinjewadi (Pune) is a hub with thousands of employees everyday commuting from the nearby residential areas like Wakad, Baner, Pimple Saudagar, which leads to a heavy traffic jams during the morning and evening hours. This has led to localized measures like the introduction of special corporate shuttle services to help the employees during their commute in a day-to-day basis [2].

Even though companies do provide transport facilities, many companies still experience a considerable financial burden because of the number of cabs which are not used to their full extent and the logistics required in managing employee transport allowances. At the same time, workers are also subject to high individual expenses when making their own trips to and from work. There is a general mobility as a service (MaaS) and ridesharing service, but they do not work in the corporate environment. They are not policy-aware, do not have employer-approval mechanisms, have no cost-allocation mechanisms, nor the required privacy controls provided by corporate human resources (HR) departments.

To fill these gaps, we present a commute optimization platform for corporate commuters, called **ConnectRide**. ConnectRide is not a public platform; it's a dual-source model where cab are company/vendors booked or employee owned (Model A & B). The major contributions of this paper are as follows: (1) a dual source matching architecture that strictly abides by corporate policies; (2) a transparent multi-factor scoring algorithm that balances route, time and trust; and (3) simulation of the platform in the Pune IT corridor to quantify the sustainability and economic impacts.

2. Literature Review

A. Shared Mobility and MaaS

Shared mobility research can be broken down into three areas: travel behaviour research, demand forecasting, pricing, and fleet optimization. Qualitative studies in recent years have demonstrated that moving from private cars to shared ones is a gradual process, where cost-savings, convenience and customizability play a significant role [1]. As regards corporate cases, Hussain et al. [3] suggested a matching framework tailored specifically for employees working in large organizations to facilitate carpooling. Additionally, heuristic strategies and matching rates have been studied within recent optimization models that have looked at carpooling from a mathematical perspective [4]. As background, two initial studies were published by Agatz et al. [5] and Furuhata et al. [6] that set a benchmark for optimization of dynamic ride-sharing.

B. Research Gap

The literature has extensively explored general dynamic ridesharing [5], [6] and consumer carsharing [7] but there are no frameworks specifically for corporate ridesharing. Current matching methods do not usually include hard filters (like vehicle approval and vehicle subsidy limits) as job-specific

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constraints. Moreover, the two-source complexity of using company owned cabs and employee owned cars within the same matching engine is not investigated often. The proposal of ConnectRide is a policy-aware, dual-source architecture to overcome this.

C. Corporate Commuting Challenges

Corporate commuting has its own set of challenges, as pointed out by Jain et al. [8]: incentives and external triggers are needed to change the behavior of employees. Operational realities and employee preferences often pose a problem for employers when they are trying to achieve sustainability. There are several different solutions available, but most are too rigid (shuttle schedules are fixed) or totally decentralized (carpool apps are without an organizational policy).

D. Matching Algorithms in Transportation

In the rideshare service, matching algorithms are usually based on spatial-temporal clustering. There are also more sophisticated optimisation techniques (e.g. multi-vehicle routing), however these are often "black boxes" to end-users. For corporate commuting, where trust and policy adherence are critical, an algorithm that is transparent, based on rules, and verifiable is preferable over opaque AI-based algorithms.

3. Methodology: The ConnectRide System Design

A. System Architecture

ConnectRide platform uses a Web-First stack. The architecture is a frontend application using React + TypeScript, and a backend API using Node.js + Express. The backend is responsible for authentication, company policy validation and the matching engine. User profiles, ride info and cost allocation are stored in a PostgreSQL database. Geocoding and travel-time is done via external routing APIs.

