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Market entry conditions and fleet health management in U.S. car-sharing operations

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Условия выхода на рынок и управление технической исправностью автопарка в операциях каршеринга в США

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Abstract

Car-sharing operators entering U.S. metropolitan markets face two decisions that most of the literature treats separately: where to launch, and how to keep a deployed fleet mechanically sound afterward. This review synthesizes peer-reviewed research on geographic market selection, regulatory entry conditions, and fleet health monitoring, and examines a recently proposed integrating framework built around a weighted market-scoring model and a Fleet Health Index. Documented market exits, including Car2Go's 2019 – 2020 withdrawal from the United States, are often attributed in this literature to entry decisions calibrated against demographic proxies and to reactive maintenance regimes that pull vehicles out of service exactly when demand peaks. The

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same period coincided with the onset of the COVID-19 pandemic and intensifying competition from subscription-based leasing, confounds the practitioner account does not address. Quantitative market-scoring methods are independently associated with higher penetration rates and lower exit frequencies than heuristic selection, and predictive-maintenance methods report unscheduled-event reductions approaching 40 percent relative to reactive baselines in industrial fleet settings. Applied to car-sharing specifically, the review finds genuine value in the diagnosis that entry conditions and fleet health should be modeled jointly, and identifies specific validation gaps, no reported weight-estimation procedure, no sensitivity analysis, no external replication, that determine how much confidence the proposed framework currently warrants.

Аннотация

Операторы каршеринга, выходящие на рынки американских агломераций, сталкиваются с двумя решениями, которые большинство работ рассматривает раздельно: где запускать сервис и как поддерживать техническую исправность развёрнутого автопарка впоследствии. В обзоре обобщены рецензируемые исследования по географическому выбору рынка, регуляторным условиям выхода и мониторингу технического состояния автопарка, а также рассмотрена недавно предложенная интегрирующая модель, построенная на взвешенном скоринге рынков и индексе технической исправности парка (Fleet Health Index). Зафиксированные случаи ухода с рынка, включая уход Car2Go из США в 2019 – 2020 годах, в этой литературе часто объясняются решениями о выходе, откалиброванными по демографическим показателям, и реактивным режимом технического обслуживания, выводящим транспортные средства из эксплуатации именно в периоды пикового спроса. Тот же период совпал с началом пандемии COVID-19 и усилением конкуренции со стороны сервисов подписочной аренды автомобилей, смешивающими факторами, которые практико-ориентированные источники не рассматривают. Количественные методы скоринга рынков независимо связаны с более высокими показателями проникновения и более низкой частотой ухода с рынка по сравнению с эвристическим отбором, а методы предиктивного обслуживания демонстрируют сокращение внеплановых простоев почти на 40 % относительно реактивных базовых показателей в промышленных автопарках. Применительно к каршерингу обзор находит реальную ценность в тезисе о необходимости совместного моделирования условий выхода на рынок и технического состояния парка, но выявляет конкретные пробелы валидации, отсутствие описанной процедуры оценки весов, анализа чувствительности и независимой репликации, которые определяют степень доверия к предложенной модели на сегодняшний день.

Keywords: car-sharing, market entry, fleet health management, predictive maintenance, market scoring, vehicle downtime.

Ключевые слова: каршеринг, выход на рынок, управление технической исправностью автопарка, предиктивное обслуживание, скоринг рынка, простой транспортных средств.

Introduction

Commercial car-sharing in the United States expanded from a handful of cooperative pilot programs in the late 1990s into an industry segment with several million active members [1]. Two decisions determine whether an individual operator captures a share of that market. The first is where to launch: which metropolitan areas, corridors, or zones offer a defensible combination of demand density, competitive white space, and regulatory receptivity. The second is how to keep the fleet mechanically capable of serving that demand once launch has occurred. Academic and practitioner literature has developed each decision largely on its own track. Market-entry research draws on international-business and platform-economics traditions that predate car-sharing by decades [2]; fleet-health research draws on predictive-maintenance traditions built originally for industrial and logistics fleets. Mamaev [3], an independent practitioner-researcher whose work on this specific integration point has not gone through conventional peer review, argues that the separation between the two literatures is a structural weakness of the field. A vehicle repositioned to correct a demand imbalance may itself be the vehicle nearest its maintenance threshold, and no shared decision architecture in the prior peer-reviewed literature accounts for that interaction. Whether Mamaev's own proposed architecture accounts for it adequately is a separate question addressed later in this review.

