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Data-driven vertiport siting: A comparative analysis of clustering methods for Urban Air Mobility

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ABSTRACT

Urban Air Mobility (UAM) has emerged as a promising solution to enhance metropolitan urban mobility. A critical determinant of UAM's success is vertiport siting, which directly influences accessibility and travel time benefits. However, existing research lacks a evaluation of different data-driven clustering approaches for vertiport placement. This study systematically compares six clustering-based vertiport allocation strategies against an expert-defined benchmark (OBUAM) in the Munich Metropolitan Region (Ploetner et al., 2020). More specifically, the travel time efficiency improvements, accessibility enhancements, and transport equity impacts are assessed across different allocation scenarios. Results indicate that clustering-based siting significantly outperforms expert-defined siting in all the three perspectives. Notably, the K-means++ approach achieves the highest travel time saving (10.05%), accessibility gains (7.16%) and the lowest Gini coefficient (0.512), demonstrating its advantages in planing vertiport locations. The inferiority of DBSCAN, OBUAM and MS scenarios reveals that neither concentrating vertiports excessively in urban centers nor distributing them too evenly across the region optimizes transport efficiency. All clustering-based methods offer a practical, data-driven alternative that does not rely on domain expertise or excessive computational resources, making them easily adaptable for real-world UAM planning. Sensitivity analyses further explore the influence of key parameters on the indicators. Findings highlight that reducing pre-flight time has a more significant impact on travel time saving, accessibility and equity than increasing UAM cruise speed, while higher fares significantly disproportionately reduce accessibility benefits and equality.

1. Introduction

As cities continue to face unprecedented growth and mobility challenges, traditional transportation systems are struggling to meet increasing demand and efficiency requirements. In densely developed urban areas, the physical and economic limitations of expanding ground-based transport infrastructure have prompted researchers to explore alternative mobility solutions in low-altitude airspace (Adamidis et al., 2024; Ploetner et al., 2020; Pukhova et al., 2021; Rothfeld et al., 2021). Urban Air Mobility (UAM) has emerged as a promising solution to complement existing transportation networks, offering potential relief to congested urban corridors and introducing new dimensions to urban mobility (Straubinger et al., 2020). Existing research has underscored a number of socioeconomic benefits and opportunities achievable through the integration of UAM into prevailing transportation systems. Tuchen et al. (2022) qualitatively asserted that UAM development could stimulate job creation through the manufacture of aircraft-related materials and vertiport construction. Moreover, both business and community development could be amplified, especially in the vicinity of manufacturing centers and vertiports. Numerous studies have also explored the potential of UAM as a solution for freight transportation (Gunady et al., 2022; Rifan et al., 2023). These studies collectively suggest that UAM could revolutionize the logistics industry, primarily due to its rapid and efficient transport capabilities. UAM could potentially ease the transportation of goods to remote areas, which are often inaccessible via conventional transportation modes. Additionally, UAM has the potential to provide high-performance services for emergency traffic or commuting trips between rural, suburban, and urban areas to improve the citizen's accessibility (Pukhova et al., 2021).

However, it is important to note that fully commercialized UAM services do not yet exist, and as a result, most research on their economic benefits remains conceptual and qualitative. The direct quantification

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of UAM's economic advantages in monetary terms is challenging, primarily due to the lack of definitive benchmarks for costs, pricing, and other financial factors. Consequently, mainstream UAM studies typically rely on indirect indicators to assess potential economic implications. One such indicator is the potential reduction in travel times and in-vehicle durations (Rothfeld et al., 2021). Naser et al. (2021) conducted a case study in Hamburg, Germany, comparing trips by taxicabs and air taxis (UAM). Their analysis suggested that air taxis could reduce travel times by up to 50% and cover distances up to 16% shorter than taxicabs. Another widely used indirect economic indicator is accessibility to job opportunities. As highlighted by Rothfeld (2021), in a baseline scenario featuring 14 stations, a UAM cruise speed of 180 km/h, and a 15 min processing time, 97% of the regions in the Munich metropolitan area experienced improved accessibility. Based on this information, the study continues to rely on indirect indicators, specifically "travel time efficiency", "accessibility to job opportunities" and "transport equity", to assess UAM's socioeconomic benefits.

The performance of UAM service is influenced by various parameters, including the number and location of vertiports, speed, number of seats, passenger processing time, etc. Central to the successful implementation of UAM systems is the strategic siting of vertiports - the ground-based infrastructure that enables take-off, landing, and passenger processing (European Union Aviation Safety Agency (EASA), 2021; Holden & Goel, 2016). The location of these facilities directly impacts the effectiveness of UAM in enhancing urban mobility (Mendonca et al., 2022; Ploetner et al., 2020). Lim and Hwang (2019) emphasized that the feasibility of UAM is more determined by the location of vertiports than their number, especially when integrated with public transport. To date, no research has quantified the extent to which the allocation of vertiports could influence the performance of UAM services when the number of vertiports is fixed. Accordingly, this study aims to investigate the impact of the UAM vertiport locations on the performance of travel time saving and accessibility improvement.

The case study of this paper located in Munich Metropolitan Area (Europäische Metropolregion München e.V. association, EMM for short), which has an approximate population of 4.5 million and encompasses 444 municipalities (Ploetner et al., 2020). The core cities include Munich, Augsburg, Ingolstadt, Landshut and Rosenheim. The geographical scope of the study area coincides with that of previous UAM studies conducted in the same region (Arellano, 2020; Ploetner et al., 2020; Rothfeld, 2021; Rothfeld et al., 2021). In order to conduct spatial analysis like accessibility assessments of UAM performance in the study area, Traffic Analysis Zones (TAZs) are necessary. In the field of transportation analysis and planning, TAZs are frequently utilized to model and analyze transportation demand and travel patterns and to generate the resolution at a more detailed level compared to larger regions. The delineation of TAZs is typically determined by land use patterns and population density. For this study, the zoning system aligns with the postal code zones for Germany, resulting in the division of the study area into 618 zones.

2. Literature review

Since vertiport siting is a complex urban planning challenge, the first step is to identify the key factors that should be considered. Through a comprehensive literature review, this study synthesizes the primary siting criteria identified in recent research (Antcliff et al., 2016; Arellano, 2020; Fadhil, 2018; Kim & Park, 2022; Otte et al., 2018; Ploetner et al., 2020; Rajendran & Srinivas, 2020). Fig. 1 presents these factors in a weighted visual representation, where font size corresponds to citation frequency in the literature. Analysis of recent studies reveals several recurring factors that are critical for vertiport siting. Density emerges as a key consideration, encompassing multiple dimensions: demand density (Rajendran & Srinivas, 2020), population density (Fadhil, 2018), and job density (Fadhil, 2018). The importance of demand is consistently emphasized across different aspects, including travel

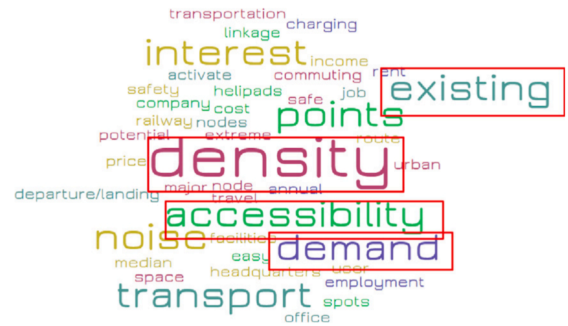


Fig. 1. Word cloud of UAM vertiport siting influential factors.

demand Arellano (2020), commute demand Fadhil (2018), and demand induction (Rajendran & Srinivas, 2020). Accessibility also plays a crucial role, with studies highlighting service accessibility (Holden & Goel, 2016) and employment accessibility (Arellano, 2020). Additionally, integration with existing infrastructure, particularly helipads and transportation systems (Fadhil, 2018), is consistently identified as vital. These key factors highlight three essential considerations for vertiport placement in urban mobility systems: alignment with travel demand patterns, seamless integration with existing transportation networks, and enhancement of metropolitan-wide accessibility.

