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Taxi Operations, Ride-Pooling Markets, And Decentralized Sharing: A Unified Review Of Supply-Demand Modelling, Market Equilibrium, And Cost-Sharing Mechanisms In Urban Mobility

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Abstract
The ecosystem of urban mobility has been radically changed by the digital platform technology, the introduction of GPS-based data collection, and the development of ride-hailing and ride-sharing. The present paper provides a unified review of three related streams of research, namely: (1) optimization of taxi fleet based on GPS trajectories data, (2) market equilibrium modelling in mixed pooling and non-pooling ride-hailing model, and (3) decentralized cost-sharing mechanisms to stable ride-sharing arrangement. Based on the theoretical groundwork of the analytical publications and the massive empirical data of places such as Xi'an (China) and New York City (USA), we compile the methodological developments in queuing theory, probabilistic supply-demand modelling and Cobb-Douglas matching functions, stable matching algorithms, and mechanism design of sharing economy solutions. We critically analyse the assumptions, limitations, and policy implications of each research stream each, and suggest a single conceptual framework which integrates the operational decision-making at the micro-level with the market equilibrium outcomes at the macro-level. As our assessment has shown, the new sustainable mobility of urban areas involves simultaneous consideration of passenger wellbeing, driver revenue, platform profitability, and traffic externalities. We identify critical research gaps and chart a future agenda addressing autonomous vehicles, dynamic pricing, multi-modal integration, and equitable service provision in the context of next-generation intelligent transportation systems.
Keywords: *Taxi fleet optimization; Ride-pooling markets; Ride-sharing; GPS trajectory data; Market equilibrium; Cost-sharing mechanisms; Stable matching; Urban mobility; Sharing economy; Demand-supply modelling*

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I. Introduction

The transportation system of cities is one of the most complex socio-technical systems of any kind that needs constant adjustment between supply, demand and economic incentives and corresponding environmental sustainability. Due to the entry of ride-hailing platforms, exemplified by Uber, Lyft, Didi, and Grab, there are unprecedented upheavals in the traditional taxi markets, thus offering opportunities and challenges to transportation planners, regulators, operators, and commuters [1-5]. The synthesis of these disruptions leads to three fundamental issues: how to find optimal calibration of the supply of taxi vehicles to achieve spatially and temporally heterogeneous demand; how to find the circumstances in which the pooled and non-pooled ride-hailing services can coexistence at market equilibrium; and how to find the cost-sharing schemes that can facilitate a decentralized ride-sharing arrangement in achieving socially efficient results.

These questions are practical and theoretical. In a ten million people metropolis, the imbalance between the supply and demand of taxis at the busiest times of the day can cost hundreds of thousands of person-hours of lost productivity, high carbon emissions, and increased traffic jams [6-9]. Improperly tuned ride-hailing platform can reduce the profits of drivers and (simultaneously) decrease the utility of the riders, thus compromising the social value phrase of shared mobility [10-13]. Furthermore, a cost-sharing arrangement with negligence to self-interest of riders will be adopted to negligible extent in the market, no matter how socially optimally it may be [14-17].

The three papers on which this review is based represent a different but closely intertwined viewpoint of these issues. Yang et al. [18] built a functional structure to compute the most efficient size of a taxi fleet based on Xi'an, China, GPS trips by taking into account queuing theory, expectant taxi-hail theories, and income limitations on drivers in a microscale space analysis. Wang et al. [19] presented the aggregate market-equilibrium model of platform provision both en-route ride-pooling and non-pooling service analytically showing the circumstances under which platform, drivers, and riders, as well as the society, are all better off due to the implementation of pooling. Chau et al. [20] considered the phenomenon of decentralized ride-sharing through the prism of the mechanism-design approach, and found theoretical limits of the ratios of social optimality of four types of fair cost-sharing mechanisms and justified these results by the New York City taxi data. Together, these researches create a set of complementary lenses that one can use to observe urban shared mobility.

The current review has the following structure. Section 2 provides methodological background and puts the reviewed studies into perspective of the larger transportation literature. Section 3 examines taxi fleet optimization on the basis of GPS-data. Section 4 discusses the market-equilibrium modeling of ride-pooling. Section 5 covers decentralized cost-sharing arrangements and stable matching. Section 6 is a synthesis of cross cutting themes and suggests a single conceptual framework. Policy implications are discussed in Section 7. Section 8 determines gaps in research and future agenda. Section 9 provides closing statements.

II. Background And Literature Context

Evolution of Taxi and Ride-Hailing Research

The historical examination of taxi markets goes back to Douglas [21], who described the taxi demand as a negative of fare and predicted waiting time and proposed the notion of dead-head (vacant) mileage to measure the efficiency of the market. This work forms the basis on which the literature on the subject has been built, and the trade-off between passenger welfare and operational efficiency is lasting. The framework was extended to competitive and regulated markets by Arnott, [22], Cairns and Liston-Heyes [23], respectively, and Schaller [24] estimated the elasticity of fares and services empirically. With the advent of GPS technology and vehicle mounted terminals in the early 2000s, new research opportunities were available in the field of taxis. High Resolution GPS data sets also allowed researchers to switch to spatially explicit, trajectory level analyses as opposed to aggregate statistical models [25-28]. Castro et al. [29] presented the estimation of traffic density using taxi GPS trajectory, and Zhan and Ukkusuri [30] were able to construct probabilistic travel-time models based on the use of Manhattan taxi recordings. Bonola et al. [31] demonstrated how small urban taxi networks had the potential to reach 80 per cent coverage of cities in 24 hours, which suggested the unrealized capacity in shared mobility.

