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Urban Car-Sharing Viability in the Knowledge Economy: A Monte Carlo-Based Planning Tool for Shared Mobility Policy

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Abstract: This study presents a Monte Carlo simulation to estimate the viability thresholds of car-sharing services in urban areas. Departing from traditional revenue-based assessments, the model uses real cost structures to identify the minimum population size required to reach critical mass. Critical mass, in this context, is defined as the number of users needed for a platform business to reach its breakeven point. The study also explains the increasing urban-rural divergence in adopting platform-based services. The findings highlight substantial urban-rural divides in service viability and offer concrete tools for policymakers to allocate resources and support infrastructure in underserved areas. This cost-based planning tool contributes to sustainable urban mobility policy by quantifying regional thresholds for service provision. To simulate these results, a multivariate model was developed that considers real market data in the car-sharing industry. The model considers several input variables to capture a broad spectrum of market conditions that feed into a final formulation providing two distinct results: an on-site service provider's critical mass and an estimation of the population required in an area for the company to reach its minimum threshold. The study provides a transparent, data-driven tool to support urban mobility planning and resource allocation. By identifying critical population thresholds for the economic viability of car-sharing services, the model enables policymakers and urban planners to make evidence-based decisions on where to facilitate or subsidise shared mobility infrastructures. The simulation was run 10,000 times to reflect a broad range of market conditions. Results from the Berlin case show a minimum viability threshold of approximately 1.12 million residents, with a probability of around 91% at Berlin's current population of 3.71 million and near-certain viability at around 5.8 million residents. In regions falling below these thresholds, the tool helps to justify targeted interventions—such as financial grants, regulatory incentives or hybrid public-private service models—to mitigate accessibility gaps and reduce urban-rural mobility disparities. As such, the model contributes to a more efficient and equitable allocation of mobility resources and supports the strategic deployment of sustainable transport solutions in underserved areas.

Keywords: car-sharing services; Monte Carlo simulation; critical mass; shared-mobility policy; urban-rural divergence; market entry thresholds; Berlin.

Introduction

Sharing replaces resource scarcity through technology and business model innovation (Ferreira & Fernandez, 2023; Lange et al., 2023). The pronounced disparity in service availability, pricing and quality between rural and urban areas underscores the need for empirical exploration (Hollman et al., 2021; Zulauf & Wagner, 2021). Illgen and Höck (2020) emphasise the necessity of evaluating actual costs and revenues to gauge profits in various network setups, especially for service providers employing service platforms (Lange et al., 2023; Wirtz et al., 2019). Failures in consumer adoption behaviour have led

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to market exits for car-sharing services such as Citroën MultiCity, Cité Lib and car2go (Hahn et al., 2020).

Urban consumers generally accept sustainable services more readily than rural households (Meelen et al., 2019; Nansubuga & Kowalkowski, 2021). Evans and Schmalensee (2010) discuss the critical mass concept, which is vital for a business's success, indicating the challenge in rural areas due to less dense populations. Recently, Aliu et al. (2025) provided evidence of managers' belief that car-sharing incentives are a suitable means for reaching sustainable development goals without considering the systemic requirements of such an initiative. This study addresses the research gap formulated by Ferreira and Fernandez (2023) of unclear obstacles that hinder collaborative consumption. Van Slyke et al. (2007) note the difficulty in assessing critical mass, which this research addresses using real-world car-sharing data. The study uses Monte Carlo simulations with car-sharing data inputs to explore the critical mass's impact on platform-based service feasibility across diverse market conditions. The model exposes the urban-rural gap and elucidates why certain services struggle in rural areas without intervention or sustainable cost reduction. This study introduces a cost-centric model for market entry, considers five fundamental factors and provides practical insights for new entrants in competitive markets.

Despite the growing interest in shared mobility, the population size required for cost-covering operation remains difficult to determine, as existing research does not link operational cost structures to user adoption and competitive market availability in a transparent way. This study addresses this gap by developing a cost-centric approach that derives the required service volume for economic viability and translates it into a population threshold using information on expected usage patterns and the availability of competing services. This provides a novel and practical mechanism for assessing critical mass, distinguishing the present contribution from prior work. Berlin is introduced as an instructive case for applying this framework due to its market maturity and the availability of detailed cost and usage data. The remainder of the article outlines the modelling approach, presents the empirical application and discusses its implications for market-entry decisions and shared-mobility policy.

Theory and conceptual background

Car-sharing is a prominent example of platforms that seek to create shared value and thus enhance economic sustainability. Generally, sharing and access-based services are regarded as 'eco-efficient services', as they exploit underused resources (Lamberton, 2016; Lefeng et al., 2020; Plewnia & Guenther, 2018). Research shows that car-sharing reduces car ownership and private vehicle kilometres travelled (Nijland & van Meerkerk, 2017) and offers the potential for substantial cost and CO_2 savings (Rabbitt & Ghosh, 2016). Wirtz et al. (2019) distinguish between ownership transfer and access-based platforms, emphasising the latter's pivotal role in sustainable production and consumption transitions (Hahn et al., 2020). Due to differing revenue models, car-sharing models, such as Zipcar, demonstrate higher vehicle utilisation than Hertz rental cars, highlighting differences in environmental impact (Münzel et al., 2018).