Previous studies have employed a range of quantitative and qualitative methods to determine appropriate locations for UAM stations. Qualitative methods were commonly used in early UAM studies for vertiport allocation. For example, Antcliff et al. (2016) proposed utilizing existing water barges, highway overpasses, and private tech business campuses as potential vertiports in their case study of Silicon Valley, Northern California, USA. Similarly, in North Rhine-Westphalia, Germany, Otte et al. (2018) suggested repurposing existing airfields as UAM stations. However, such qualitative approaches heavily rely on short-term constraints, such as existing infrastructure and land-use patterns, making it difficult to integrate them with the long-term travel demand potential of UAM. To address these limitations, Ploetner et al. (2020) developed a more comprehensive approach as part of the OBUAM project, specifically focusing on the EMM region. In this project, UAM vertiport locations were manually determined by experts in a workshop, resulting in low-, medium-, and high-density UAM networks with 24, 74, and 130 stations, respectively. The OBUAM project serves as a critical reference framework for subsequent studies, and this paper also uses the medium-density scenario from that project as a comparison group. However, due to its manual nature, this method is challenging to apply directly to other regions with different land-use characteristics and traffic demand patterns. To overcome these challenges, Arellano (2020) introduced a demand-based, semi-automatic vertiport siting approach for the same study area. Their methodology utilized a GIS-based multi-criteria decision analysis framework, incorporating key factors influencing vertiport placement, ranking them, and establishing a systematic siting framework. However, their findings indicated that this method resulted in lower trip time savings compared to the manually designed networks in the OBUAM project (Ploetner et al., 2020).

A widely used quantitative method for vertiport allocation is clustering, which involves dividing demand points into clusters to identify potential vertiport locations. Lim and Hwang (2019) extracted commuter origins from existing data in the Seoul Metropolitan Area, Korea, and applied K-means clustering to determine suitable vertiport locations by identifying cluster centroids. Jeong et al. (2021) expanded on this approach, integrating population and commuter demand data for the same study area. In another study conducted in Los Angeles, USA, and London, UK, Holden and Goel (2016) employed a combined approach using the K-means clustering algorithm and network optimization to maximize trip coverage. Their results indicated that with

25 stations, UAM could accommodate 60% of long-distance trips in Los Angeles and 35% in London. Another category of quantitative UAM vertiport siting methods is optimization-based siting. Most previous studies aim to minimize travel time (Rothfeld, 2021; Willey & Salmon, 2021), minimize travel cost (Guo, 2024; Wu & Zhang, 2021), maximize profitability (Rath & Chow, 2022; Wang et al., 2022), or maximize UAM ridership (Rath & Chow, 2022). Optimization-based methods guarantee optimal or near-optimal solutions with respect to the objective function. However, they require substantial computational resources to solve large-scale NP-hard problems, particularly when integrated with existing transportation systems (Wu et al., 2025). Conversely, clustering-based methods are computationally efficient, easy to implement, and require minimal expertise. Additionally, they are inherently demand-oriented and, according to Guo (2024), outperform optimization-based methods in terms of demand coverage. Therefore, this study adopts clustering-based methods to explore their potential and effectiveness in the vertiport siting problems.

The literature review highlights existing applications of clustering for vertiport allocation in South Korea, the USA, and the UK. Each study follows a common approach: extracting demand data points and applying clustering algorithms to determine vertiport locations. Previous studies have predominantly utilized K-means clustering for UAM siting, with limited exploration of alternative clustering methods. Additionally, little attention has been given to the critical relationship between vertiport locations and urban accessibility as well as equality. Most prior research has focused on travel time, modal share, and operator profitability, leaving a gap in understanding how vertiport siting decisions affect transportation accessibility and equality across different urban population segments. To address these research gaps, this paper aims to explore the feasibility of various clustering techniques for vertiport location selection and analyze their impact on urban mobility enhancement, specifically in terms of travel time savings, accessibility improvements and transport equity. Identifying the optimal solution falls within the domain of optimization problems, which is beyond the scope of this study.

3. Methodology

3.1. Data sources

For EMM region, an agent-based travel demand simulation model Microscopic Transportation Orchestrator (MITO) was developed by Moeckel et al. (2020), which is based on the OpenStreetMap data and the Simple Integrated Land Use Orchestrator (SILO) (Ziemke et al., 2016) generated synthetic population. The SILO model is calibrated to closely match observed land use changes from 2000 to 2010 through backcasting (Moeckel et al., 2020). When generating travel demand, the number of trips for each household is determined using Monte Carlo sampling, while household travel time budgets are estimated based on trip purpose, household size, income, and other relevant household variables. Commuting trip destinations are predefined in synthetic populations, whereas other destinations are selected using a logit-based choice model that adheres to the available travel time budget. Travel modes are assigned through a nested mode choice model. The preferred arrival times for commuting trips are determined based on an arrival time distribution derived from survey data. Finally, all modules are calibrated, and the MITO model is validated using the German national household survey (Lenz et al., 2010) and observed traffic count data (BASt, 2022) in the EMM area. Since MITO generates travel demand on a microscopic level, the attributes of each individual, such as car ownership, income, age, and education, are all considered when making travel decisions (e.g., mode choice).

Similar to preceding studies (Lim & Hwang, 2019; Ploetner et al., 2020), UAM demand in this study is conjectured from demographic data using the home locations of individuals. Additionally, from the travel demand generated by MITO, it is evident that home-based trips

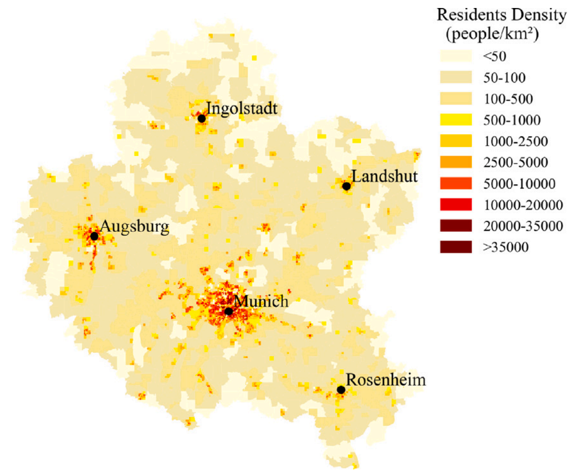


Fig. 2. Residents density in EMM region.

account for the majority of all trips. Therefore, the home locations of the synthetic population were used as the raw demand data point to reflect travel demand and for clustering analysis later. The distribution of home location is visualized as a residents density map and is shown in Fig. 2.

3.2. Vertiports allocation methods

As highlighted in the literature review, K-means clustering is a widely used method for UAM vertiport placement in South Korea, the USA, and the UK. However, limited studies have applied clustering techniques to address vertiport placement challenges in European countries. This study employs five clustering algorithms: DBSCAN, K-means, agglomerative hierarchical clustering, Gaussian mixture model (GMM), and mean shift clustering. To ensure comparability with prior studies (Arellano, 2020; Ploetner et al., 2020), the number of clusters in all algorithms is either predefined or adjusted to 74, resulting in 74 centroids representing vertiport locations. The expert-placed vertiport scenario from the OBUAM project is used for comparison. The OBUAM project consortium conducted four workshops with stakeholders, including representatives from Munich Airport, the Chamber of Industry and Commerce of Upper Bavaria, and the cities of Munich and Ingolstadt. During these workshops, various trip purposes—such as commuting, business, tourism, etc. are considered to inform vertiport placement. The experts were asked to identify relevant locations for each trip purpose, considering coverage of major agglomerations, employment centers, transportation hubs, and densely populated areas with a high share of high-income residents.

3.2.1. K-means clustering

The fundamental concept of this algorithm is to assign data points to K clusters through an iterative procedure, maximizing the similarity of data points within each cluster and minimizing the similarity between different clusters (Hartigan & Wong, 1979). The algorithm follows a process that involves initializing K centroids, calculating the distance between each data point and the centroid, assigning data points to the cluster with the nearest centroid, updating the centroid positions, and repeating this process until convergence. However, clustering results are highly sensitive to the initial location of centroids. The effect of this feature has not been accounted for in all previous studies using K-means clustering in vertiports allocation. In this study, two distinct initialization methods result in two scenarios: one where the initial centroids are set as the OBUAM vertiport locations, referred to as the KM_{OBUAM} scenario, and another where the K-means++ technique is employed for initialization, referred to as the KM++ scenario. The K-means++

algorithm offers an improved initialization approach by selecting initial centroids that are more widely distributed. This smarter initialization leads to enhanced clustering outcomes and reduces sensitivity to initial conditions. Both scenarios employ a total of 74 vertiports, with the number of clusters (K) set to 74.