The development of ride-hailing apps in the 2010s changed the competitive environment in its essence. Ukkusuri and Zhang [32] developed equilibrium models with Uber and Lyft and found the taxi market in New York to be probably oversupplied and unready to be overpriced. Ke et al. [33] showed that in exclusive ride-pooling markets, the optimal fares are under the optimal fares in solo markets, which would have been counter-intuitive results under specific conditions, and has significant regulatory consequences.

Ride-Pooling and Ride-Sharing Research

Initial studies on ride-sharing have mainly focused on algorithmic performance: how to pair riders with vehicles in real-time with minimum computation costs [34-37]. Santi et al. [38] took advantage of 170 million New York taxi passengers to demonstrate that almost every trip could be shared with time lost of under half a minute–an impressive measure of the shareability of urban rides. As demonstrated by Vazifeh et al. [39], optimization based on networks may have the effect of decreasing the taxi fleet in New York by 30 percent and maintaining the same quality of service. Alonso-Mora et. al. [40] designed scalable dynamic route generation and ride-sharing algorithms of high capacity.

The pooling-based market-equilibrium modeling is more recent. Jacob and Roet-Green [41] used the queuing theory to design ideal price menus to platforms where they can get individual and pooled rides. The equilibrium conditions of pre-trip pooling in the presence of endogenous congestion were developed by Zhang and Nie [42] and the equilibrium conditions in the differentiation between pooling sizes of various operators was developed by Zhang and Zhang [43]. Interestingly, all these previous works had simplified the en-route pooling assuming three traffic states (cruising, half-occupied, fully-occupied), which makes the contribution by Wang et al. [19] that more important.

Cost-Sharing and Mechanism Design

Cost sharing theory in transportation is based on the theory of cooperative game theory and the theory of the public good [44-47]. In the ride-sharing problem, Anshelevich et al. [48] studied the price of anarchy of stable matching, and Chau and Elbassioni [49] measured the inefficiency of fair cost-sharing mechanisms in riding economic environments. Wang et al. [50] examined the case of stable matching in dynamic ride-sharing systems and Rasulkhani and Chow [51] came up with route-cost assignment models that took into account both user and operator behavior. The work by Chau et al. [20] adds to the literature by providing both theoretical constraints and a wide range of empirical confirmations on the basis of real-world taxi trip examples.

Figure 1: Conceptual Evolution of Urban Taxi and Ride-Sharing Research

Era	Key Developments	Representative Works	Data Approach
1970s–1990s (Classical)	Aggregate taxi market models; Price/entry regulation; Deadhead rate analysis	Douglas (1972); Arnott (1996); Schaller (1999)	Aggregate statistics; Travel surveys
2000s (GPS Era)	GPS trajectory analysis; Spatial demand mapping; Vehicle routing optimization	Castro et al. (2012); Zhan & Ukkusuri (2015); Bonola et al. (2016)	GPS logs; Vehicle terminal data
2010s (Platform Era)	Ride-hailing market models; Ride-sharing algorithms; Fleet optimization models	Santi et al. (2014); Alonso-Mora et al. (2017); Vazifeh et al. (2018); Yang et al. (2019)	App platform data; Open trip datasets; GPS big data
2020s (Equilibrium Era)	Market equilibrium with pooling; Decentralized mechanisms; Stakeholder welfare analysis	Ke et al. (2020); Zhang & Nie (2021); Wang et al. (2025); Chau et al. (2020)	Hybrid: analytical + large-scale empirical

Table 1: Evolution of taxi and ride-sharing research across four major eras, showing key methodological shifts from aggregate models to large-scale empirical equilibrium analyses.

III. GPS-Data-Driven Taxi Fleet Size Optimization

Problem Formulation and Data Infrastructure

Yang et al. [18] discuss one of the most practically consequential issues in transportation in cities, which is how many taxi vehicles should be licensed in a particular city. Unlike previous research based on the aggregated travel survey data or macro-level indicators, the authors base their approach solely on the GPS trajectory data and thus gain spatial accuracy, temporal detail and behavioral inferences which cannot be offered by the aggregate methods.

It is based on the empirical data included in 12,115 taxis in Xiang China, which produced approximately 30 million GPS scan records per day in May 2014. Each entry includes: vehicle license plate (unique identifier), time, longitude and latitude (to five decimal places), altitude, instantaneous speed, driving direction, occupation of passenger (occupied/vacant/off), total miles driven, and total operation time. The reporting interval of 30 seconds makes the reconstruction of the trajectories almost continuous.

Another important preprocessing phase is geographic information matching to ensure that the GPS coordinates are matched to the road network. This is achieved using ArcGIS spatial analysis, first a unified coordinate system (Xi'an -1980 plane coordinates are converted into WGS-1984 to allow GPS data) is created, then shortest distance assignment of roads and directional matching is carried out. Its outcome maps the GPS location to a unique road section and direction of movement to facilitate demand and supply at a road-section level [52,53].

Taxi Operation Indices: Mileage and Time Utilization

Nevertheless, there are two important operational metrics which give empirical data in the manner of fleet sizing. The mileage utilization rate which is given as K = g'z/gz is the percentage of the total kilometers travelled that is occupied by passengers. A large mileage utilization is a good sign of effective supply and demand matching, whereas a low value is an excessive supply or poor spatial matching. The utilization rate of daily mileage in Xi'an was 66 percent and during the morning and evening peak hours, it was 76 percent and 75 percent, respectively.

The rate of time utilization (which is computed in a similar manner as carrying time to the total operating time) showed a correlation coefficient over 0.95 with the mileage utilization, hence confirming the conformity of the two measurements. Their time distribution exhibits two peaks during the day relating to the commuting times (8.00 AM and 6.00 PM during the working days), weekday and weekend distributions display a significant dislocation with the peaks at the weekends of the day appearing about three hours later, which is also in line with the difference in mobility behavior [54].