Documented market exits recur around a similar diagnosis, though the diagnosis is contested. Car2Go withdrew from all of its American markets between 2019 and 2020, and BMW's ReachNow exited Seattle and Brooklyn in the same window, in each case after membership growth that looked healthy on conventional adoption metrics [4]. Practitioner accounts attribute the failure primarily to entry decisions calibrated against population and income proxies that miss the operational variables determining unit economics: transit-substitution density, existing for-hire supply saturation, and the local availability of qualified fleet operators [5]. That attribution deserves scrutiny on its own terms. Both exits occurred as the COVID-19 pandemic collapsed urban trip demand across every shared-mobility category at once, and both operators faced intensifying competition from subscription-based leasing products aimed at exactly the customer segment car-sharing relies on. A scoring-error explanation and a demand-shock explanation are not mutually exclusive, but the practitioner literature examined here presents only the former. The Results and discussion section returns to this gap.

Firnkorn [6] offers an independently documented instance of the same entry-scoring problem in a different national context. A free-floating operator in Germany expanded its service area using population-density projections, and utilization fell sharply once the area exceeded the zone that trip-origin density actually supported. Unlike the Car2Go and ReachNow cases, this account comes from a peer-reviewed empirical study, not from after-the-fact practitioner analysis, and it isolates the scoring mechanism more cleanly because no pandemic or major competitive shock coincided with the observed decline.

Entry-condition failures compound with a second, mechanically distinct problem. Under reactive maintenance, a vehicle is serviced only once a fault becomes observable, and the resulting out-of-service periods should in principle extend longest exactly when zone-level demand is highest, since usage intensity drives both demand and mechanical stress. That claim is a logical inference about a shared driver, however; none of the sources reviewed here isolate and measure the correlation directly against fleet-level operating data. The two failure modes still compound each other in practice: a fleet entering an underscored market with too few vehicles has less slack to absorb the vehicles that reactive maintenance removes from service at the worst possible moment.

Materials and methods

Coverage was built from peer-reviewed literature indexed in Transportation Research Part A, Transportation Research Part B, Transportation Research Part E, Transport Policy, Business Strategy and the Environment, Organization & Environment, Sustainability, WIREs Data Mining and Knowledge Discovery, and Energies. Search terms combined «carsharing,» «car-sharing,» «market entry,» «market selection,» «predictive maintenance,» «fleet health,» and «vehicle damage detection.» Three inclusion criteria applied. A study had to address either the geographic and regulatory conditions governing car-sharing market entry, or the technical methods used to monitor, predict, or manage vehicle condition within an operating fleet. Studies confined to ride-hailing driver-side labor questions without a fleet-ownership component were excluded. Studies addressing vehicle maintenance in contexts unrelated to shared or commercial fleets were excluded unless directly relevant as methodological precedent for an included fleet-health study.

Results and discussion

Firms entering geographically dispersed markets have historically followed a psychic-distance logic: expansion targets markets that feel familiar based on managerial experience, and objective demand characteristics only correct that bias in later expansion rounds [7]. Brouthers and Nakos [8] tested this pattern directly against a scored alternative. Firms applying quantitative scoring criteria to candidate markets achieved higher penetration rates and lower exit frequencies than firms relying on experiential judgment, and the performance gap traced specifically to the scoring methodology, independent of industry or firm size. Car-sharing entry decisions have followed the heuristic pattern more often than the scored one. Firnkorn [6] documents a free-floating operator expanding its service area on population-density projections and reports utilization falling sharply once the area exceeded the zone that trip-origin density actually supported.

Regulatory and municipal conditions add a second entry variable that scoring frameworks imported from general platform economics do not capture. Shaheen, Cohen, and Martin [9] document that carsharing parking policy in North America varied by jurisdiction, from formal, legislated space allocation in California to informal arrangements negotiated city by city, and this variation materially affected the fixed cost an operator faced before a single vehicle generated revenue. Namazu, MacKenzie, Zerriffi, and Dowlatabadi [10] found that carsharing membership diffusion within a metropolitan area correlated more strongly with proximity to parking infrastructure than with income or age. Rotaris and Danielis [11] extended this line of inquiry to smaller towns and rural areas: the viability threshold for carsharing service depends on population density nonlinearly, with a floor below which no pricing or fleet-sizing adjustment restores viability.