3.2.2. Gaussian mixture method clustering

The Gaussian mixture model (GMM) is a clustering algorithm that employs a probabilistic model, enabling the inclusion of uncertainty and noise while representing the data distribution. Unlike K-means clustering, GMM does not necessitate spherical-shaped clusters and is better suited for accommodating various cluster shapes. The basic idea of GMM is to consider the data set as a mixture of several Gaussian distributions; each Gaussian distribution corresponds to a cluster. Consequently, the GMM algorithm requires the estimation of the mean, covariance matrix, and cluster weights for each Gaussian distribution. In this specific case, the initialization of GMM clustering utilizes the widely adopted K-means++ method, which is readily available as a built-in parameter in the Python scikit-learn library (Pedregosa et al., 2011), for the same reason to alleviate its high sensitivity to initialization. Alongside initial parameter configurations, the covariance type significantly influences the cluster shape. Experimentation reveals high similarity in centroid (vertiport) distributions with ‘full’, ‘diag’, and ‘spherical’ covariance types. This similarity is further corroborated by the analogous shapes produced by Ripley’s K-function for the three sets of centroids, which is a common measure to characterize spatial patterns of points (Haase, 1995). Conversely, a ‘tied’ covariance type leads to the coalescence of all cluster centers at virtually the same location, an outcome patently unfavorable in practice. Hence, for the construction of the scenario, the ‘full’ covariance type was selected as a representative model. As a hyperparameter, the number of clusters is also set to 74. This scenario is denoted as the GMM scenario.

3.2.3. DBSCAN clustering

DBSCAN (Density-Based Spatial Clustering of Applications with Noise) dynamically discovers clusters based on the density of data points in the feature space. The algorithm identifies core points, which have a sufficient number of neighbors within a specified distance (ε), and non-core points, which are close to core points but have fewer neighbors. By connecting core points and their nearby non-core points, DBSCAN forms dense regions, which represent clusters. Points that do not belong to any cluster are considered noise. DBSCAN is particularly useful for datasets with irregularly shaped clusters, varying cluster densities, and noisy data. The number of clusters can be regulated to 74 by appropriately adjusting the ε and the minimum number of points in the neighborhood for density (MinPts). The vertiports allocation scenario generated by this clustering is denoted as the DBSCAN scenario.

3.2.4. Agglomerative hierarchical clustering

Agglomerative hierarchical clustering treats each data point in the dataset as a separate cluster and gradually merges the most similar clusters until all data points are in the same cluster. The similarity between clusters, in this case, is defined as the Euclidean distance and calculated by the ward linkage method. The ward linkage method aims to minimize the error sum of squares (ESS) by merging two clusters into a single cluster at each step. At the end of clustering, a dendrogram will be generated and could be cut from any level to get different numbers of clusters. This scenario is referred to as the HC scenario.

3.2.5. Mean shift clustering

Mean shift clustering is a non-parametric density-based clustering algorithm. Its objective is to identify clusters in data by iteratively shifting points towards regions of higher density with the utilization of a mean shift vector. The mean shift vector is typically computed using a Gaussian kernel function. The shifting process continues until convergence, where points settle around local maxima. In this algorithm, the number of clusters is not specified in advance but is obtained by adjusting the bandwidth. Increasing the bandwidth leads to a decrease in the number of clusters. After multiple attempts, with the bandwidth set to around 5600, the algorithm yields a total of 74 clusters for the demand points in this case. This scenario is denoted as the MS scenario.

To facilitate a clear comparison of these six clustering algorithms, their core principles, advantages, and shortcomings in vertiport siting problems are summarized in Table 1.

Fig. 3 visualizes the clustering results, displaying the vertiport locations on the map, including those proposed in the OBUAM project (referred to as the OBUAM scenario). In both the OBUAM and DBSCAN scenarios, a high concentration of vertiports is observed in urban areas of major cities and peri-urban regions, with Munich being a notable example. In particular, the DBSCAN scenario exhibits few vertiport sites in rural areas. Since DBSCAN identifies clusters based on data point density, areas with sparse data may not meet the algorithm’s clustering criteria and are labeled as noise. Among the remaining five scenarios, the KM_{OBUAM} scenario stands out with a denser distribution of stations in and around Munich, highlighting the substantial impact of initialization settings in K-means clustering. The HC, KM++, and GMM scenarios exhibit similar spatial distribution patterns, featuring higher vertiport concentrations near Munich and a relatively more even distribution in other regions. Conversely, the MS scenario presents a sparser placement of vertiports near major cities and a more evenly distributed pattern in rural areas, as it requires a larger bandwidth setting to achieve 74 clusters.

3.3. UAM scenario configurations

In this study, all parameters that could influence the travel time of UAM would be determined by the review of previous studies, as shown in Table 2.

3.4. Travel efficiency improvement assessment

For both travel time efficiency and accessibility improvements assessment, travel time is an essential input. The MATSim-UAM extension provides a framework for simulating UAM trips and integrating them into multimodal transport networks. To measure travel time with UAM, we employ the Travel Time Calculator, a component of the MATSim-UAM framework developed by Rothfeld (2021). This tool estimates trip durations based on predefined routing parameters and scenario-specific network constraints. The Travel Time Calculator operates by computing expected UAM travel times based on the following key factors:

- Scenario Network Configuration: The MATSim scenario includes an normal ground network integrated with airspace network composed of predefined vertiport locations, inter-vertiport connections, and associated flight parameters. UAM routes are generated based on network topology and available vertiport infrastructure.
- Trip Segmentation and Routing: UAM travel time is divided into three major phases. Ground access/egress time is modeled using the existing ground transport network for first-mile and last-mile connections. Airborne time is determined based on the direct aerial distance between origin and destination vertiports and aircraft cruise speed. Pre-flight and processing time is predefined and includes check-in, security screening, and potential waiting at vertiports.
- MATSim-based Iterative Simulation: To optimize computational efficiency, the Travel Time Calculator runs as a post-processing module within MATSim, rather than requiring a full simulation for each calculation. A full MATSim simulation is executed in prior to travel time calculations, and the NetworkChangeEvent file—recording congestion states for each link at each time step—is used. This allows expected travel times for each trip to be computed offline while accounting for network congestion.

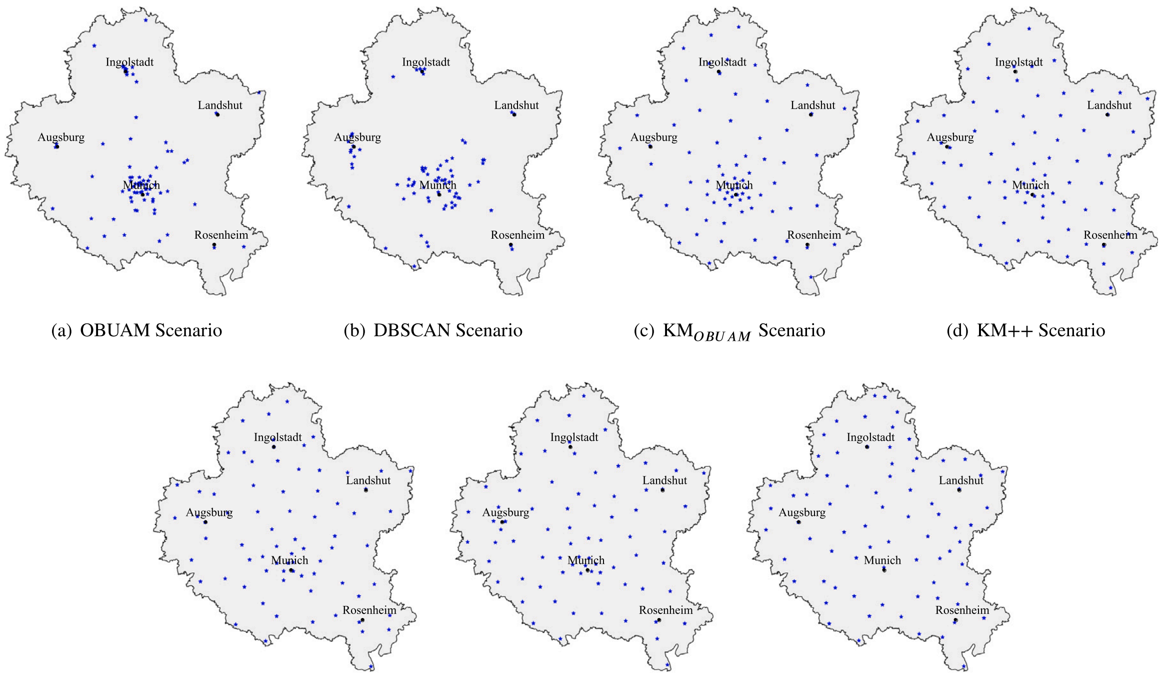
Table 1
Comparison among clustering algorithms.