Figure 2: Mileage Utilization Rates in Xi'an by Time Period

Time Period	Weekday Utilization	Weekend Utilization	Relative Change
00:00–03:00	55–60%	60–65%	+5% (weekend higher)
03:00–04:00	38–42% (trough)	40–44%	Near-equal
07:00–09:00	74–76% (AM peak)	62–66%	−12% (weekday higher)

11:00–12:00	65–70%	72–75% (late peak)	+7% (weekend higher)
15:00–16:00	60–64% (2nd trough)	62–65%	Near-equal
17:00–19:00	73–75% (PM peak)	73–75%	Equal (overlap)
20:00–22:00	70–74%	72–76%	+2% (weekend slightly higher)

Table 2: Estimated mileage utilization rates in Xi'an by time period and day type, synthesized from Yang et al. [18]. AM and PM peaks show strong weekday dominance; weekend patterns lag by 2–3 hours.

Taxi-Hailing Probability Model

The taxi-hailing difficulty model is the probabilistic one that is located on the Poisson process assumption of taxi arrival to a specific road section. We have: The probability that a given number of taxis, k, will arrive during a given waiting time, x, can be determined by using the standard Poisson formula p_k = (λx)^k e^{-λx} / k!. In more practical terms the likelihood that a passenger manages to hail a taxi at a waiting time p is given as the function of the time utilization rate at the section level of 0 0 0 and the number of taxis that are observed to arrive:

$p = 1 - exp[-(n_1 + n_2)/t \times p(1-o)]$

In which, n1 and n2 represent the occupation and vacant cabs observed in time t on the section. The importance of this formulation lies in it directly connecting the observable GPS data (taxi counts, status of occupancy) with the passenger level of measure of service quality (probability of successfully hailing). The criteria of 75 per cent probability in five minutes were chosen as the indicator of determining the areas that could be considered as difficult-to-hail, yet the authors add that the criterion is arbitrary and situational [55].

Queuing Theory for Unmet Demand Estimation

In the case of road segments that have been defined as difficult-to-hail, the model switches to a birth-and-death queuing model (M/M/1/K with impatient customers) to measure unmet demand. Passengers enter using a Poisson process with rate λ, empty cabs enter using a Poisson process with rate μ (the service rate), and waiting passengers leave the queue using a Poisson process with rate δ > 0 (where pk is the queue length, and u is the rate parameter of the abandonment process). Stable probability of the queue of a particular number of passengers, k, is determined recursively.

The most important output is the average system queue length, which is denoted by m s and it is the number of passengers that do not make trips because of lack of taxi in their tolerance. The cumulative service mileage w_n is then determined by adding together the unmet trip counts (m_i) in all of the hard to hail segments of the product and the average trip distance on that segment (l_i). This is a spatially disaggregated calculation that does not assume homogeneity of distribution as afflicts aggregate techniques [56].

Fleet Size Calculation and Income Constraint

The incremental taxi volume that will be necessary to satisfy unmet demand is; χ = φ · w_n / L'_a, where φ is a satisfaction coefficient (0 to 1), w_n is the total unmet taxi mileage in the peak period, and L'_a is the average effective mileage furnished over a unit time per taxi. When the model is applied to the May 2014 data about Xi'an in the peak hours (8:00 -13:00 and 17:00 -22:00), the incremental volumes are between 654 taxis (lowest demand period, 22:00) and 2,237 taxis (highest demand period, 18:00).

The second stage analysis is important to assess the income effect of varying fleet expansion levels on the existing drivers. The income variation index ε = 1 − c_u/c_o (where c_u and c_o are post- and pre-expansion average income) to socially acceptable income reductions. The incremental fleet recommended at the social optimum (e = 0.10) is 1,286 vehicles, which is 66 1 /4 of peak unmet demand satisfaction. The pre-adjustment and post-adjustment data of the income of drivers (see Table 3) demonstrate the trade-off in detail: decreasing at 8:00 AM to 45.42, and then to 44.43 units per hour (2.2-percent and 10.7-percent), and then at 6:00 AM, to 20.12, and then, to 17.97 units, respectively, the most strongly affected time.

Figure 3: Pre- and Post-Adjustment Taxi Driver Hourly Income (Xi'an, Single Shift)

Hour	Pre-Adjustment	Post-Adjustment	Change	% Change
06:00	20.12	17.97	−2.15	−10.7%
07:00	41.09	32.66	−8.43	−20.5%
08:00	45.42	44.43	−0.99	−2.2%
09:00	44.07	43.22	−0.85	−1.9%

10:00	43.30	38.19	−5.11	−11.8%
11:00	43.51	37.44	−6.07	−13.9%
12:00	42.75	36.30	−6.45	−15.1%
13:00	44.64	38.26	−6.38	−14.3%
14:00	44.40	35.11	−9.29	−20.9%
15:00	35.65	28.33	−7.32	−20.5%
Total	**404.96**	**351.92**	**−53.04**	**−13.1%**

Table 3: Pre- and post-fleet-expansion taxi driver hourly income in Xi'an (1,286 additional vehicles; ε ≤ 0.10 income constraint). Orange values highlight hours where income reduction exceeds 10%. Source: Yang et al. [18].

Critical Assessment

Yang Yang et al. (2023) introduce a framework that has a highly important methodological progression compared to the aggregate taxi planning models. It is remarkable that their method has a spatial granularity, allowing the diagnostics of the demand in sections; the incorporation of queuing theory to estimate unmet demand; the clear constraints of income protection; and empirical validation using large-scale GPS data. The above strengths help in a better appreciation of the on-demand mobility dynamics in the modern urban context.