Despite their potential, several car-sharing programmes have failed, prompting service providers' market exits for unclear reasons, particularly in consumer adoption behaviour. Simulations indicate that a station-based model with fixed drop-off and pickup spots, competitive pricing, and an e-car fleet might yield better success (Perboli et al., 2018). The failure of the car-sharing programme during an initial field study shows that simply liking the idea of car-sharing is not a reliable indicator of whether people will use it. Namazu and Dowlatabadi's (2018) research shows that only station-based systems (e.g., Avis, Enterprise, Hertz or Sixt) effectively replace private car ownership, whereas free-floating systems (similar to app-based e-scooter rentals in modern metropoles, e.g., Lime, Tier or Voi) are more of an added mobility option for users. Furthermore, according to Plewnia and Guenther (2018), a reduction in CO_2 emissions can be achieved only if there is a shift towards using hybrid or electric vehicles.

The key question is whether the programme is suitable for people and their real-life situations (Hahn et al., 2020; Hossain & Mozahem, 2022). If a platform can fulfil most of the customers' needs at a competitive price, facilitated by a vast network and a variety of offerings, then the possibility of customers switching to other platforms becomes less likely. However, if the price and quality of services (such as surge pricing and lack of availability of suitable accommodation in the shared housing market) are perceived to vary, then users may sign up on multiple platforms (known as multi-homing) and switch between them for each transaction. Once multi-homing is established, the negligible switching costs can lead to direct and fierce competition between platforms (Wirtz et al., 2019). De Lorimier and El-Geneidy (2013) identify positive associations between car-sharing utilisation and variables such as available vehicle count, proximity to metro stations, member density and accessible large retail outlets. Kim et al. (2017) outline the determinants influencing people's inclination towards car-sharing, revealing that factors such as time constraints, reduced spontaneity and higher variability in travel times negatively impacted individuals' intentions to use such services. Building on this perspective, Wappelhorst et al. (2014) emphasise the integration of car-sharing within an intermodal transportation system, advocating for a more comprehensive approach. In contrast to its viability in urban settings, Wappelhorst et al. (2014) suggest a potential challenge to the efficacy of car-sharing programmes in rural areas. The authors question the adaptability and feasibility of such services in less densely populated regions.

The breakeven volume is crucial for any business, especially new ventures. It represents the point at which fixed and variable costs have been covered, and the business is no longer operating at a loss, thus avoiding potential losses. At this point, the business has achieved critical mass. According to Evans and Schmalensee (2010), reaching critical mass is essential for platform businesses to survive, even without fixed costs or economies of scale. They explain that platform businesses must attain critical mass when launched to ensure their survival. Consequently, breakeven points significantly affect economic investments in shared economic platforms. Illgen and Höck (2020) state that sharing efforts face a large capital investment to initiate a sharing enterprise that will initially yield low margins and profits. Therefore, entrepreneurs must understand the factors that determine critical mass before they invest. The concept of breaking even is strongly connected to critical mass. The critical mass for a service-based entity can be defined using the number of times that a service is provided (SP).

Potential sharing participants operate in a cultural context beyond purely economic rationality, so consumers' cultural context must be considered (Galina et al., 2018). Van Slyke et al. (2007) contribute corresponding evidence in interactive communications innovations. They discuss the importance of perceived critical mass to potential adopters of communication innovations. According to Rong et al. (2021), sharing economy platforms are often faced with challenges related to social ethics and culture and are susceptible to social and institutional uncertainties.

Building on these strands, the present study draws three elements from the literature that directly inform the operationalisation of the model. First, research on usage intensity, adoption determinants and service frequency in free-floating and station-based systems provides the empirical base for estimating the expected use of service (EUS), which reflects typical utilisation patterns within a given population. Second, studies on competition, fleet availability and spatial coverage inform the notion of available equivalent services (AES) by highlighting how the presence and density of incumbent providers shape the effective availability of substitutable mobility options. Third, breakeven and cost-structure literature underscores the relevance of linking fixed and variable costs to the service volume required for viability, which forms the foundation for translating cost-based requirements into a population threshold. Taken together, these lines of research offer a coherent framework that motivates the model's inputs and

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assumptions and clarifies how the study integrates insights from prior work into a cost-centric assessment of car-sharing viability.

Methodology

The model and its theoretical background

The model has five main areas of input: fixed costs, variable costs, prices, expected use of the service and available number of equivalent services. The input values for each domain were obtained from a combination of official statistics, provider disclosures, established market reports and documented market price information. For several cost components (such as software, web infrastructure or set-up expenses), official or provider-filed data are not publicly available in a standardised form. In these cases, curated industry directories and reputable web-based sources were consulted to approximate realistic market ranges. These values were cross-checked for internal consistency and used to construct broad intervals that reflect the heterogeneity of market conditions. This approach ensures transparency about source quality while avoiding unsupported precision in domains where detailed official data are unavailable. Each area is broken down into various subcategories, which vary according to the sector in question.