B. Synthetic Data Generation

Since real-world pilot data requires extensive legal and privacy approvals, we constructed a synthetic dataset representing 500 employees commuting to the Hinjewadi IT Park. The dataset generation followed three steps:

1) *Spatial Distribution:* Employees were distributed across five residential clusters (Wakad, Baner, Pimple Saudagar, Aundh, and Kothrud) based on approximate population densities.
2) *Temporal Distribution:* Commute times were modeled using a normal distribution, peaking between 8:30 AM and 9:30 AM, reflecting typical corporate shift timings.
3) *Baseline Behavior:* In the baseline scenario, 80% of employees were modeled as driving alone, while 20% utilized company-provided cabs that operated at an average 40% capacity.

C. Simulation Setup and Performance Metrics

The ConnectRide algorithm was simulated using Python. The matching window was set to 30 minutes, and the maximum allowable detour was capped at 15% of the original route distance. We evaluated the system using four primary metrics:

1) *Average Vehicle Occupancy (AVO):*

$$AVO = \frac{\text{Total passengers}}{\text{Total vehicles}} \quad (1)$$

2) *Match Success Rate (MSR):*

$$MSR = \left(\frac{\text{Confirmed matches}}{\text{Total eligible requests}}\right) \times 100 \quad (2)$$

3) *Vehicle Kilometers Traveled (VMT) Reduction:* We calculated the total distance traveled by all vehicles in the baseline versus the pooled scenario.

$$VMT_{\text{reduction}} = \left(1 - \frac{VMT_{\text{pooled}}}{VMT_{\text{baseline}}}\right) \times 100 \quad (3)$$

4) *Estimated Cost Savings:* Calculated by comparing the baseline per-employee transport expenditure against the allocated pooled costs.

D. Simulation Parameters and Multiple Runs

To ensure statistical reliability, the simulation was executed 50 independent times using different random seeds for the synthetic dataset. The results reported in this paper represent the mean values across these 50 runs. Table 1 outlines the core parameters used in the simulation environment.

E. Operating Models

ConnectRide utilizes a single matching engine to serve two distinct ride sources.

Model A (Company/Vendor Cab): Authorized admins create pooled bookings. The system identifies potential passengers,

Table 1
Core parameters of the simulation environment

Parameter	Value
Employees (synthetic)	500
Residential clusters	5
Departure time	Normal, μ = 08:30 AM, σ = 15 min
Baseline mode share	80% drive alone; 20% company cabs (40% capacity)
Matching window	30 min
Maximum detour	15% of original route distance
Time-window deviation (σ)	10 min
Baseline cost per employee	$9.00 per day (18 km at $0.50/km)
Emission factor	120 g CO_2 per km (average sedan)
Independent runs	50 (master seed 42)
Software	Python 3.10, NumPy, Pandas, SimPy

handles approvals, and records cost allocation. Savings are realized only if pooling avoids a separate trip.

Model B (Employee-Owned Car): Verified employees offer rides with destination, schedule, spare seats, and maximum acceptable detour. Drivers accept or decline requests, and the app displays the agreed cost contribution.

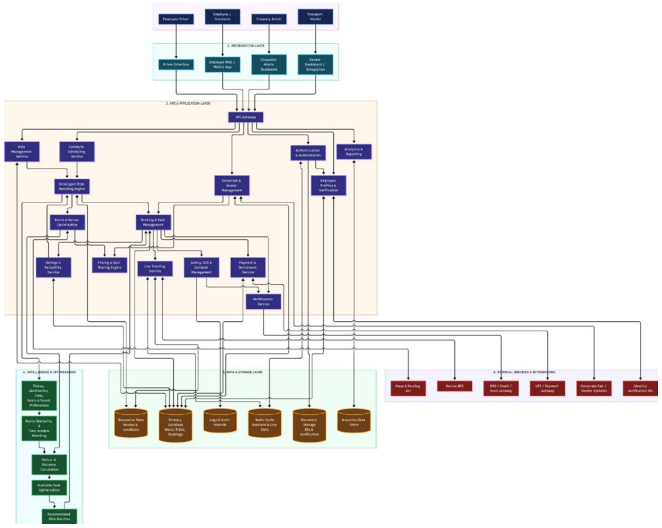


Fig. 1. The ConnectRide local architecture flow, adapted from the system blueprint.