To begin with, the authors have employed 6 modeling assumptions which are relatively limiting. The claim of a first come first serve policy in cruise hailing overlooks the impact of app-based dispatch algorithms, which had already attained huge market shares in Chinese cities in 2014. Second, the lack of telephone and network booking modes restricts the usage of the model to contemporary markets these platforms, including Didi. Third, the model is restricted to a particular time frame and competition situation by using a snapshot that was calibrated on May 2014 data; periodic calibration is required to generalise. Fourth, the income constraint that is formalised as (ε ≤ 0.10) is an administrative decision, and not a revealed-preference parameter; an acceptable reduction in income level should preferably arise out of empirical investigations into driver behaviour. Fifth, induced demand effects are not considered in the model: the introduction of 1,286 cabs would probably encourage new patrons currently unusing cabs, which would suggest that the actual fleet need can be even greater than the one estimated [57,58].

IV. Market Equilibrium In Mixed Pooling And Non-Pooling Systems

Conceptual Framework and Modeling Approach

Wang The article by Wang et al. (2022) constructs an aggregate market-equilibrium model of a ride-hailing platform which provides enroute pooling and non-pooling services in parallel. The new model lies in its consideration of enroute pooling - which is pooling that is caused after the ride has started - as separate pooling of pre-trip pooling, which involves booking of both riders prior to take-off. En-route pooling produces a 3-state vehicle space, cruising, half-occupied, fully-occupied, which leads to entirely new equilibrium behaviour compared to all previously analysed market structures.

The model has exogenous inputs, including total ride-hailing demand, N, D, and the upfront pooling price, F p, the non-pooling price, F np, and the pooling pre-selection ratio, b (a probability of a cruising vehicle being called to a pooling versus non-pooling destination on encounter). For the endogenous determination, the model finds the waiting times of pooling and non-pooling riders (w p, w n p), the probability of pairing (P p), the average detour time (D), the number of vehicles in each state, and the mode split of riders (f p).

The matching process uses a Cobb Douglas matching function used in the literature of the ride-hailing equilibrium (References 59 62) that associates the aggregate matching rate between vehicles and riders with the number of vehicles and riders, raised to the matching elasticity parameters of the vehicles, and the riders, denoted as a. This model embodies the thick market externality: as the number of vehicles and riders rises, waiting times by each constituent in the network decreases, which generates positive network effects and is at the core of platform business models [63,64].

Key Equilibrium Properties

In the paper, four classy propositions on the enroute pooling equilibrium are formulated. The matching rate of half-occupied vehicles is less than that of cruising vehicles at any point in time (Proposition 2), as half-occupied vehicles are only capable of matching a subset of compatible pooling riders, a set that is always smaller than the set of all waiting riders.

Proposition 3 shows that there is a very important asymmetry on the waiting times which is determined by the pre selection ratio, b. At the limit of only cruising vehicle-pooling encounters are accepted (i.e., when b = 1), there is a reduced wait time of pooling riders as compared to non-pooling riders, whereas the converse is true at lower values of 0.5b. The direct consequences of this finding on platform design are that high values of b form a virtuous circle to make pooling appealing due to reduced wait times, and that low values of b, which can be implemented to ensure non-pooling quality service, in fact discourage adoption of pooling.

As shown in proposition 4, the total probability of pairing P_p = 2P_w, and the probability of pairing during the waiting times P w = 50% in all cases. This classy outcome is obtained by the fact that the en route pooling is symmetric: the probability of each successful pairing is to have one rider pairing when waiting in the origin and one rider pairing in the enroute so the two are equal and less than half the total probability of pairing.

Figure 4: Summary of Key Market Equilibrium Properties (Wang et al., 2025)

Proposition	Statement	Implication	Condition
Prop. 2	M_h ≤ M_c always	Half-occupied vehicles less efficiently matched than cruising vehicles	Any (D, N, F_p, F_np, β)
Prop. 3a	If β=1: w_p ≤ w_np	Full pre-selection → pooling riders wait less	β = 1
Prop. 3b	If β≤1/2: w_p ≥ w_np	Heavy pre-selection rejection → pooling riders wait more	β ≤ 1/2
Prop. 4	P_p = 2P_w; P_w ≤ 0.5	Pairing prob. splits evenly between waiting and en-route; majority paired en-route	Any (D, N, F_p, F_np, β)
Prop. 5	∂f_p/∂N > 0	More vehicles → higher pooling adoption proportion	Any returns to scale
Prop. 5	∂f_p/∂β > 0	Higher pre-selection ratio → more pooling demand	Any returns to scale
Prop. 6	Drivers prefer pooling iff D < D*_v	Low demand → pooling benefits drivers; high demand → harms drivers	Any (N, F_p, F_np, β)
Prop. 8	Platform prefers pooling iff D > D*_k	High demand → pooling benefits platform profits	Constraint 1 (equal utility)
Prop. 9	Riders benefit iff D > D*_o	High demand → pooling benefits riders	Constraint 2 (equal prices)
Prop. 10	Society benefits iff D > max{D*, D*_o}	High demand → pooling beneficial for social welfare	Constraints 3 & 4

*Table 4: Summary of key analytical propositions from Wang et al. [19] regarding market equilibrium in mixed pooling/non-pooling ride-hailing. Critical demand thresholds D*_v, D*_k, D*_o, D* determine stakeholder benefit conditions, with D*_o < D*_v < D*_k always holding.*

Stakeholder Welfare Analysis

The most policy-related addition of Wang et al. (2022) perhaps is the systematic comparison of stakeholder welfare in mixed markets (pooling + non-pooling) and solo markets (non-pooling only). The analysis finds that there exist entirely different critical demand thresholds between each group of stakeholders, namely, pooling benefits riders, pooling harms drivers, and pooling benefits the platform, with the order always being of type: D*_o (riders benefit from pooling), D*_v (drivers lose from pooling), and D*_k (platform benefits from pooling), with the ordering D*_o < D*_v < D*_k always holding.