Algorithm	Core Principle	Advantages for Vertiport Allocation	Limitations for Vertiport Allocation
K-means ++	Iteratively assigns points to clusters by minimizing intra-cluster variance.	• Ensures well-distributed vertiports with balanced demand coverage. • Computationally efficient and scalable for large-scale UAM planning. • Allows control over the number of vertiports, aligning with planning constraints.	• Assumes clusters are spherical, which may not fully capture irregular demand patterns.
DBSCAN	Density-based clustering; forms clusters based on point density.	• Adapts to real-world demand distributions by detecting high-density regions.	• Hard to control the number of vertiports, making planning difficult when a fixed number of sites is required. • Some regions may be classified as noise and excluded from vertiport allocation.
GMM	Probabilistic model assuming data points belong to multiple Gaussian distributions.	• Assigns probability-based memberships, allowing flexible vertiport placements. • Can model overlapping demand areas better than K-means, useful for multi-purpose vertiports. • Allows control over the number of vertiports, aligning with planning constraints.	• Computationally more expensive than K-means.
HC	Builds a tree-based cluster structure by recursively merging or splitting clusters.	• Supports multi-scale planning, making it useful for both regional and local vertiport allocation. • Can be used to evaluate different cluster numbers before final selection.	• High computational cost for large datasets. • Results depend on the chosen linkage method, requiring careful selection.
MS	Identifies dense areas by shifting data points toward local density peaks.	• Suitable for detecting natural demand centers.	• Hard to control the number of clusters, which may lead to too many or too few vertiports for operational feasibility. • High computational cost, limiting scalability in large regions.

Table 2
Overview of key parameter setups.

Parameter	Existing Value Definition(s)	Baseline Value	Values for Sensitivity Analysis
Processing Time	Existing literature defines it as a variable with a wide range, shown below in minutes: 0, 10, 20 (Ploetner et al., 2020); 0, 15, 30 (Rothfeld, 2021); 0, 4, 8, 12 (Balac et al., 2019).	15 min	0, 5, 10, 15, 20, 25, 30 min
Cruise Speed	Ploetner et al. (2020) studied 8 scenarios between 50–350 km/h.	350 km/h	200, 250, 300, 350, 400 km/h
UAM Pricing	Holden and Goel (2016): 1.5 €/pkm (short term), 0.2 €/pkm (long term); Balac et al. (2019): 6.1 €+ 0.6–4.2 €/pkm; Wu and Zhang (2021): 9.2–27.6 €+ 0.5–1.0 €/pkm; Ploetner et al. (2020): 4.94 €/km.	1.0 €/pkm	0.8, 1.0, 1.2, 1.4, 1.6 €/pkm
VTOL Altitude	When flying over cities and dense areas, aircraft should operate 300 m above the highest obstacle; in other cases, 150 m above ground level (Justiz, 2015). For the study area, the height of Olympic Tower defines it to be 591.28 m (muenchen.de, 2023).	600 m	/
Vertical Speed	Experts consulted the performance benchmark of UAM vehicles in Shamiyeh et al. (2018) as 10 m/s.	10 m/s	/

In order to evaluate the time efficiencies in UAM scenarios with various vertiport locations, all trips with motorized transport mode (i.e. car as a driver, car as a passenger, public transport including regional trains) are extracted from the MITO generated trips' data. These trips contain information on origin and destination location, departure time, travel time, mode, and travel distance. By using the Travel Time Calculator mentioned above, the travel times with UAM (if available) for those trips are calculated and compared with their original travel



(a) OBUAM Scenario (b) DBSCAN Scenario (c) KM_{OBUAM} Scenario (d) KM++ Scenario

(e) GMM Scenario (f) HC Scenario (g) MS Scenario

Fig. 3. Vertiports allocation scenarios.

times with ground-based modes. To quantify the improvement of time efficiency, with the same definition in Rothfeld et al. (2021), a time-saving ratio r_{tts} for each trip is defined in Eq. (1). Since this study aims to explore the potential benefits of UAM, only actual improvements brought by UAM are considered. If UAM results in longer travel times than ground transport for a particular trip, the calculated r_{tts} value would be negative. However, in this context, negative values do not represent meaningful "negative improvement"—they simply indicate that UAM does not provide a benefit for that trip. Therefore, the negative values are rounded up to zero, ensuring that r_{tts} exclusively captures actual time savings.

$$r_{tts} = min\{1 - \frac{t_{uam}}{t_{gb}}, 0\} \tag{1}$$

3.5. Accessibility improvements assessment

The success of transportation projects in enhancing urban mobility is fundamentally tied to their accessibility impact—the ease with which residents can reach desired destinations and opportunities (Silva et al., 2023). These measures serve as crucial indicators for assessing how transport infrastructure investments influence inhabitants' participation in socioeconomic activities at the metropolitan scale. Building upon prior research on infrastructure proximity (Büttner et al., 2024; Silva et al., 2023) and service coverage area (Beyazit et al., 2023; Jehle et al., 2022), this study employs a cumulative opportunities measure, as defined by Geurs and Van Wee (2004) and applied in Rothfeld (2021). This integrative approach accounts for both the spatial distribution of opportunities and travel cost impedance, providing deeper insights into accessibility patterns. The applied metric is mathematically expressed in Eq. (2).

$$A_i = \sum_{j=1}^{n} D_j e^{-\beta c_{ij}} \tag{2}$$

Where, A_i is the quantified measure of accessibility in zone i, n is the number of zones, and D_j is the number of job opportunities in zone j. Given the relatively small size of the TAZs used in this study, synthetic trips between zone centroids are used to approximate commuting travel between zones. The notation c_{ij} represents the generalized travel cost for synthetic trips from the centroid of zone i to zone j, calculated as the sum of monetary travel costs and non-monetary travel time. Travel time is converted into monetary values by multiplying it by the VOT. In the case study, VOT is set according to Axhausen et al. (2015) at 4.54 €/h for trips below 50 km and 12.58 €/h for trips exceeding 50 km. The parameter β represents cost sensitivity and plays a crucial role in calculating location-based accessibility using the gravity model. It acts as a trade-off between travel cost and the number of available opportunities when assessing accessibility. A higher β value indicates that as travel costs increase, the weight assigned to distant opportunities declines more sharply. Conversely, a lower β value results in a slower decay, allowing opportunities farther away to retain greater influence. As stated by Geurs and Van Wee (2004), the plausible range of β varies from 0.01 to 1. In this study, we selected $\beta = 0.05$ as the baseline and conducted a sensitivity analysis to evaluate its impact. The accessibility of each zone with ground-based transportation modes and UAM is calculated and compared. The accessibility improvements ratio r_{ai} is calculated accordingly. Unlike the time savings ratio, which is trip-based, the accessibility in this context is zone-based. A mathematical expression is shown in Eq. (3). Similar to the definition of r_{tts}, only actual improvements in accessibility are considered. A higher generalized cost for UAM compared to ground transport of synthetic trips between zone centroids does not indicate a reduction in accessibility for the zone pairs but rather the absence of improvement. Therefore, all negative values of r_{ai} are set to zero.

$$r_{ai} = min\{\frac{A_{uam}}{A_{gb}} - 1, 0\} \tag{3}$$

3.6. Transport equity assessment

Ensuring equitable access to activity opportunities is a fundamental aspect of sustainable urban mobility planning. Transport equity assesses whether different population segments receive fair benefits from accessibility improvements. It is commonly evaluated using distributional measures that quantify how accessibility gains are allocated among various population groups. A widely used approach in transport equity studies is the Lorenz curve, which graphically represents the cumulative share of accessibility improvements against the cumulative share of the population, ordered from least to most advantaged (Qin & Liao, 2022). To quantify equity, the Gini coefficient is derived from the Lorenz curve and measures the degree of inequality in accessibility benefits. A Gini coefficient of 0 indicates perfect equity (equal distribution of benefits across all groups), while a coefficient of 1 denotes maximum inequality (one group receives all the benefits). The Gini coefficient is calculated using Eq. (4):

$$G = 1 - 2\sum_{k=1}^{m} P_k A_k \tag{4}$$

where P_k is the cumulative share of population group k, ordered by accessibility improvement; A_k is the cumulative share of received accessibility improvement (r_{ai}) for that population group; and m represents the number of income groups. The Lorenz curve plots P_k against A_k, providing a visual assessment of equity in accessibility improvements. Since r_{ai} in this study is calculated on a zone-based level (Eq. (3)), the accessibility improvement received by each income group is estimated as the weighted average of r_{ai} across all zones, with the ratio of population size in the respective income group in each zone and the total population serving as the weight.