The input data feeds into a final formula that transforms the data into actionable information. For each value (except taxes), an array is created between the lowest possible value found on the market and the highest possible value on the market to consider all possible outcomes. Then, for each area of input, the model randomly picks a value within this array and feeds it into each area's total (e.g., total fixed costs). To specify the stochastic inputs, the model draws on empirically grounded intervals derived from official statistics, provider disclosures, established market reports and documented price ranges. These sources typically provide point estimates or bounded ranges rather than granular underlying data that would allow the reliable derivation of parametric distributions or empirical dependence structures. Accordingly, uniform sampling within these empirically justified intervals is applied as a transparent and conservative approach under the given data conditions. Independence between input variables is likewise maintained to avoid the introduction of ad hoc correlation patterns not substantiated by available evidence. The comparatively broad intervals ensure that the simulation covers both optimistic and pessimistic combinations of inputs, which is consistent with the exploratory purpose of the model. These modelling choices are acknowledged as simplifications and are noted as potential areas for further methodological refinement. The model automatically inserts these into the final formula. Finally, the formula is simulated 10,000 times with many possible outcomes to reduce statistical error. The results are then grouped into ranges of population sizes (range 1 = 0–100,000, range 2 = 100,001– 200,000 and so on). The model applies to each population range an entity's likelihood of covering the starting and operating costs.

Using Monte Carlo simulation constitutes a practical approach for estimating the critical values or power of the test of a novel hypothesis. Due to the computational complexity arising from the stochastic nature of certain variables, a reduction in uncertainty is required. The model applies a random selection of several values within the indicated ranges, which may result in unreliable outcomes from a single test. For instance, if the model randomly selects a situation in which all costs are extremely high, this outcome may not be representative of all situations. To reduce uncertainty, a Monte Carlo simulation was used to repeat the simulations many times, which helped to ensure more reliable results. Monte Carlo simulation addresses the uncertainty by converting uncertain variables into deterministic values that are randomly selected and repeatedly sampled. To simulate the results using this method, a model was created using an Excel spreadsheet and Microsoft VBA. This model transforms data into useful information for service providers and policymakers by estimating the critical mass for a project and, more importantly, the number of residents needed in an area to achieve critical mass (N).

Companies may offer different services (for example, a car-sharing service may offer expensive or cheaper cars, or electric or combustion engine vehicles). Usually, they choose among a wide selection of products. Different service qualities, suppliers, offers and economic conditions result in different costs and situations for the company. Monte Carlo simulations captured this diversity in the present study. Ranges were selected for every input, and the model randomly picked a value within these ranges. We used a simple random command in Excel to generate the random picks, as the distributions were not assumed to be normal. The model thus produces many possible scenarios, ranging from more optimistic to more pessimistic results. These ranges are described by the average ± standard deviation (when available) or range (maximum - minimum) for each input domain. Every randomly picked value then feeds into the formula that provides the critical mass of population as represented by *N*. The many possible situations mean that the result may contain outliers created by using the lowest possible costs and the highest prices, creating an unrealistic situation. Monte Carlo simulations reduce these sampling errors by running the model multiple times. Our model ran 10,000 times, therefore estimating 10,000 possible critical masses and population sizes needed to achieve each respective critical mass (*N*). *N* is then divided into various possible ranges, and the model tabulates how many results fall into each range. This yields the probability that a given critical mass is achieved.

The general principle behind this model is the breakeven point, defined as the situation in which total revenues less variable and fixed costs produce zero profits or as the volume of production at a given price necessary to cover all costs (Hillier & Lieberman, 2009). It is computed as:

$$Q = C_F / (P - C_V) \quad [1]$$

where P = price, Q = quantity of production, C_F = fixed costs and C_V = variable costs. In the established definition of breakeven point, a breakeven point is achieved when $R - C_T = 0$, where R = revenue = $P * Q$ and C_T = total costs = $C_F + C_V$. Thus, the calculation is:

$$(P * Q) - (C_F + C_V) = 0 \quad [2]$$

and the production breakeven point $Q = C_F / (P - C_V)$ from equation [1] can be used. However, these definitions are oriented towards businesses dealing with physical goods, such as manufacturers, wholesalers and retailers. Entities offering services do not have a volume of production but rather the number of times that a service is provided (SP). Therefore, we can replace Q with SP as follows:

$$SP = C_F / (P - C_V) \quad [3]$$

The breakeven point can be defined as the numerical unit volume of service that must be provided at a given price to cover all costs. The ($P - C_V$) equation, a covering allowance, defines the allowance that is necessary for the payment of fixed costs. It will be denoted here as the contribution margin. The service provider must assess which revenues and prices are needed for SP to reach $R - C_T = 0$ to deduce the breakeven point and critical mass of a service-based entity. The aim of this research was to determine the necessary users in a specific area to ensure that the entity reaches the required SP. Critical mass does not equal SP, because each user could use the service multiple times, and we must assess this EUS. This can be done by examining presently served areas that are similar in culture, population and public transport, as well as exploratory surveys and the volumes of incumbent competitors. SP is the dependent variable here. Where $SP = C_F / (P - C_V)$, it is the output of the simulation trials. It is also affected by the number of available competitors, which is not in the $SP = C_F / (P - C_V)$ model at this point. The end result of the model is how many SP are available given the number of competitors and the probability that the SP actually found in an area exceeds that required to meet or exceed the $SP = C_F / (P - C_V)$ breakeven point.