F. Matching Engine Architecture

The matching engine operates in three phases:

Phase 1: Hard Filters. Before any scoring occurs, the system applies strict eligibility constraints:

- Date and departure-time compatibility (within a configurable window).
- Feasible route overlap and maximum detour constraints.
- Available seats and vehicle capacity limits.
- Company policy compliance (approved vendors, account status).

Phase 2: Weighted Scoring. Eligible matches are ranked using a multi-factor algorithm. The composite score S for a match is calculated as:

$$S = \sum_{i=1}^{n}(w_i \cdot f_i) \tag{4}$$

Where w_i represents the weight of factor i, and f_i is the normalized score of that factor.

The factors f_i in the weighted scoring equation are mathematically defined and normalized between 0 and 1:

- *Route Similarity (f_{route}):* Calculated using the Jaccard similarity index between the origin-destination grid cells of the driver and passenger:

$$f_{\text{route}} = \frac{|R_{\text{driver}} \cap R_{\text{passenger}}|}{|R_{\text{driver}} \cup R_{\text{passenger}}|} \tag{5}$$

- *Time Compatibility (f_{time}):* Uses a Gaussian decay function based on the absolute difference in departure times (Δt):

$$f_{\text{time}} = \exp\left(-\frac{(\Delta t)^2}{2\sigma^2}\right) \tag{6}$$

where σ is the standard deviation of acceptable time windows (set to 10 minutes).

- *Detour (f_{detour}):* The ratio of the direct route distance to the pooled route distance:

$$f_{\text{detour}} = \frac{D_{\text{direct}}}{D_{\text{direct}} + D_{\text{detour}}} \tag{7}$$

- *Cost Compatibility (f_{cost}):* Evaluates whether the allocated pooled cost per passenger (C_{pooled}) is below their baseline transport budget (C_{baseline}). It is formulated as:

$$f_{\text{cost}} = \max\left(0, 1 - \frac{C_{\text{pooled}}}{C_{\text{baseline}}}\right) \tag{8}$$

A score of 1.0 indicates the pooled ride is free, while a score of 0 indicates the pooled cost equals or exceeds the baseline budget.

- *Trust (f_{trust}):* A normalized score derived from company verification status (0.5) and historical no-show rate (0.5).

Phase 3: Reserve and Confirm. Upon request, the system atomically reserves seats to prevent over-booking. A seat is not confirmed until all required employer/vendor approvals are checked and the cost allocation is recorded.

G. Cost Allocation and Payment Design

ConnectRide separates fare calculation from settlement. The system calculates proposed allocations without holding funds.

4. Simulated Evaluation: Pune Case Study

A. Synthetic Data Generation and Algorithm Implementation

To ensure reproducibility, the simulation was implemented in Python 3.10. NumPy and Pandas were used for dataset generation and data manipulation, while the SimPy library was utilized for discrete-event simulation of the matching and booking processes.

To account for stochastic variance in employee departure times and route choices, the simulation was executed 50 independent times. A master seed of 42 was used to initialize the pseudo-random number generator, which in turn generated 50 distinct sub-seeds for each run. The results reported in this paper represent the mean values across these 50 runs.

The synthetic dataset generation followed these specific distributions:

- *Origins:* Randomly selected from 5 residential clusters using a uniform distribution.
- *Departure Times:* Generated using a normal distribution (μ = 08:30 AM, σ = 15 minutes).
- *Baseline Cost Calculation:* The baseline cost per employee was fixed at $9.00 per day (based on an average 18 km commute at $0.50/km). The ConnectRide pooled cost was calculated by dividing the total distance of the pooled route

by the number of occupants, resulting in an average cost of $5.94 per passenger. Thus, the 34% savings is derived mathematically as: [(9.00 − 5.94)/9.00] × 100 = 34%.