4. Results

4.1. Travel efficiency improvement

Fig. 4 illustrates the average travel time savings ratio (r_{tts}) for trips over Euclidean distances in 10 km bins across all scenarios. None of the scenarios exhibit significant travel time savings for short trips. The overall trend indicates that the average r_{tts} increases as travel distance grows. The curves display an elbow point at 35 km, suggesting that UAM begins to demonstrate significant time-saving advantages over ground transportation when travel distances exceed this range. However, in the OBUAM and DBSCAN scenarios, the r_{tts} curves reach an inflection point beyond 75 km, meaning that UAM under both vertiport siting strategies fails to deliver greater time-saving benefits as travel distances continue to increase. This seemingly counterintuitive result arises because both solutions overconcentrate vertiports in Munich's urban area while providing fewer vertiports in rural areas and near other cities. Most trips exceeding 75 km occur between Munich and the countryside or between Munich and other cities. Consequently, for these trips, one trip end (either the origin or destination) may have easy access to a vertiport, while the other end may not, limiting overall travel time savings. Interestingly, for extremely long trips (> 145 km), some scenarios—such as HC and MS—also show a declining trend. This occurs due to the limited number of such trips, resulting in a highly fortuitous outcome.

All scenarios could gain a tangible travel time saving when the distance is beyond 25–30 km, which is more optimistic than in Rothfeld et al. (2021) (35–60 km). Moreover, for trips above 40–50 km, an average time saving of over 10% could be achieved by introducing UAM. According to the value of time (VOT) theory (DeSerpa, 1971), this level of time savings can have substantial implications for various stakeholders, including individuals, businesses, and the overall economy. At approximately 45 km, the gap between the DBSCAN and OBUAM curves and the other curves gradually widens, indicating the superiority of other clustering scenarios in travel time saving effects among long distance trips.

Among all clustering scenarios, the DBSCAN scenario performs the worst in terms of time savings for trips longer than 35 km, even underperforming the OBUAM scenario. This is primarily due to its lack of rural vertiports and overconcentration of urban sites. The MS scenario also exhibits slightly inferior performance compared to other methods for trips shorter than 70 km, which can be attributed to its

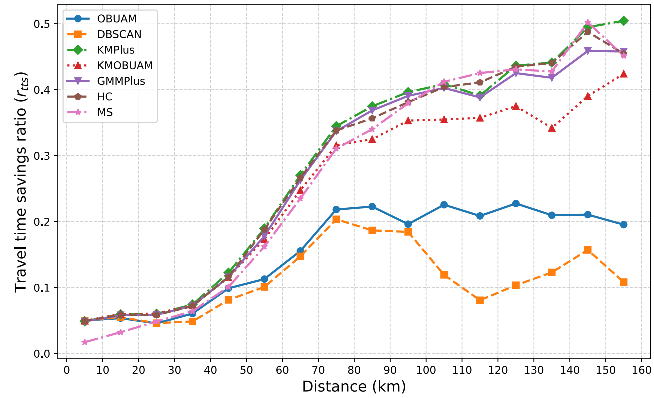


Fig. 4. Average r_{tts} of trips with different distance.

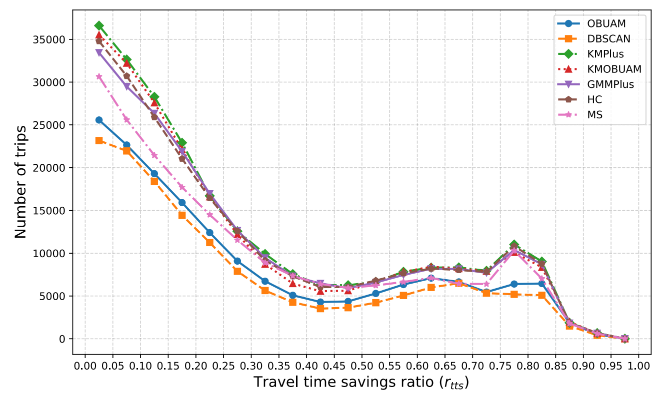


Fig. 5. Number of trips above 25 km in each r_{tts} range.

Table 3
Average r_{tts} of trips above 25 km.

Solution	Average r_{tts} (%)	Number of trips with $r_{tts} > 0$	Number of trips with $r_{tts} > 0.5$
OBUAM	7.26	171425	46042
DBSCAN	6.29	153439	39279
KM++	**10.05**	**241403**	**61684**
KM_{OBUAM}	9.62	232631	60042
GMM	9.71	229545	60575
HC	9.74	230566	60575
MS	8.65	202548	52523

lower number of urban vertiports. As a result, it provides limited time-saving benefits for shorter trips. Conversely, the KM_{OBUAM} scenario demonstrates weaker performance for long trips (> 70 km), which, similar to the OBUAM and DBSCAN scenarios, can be linked to its higher concentration of urban vertiports. This finding further underscores the sensitivity of K-means clustering to initial search points. Since long-distance trips primarily occur between urban and rural areas, a lack of rural vertiports can significantly reduce UAM's time-saving potential. In short, the relationship between the vertiports layout and the travel time saving benefits of UAM could be summarized as follows: sparse rural vertiports (e.g., OBUAM, DBSCAN, KM_{OBUAM} scenarios) limit UAM's time-saving effect for long trips, while a scarcity of urban vertiports (e.g., MS scenario) hinders time savings for short trips.

To provide a more explicit comparison of travel time savings across scenarios, the distribution of trips over 25 km across different r_{tts} bins is plotted in Fig. 5. The x-axis represents r_{tts} values (ranging from 0 to 1 with an interval of 0.1), while the y-axis indicates the number of trips for each r_{tts} interval. Additionally, Table 3 presents the average r_{tts} for all trips exceeding 25 km, along with the number of trips achieving any travel time savings and those with $r_{tts} > 0.5$. From

(a) OBUAM r_{ai} (b) DBSCAN r_{ai} (c) KM$_{OBUAM}$ r_{ai} (d) KM++ r_{ai}

(e) GMM r_{ai} (f) HC r_{ai} (g) MS r_{ai} (h) legend

Fig. 6. Spatial distribution of r_{ai}.

Fig. 5, it is evident that the KM++, KM$_{OBUAM}$, GMM, and HC scenarios include a greater number of trips at all r_{tts} intervals compared to other scenarios, reinforcing their superior performance in travel time savings. The concrete values in Table 3 provide further insights. For example, the KM++ vertiport siting solution resulted in 70,000 more trips with actual travel time savings and enabled over 15,000 trips to achieve more than 50% time savings compared to OBUAM. Conversely, for all trips exceeding 25 km, the time-saving effects of DBSCAN, OBUAM, and MS scenarios are comparatively weaker. These findings demonstrate that placing urban area vertiports either too sparsely or too densely is not conducive to achieving overall time savings. Among all the scenarios, the KM++ scenario demonstrates the most significant time efficiency improvement.

Moreover, given the similarity in shape among the r_{tts} cumulative frequency curves of the seven scenarios, an 2-by-2 Analysis of Variance (ANOVA) is conducted on the r_{tts} of all trips and proves that they are statistically different at a confidence level of 95%. The formal results of ANOVA tests are shown in Table A.1 of Appendix.

4.2. Accessibility improvement

As job opportunity accessibility improvements are assessed using a zone-based approach, it is essential to examine both their spatial distribution and the underlying factors influencing these patterns. Fig. 6 illustrates the spatial variation of r_{ai} across different vertiport allocation scenarios within EMM area, highlighting notable regional disparities. The second column of Table 4 presents the average r_{ai} across all zones, offering a clearer understanding of the extent of accessibility enhancement achieved under different scenarios. This section discusses the observed patterns and their underlying causes.

Extent of accessibility improvement: The KM++ scenario achieves the highest r_{ai} (7.16%), which is 2.5 times that of the DBSCAN scenario, indicating that it provides the most significant accessibility enhancement across zones. DBSCAN and OBUAM scenarios exhibit the lowest average r_{ai}, highlighting their limited effectiveness in improving accessibility. Other scenarios (GMM, HC, MS, and KM$_{OBUAM}$) achieve moderate improvements.

Rural and suburban gains: Accessibility improvements across the EMM region reveal notable regional disparities. The KM++ scenario delivers the most substantial accessibility benefits in rural and peri-urban areas, particularly in counties surrounding Ingolstadt and Landshut, as well as in regions near Weilheim (southwest of the study area). Other clustering-based scenarios (KM$_{OBUAM}$, GMM, HC, and MS) also consistently demonstrate higher accessibility gains in these areas. In contrast, DBSCAN and OBUAM scenarios provide limited accessibility benefits, with only a few rural regions experiencing noticeable improvements.