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The second aspect that is considered is the available number of *AES* offered in the same area. In the example of car-sharing, this refers to how many cars are already offered by car-sharing companies in the same area. However, both competitor companies' cars and the number of cars the entity itself wants to bring to the area must be considered as though each car is competing with the others. Once these values have been estimated, the following formula calculates the number of people needed in an area to reach the level of *SP* so that $R - C_T = 0$:

$$N = (SP \times EUS) / AES \quad [4]$$

where N = number of residents needed to achieve critical mass, *EUS* = expected use of service and *AES* = available equivalent services. In this context, AES serves as an aggregate proxy for the overall availability of substitutable services. The measure does not differentiate between vehicle types, service quality or spatial coverage, as such detailed information is not publicly reported in a standardised form. Introducing provider-specific weights without robust empirical data would risk imposing ad hoc assumptions. As a result, AES is treated as a homogeneous indicator of market availability, with the associated bias acknowledged and outlined as an area for further refinement in future research. This formula assumes that all competing services are equal in their appeal. Furthermore, in this formulation, SP denotes the annual number of service provisions required to reach the breakeven point, expressed in trips per year. The variable EUS represents the expected annualised use of the service per resident. Although the underlying empirical usage evidence is reported as daily trips per vehicle or per capita, these figures are converted into an annual utilisation rate before implementation in equation [4]. As a result, all components share an annual time basis, ensuring dimensional consistency.

Exemplifying application to the car-sharing industry

Free-floating car sharing allows users to pick up and drop off vehicles anywhere within the provider's business area. The authors demonstrated this model in Berlin, a city with high car-sharing density. Jia et al.'s (2020) economic analysis of cost and monetary revenue in the operation of electric car-sharing was adapted to the car-sharing market in Berlin. Additional market analysis was conducted to retrieve data from existing operational car-sharing businesses as well as from Statista, Berlin, the European Commission, European Parliament, Organisation for Economic Co-operation and Development (OECD), the United Nations and the World Bank (Appendix).

Fixed costs

The first data needed to input into the model are fixed costs, as they are particularly influential. To identify the main areas of fixed costs, the financial statements of existing companies were studied. The selected fixed cost areas are described below.

a. Gross employment costs (including net salaries and taxes)

Two main variables are needed: how many employees and the costs of each of them.
Two to five employees are required to start a car-sharing company when most of the operations are done through third parties (e.g., external software providers). Three to five employees are needed if these operations stay within the company (Loose et al., 2006). Thus, in the model, a value is randomly picked from an array of between two and five employees. Empirically, the Share Now car-sharing service had approximately 13 employees in Berlin, with an estimated employment growth of 10%–15% since its 2018 start-up. In Berlin, the average gross wage for employees in car-sharing service–related jobs ranged between €32,580 and €52,172. The model randomly picks within this range. The model multiplies the randomly generated number of employees and wage, yielding gross employment cost:

$$\textit{Gross employment cost} = \textit{employee number} \times \textit{gross wage} \quad [5]$$

b. Property rental costs
Free-floating car-sharing services generally require renting a small/medium-sized office, but, unlike in station-based car sharing, no parking spaces. Office size ranged between 50 m^2 and 80 m^2, with a price between €36.50/m^2 and €42.50/m^2. These values were estimated from the average Berlin prime rent of
€39.50 with a standard deviation of €3.00. The model randomly picks a combination of values and estimates the rent:

$$\textit{Office rent cost} = \textit{price per } m^2 \times \textit{office size} \quad [6]$$

c. Company insurance premium
German and international insurance companies charge premiums ranging from €3,000 to €7,000 per year. As the cars in the model were assumed to be rented, no vehicle insurance was modelled.

d. Office equipment, phone bills, electricity, heating and other utilities
Office equipment, utilities, phone bills, etc., cost approximately €1,844 per year (standard deviation: €300). Therefore, the model randomly picked a value between €1,544 and €2,144.

e. Company founding costs
Founding costs range between €1,000 and €3,000, which can be depreciated in one to seven years. Additional expenses include the application for the German Commercial Register, notarising the articles of association and company formation fees.

f. Website development and periodic maintenance costs
Customers book, locate vehicles, manage and pay through websites or mobile apps. Market investigation conducted by the author team yielded costs of €3,925–€28,106, from which the model randomly selected a value. A depreciation schedule between one and seven years was then randomly picked. A periodic maintenance cost between €500 and €2,000 yearly was also randomly picked and added to the fixed costs.

g. Marketing costs
There is no rule for advertising costs. Other car-sharing providers spend between €3,000 and €10,000 per year. The model is randomly selected from this range.

h. Unplanned maintenance not covered by insurance
The range of unplanned maintenance was €1,500–€5,000 per year.

i. Owner's wage
The owner's wage includes annual compensation for time, effort and risk taken. In Berlin, managers earn an average salary of €96,990, with a median of €95,685, plus a bonus of €6,188. A 10% overhead is added to account for the risk taken. To calculate the wage, a random amount between €67,490 and €120,575 was selected.

$$\textit{Owner's wage} = \textit{selected wage} + (\textit{selected wage} \times 0.1) \quad [7]$$

j. Car-sharing app/software
A car-sharing app/software provides customers continuous access to their account, displays the nearest car's location, pricing and model information, unlocks the car and allows mobile payment. To calculate the annual cost, the authors considered 18 software providers' prices. Setup costs were depreciated randomly between one and seven years randomly and added to the yearly costs.