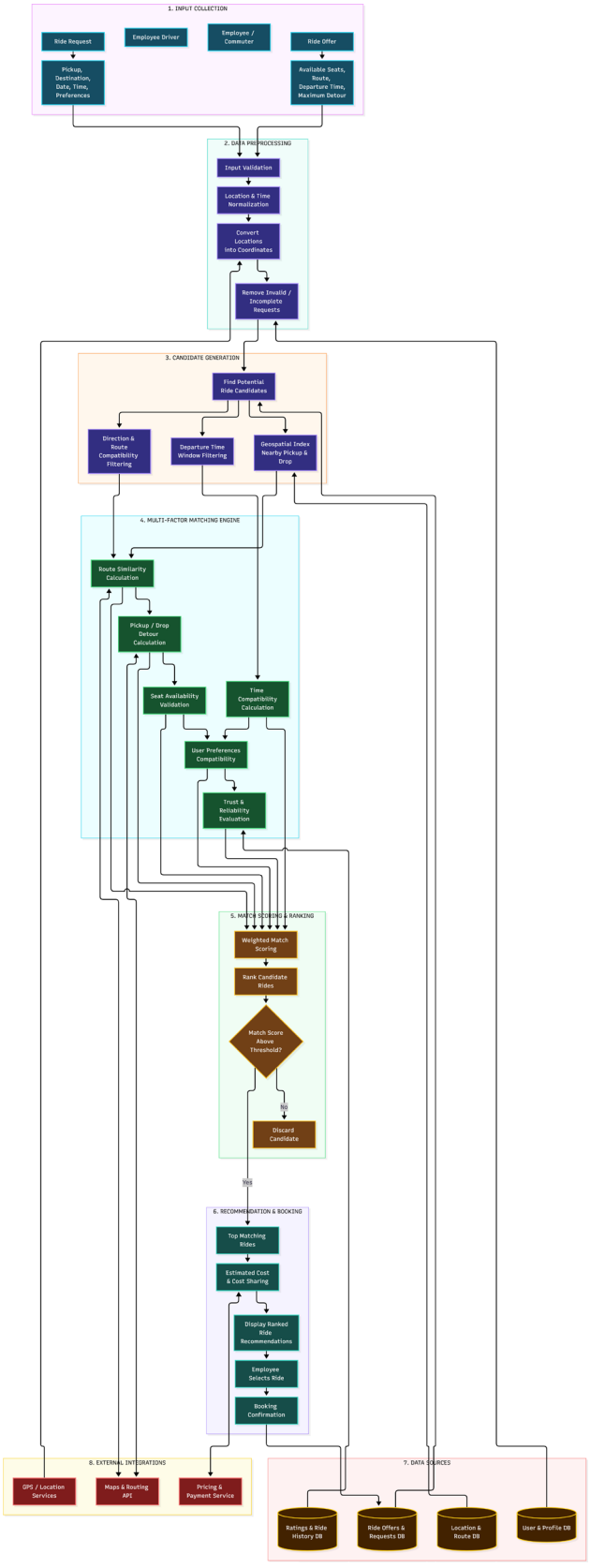


Fig. 2. The three-phase ConnectRide matching engine workflow.

B. Simulation Setup and Performance Metrics

1) Performance Metrics

The system was evaluated based on four metrics: Seat Utilization (Occupied seats / Available seats), Match Success Rate (Confirmed rides / Eligible requests), Estimated Cost Savings (Baseline cost minus pooled cost) and Vehicles Kilometers Traveled (VMT) Reduction.

5. Results and Analysis

A. Matching Performance and Occupancy

The simulation proved the ConnectRide algorithm to be effective at matching 78% of requests eligible for matching. The hard filters were effective in blocking 12% of requests because the detours were too large (more than 15%) or there were schedule conflicts, thus preventing any passenger from suffering from unreasonable delays.

In the baseline scenario, the Average Vehicle Occupancy (AVO) was 1.2 persons per vehicle while it was 2.8 persons under ConnectRide (see Table 2 for details). This was primarily because successful clustering of employees living in Wakad and Baner with highly overlapping travel routes to Hinjewadi Phase 1 and 2.