This ranking carries a very powerful implication: no level of demand is at which pooling only maximally benefits all the stakeholders. Pooling in the demand range, (D*_o, D*_v) gives a benefit to riders and can give a benefit to the platform (given the pricing), however, it always decreases the income of the drivers. Beyond D V, pooling is a win to the riders, the platform, and the society, but to the drivers, it is always a loss. Pooling introduction is a redistribution between drivers and riders and the platform that could be a reason why incumbent drivers consistently do not accept ride-pooling in the real-world markets [65,66]

The numerical validation with parameters calibrated to Hong Kong (δ_r = 60 HKD/h, t_s = 0.4 h, c_v = 50 HKD/h) found D*_o ≈ 465 trips/h, D*_v ≈ 686-715 trips/h, and D*_k ≈ 1,669-1,754 trips/h. These analytical findings are confirmed by simulation experiments performed on a grid network of size 10 x 10 km, where the transition of solo-market-superior to mixed-market-superior platform profit and the transition of social welfare was found to be around 300400 riders/h and 400500 riders/h respectively.

V. Fair Cost-Sharing Mechanisms And Decentralized Stable Matching

Four Cost-Sharing Paradigms

The usefulness of the analysis proposed by Chau et al. [20] lies in the fact that it is based on the practical observation that the adoption of ride-sharing is inherently reliant on the perceptions of the commuters regarding the fairness of the cost-sharing arrangement. Commuters who feel that their individual payment imposed on them is unfair (or above what they would have paid had they individually paid), will just refuse to ride. (Even when a centralized planner can identify the socially optimal ride-sharing assignment (that of minimum total transportation cost)). This leads to the analysis of four fairly cost-sharing arrangements in particular: Equal cost-sharing (eq) is a division of the shared ride cost by half. This is intuitive but has the potential to generate a low utility to low-cost riders who share with high-cost riders. Egalitarian cost-sharing (ega) is a pattern of payment whereby the per rider incurs equal saving compared to their individual rides- reflecting the fairness concept of equal benefit. Proportional cost-sharing (pp) imposes payments based on the standalone cost of each rider, i.e., reflecting the sense of fairness, the notion of proportional contribution to the system is made by those who place greater burdens on it. Segment-based cost-sharing (sb) apportions costs solely on a basis of the road segments used by each rider, and the segments shared are divided equally- achieving the notion of fairness of direct contribution to the trip route.

Figure 5: Comparison of Four Fair Cost-Sharing Mechanisms

Mechanism	Formula	Fairness Concept	Risk of Negative Utility	Matching Outcome (Example)	Social Optimality Bound
Equal (eq)	p_i = c(r)/2	Equal cost contribution	High (if c_i << c_j)	M_2 = {(i,j),(k),(l)}	≤ 3/2
Egalitarian (ega)	p_i = [c(r)+c_i−c_j]/2	Equal monetary saving	None (u_i = u_j always)	M_1 = {(i,k),(j,l)} ✓	≤ 3/2
Proportional (pp)	p_i = c_i · c(r)/(c_i+c_j)	Proportional to standalone cost	Low	M_1 = {(i,k),(j,l)} ✓	≤ 3/2
Segment-based (sb)	Split by shared/exclusive segments	Direct cost contribution	Moderate (depends on geometry)	M_2 = {(i,j),(k),(l)}	≤ 3/2

Table 5: Comparison of four fair cost-sharing mechanisms from Chau et al. [20]. All four share the same theoretical social optimality bound of 3/2. ✓ denotes social-optimal stable outcome in the worked example of Fig. 2 in the original paper.

Theoretical Social Optimality Bounds

The major theoretical finding of Chau et al. [20] is that in all four equitable cost-sharing schemes the ratio of the social cost of any stationary ride-sharing placement to the social cost of the global optimum is confined above by 3/2, even when varying the quantity of commuters, the road network topology, and even the peculiarities of the trip. It is a remarkably impressive outcome: it implies that decentralized ride-sharing which is driven by the pure goal of cost minimization on the individual level performs at least half the total cost that the centralized benevolent planner would be able to perform.

The proof method is classy and consistent in all the four mechanisms. Given any stable assignment M and optimal assignment M we have any (i, j) [?]. Stability means that no commuter would be able to pay less by switching which leads to inequalities with c{i,j} and c{i,k} as well as c{j,l} in M. Together with the triangle inequality-type property c i,k) [?] max c i, c k (both shared ride is not less expensive than either standalone ride), the bounds follow. This mathematical framework brings together under a shared algebraic framework the four mechanisms with extremely different payment formulas [67,68].

The paper also demonstrates that with equal, egalitarian and proportional mechanisms, the stable matching algorithm (a variation of the Gale-Shapley algorithm) tends to end in a finite number of rounds since such mechanisms cause no cyclic preferences. Cost-sharing based on segments can in theory cause cyclic preferences, but empirical studies indicate that this is uncommon in reality.

Empirical Findings from NYC Taxi Data

The empirical research utilizes the NYC taxi trip data (2013), and it is analysed on a daily basis of more than 450,000 trips. The analysis concentrates on 5 one-hour windows on a weekday (January 4, 2013) as well as a weekend (February 23, 2013). A number of empirically-significant results are obtained: The matching rate in various mechanisms differs considerably, with egalitarian and proportional mechanisms matching 22-23 per cent of commuters, and equal and segment-based matching 27-30--intuitive converse. The reason is that equal cost-sharing though potentially negative in utility will produce greater incentives to form partners in some commuters. Social optimal matching attains 14% matched pairs since it does not take into consideration stability pairing some commuters who would, individually, not want to share [69].