Results: step one

At this point, all total cost categories except the number of vehicles are calculated and identified as total yearly fixed costs without car leasing or interest costs. This allows the model to estimate how many cars are needed for the car-sharing provider to achieve critical mass. The model sums all the costs found in paragraphs *a* to *j* as $C_F - A$, where A equals the cost of car leasing and all other connected costs. We use the formula below to calculate the number of trips per year to cover C_F.

$$\#trips = (C_F - A) / (P - C_V) \quad [8]$$

The first part of the formula aims to identify how many trips and, therefore, how many cars would be needed to cover all the fixed costs the company sustains. It would be illogical to consider the cost of the cars to calculate the number of cars needed. For this reason, the cost of cars is separated from other fixed costs ($C_F - A$). Dividing this by 365, we get the trips needed each day ($W1$):

$$W1 = (C_F - A) / (P - C_V) / 365$$

Habibi et al. (2017) found that car-sharing vehicles in Berlin could make 5.3 trips per day (denoted as X), with a standard deviation of 1.8. X is randomly picked by the model between 3.5 (5.3 – 1.8) and 7.1 (5.3 + 1.8). Dividing $W1$ by X reveals how many cars are needed ($W2$) to cover $C_F - A$ (the number of cars needed to achieve critical mass).

$$W2 = W1 / X \quad [9]$$

k. Car leasing costs
Car-sharing providers choose a model to suit their clientele in the luxury, cost or convenience segments. The model considers all the available cars offered by existing car-sharing providers in Berlin. Providers can choose models costing from €70 to €599 monthly. The provider prices are used to create an array of numbers between these two values, allowing all leasing costs to be included. The model then randomly picks a value from this array and multiplies it by 12 to get the yearly leasing cost, which is multiplied by X to calculate the total yearly leasing cost:

$$Total\ leasing\ costs = leasing\ cost\ per\ year \times number\ of\ vehicles\ (X) \quad [10]$$

Leasing was chosen over vehicle ownership because many providers have adopted leasing to lower initial investments. Leasing cost includes insurance and taxes, which facilitates model calculation. Future research could give more commonly used models a higher probability of being picked and could include more than one car model, unlike the present multivariate model.

l. Vehicle periodic maintenance
Beyond required service, such as oil and tyre changes, higher quality car-sharing services will make sure that the cars are always cleaned and ready for use, whereas lower quality providers may try to save money by limiting maintenance. Research found a range of €100 to €200 per year, which was put into the model selection process.

Results: step two

By simply adding the costs (excluding interest costs for a bank loan) for car leasing and vehicle periodic maintenance to the result of step 1, we obtain the total fixed costs in step 2.

m. Interest costs for initial investment
Most people cannot afford or do not want to use their own money to finance this investment, so they obtain a bank loan and pay interest. European Central Bank (2025) data indicate the composite cost of borrowing for non-financial corporations with a range

between 1.44% and 2.29%. The model randomly picked a value, multiplied it by the fixed costs and added this value to the fixed costs to find the total fixed costs:

Fixed costs = fixed costs step 2 + (fixed costs step two × interest rate) [11]

Results: step three

Finally, adding the interest cost of getting a bank loan to the result of step 2 provides the total fixed costs for a car-sharing provider.

Variable costs

Variable costs in car-sharing consist mainly of fuel costs, regular maintenance costs and electronic payment fees.

a. Fuel costs
Electric vehicles are becoming more prevalent in the car-sharing market. The researchers compared electric, petrol and diesel vehicles to calculate each trip's fuel cost. Electric cars average 0.201 kWh per kilometre, with costs ranging from €0.14 to €0.42 per kilometre per trip. Petrol costs range from €0.24 to €0.86 per kilometre per trip. The model selected variable fuel costs between €0.14 to €0.86.

b. Periodic maintenance
Field research estimated periodic maintenance to be between €0.40 and €0.90 per trip. These costs consist of parking costs, periodic vehicle inspection for damage, changing engine oil, water and tyre degradation.

c. Electronic payment fee
Four main market players controlled most of the online transactions. The average online payment fee, weighted by usage, was 1.97%.

Taxes

The research goal was to find the critical mass that achieves the breakeven point. Trade, corporation and income taxes are thus not relevant to the breakeven analyses. Payroll tax was already considered in the gross costs of employees, and church tax applies only to the cases of businesses affiliated with churches, which is not the case in car sharing. This leaves only Value Added Tax, so taxes are considered as a variable cost.

Prices

Real market prices from October 2022 for Share Now, SIXT share and WeShare were used. Share Now, SIXT and WeShare offer minute-based tariffs based on car model, service length and kilometres travelled. The model calculates the average price per trip, randomly selecting a trip duration between 25.8 and 33.8 minutes. The model multiplies the randomly chosen trip duration by the selected price for each car-sharing company, resulting in three prices per trip. The model randomly selects one of these prices, subtracts variable costs and calculates the contribution margin per trip.

$$CM = P - C_V \qquad [12]$$

Dividing total costs (C_T) by CM estimates how many trips are needed by all cars to cover C_T.