Limited impact in urban centers: No scenario significantly improves accessibility within Munich and its surrounding areas, despite the presence of multiple vertiports in these locations under the OBUAM and DBSCAN scenarios. Two key factors may explain this: (1) the interaction between travel time savings and opportunity distribution and (2) the competitiveness of ground transportation for short trips. First, accessibility in this study is influenced by both travel time reductions and the spatial distribution of employment opportunities. Munich and its suburban areas already have a high concentration of job opportunities, leading to elevated baseline accessibility levels. Consequently, the potential for additional improvements from UAM is less pronounced compared to rural areas, where employment opportunities are more dispersed. Second, Munich's existing transportation infrastructure is highly developed, featuring an efficient public transit system and well-connected road networks. According to Arbeit (2023), 87.9% of Munich's residents commute within the city or to adjacent counties (e.g., Dachau, Freising, Starnberg), typically covering distances below 20 km. UAM struggles to compete with ground-based transport for these short trips due to additional access/egress times, waiting periods, and security processing. These findings align with previous studies (Pukhova et al., 2021) indicating that UAM is not well-suited for short intra-urban commutes, particularly in cities with robust existing transportation networks.

Similarly, a 2-by-2 ANOVA test is conducted for all zones' r_{ai} of all 7 scenarios. The results indicate that most scenarios are statistically different from others at the 95% confidence level. However, some scenario pairs—GMM and MS, GMM and KM++, GMM and HC, as well as HC and KM$_{OBUAM}$—show no statistically significant differences, even at the 85% confidence level. The formal results of the ANOVA tests are presented in Table A.2 of Appendix.

Table 4
Average r_{ai} of all zones and gini coefficient of all population income groups against r_{ai}.

Solution	Average r_{ai} (%)	Gini coefficient
OBUAM	3.18	0.627
DBSCAN	2.71	0.626
KM++	**7.16**	**0.512**
KM_{OBUAM}	5.98	0.516
GMM	6.67	0.515
HC	6.85	0.527
MS	6.45	0.598

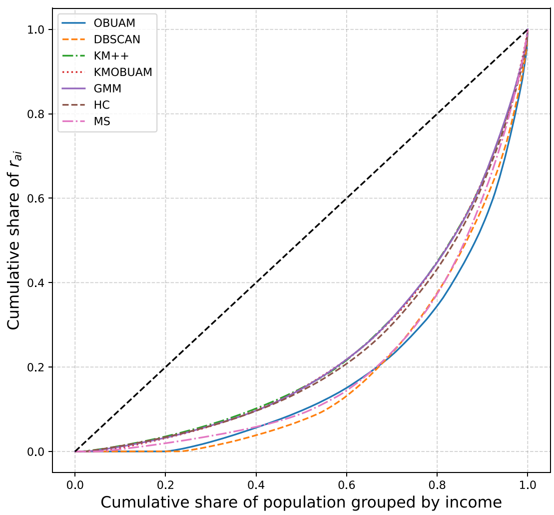


Fig. 7. Lorenz curve for cumulative share of r_{ai} against population income group.

4.3. Transport equity

The results of the accessibility improvement analysis reveal significant spatial disparities in accessibility benefits, particularly between urban and rural areas. This section visualizes and analyzes disparities among different sociodemographic groups. The evaluation of transport equity using Lorenz curves (Fig. 7) and the Gini coefficient (last column in Table 4) provides valuable insights into accessibility disparities across different socioeconomic groups. The findings demonstrate substantial variations in equity among the tested vertiport allocation scenarios, highlighting the crucial role of spatial vertiport distribution in ensuring fair accessibility benefits. Among the siting scenarios, KM++, GMM, and KM_{OBUAM} exhibit the lowest Gini coefficients, indicating a more balanced distribution of accessibility benefits across income groups. The HC scenario shows moderate equity performance with slightly higher Gini values, suggesting that its vertiport placement strategy provides reasonable accessibility improvements for diverse socioeconomic groups. In contrast, the DBSCAN and OBUAM scenarios yield the highest Gini coefficients, indicating severe disparities, as accessibility benefits are highly concentrated in specific zones—primarily in the southwest of the study area, which is considered a typical affluent region. The MS scenario also yields relatively higher Gini coefficient, suggesting that this siting strategy tends to favor certain population groups over others regarding accessibility improvements.

These findings indicate that most clustering-based vertiport siting methods outperform the hand-placed approach used in the OBUAM scenario in terms of transport equity. However, certain clustering methods (e.g., DBSCAN and MS) aggravate existing accessibility inequalities. A key observation from the results is that scenarios prioritizing vertiport placement in urban centers tend to exhibit higher inequity, as accessibility improvements are concentrated in high-income areas while economically disadvantaged zones are overlooked. Interestingly, the MS scenario, which distributes vertiports evenly across the region, also yields relatively high Gini coefficients. This seemingly paradoxical result can be explained by variations in population density and UAM demand elasticity. In low-density suburban and rural areas, evenly placed vertiports may still fail to provide significant accessibility benefits due to lower UAM travel demand, limited transit connections, and fewer job opportunities. Conversely, in urban zones with high population densities, even a small improvement in UAM services can generate substantial aggregate accessibility gains, disproportionately benefiting those regions. This imbalance contributes to a higher Gini coefficient, despite the spatially even distribution of infrastructure throughout the study area. Finally, scenarios demonstrating superior equity performance emphasize a more balanced vertiport distribution, ensuring that a larger proportion of the population benefits from UAM services.

5. Sensitivity analysis

The performance of UAM services is highly dependent on key operational and sensitivity parameters, such as cruise speed, pre-flight processing time, UAM fare and cost sensitivity parameter (Ploetner et al., 2020; Wu & Zhang, 2021). Understanding the impact of these parameters is crucial for assessing UAM's effectiveness in enhancing travel time efficiency, accessibility and transport equality. This section presents a structured sensitivity analysis to evaluate how variations in these parameters influence the key socioeconomic benefits brought by UAM.

5.1. Impact on travel time savings

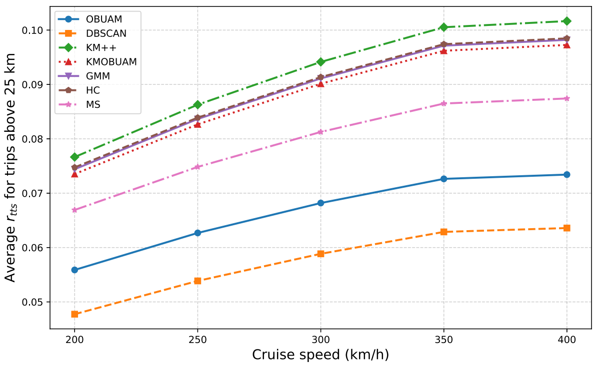
Fig. 8 illustrates the variation in average travel time savings ratio (r_{tts}) for long-distance trips (≥ 25 km) under different cruise speed and pre-flight processing time settings. The results indicate the following:

- **Cruise speed**: Increasing cruise speed leads to higher travel time savings, but the effect is marginal for medium-distance trips. For instance, raising the cruise speed from 250 km/h to 350 km/h reduces travel time by only two minutes on a 30 km route.
- **Pre-flight processing time**: Reducing pre-flight processing time has a more significant impact on travel time savings, exhibiting a near-exponential relationship. This suggests that optimizing pre-flight procedures may be more effective than merely increasing cruise speed, particularly for metropolitan UAM applications where trip distances are typically moderate.
- The superiority of clustering-based siting solutions (KM++, KM_{OBUAM}, GMM, and HC) remains consistent across all sensitivity analysis scenarios, reinforcing their robustness in improving UAM travel efficiency.