The theoretical 3/2 bound is significantly more empirically social optimum ratios of all mechanisms, and always within the range 1.0-1.2. A proportional and egalitarian mechanism is more likely to result in lower social costs and higher social utilities (a total savings of standalone rides) than equal and segment-based mechanisms. Segment based mechanism has the lowest delay ratios between matched pairs (average delay of 1.1 with more than ninety percent under 1.4) which implies that it is more effective at pairing geometrically similar trips.

Interesting patterns are found in the matching structures of stable structures of cost sharing: equal cost sharing tends to be more homophilic in that commuters are matched, with similar standalone costs (homophilic); egalitarian, proportional and segment-based mechanisms tend to match commuters in a more heterogeneous way-long-distance riders with short-distance riders. The equity implication of this diversity effect is also of significant importance as it would be more appropriate to hypothesize that more advanced cost-sharing strategies can enhance mobility equity by allowing low-income cross-subsidy of shorter trips [70,71].

Figure 6: Empirical Social Optimality Results — NYC Taxi Data (Chau et al., 2020)

Metric	Equal (eq)	Proportional (pp)	Egalitarian (ega)	Segment-based (sb)	Social Optimum
% Commuters Matched (Weekend 12-1PM)	~30%	~22%	~23%	~27%	~14%
Social Optimality Ratio (Weekday)	1.05–1.15	1.00–1.05	1.00–1.05	1.05–1.10	1.00 (baseline)
Social Optimality Ratio (Weekend)	1.05–1.20	1.00–1.08	1.00–1.08	1.05–1.12	1.00 (baseline)
Average Delay Ratio	~1.12	~1.10	~1.12	~1.08	N/A
Diversity (Standalone Cost Ratio)	~70% > 0.8	~60% > 0.8	~65% > 0.8	~65% > 0.8	N/A
Normalized Utility Distribution	More at lower end	~15% at max (0.5)	Similar to eq	Similar to ega	N/A
Cyclic Preference Risk	None	None	None	Low (rare)	N/A

Table 6: Empirical performance metrics for four cost-sharing mechanisms applied to NYC taxi sharing. All social optimality ratios fall well below the theoretical 3/2 bound. Source: Chau et al. [20].

VI. Synthesis: A Unified Conceptual Framework

Three Levels of Urban Shared Mobility Analysis

The three papers reviewed all cover the theme of urban shared mobility in three different yet related levels of analysis. The operational level [18] deals with the alignment of physical supply to demand: how many vehicles are needed, where, and when using available spatial patterns of taxi use? The strategic interaction, with platform, drivers and riders, is a concern of the market equilibrium level [19] because, under what pricing and dispatching strategies, the system is in equilibrium, and who is the winner? The level of mechanism design [20] relates to the regulations of interaction between individual commuters: in the light of the price of a joint ride, how do we allocate the cost of sharing out to promote sharing and consider personal rationality?

An integrated framework acknowledges that such decisions are made at either level (significantly limiting and defining a result at the other level). Operational decisions (fleet size) decide the availability of vehicles which fixes the equilibrium waiting times (market). The mode choices of individual riders are given by pricing strategies (market) and are what make the effective demand observed by the corresponding mechanism (mechanism design). And cost-sharing norms (mechanism design) determine the extent to which riders will ever even share, which will re-feed the equilibrium of the market.

Figure 7: Unified Three-Level Framework for Urban Shared Mobility Analysis

Level	Primary Paper	Key Inputs	Key Outputs	Stakeholders	Core Method
Operational (Fleet Sizing)	Yang et al. [18]	GPS trajectory data, road network, income threshold	Optimal fleet size, unmet demand map, income impact	Taxi operators, drivers, regulators	Queuing theory + Poisson process + income constraint

Market Equilibrium (Platform Strategy)	Wang et al. [19]	Total demand D, fleet size N, prices F_p, F_np, ratio β	Waiting times, pairing probability, stakeholder welfare	Riders, drivers, platform, society	Cobb-Douglas matching + equilibrium analysis + sensitivity
Mechanism Design (Sharing Arrangement)	Chau et al. [20]	Commuter trip data, road network, cost-sharing rule	Stable matching assignment, social optimality ratio	Individual commuters, platform	Stable matching + social optimality bounds + NYC data

Table 7: Unified three-level analytical framework synthesizing the three reviewed papers. Each level addresses a different decision horizon and set of stakeholders, yet the outputs of each level serve as inputs to adjacent levels.

Cross-Cutting Themes

A number of cross-cutting issues can be identified through comparative analysis of the three articles. The former is the supply-demand feedback loop: all three articles wrestle with the endogenous nature of the supply and demand in the taxi markets. Yang et al. take the demand as an exogenous factor (the current travel habits remain the same), though they note that new taxis will cause new demand. Demand modeling in Wang et al. is an endogenous mode split between a pooling and non-pooling but total demand is exogenous. Chau et al. consider both the supply and demand to be given. A fleet size-pricing-sharing incentive integrated model endogenizing demand responses simultaneously is also an important methodological gap.

The second theme is tension between the rationality of the individual and the social optimality. This tension is realized in different forms at the different levels: in the case of Yang et al., it is the trade-off between driver income and passenger welfare in fleet sizing; in the case of Wang et al., it is the impossibility of simultaneous Pareto improvement of all the parties under pooling introduction; in the case of Chau et al., it is the price of anarchy (at most 50) between decentralized self-interested matching and centralized optimal assignment. The universal nature of this tension implies that the shared mobility markets in the city must necessarily be subject to regulation in order to align the social objectives with the profit motives of the individual consumers [72,73].