Expected use of service

The same person may use car-sharing more than once in the same day (for example, to and from work), so we must know the number of daily trips. This can be computed as:

*(number of cars * average #trips per car) / population size* [13]

Habibi et al. (2017) conducted a study to analyse how often and when people use free-floating car-sharing services in Berlin. They found that there were 3,774 vehicles available and that, on average, each vehicle was used 5.3 times per day. According to official records, 3,711,629 people were living in Berlin on December 31, 2017. Using a formula, the expected usage rate of free-floating car-sharing services was calculated to be 0.5389%. However, the adoption rate of this service has increased by 48% since then, bringing the current rate to 0.7975% (Habibi et al., 2017). Network effects (Evans & Schmalensee, 2010) may cause additional people to start using car-sharing services, because the utility increases as other users join the network. As new cars enter the market, this will attract even more consumers. In fact, since 2017, car-sharing users have grown by 48%. Thus, a more appropriate derived value for the EUS (0.7975%) should be used as explained above. The model uses a 10% yearly growth in the usage rate for the next seven years based on bankruptcy time horizons. However, the critical mass value is a single value that suggests whether it is viable to start an entity at a given moment in time. To consider possible growth rates, the model has to randomly add to the original value of 0.7975% an additional value between 0% and 0.7566%. By doing so, it considers a pessimistic scenario in which the market does not grow at all and an optimistic scenario in which the market keeps on growing by 10% each year, as well as all possible scenarios between these two extremes. The final formulation to estimate the EUS follows:

*EUS = 0.007975 + rnd() * 0.007566* [14]
where *rnd()* randomly generates a value between 0 and 1.

Many other research studies have tried to determine the EUS of car sharing. Becker et al. (2017) analysed user groups and potential usage patterns in Swiss cities. Wappelhorst et al. (2014) studied the potential adoption rate of electric car sharing in rural and urban areas. Data could also be obtained through surveys or directly from car-sharing providers.

Available equivalent services

To determine the AES for a new entity entering the market, we need to consider the number of vehicles required to cover fixed costs, which varies according to the random pick within an array. The model predicts that around 27 cars would be needed to cover fixed costs of €263,404 and provide approximately 31,200 trips per year, resulting in a total of 5,841 AES (including the new entity's 27 cars). Having calculated the AES, we have retrieved the last piece of the puzzle and can apply it to our formula for calculating the necessary critical mass: *N = (SP × EUS) / AES.*

Findings and discussion

The results show that, given the conditions of the Berlin market, the lowest critical mass can be found at 1,122,102 people. In other words, at a population under this value, no company has the possibility of being successful, so if Berlin had fewer than 1.1 million residents, no rational car-sharing provider would offer service there. However, as humans are not fully rational and there may be an information asymmetry, some businesses could decide to offer their services in these areas anyway, but these would fail in short order due to unprofitability. The results thus show that as the resident population size grows, so does the likelihood of success. According to the model, unless there are cases of particularly bad management or unexpected critical events (e.g., earthquakes, pandemics, etc.), with a population size of approximately 5.8 million, car-sharing companies would have a 100% probability of being successful and covering all their costs. Although these results refer strictly to Berlin's conditions, it is still possible to conclude that it would be hard to offer such a service in small residential areas, therefore proving the urban-rural divergence.

As presented in Table 1, the Monte Carlo simulation was run 10,000 times to determine the number of results that fell into each population size category, highlighting the number of instances in which a company was successful based on population size. Summing up the successful cases allows calculating the likelihood of a car-sharing provider being successful. The results are presented as a percentage, which represents the likelihood of a car-sharing provider being successful based on the corresponding population range.

Table 1. Likelihood of a car-sharing business being successful according to the resident population size, given the Berlin market situation

Population size	Number of cases in which the corresponding population size allowed the car-sharing entity to achieve its critical mass	Likelihood of achieving critical mass (non-cumulative)
0 - 200,000	0	0.00%
200,001 - 400,000	0	0.00%
401,000 - 600,000	0	0.00%
600,001 - 800,000	0	0.00%
800,001 - 1,000,000	0	0.00%
1,000,001 - 1,200,000	329	3.29%
1,200,001 - 1,400,000	606	9.35%
1,400,001 - 1,600,000	713	16.48%
1,600,001 - 1,800,000	761	24.09%
1,800,001 - 2,000,000	895	33.04%
2,000,001 - 2,200,000	856	41.60%
2,200,001 - 2,400,000	833	49.93%
2,400,001 - 2,600,000	771	57.64%
2,600,001 - 2,800,000	843	66.07%
2,800,001 - 3,000,000	699	73.06%
3,000,001 - 3,200,000	528	78.34%
3,200,001 - 3,400,000	494	83.28%
3,400,001 - 3,600,000	443	87.71%
3,600,001 - 3,800,000	303	90.74%
3,800,001 - 4,000,000	248	93%
more than 4,000,001	678	100%
Total	10,000	

Source: own processing

Given Berlin's population of 3,711,629 people, car-sharing companies offering their services there enjoy a very high probability of being successful (approx. 91%), which explains its competitive market in which many providers operate and why those entities manage to make a profit. It also explains why new companies may be interested in joining the market. Importantly, these values were calculated strictly based on costs, prices, EUS and AES sustained by car-sharing providers in the Berlin area, so they are likely to change in other areas and are expected to increase in rural settings, which would further confirm our conclusions.

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These findings are consistent with prior work demonstrating that car-sharing viability depends strongly on utilisation intensity and fleet availability in dense urban settings. Higher trip frequencies and vehicle-accessibility levels, as documented in Berlin and other metropolitan areas (Habibi et al., 2017; de Lorimier & El-Geneidy, 2013), correspond to the population ranges in which the model identifies the steepest increases in viability. Likewise, research on adoption determinants has shown that car-sharing functions effectively only when sufficient demand concentration is present and when users face reliable service levels (Kim et al., 2017; Namazu & Dowlatabadi, 2018). The observed urban–rural divergence aligns with evidence that car-sharing programmes tend to struggle in less densely populated regions due to weaker network effects and limited scale (Illgen & Höck, 2020; Wappelhorst et al., 2014). Furthermore, the finding that high population thresholds are required echoes earlier studies on critical mass in platform markets, which emphasise the importance of achieving sufficient usage volume for economic sustainability (Evans & Schmalensee, 2010).