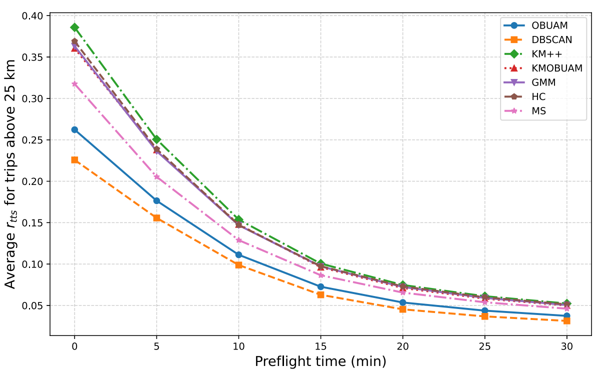
5.2. Impact on accessibility improvements

Fig. 9 illustrates the sensitivity of accessibility improvement (r_{ai}) to variations in cruise speed, pre-flight processing time, UAM fare, and the cost sensitivity parameter (β). The findings reveal the following insights:

- **Cruise speed & pre-flight time:** Accessibility improvements (r_{ai}) exhibit an approximately linear relationship with these parameters. Similar to travel time savings, reducing pre-flight processing time is more effective in enhancing accessibility than increasing cruise speed.
- **UAM fare:** The affordability of UAM services plays a critical role in accessibility enhancement. At lower fares (e.g., 0.8 €/pkm), UAM significantly improves accessibility across study zones. However, even a slight fare increase (e.g., from 0.8 €/pkm to 1.2 €/pkm) substantially diminishes the accessibility benefits, with average r_{ai} approaching zero in most siting scenarios.

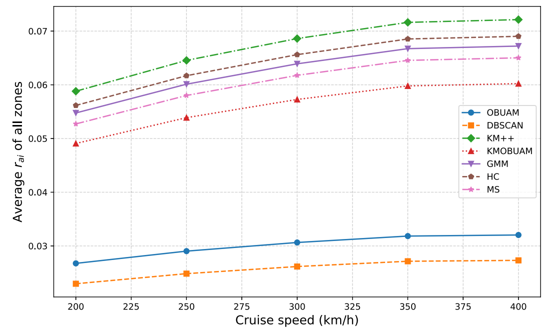


(a) Sensitivity of r_{tts} to cruise speed

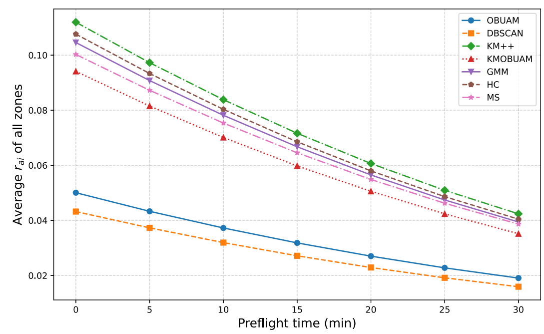


(b) Sensitivity of r_{tts} to pre-flight processing time

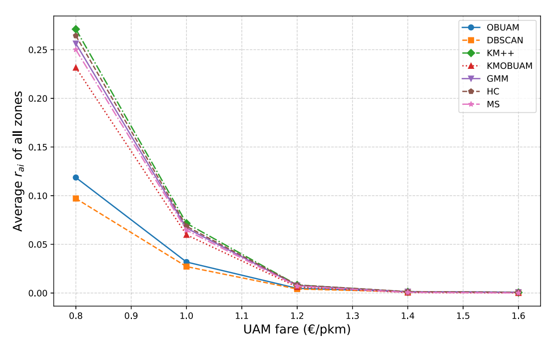
Fig. 8. Sensitivity analysis against travel time saving.



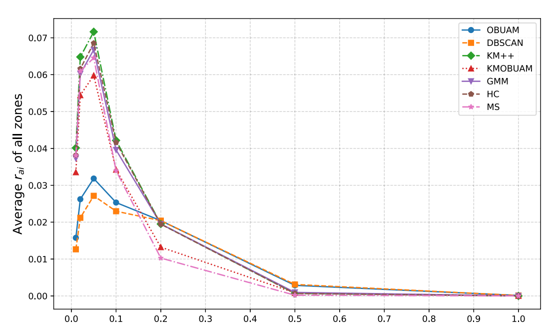
(a) Sensitivity of r_{ai} to cruise speed



(b) Sensitivity of r_{ai} to pre-flight processing time



(c) Sensitivity of r_{ai} to UAM fare



(d) Sensitivity of r_{ai} to cost sensitivity parameter β

Fig. 9. Sensitivity analysis against accessibility improvements.

- **Cost sensitivity parameter** (β): The relationship between β and accessibility is complex and nonlinear. As β increases from 0.01 to 1, r_{ai} first rises, peaking at $\beta = 0.05$, before declining. This suggests that moderately high cost sensitivity parameter leads to the greatest differentiation in accessibility improvements across siting scenarios. Interestingly, when β is increased to 0.2, the OBUAM and DBSCAN scenarios surpass KM_{OBUAM} and MS in accessibility improvement, indicating complex trade-offs between cost and number of job opportunities at different locations by calculating accessibility.

5.3. *Impact on transport equity*

The transport equity assessment is sensitive to variations in key operational and economic parameters. This section presents a sensitivity analysis to examine how changes in pre-flight time, UAM fare, and cruise speed affect the equity of accessibility improvements across different vertiport allocation scenarios. The Gini coefficient is used as the primary metric to evaluate distributional effects, and the results are visualized in Fig. 10.

- Cruise speed: The transport equity of accessibility improvements is relatively insensitive to changes in cruise speed. The Gini coefficients for all scenarios decrease slightly as cruise speed increases and remain nearly stable when cruise speed exceeds 300 km/h.
- Pre-flight time: Pre-flight time represents the additional waiting and boarding time required before departure. As pre-flight time increases from 0 to 30 min, the Gini coefficient increases linearly across all scenarios, indicating growing inequity. Although the slopes vary across scenarios, all Gini coefficients show a significant correlation with pre-flight time.
- UAM fare: Fare levels directly influence affordability and accessibility, particularly for low-income populations. Among these operational parameters, fare exerts the strongest impact on transport equity. As UAM fare increases from 0.8 to 1.6 €/pkm, the Gini coefficients for all scenarios rise sharply, approaching 1 at 1.6 €/pkm, indicating extreme inequality in accessibility improvements. This analysis underscores the necessity of fare subsidies or

tiered pricing models to mitigate equity disparities, particularly in high-fare scenarios.

6. Conclusion

This study evaluates six UAM vertiport allocation scenarios using various clustering algorithms, comparing their impacts on urban mobility through travel time efficiency, accessibility improvements and transport equity. The findings demonstrate how different spatial allocation patterns significantly influence UAM's potential to enhance metropolitan transportation networks.

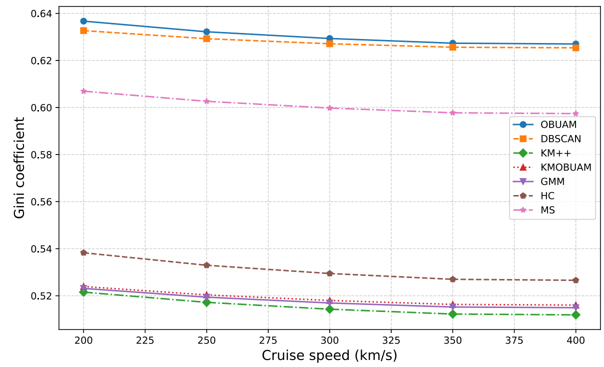
The spatial distribution analysis reveals distinct patterns in vertiport placement, from concentrated urban deployments to dispersed regional allocations. These patterns directly affect UAM's ability to complement existing urban transportation systems. While OBUAM and DBSCAN scenarios focus heavily on Munich's core, potentially reinforcing existing center-focused mobility patterns, other scenarios like KM++ and GMM achieve a more balanced distribution that better serves the broader metropolitan mobility needs, particularly for the rural areas where other transport networks are not as well developed.

The performance analysis reveals that appropriate vertiport placement can significantly enhance regional mobility, particularly for trips exceeding 25–30 km. For longer journeys over 40–50 km, the average travel time-saving ratio exceeds 0.1, indicating UAM's potential to substantially improve regional connectivity. However, the analysis reveals that both extremes of vertiport distribution - excessive urban concentration (as seen in OBUAM, DBSCAN, and KM_{OBUAM} scenarios) and overly sparse distribution (as demonstrated in the MS scenario) - fail to optimize metropolitan mobility in terms of travel time savings. Most clustering scenarios, except DBSCAN, outperform the expert-placed OBUAM scenario in reducing travel time.