The third theme is spatial heterogeneous demand and supply. Yang et al. consider this most directly with road-section-level analysis, Wang et al. with an aggregate spatial model (homogeneous city), Chau et al. a road network model though pairwise matchability is considered. An equilibrium model of a completely spatially disaggregated market that reflects intra-city heterogeneity in the density of demand, distribution of income, and competitive conditions is still an open challenge.

Data requirements and empirical validation is the fourth theme. Yang et al. use proprietary taxi GPS data that researchers or regulators might not have. Calibration of Wang et al. is made to partial reference parameter values to previous literature. The taxi trip dataset in NYC is publicly available, which is an advantage to the study by Chau et al. Infrastructure A top priority of the field is the development of standardized open datasets of ride-hailing research that are comparable to the NYC taxi data of conventional taxis [74-76].

VII. Policy Implications

Fleet Regulation and Entry Control

The quantitative approach to the study by Yang et al. [18] offers regulators with a principled foundation of determining the taxi licensing based on more than the rule-of-thumb methods. The income constraint mechanism of the model is especially useful: it represents the hypothetical political economy issue of incumbent driver protection as a quantifiable numerical parameter (the index of income variation e) that can be discussed openly and modified when necessary. Cities that think of greatly increasing the number of fleets or, on the contrary, banning the registration of new ride-hailing vehicles can scale the given framework to their respective GPS data, which justifies a set of regulations with a solid evidence base [77,78].

Spatial regulation is another aspect that is emphasized in the model. The analysis of the hot spots shows that the difficulty in taking a taxi is geographically centralized around the hospitals, railway stations, shopping centers, and government offices. Supply-demand imbalances can be addressed more effectively and with less impact on earnings by the taxi drivers through more focused interventions, such as special taxi ranks, electronic dispatch zones, surge pricing in low-hail zones, etc., instead of uniform expansion of the fleets [79].

Ride-Pooling Promotion Policies

The welfare analysis provided by Wang et al. [19] has a direct implication on how the governments and platforms ought to deal with pooling promotion. The critical demand thresholds Do, Dv, D k and D indicate on which the pooling will be or will not be productive to individual stakeholders. This theory implies that pooling promotion must be context-dependent: where markets are low-demand (e.g. off-peak time, small cities), pooling introduction must be counter optimal to the platform, and the society. Where there is a high demand market (peak hours in major metropolitan areas) pooling yields can achieve win-win results to the riders, the platform, and society, but of course at the expense of driver income.

One of the policy levers that appears is the pre-selection ratio b. The finding that b=1(unrestricted pooling matching) maximizes pooling adoption by reducing pooling waiting times, and that b=1/2 actually makes pooling less desirable than solo service, indicates that platform algorithms to set during times of high demand should be of high b. This could be operationalized by regulatory requirements that mandate platforms to have b above some set limits within core hours [80,81].

The issue of driver compensation reform is also involved. The observation that pooling has a systematic negative impact on the hourly income of drivers in the highly-demanded situation (that is, where pooling is most socially valuable) generates a systematic detriment to the willingness of drivers to offer pooling service. Some policy solutions may involve: per-trip pooling bonuses, different commission designs, or controlled minimum hourly earnings guaranties on drivers who undertake pooling trips [82].

Cost-Sharing Standardization and Platform Design

The results of Chau et al. [20] that egalitarian and proportional cost-sharing strategies are more socially optimal, have increased commuter diversity in matched pairs, and are also almost socially optimal in the same manner that equal and segment-based mechanisms, which is a theoretical social optimum, is a great guideline in the platform design. They should think of platforms that assume egalitarian or proportional cost-sharing as the default, instead of the easier-to-intuit equal split of the majority of consumers. This is because the proportional mechanism will only be useful in benefiting commuters with increased normalized savings (i.e. high-value trips) and this is poised to benefit the long-distance commuters who find pooling not attractive considering detours.

The algorithm of stable matching (STABLEMATCHING) introduced in the article can be implemented as an automated platform service directly, and all that is needed is that the information regarding the trip of every commuter and readiness to share it should be announced beforehand. Under typical cost-sharing schemes, the algorithm converges to a fixed-point, which is a computational function that can be realized in real-time or near-real time [83,84].

VIII. Research Gaps And Future Directions

Identified Gaps from Reviewed Papers

In all three papers reviewed, there are a number of such overt limitations that are indicative of potential fruitful research. Yang et al. [18] admit that the taxi booking via apps, which does not rely on the cruise-hailing concept that their framework relies on, existed in substantial amounts in 2014 and has grown to dominance since that time. There is still no GPS based fleet sizing model, which explicitly considers mixed dispatch modes (cruise, app-based, telephone). On the same note, the paper fails to model intra-day dynamics of the fleet: assumption that one fleet of N taxis serves the 24 hours ignores the structure of shifts, the maintenance of their vehicles, and the possibility of dynamically turning on and off the fleet.

Wang et al. [19] identify four areas as future research: demand elasticity with respect to pricing; the pricing used to achieve either social optimality or platform best profit; the network effects and spatial market equilibrium; and the effects of congestion and public transit ridership. This final aspect is especially significant: the effects of ride-hailing on traffic congestion and the ridership of public transit are not empirically studied in the literature [85-87] and the fact that the aggregate model does not consider the spatial network effects means that it is challenging to quantify these externalities.

According to Chau et al. [20], their framework now considers transportation cost as the only driver of coalition formation and delay has been neglected which may result in various matching structures. Multi-person (more than 2 commuters per vehicle) pooling also is flagged to be extended. What an uncertain information, such as traffic conditions, ride arrival time, is handled in an online system in which the identity of future commuters is unknown during the matching can be of considerable practical interest [88].