Mamaev's framework, examined in this review, proposes a six-variable weighted scoring model for this class of entry decision, combining population density, proximity to public transit stops, vehicle registration density per capita, a mobility-service saturation index expressed as the ratio of licensed for-hire vehicles to working-age population, and an entrepreneurial-operator-availability score derived from county-level small-business formation rates [12, 5]. Each variable is normalized by min-max transformation and combined through assigned weights; the reported specification assigns 0.15 to the mobility-saturation index and 0.10 to operator availability. The model extends the logic Brouthers and Nakos [8] validated empirically for SMEs generally into variables specific to car-sharing unit economics. Extends is the operative word: unlike the Brouthers and Nakos study, no comparable empirical test of penetration and exit outcomes accompanies the six-variable specification in the sources reviewed here.

Comparative evidence across national contexts supports a broader point: market condition is not reducible to a single density figure. Wang, Zhu, Wei, Jiang, and Yamamoto [13] develop an eight-metric assessment framework for carsharing business development spanning China, Europe, Japan, and the United States. Market condition, parking condition, electric-vehicle deployment, and vehicle maintenance appear as separate, independently weighted dimensions in their model, and their comparative case analysis finds that operators in different regulatory environments succeed or fail along different subsets of these eight metrics. That finding argues against a universal entry-scoring formula and toward market-specific calibration, a direction consistent with Rotaris and Danielis [11] and with the practitioner scoring model discussed above, reached through unrelated methods.

Fleet-management research addressing vehicle condition specifically is younger and thinner than the market-entry literature. Foundational work on shared-vehicle fleet operations, including Nair and Miller-Hooks [14] and Kek, Cheu, Meng, and Fung [15], formulated relocation and allocation as stochastic and combinatorial optimization problems treating each vehicle as simply available or unavailable, with no representation of gradual degradation short of outright failure. Reactive maintenance built on that binary assumption services a vehicle only once a fault is observable, and the resulting downtime tends to concentrate during periods of peak demand, when usage intensity is highest for both.

Two adjacent literatures have begun to close this gap. Hasan, Nguyen, Boo, Jahani, and Ong [16], in a systematic review of artificial-intelligence-based vehicle damage detection spanning insurance, resale, and fleet-management applications, find that deep-learning image classification has matured enough for operational deployment. Dataset limitations persist, however, particularly the underrepresentation of minor and underbody damage in training data, and these gaps constrain detection accuracy for exactly the damage categories most relevant to shared-fleet wear. Cavus, Dissanayake, and Bell [17] report complementary progress in electric-vehicle battery health prognostics, predicting degradation trajectories from telematics-derived charge and discharge data. Chaudhuri and Ghosh [18] demonstrate a hierarchical fuzzy support-vector-machine architecture for industrial IoT vehicle fleets that classifies component health from telematics streams at lower computational cost than comparable ensemble methods, a property that matters for any system meant to run on a short refresh cycle across a large fleet.

Mamaev framework proposes a single composite Fleet Health Index to unify these signal streams, mileage, age, maintenance history, sensor telematics, and availability, into one scalar per vehicle, computed as a weighted linear combination of five normalized sub-indicators and updated on a rolling basis [3]. Vehicles below an operator-defined maintenance threshold are excluded from trip allocation pending service; vehicles below a lower retirement threshold are flagged for decommissioning review. A least-squares trend projected fourteen days forward over the trailing thirty-day index history generates anticipatory maintenance alerts before either threshold is crossed. The index feeds a mixed-integer linear program that jointly assigns vehicles to zones and schedules repositioning, turning vehicle health into a hard allocation constraint. The reported comparative analysis, higher utilization, less downtime, lower repositioning cost, comes entirely from the same source that designed the index. No outside dataset or independent research team has yet tested it. Table 1 summarizes the quantitative claims reported across the peer-reviewed literature in both domains.

Table 1.

Quantified findings reported in the peer-reviewed market entry and fleet health literature

Domain	Study	Reported finding
Market entry	Brouthers & Nakos [8]	Quantitative market scoring associated with higher penetration and lower exit rates than experiential selection
Market entry	Firnkorn [6]	Utilization falls sharply once free-floating service area exceeds the zone supported by actual trip-origin density
Market entry	Namazu, MacKenzie, Zerriffi, & Dowlatabadi [10]	Carsharing diffusion correlates more strongly with parking-infrastructure proximity than with income or age demographics
Market entry	Rotaris & Danielis [11]	Carsharing viability threshold in small towns and rural areas is nonlinear in population density
Market entry	Wang, Zhu, Wei, Jiang, & Yamamoto [13]	Eight independently weighted metrics needed to compare carsharing viability across national contexts
Fleet health	Hasan, Nguyen, Boo, Jahani, & Ong [16]	AI damage detection mature for deployment; dataset gaps persist for minor and underbody damage
Fleet health	Cavus, Dissanayake, & Bell [17]	AI-driven prognostics predict EV battery degradation from telematics data
Fleet health	Chaudhuri & Ghosh [18]	Hierarchical fuzzy SVM classifies fleet component health with lower computational overhead than comparable ensembles