Taken together, the results extend this literature by quantifying these relationships in a cost-based framework and illustrating how utilisation patterns and competitive availability translate into population-level feasibility. Although the model is exploratory in nature, the threshold patterns are consistent with the expected influence of key economic drivers. Higher variable costs or lower trip prices would increase the required population threshold, whereas higher usage intensity reduces it, mirroring findings in the literature on utilisation and fleet performance in urban car-sharing markets. A qualitative validity check also suggests alignment with real-world outcomes: Berlin's estimated viability probability of around 91% corresponds to its competitive provider landscape, while smaller cities with limited adoption have historically faced market exits. These reflections help situate the simulated probabilities within broader empirical evidence, even though formal back-testing or global sensitivity techniques could not be implemented due to the absence of historical data at comparable granularity.

Contributions and implications

Implications for research

This research proposes a novel approach to identify the critical mass for businesses entering a market, independent of revenue considerations. The model developed for this purpose considers five primary input areas: fixed costs, variable costs, prices, expected service utilisation and the availability of equivalent services. By focusing on cost-centric thresholds rather than revenue-centric metrics, this approach offers a unique perspective on the foundational requirements for businesses venturing into a market. The model encompasses a holistic framework by considering the five crucial input areas, ensuring a nuanced analysis that integrates multifaceted elements impacting market entry viability. By delving into fixed and variable costs alongside pricing and service utilisation expectations, this research provides a comprehensive understanding of cost dynamics. This holistic view enables a more robust evaluation of the feasibility and sustainability of market entry strategies. The model's incorporation of the available number of equivalent services adds a layer of realism to the analysis. Understanding the competitive landscape and the market saturation level is pivotal in making informed decisions regarding market entry. The insights derived from this research have direct implications for new entrants. Understanding the critical mass necessary for successful market penetration, devoid of revenue considerations, offers actionable insights and guidance for businesses aiming to establish themselves in a competitive market environment. Overall, this research proposes a cost-centric approach to determine the essential thresholds for market entry while accounting for diverse input parameters critical to business decision-making in dynamic market landscapes, such as car sharing. By providing a realistic, comprehensive analysis of the requirements for market entry, this research can help new entrants make informed decisions and establish themselves successfully in a competitive market.

Implications for urban planners and policymakers

This study introduces a simulation-based decision support tool that can assist urban planners and policymakers in evaluating the viability of car-sharing services across diverse population settings. It highlights the minimum population density required for car-sharing services to become profitable and can inform business decisions regarding expansion into rural areas. The declining rural populations in many regions make it increasingly important for businesses to evaluate their chances of success and survival in these areas. The model is a transparent planning tool that can be used to anticipate the spatial dynamics of shared mobility. This enables urban mobility infrastructure to be distributed more efficiently. It also supports the development of adaptive, location-specific planning, allowing for simulation of future scenarios based on factors such as dynamic cost structures, pricing schemes and demographic trends.

Consistent with Hahn et al. (2020), it is important to recognise that an optimal car-sharing model may come with high costs. This could directly impact the price and user base of the service, reducing its economic feasibility. Therefore, car-sharing providers should evaluate different business models based on their economic viability. For instance, they should determine the monthly fee required to offer a free-floating, full-service model that operates exclusively on electric vehicles. However, this monthly fee could discourage some customers who need the service only in emergencies, and they may not find it financially viable to use such a programme. By determining the minimum population thresholds required to achieve cost-covering operation, the model enables evidence-based decisions about where such mobility services can be efficiently deployed, and where public intervention may be necessary to bridge viability gaps. The models' most transformative potential lies in public-sector application: it equips policymakers with a robust method to assess the territorial feasibility of platform-based services and supports the design of targeted incentives to counteract urban–rural disparities. As such, it aligns with broader goals of sustainable urban transition, equitable mobility access and evidence-based transport governance.

Overall, this article presents a model that can be adapted to specific regional needs and guide policymakers in making informed decisions about resource allocation. One potential application of the model is to help policymakers find the appropriate level of financial grants for regions that do not meet the threshold. This would help to promote economic development in rural areas, which may be struggling due to a lack of investment in infrastructure, education and other areas. By identifying areas that require the most investment and allocating resources accordingly, policymakers can work towards creating economic opportunities in rural regions. Table 1 also indicated the population ranges in which viability shifts most markedly. Berlin's position at 3.71 million residents, with an estimated 91% probability of cost-covering operation, falls within a range where further increases in population size yield only limited additional gains. In contrast, regions below approximately 2.6–3.0 million residents exhibit the steepest improvements in viability with rising population. This pattern helps identify where limited public support or facilitation measures may have the greatest effect on enabling service provision. Service-based businesses operating in rural areas, those seeking to expand and start-ups in the sharing economy can benefit from the findings presented here and can make more informed decisions regarding their operations and pricing strategies. The present contribution asserts that policymakers could benefit from using practical, transparent tools to allocate resources in different areas and reduce the ongoing divergence between rural and urban areas of interest.