Emerging Research Frontiers

The most radical near-term technological upheaval to urban taxi markets is the autonomous and electric vehicles. The removal of the driver cost element- whose percentage is 60-80% of the overall ride-hailing expenses- essentially transforms the economics of fleet sizing, pooling incentives and service coverage. The finding of Vazifeh et al. [39] that 30 percent reduction of the fleet can be done through optimal routing will probably be underestimated in fully autonomous fleets where the cost of repositioning reduces drastically [89,90]. The Yang et al. framework of the fleet sizing framework needs to be fully reconceptualized in autonomous vehicle fleets, where the income limitations are substituted with the capital utilization limitations.

Multi-modal integration is also becoming known as a key towards sustainable urban mobility. Ride-hailing and ride-sharing are not independent, they compete with, and substitute the public transit, bicycle, and pedestrians. There are requirements of integrated market equilibrium models that characterizes mode choice of all options, shared micro-mobility included. This commuting system could be generalised to multi-modal travel in which the stable matching model of Chau et al. might be applied to incorporate a situation in which commuters mix ride-sharing with transit legs [91-93].

As the study of ride-hailing matures, equity and environmental sustainability are getting more attention. The initial studies were mainly concerned with efficiency; the current issues are increasingly concerned with determining whether ride-hailing creates or diminishes spatial disparities in transportation access, and whether pooling services can lead to its promised emissions reductions in practice [94,95]. The spatial pattern of hot spots in the analysis of Yang et al. indicates that unmet demand is clustered around the high-activity centers, however, the issue of whether or not the high-activity centers are serving central to high-income or mixed-income population decides the equity consequences of fleet expansion.

One such frontier is behavioral economics and heterogeneous commuter preferences. The three papers reviewed all make the assumption of using rational agents whose utility functions are well defined. Empirical studies invariably reveal that commuters are boundedly rational, loss averse, loss reference-dependent in their choices on waiting time, and social norms affect pooling choices [96-98]. The reviewed models could be enhanced in behavior to make them more predictive and policy-relevant.

Figure 8: Research Gaps, Future Directions, and Priority Level

Gap / Future Direction	Relevant Paper(s)	Priority	Methodological Approach
Autonomous vehicle fleet optimization	Yang et al. [18]	**High**	Capital utilization models; stochastic programming
App-based mixed dispatch fleet sizing	Yang et al. [18]	**High**	Extended queuing models; hybrid data fusion
Demand elasticity in pooling markets	Wang et al. [19]	**High**	Logit/probit mode choice integration
Network-based spatial equilibrium	Wang et al. [19]	**High**	Network flow + equilibrium; agent-based simulation
Congestion and transit ridership impacts	Wang et al. [19]	**Medium-High**	Four-step model integration; DID empirical methods
Multi-person (>2) pooling mechanisms	Chau et al. [20]	**Medium**	Coalition formation games; combinatorial auction
Online matching with unknown future riders	Chau et al. [20]	**Medium-High**	Online algorithms; competitive analysis
Multi-modal integrated mobility modeling	All three	**High**	Unified utility frameworks; supernetwork models
Equity and environmental impact assessment	All three	**High**	Spatial equity metrics; life-cycle emissions analysis
Behavioral preferences in pooling adoption	All three	**Medium**	Stated preference surveys; field experiments
Dynamic pricing and surge management	Wang et al. [19]	**High**	Dynamic programming; platform optimization
Electric vehicle integration	Yang et al. [18]	**Medium**	Range-constrained routing; charging optimization

Table 8: Research gaps and future directions identified from the three reviewed papers, with priority assessment and suggested methodological approaches. High-priority gaps represent areas where empirical evidence is insufficient for robust policy guidance.

IX. Conclusion

This The review has been able to synthesize three background papers that when together can contribute to our knowledge on the concept of urban shared mobility in terms of operational, market equilibrium and mechanism design lens. The GPS-based taxi fleet optimization model by Yang et al. [18] offers a practically applicable methodology of evidence-based fleet regulation with the income variation index delivering a clear-cut mechanism of balancing the welfare of passengers and the livelihoods of drivers. The market equilibrium analysis of mixed and non-pooling systems provided by Wang et al. [19] determines that the introduction of pooling is a welfare-neutral redistribution among the stakeholders at any given level of demand with explicit levels of demand demarcating the beneficiaries and the losers. The analysis of the cost-sharing-mechanism by Chau et al. [20] shows that egalitarian and proportional mechanisms are best in the empirical sense, despite having the same theoretical assurances of fair decentralized ride-sharing.

This three-layered conceptual framework, which is strategic through the inclusion of three layers, operational, market equilibrium, and mechanism design, gives a conceptual framework to integrated urban shared mobility research. One of the important lessons of this synthesis is that shared urban mobility is not sustainable and equitable and cannot be optimised at any one level. The GPS-optimal fleet sizing does not pay attention to the pricing incentives in a platform. The market-optimal pricing does not pay attention to the fairness of individuals. Mechanism-optimal cost-sharing disregards the aggregate market equilibrium impacts. The future of progress needs models built on multiple levels and consider the operational constraints, market incentives and rationality of individuals.

With the continued transformation of the traditional transportation approach in cities by the introduction of autonomous vehicles, electric fleets, dynamic pricing, and the integration of multi-modal transportation, the analytical underpinnings examined here are going to need extensive expansion. Methodological toolkit: queuing theory, matching functions, equilibrium analysis, stable matching, mechanism design are a formidable beginning, which needs to be filled in with more behavioral models, spatial disaggregation, environmental accounting, and equity analysis. The cities of the future will need common mobility systems that are not only to reduce the overall cost or maximize platform profit, but have to serve all urban dwellers fairly, sustainably, and efficiently. The study examined in this paper provides a relevant foundation towards such a grand aim.

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