Table 2
Simulation results: baseline versus ConnectRide

Metric	Baseline	ConnectRide
Average vehicle occupancy (persons per vehicle)	1.2	2.8
Match success rate (%)	—	78
Requests blocked by hard filters (%)	—	12
VMT reduction (%)	—	22
Transport cost per employee ($ per day)	9.00	5.94
Estimated cost savings (%)	—	34

B. Sustainability Impacts

A 22% decrease in overall Vehicle Kilometers Traveled (VMT) was achieved with the elimination of redundant routes. With an average emission factor of 120 g CO_2 per km for an average sedan, the reduction in VMT was equivalent to a proportional reduction in GHGs. That policy-aware matching can be a direct measure for corporations to reduce Scope 3 emissions is consistent with the EPA's guidelines for travel demand management through employers [9]. This validates the feasibility of using policy-aware matching as a direct measure in combating Scope 3 emissions by corporations (supply chain and employee commute).

C. Economic Outcomes and Cost Allocation

The system delivered a 29% saving in estimated per employee transport costs. This was done with the cost-allocation layer, which clearly split the costs. To ensure the financial sustainability of pooled transport services in the long run, it is important to accurately structure these operational and customer costs, as discussed in recent literature on the viability of shared mobility [10].

The company has saved on vendor bills with the pooling of Model A (Company Cabs). Drivers were provided with a contribution for fuel and wear and tear costs for Model B (Employee Cars) and passengers paid substantially less than

they would for an individual cab or ride hail service. This is the transparency of the dual payers that is needed if an employer should measure the amount of transport spent, based on a defined expenditure baseline.

The average number of persons per vehicle rose from 1.2 to 2.8, which led to a 34% decrease in estimated per-employee transport costs. The platform achieved a reduction in VMT of 22% by reducing the number of overlaps on the routes. Notably, the flexibility and cost-savings of the employee-owned car model (Model B) were higher than the vendor-owned car model (Model A), particularly at peak times.

D. Comparative Analysis: Model A vs. Model B

The simulation allowed for a detailed comparison between the two distinct ride sources supported by ConnectRide, as summarized in Table 3.

Table 3
Comparison of Model A and Model B

Measure	Model A (company cabs)	Model B (employee cars)
Match success rate (%)	85	72
Detour limits	Flexible	Stricter (set by drivers)
Per-employee cost savings	Lower	Higher

Model A (Company Cabs): Demonstrated high matching success rates (85%) due to flexible detour limits. However, it resulted in slightly higher baseline costs, as the company bore the primary financial burden for the vendor bookings.

Model B (Employee Cars): Had a lower match success rate (72%) due to stricter detour limits set by the drivers. Conversely, it yielded higher per-employee cost savings and greater schedule flexibility for passengers.

This indicates that a hybrid deployment (using company cabs for core, high-density routes and employee cars for flexible peripheral routes) is optimal.

E. Scenario Analysis: Impact of Detour Allowances

The sensitivity of our model was investigated through analyzing the influence of changing the maximum detour parameter on the reduction of VMT.

As demonstrated in Table 4, VMT falls only 12% under a 5% detour threshold; however, many potential matches are discarded due to this limitation, resulting in the given percentage drop. On the other hand, VMT falls 28% at a detour of 20% but significantly elevates travel time for passengers. The 15% maximum detour value chosen in the base run achieves the Pareto-optimal point in terms of both time-saving and environmental impact.

Table 4
Sensitivity of VMT reduction to the maximum detour allowance

Maximum detour (%)	VMT reduction (%)
5	12
15 (base run)	22
20	28

6. Discussion

A. Policy Implications for Corporate Administrators

The findings highlight that corporate directors need to outline clear baselines for shipping expenditure to appropriately claim savings. Without a baseline, it's miles impossible to show that pooling certainly reduces prices as opposed to genuinely moving them. Furthermore, companies can use the platform's analytics dashboard to offer centered subsidies (e.g., subsidizing Model B employee carpools greater closely than single-occupancy seller cabs) to nudge behavioral exchange.