Two decades separate Brouthers and Nakos [8] from the practitioner framework proposed here, yet the underlying diagnosis has not changed: heuristic, single-variable decisions underperform structured, multi-variable ones, in market entry and in fleet allocation alike. Nair and Miller-Hooks [14] made the equivalent case for fleet allocation over a decade ago. What is new is the attempt to run both decisions through one shared architecture instead of two disconnected ones. That ambition is worth taking at face value even though its current execution is not.

Start with the market-scoring weights. The framework reports 0.15 on the mobility-saturation index and 0.10 on operator availability, figures presented without an estimation procedure or a sensitivity analysis showing how rankings would shift under different values. Brouthers and Nakos [8] showed that scoring benefits depend on the scoring methodology itself; an arbitrary weighting scheme dressed in the language of formal scoring could reproduce the very heuristic failure it claims to replace. A companion piece by Mamaev reports an ordinary-least-squares recalibration step meant to update the weights from post-launch performance data [12].

Its five sub-indicator weights are stated as operator-configurable defaults, not derived from failure data, and nothing in the reported analysis tests them against an equal-weighted baseline or against the threshold rules Chaudhuri and Ghosh [18] already established for industrial IoT fleets.

The mixed-integer program that consumes the index is otherwise standard: comparable formulations have run against real Zipcar and car2go data in the fleet-management literature for over a decade. What the framework adds is the health constraint, nothing more, and that constraint's fifteen-minute recomputation cycle has not been tested at the scale, dozens of zones and thousands of vehicles, where solver time typically becomes the bottleneck.

Car2Go and ReachNow both exited in 2019 – 2020, and the practitioner literature attributes both exits to entry-scoring failure. Neither account engages with two obvious competing explanations. The first is macroeconomic: both withdrawals occurred as the COVID-19 pandemic suppressed urban travel demand across every mode, shared and private, simultaneously, which would have depressed utilization regardless of how well the original entry decision had been scored. The second is competitive: the same period saw rapid growth in subscription-based vehicle leasing aimed at the customer segment carsharing depends on, a substitution effect entirely separate from zone-level scoring accuracy. A scoring failure and a demand shock can coexist and even reinforce each other, but attributing the outcome to scoring alone is the kind of single-cause narrative a rigorous post-mortem should test against alternatives, not assume by default.

The market-entry literature reviewed draws heavily on European and Asian carsharing markets; generalizing to the more fragmented U.S. regulatory landscape, where parking and licensing authority sits with individual municipalities and not a national regulator, has not been systematically tested beyond the case evidence in Shaheen, Cohen, and Martin [9]. The fleet-health literature reviewed draws primarily on electric-vehicle and industrial-IoT contexts, and direct validation on the mixed internal-combustion and electric fleets typical of urban car-sharing remains limited. This review's own narrative protocol, without a systematic screening record, is a further limitation already noted in the Materials and methods section.

Conclusion

Market entry and fleet health in U.S. car-sharing operations have been studied by two literatures that rarely speak to each other. A practitioner framework now proposes to close that gap, and the proposal is worth taking seriously on its diagnosis even though its numbers are not yet earned. The weighted market-scoring approach extends a methodology Brouthers and Nakos [8] validated empirically for SMEs into car-sharing-specific variables, weighting demand-substitution and infrastructure-access measures above raw demographic projections, a direction consistent with what Namazu et al. [10] and Rotaris and Danielis [11] found independently through different methods. The Fleet Health Index adds vehicle condition as a hard constraint to allocation mathematics already validated elsewhere, a genuinely useful move: no prior commercial system in the literature reviewed enforces that constraint jointly with zone-level allocation. What has not happened is independent, adversarial testing, against operator data the framework's author did not collect, of the kind the peer-reviewed studies in Table 1 have already passed for narrower, single-domain claims. Until that testing happens, the framework belongs in the same category as the market-entry failures it seeks to explain: a plausible diagnosis, competing with unexamined alternatives, awaiting the kind of evidence that would settle the question either way.

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