Limitations and further research

This research presents a model for new car-sharing businesses, with some limitations. The model may not be directly applicable to existing companies seeking expansion. Furthermore, assigning higher probabilities to lower-cost options is crucial for cost-effective alternatives. In regions with high tourism, the minimum density of inhabitants

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required for profitability may be lower due to an influx of tourists, influencing the model's outcomes. Future research could explore its ability to analyse services other than car-sharing, but the location of rural areas could be a potential limitation. The accuracy of the model may be limited by factors such as the pricing dynamics and cultural norms of the area. To refine the model, future research should examine unaddressed variables, such as the impact of tourists on car-sharing services, the spatial dynamics between rural and urban areas and the network effect's influence on usage patterns. Another limitation concerns the assumption that available equivalent services are homogeneous in appeal. Due to the absence of detailed public data on fleet composition, coverage quality and service differentiation, AES is modelled as an aggregated, unweighted measure. Future studies could incorporate weighting schemes once more granular and comparable data become available.

Conclusions

Our study contributes to understanding the challenges of implementing services such as car-sharing in rural areas. Previous studies have highlighted the ambiguity in consumer adoption or non-adoption. Through simulation, we demonstrate that providing car-sharing services in rural areas is unfeasible or can be sustained only at significantly higher costs. Our approach offers valuable insights into the cost-intensive nature of providing services in such areas. It can serve as a reference point for policymakers, businesses and researchers grappling with the complexities of rural service accessibility and sustainability.

Taken together, the results indicate that the minimum population threshold for cost-covering operation in the Berlin context is approximately 1.12 million residents, with viability rising to around 91% at Berlin's current population of 3.71 million and reaching the top probability band in large metropolitan areas. These figures reinforce the substantial urban–rural divergence suggested in earlier studies and illustrate the scale required for shared-mobility services to operate sustainably. The conclusions should be interpreted in light of the model's scope and assumptions, including the Berlin-specific parameterisation, the use of EUS and AES to translate service requirements into population thresholds and the reliance on independent, uniformly distributed inputs. For practical application, this study offers planners a transparent way to identify population ranges in which viability increases most markedly and to determine where targeted facilitation or support measures may be most effective.

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Appendix

Website	Category	Sub-category
https://rocketreach.co/umi-urban-mobility-international-gmbh-profile_b452bb71fc8d4b76	Fixed costs	Gross employment costs
https://teleport.org/cities/berlin/salaries/	Fixed costs	Gross employment costs
https://www.salaryexpert.com/salary/job/secretary/germany/berlin	Fixed costs	Gross employment costs
https://www.bmf-steuerrechner.de/	Fixed costs	Gross employment costs
https://www.opi.net/news/channel/003-wholesalers/united-stationers-office-supply-spend-across-business-size/	Fixed costs	Office equipment & other utilities
Industrial electricity prices including tax in Germany 1998-2022 | Statista	Fixed costs	Office equipment & other utilities
https://www.companyformationgermany.com/	Fixed costs	Company funding costs
https://russianvagabond.com/cost-of-setting-up-business-in-germany-how-much-will-you-need/	Fixed costs	Company funding costs
https://allaboutberlin.com/guides/start-a-business-in-germany	Fixed costs	Company funding costs
https://fulfilli.com/web-development-costs/?de	Fixed costs	Web development costs
https://www.salaryexpert.com/salary/job/manager/germany/berlin	Fixed costs	Owner's wage
https://www.investopedia.com/best-car-rental-software-5091851	Fixed costs	Car-sharing app/software
https://www.softwareworld.co/best-car-rental-software/	Fixed costs	Car-sharing app/software
https://sourceforge.net/software/car-rental/	Fixed costs	Car-sharing app/software
https://jugnoo.io/taxi-software/pricing/	Fixed costs	Car-sharing app/software
https://www.capterra.com/p/135421/Car-Rental-Software/	Fixed costs	Car-sharing app/software
https://www.thebalancesmb.com/best-car-rental-software-5119211	Fixed costs	Car-sharing app/software
https://www.sixt-neuwagen.de/leasing/vw-volkswagen/up/schraeghecklimousine	Fixed costs	Car leasing costs
https://sdw.ecb.europa.eu/reports.do?node=1000004935	Fixed costs	Interest costs for the initial investment
https://www.globalpetrolprices.com/Germany/electricity_prices/	Variable costs	Fuel costs
http://urn.kb.se/resolve?urn=urn:nbn:se:hh:diva-35485	Variable costs	Fuel costs
https://doi.org/10.1016/j.trc.2021.102966	Variable costs	Fuel costs
https://www.mylpg.eu/stations/germany/prices	Variable costs	Fuel costs
https://cmspi.com/eur/blogs/scheme-fees-in-germany/	Variable costs	Electronic payment fees
https://www.iamexpat.de/career/entrepreneur-germany/business-taxes	Taxes	
https://www.share-now.com/de/en/pricing-berlin/#footnotes	Prices	
https://www.sixt.de/share/car-sharing/berlin/#/	Prices	
https://www.we-share.io/de/berlin	Prices	
https://www.berlin.de/umweltatlas/en/land-use/population-density/2017/map-description/	Expected Use of Service	
https://www.statista.com/study/26783/car-sharing-in-germany-statista-dossier/	Expected Use of Service	
http://urn.kb.se/resolve?urn=urn:nbn:se:hh:diva-35485	Expected Use of Service	
https://www.statista.com/study/40459/mobility-services-report/	Expected Use of Service	