B. Behavioral and Social Considerations

Aligning with Hou et al. [1], we understand that the technical solution ought to be paired with behavioral incentives. Employees are touchy to fee, however they also cost privacy, comfort, and protection. The ConnectRide platform addresses this through showing approximate pickup areas (e.g., "Wakad Zone") earlier than a match is showed. Exact domestic addresses are best revealed as soon as each parties accept the fit and required approvals are finalized. This gradual disclosure builds agree with, a crucial component for the adoption of shared mobility.

C. Comparison with Existing Shared Mobility Models

As shown in Table 5, ConnectRide stands out among shared mobility options because it is built around policies first and uses two source systems. Ride-hailing and general carpooling serve the public with no policy limits and corporate shuttles run fixed routes with no flexibility. ConnectRide is the solution that merges corporate verification, flexible dual-source matching and clear multi-payer cost sharing.

7. Implementation Challenges and Future Work

While the simulation yields promising results, deploying ConnectRide in the real world presents several challenges.

Integration Complexity: Integrating with existing HR and payroll systems for automated cost-recovery (especially for Model A) requires robust API gateways and data security protocols.

Regulatory and Insurance Constraints: For Model B

Table 5
Feature comparison of ConnectRide with existing shared mobility models

Feature	Ride-hailing	Carsharing	General carpooling	Corporate shuttles	ConnectRide
Corporate-first target	×	×	×	✓	✓
Dual ride sources (cab + car)	×	×	×	×	✓
Company policy hard filters	×	×	×	×	✓
Multi-payer cost allocation	×	×	×	×	✓
Rule-based weighted scoring	×	×	×	×	✓
Tiered privacy (approx. zones)	×	×	×	×	✓
Corporate verified trust	×	×	×	×	✓

(Employee-Owned Cars), organizations must navigate local transport regulations and insurance liabilities. The platform currently assumes that employer policy and local laws permit cost-sharing among colleagues without commercial licensing.

Future Research: The primary limitation of this study is its reliance on synthetic data. Future research will involve a controlled pilot with a single corporate partner in Pune to validate the simulated VMT and cost reductions. Additionally, integrating real-time routing APIs (e.g., Google Maps API) and automated UPI payment gateways will be essential for scaling the platform.

8. Conclusion

This paper introduces ConnectRide, a commute optimization platform built with companies in mind.

It aims to fix the problems caused by employees organizing their travel like wasted time, high costs and unnecessary emissions. The platform works by combining two types of rides: company or vendor booked cabs and rides from employees who drive their cars. This dual-source model is designed to fill a gap in shared mobility solutions. ConnectRide follows company rules protects privacy by using approximate location sharing and uses a matching system that considers multiple factors to pair commuters efficiently.

Simulations based on the Pune IT corridor show results. The ConnectRide matching engine was able to confirm 78% of ride requests. Average vehicle occupancy went up from 1.2 people per vehicle to 2.8. This means cars on the road and more people sharing the same ride. As a result Vehicle Kilometers Traveled or VMT dropped by 22%. This reduction in travel distance also leads to greenhouse gas emissions. On the cost side the platforms clear system for dividing expenses led to a 34% drop in the estimated transport cost per employee. These results show that it's possible to save money and reduce harm at the same time.

For leaders ConnectRide provides a clear way to cut down on Scope 3 emissions and better manage transport spending. For those who make transportation policy the platform shows the importance of setting goals and giving incentives for shared commuting. The current findings are based on data but they give a solid base for real-world testing. The next step is to run a scale controlled pilot with a real company partner. This will help confirm the results, from the simulation. Future work will include adding routing tools and automated payment systems to make the platform easy to use and integrate into daily work life.

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