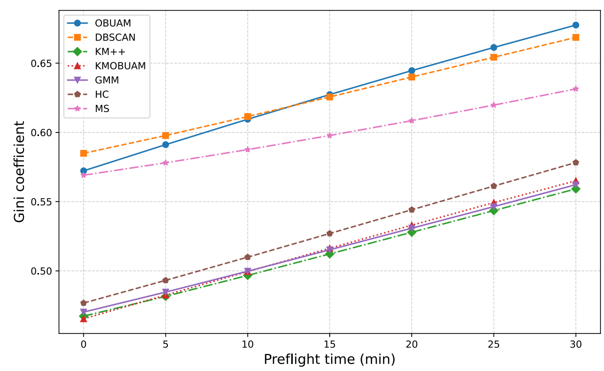
The accessibility analysis further emphasizes how vertiport placement influences the distribution of mobility benefits across the metropolitan region. While all scenarios except DBSCAN surpass OBUAM in improving regional accessibility, their limited impact on Munich's core area suggests the need to carefully consider UAM's role in complementing existing urban transport networks. The KM++ scenario emerges as particularly effective in enhancing metropolitan-wide job opportunities access. The significant performance gap between KM++ and KM_{OBUAM} scenarios highlights how initialization methods can substantially affect mobility outcomes. The transport equity shows a similar patterns as the other two indicators. With the lowest Gini coefficient, KM++ scenario still yields the best equity performance across all scenarios. The expert-placed OBUAM scenario and DBSCAN scenario show inferiority regarding the equity due the excessive number of vertiports in Munich center and the lack of vertiport in rural areas.

The sensitivity analysis for these three indicators against UAM operational parameters illustrated meaningful insights. All of these three perspectives of UAM performance are sensitive to UAM preflight processing time. Travel time saving, accessibility enhancement and transport equity are all less sensitive to cruise speed due to its limited potential in reducing travel time for trips within metropolitan. UAM fare is an extremely important factor that significantly impact the performance of accessibility improvements and equity. These findings imply the necessity of reducing the extra waiting and boarding time in order to increase the social benefits and attractiveness of UAM services. While assessing the accessibility improvements, the cost sensitivity factor in the accessibility gravity-model also show significant and complex non-linear impact on accessibility improvements.

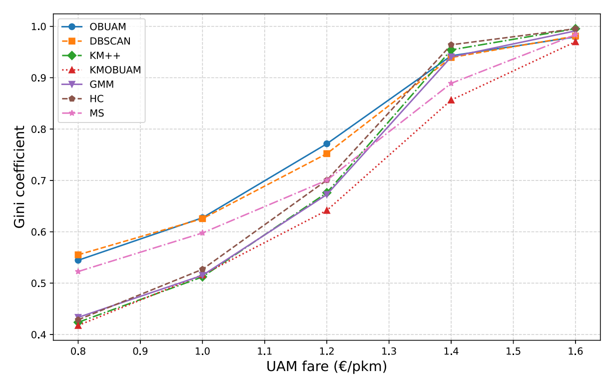
This research demonstrates the value of clustering-based approaches for planing UAM infrastructure placement within metropolitan mobility



(a) Sensitivity of Gini coefficient to cruise speed



(b) Sensitivity of Gini coefficent to pre-flight processing time



(c) Sensitivity of Gini coefficient to UAM fare

Fig. 10. Sensitivity analysis against Gini coefficient.

systems. As cities worldwide explore UAM integration, these methods offer an efficient, reproducible approach to infrastructure planning that can enhance metropolitan accessibility and connectivity. The superior performance of the systematic and data-driven clustering methods over expert placement suggests their potential as valuable tools for future urban mobility planning, particularly as UAM services expand to more metropolitan regions worldwide.

7. Limitations and future research directions

While this study provides valuable insights into strategic vertiport siting and the theoretical socioeconomic benefits of UAM, several limitations must be acknowledged, stemming from both methodological and data constraints. Future research could extend this work in four key directions.

Table A.1
Results of one-way ANOVA test for r_{tts}.

Solution 1	Solution 2	F-statistic	p-value	Significant (p<0.05)	Significant (p<0.10)	Significant (p<0.15)
DBSCAN	OBUAM	56.8340094	4.74E−14	Yes	Yes	Yes
DBSCAN	KM++	4462.54997	0	Yes	Yes	Yes
DBSCAN	KM_{OBUAM}	4259.07085	0	Yes	Yes	Yes
DBSCAN	GMM	3254.73726	0	Yes	Yes	Yes
DBSCAN	HC	3890.77272	0	Yes	Yes	Yes
DBSCAN	MS	33937.9573	0	Yes	Yes	Yes
GMM	MS	58271.1152	0	Yes	Yes	Yes
GMM	OBUAM	2468.73748	0	Yes	Yes	Yes
GMM	KM++	94.663252	2.26E−22	Yes	Yes	Yes
GMM	KM_{OBUAM}	66.9739422	2.75E−16	Yes	Yes	Yes
GMM	HC	28.5148198	9.30E−08	Yes	Yes	Yes
HC	KM_{OBUAM}	8.06249604	0.0045191	Yes	Yes	Yes
HC	KM++	19.2306652	1.16E−05	Yes	Yes	Yes
HC	OBUAM	3028.24816	0	Yes	Yes	Yes
HC	MS	60847.6593	0	Yes	Yes	Yes
KM_{OBUAM}	MS	62366.7269	0	Yes	Yes	Yes
KM_{OBUAM}	OBUAM	3354.48277	0	Yes	Yes	Yes
KM_{OBUAM}	KM++	3.69359378	0.02183329	Yes	Yes	Yes
KM++	MS	63130.0573	0	Yes	Yes	Yes
KM++	OBUAM	3535.93871	0	Yes	Yes	Yes
MS	OBUAM	37053.6325	0	Yes	Yes	Yes

Table A.2
Results of one-way ANOVA test for r_{ai}.

Solution 1	Solution 2	F-statistic	p-value	Significant (p<0.05)	Significant (p<0.10)	Significant (p<0.15)
DBSCAN	OBUAM	5.59979075	0.01811637	Yes	Yes	Yes
DBSCAN	KM++	263.840148	6.47E−54	Yes	Yes	Yes
DBSCAN	KM_{OBUAM}	166.914413	6.62E−36	Yes	Yes	Yes
DBSCAN	GMM	227.332041	2.82E−47	Yes	Yes	Yes
DBSCAN	HC	247.97633	4.73E−51	Yes	Yes	Yes
DBSCAN	MS	199.064948	5.11E−42	Yes	Yes	Yes
GMM	MS	0.24979005	0.61731205	No	No	**No**
GMM	OBUAM	155.614893	1.01E−33	Yes	Yes	Yes
GMM	KM++	1.42948529	0.23207816	No	No	**No**
GMM	KM_{OBUAM}	4.1453506	0.04196222	Yes	Yes	Yes
GMM	HC	0.43363441	0.51033381	No	No	**No**
HC	KM_{OBUAM}	7.2456651	0.00720335	Yes	Yes	Yes
HC	KM++	0.29021694	0.59017871	No	No	**No**
HC	OBUAM	172.513092	5.57E−37	Yes	Yes	Yes
HC	MS	3.30728168	0.05310917	No	Yes	Yes
KM_{OBUAM}	MS	3.62217375	0.03629696	Yes	Yes	Yes
KM_{OBUAM}	OBUAM	107.520849	3.27E−24	Yes	Yes	Yes
KM_{OBUAM}	KM++	10.3784123	0.00130826	Yes	Yes	Yes
KM++	MS	2.78028078	0.09568517	No	Yes	Yes
KM++	OBUAM	185.902226	1.56E−39	Yes	Yes	Yes
MS	OBUAM	135.11235	1.03E−29	Yes	Yes	Yes

First, the analyses are conducted under idealized conditions, excluding operational constraints such as vertiport capacity, UAM vehicle availability, and maintenance requirements. These factors are pivotal in real-world scenarios, as they directly impact the feasibility, efficiency, and safety of UAM services. Incorporating these constraints requires detailed simulations and modeling efforts, as well as additional assumptions—which is inherently challenging given the current absence of real-world UAM operation data. Future research should aim to integrate these operational factors to bridge the gap between theoretical planning and practical implementation, ensuring a more robust and comprehensive evaluation of UAM systems.

Second, while this study focused on job accessibility, due to data limitations, future research should consider access to other key urban opportunities like healthcare, education, and leisure facilities. This broader accessibility analysis would better reflect UAM's comprehensive impacts on urban mobility and quality of life across different trip purposes and population groups.

Last, quantifying externalities like environmental impacts and induced traffic congestion near vertiports will be crucial for understanding the full impact of UAM on urban mobility systems (Wang et al., 2023). This includes analyzing how vertiport locations affect local traffic patterns, noise exposure, and emission pollution in surrounding neighborhoods, helping planners optimize UAM's integration with existing transportation networks while minimizing externalities on local urban communities.

CRediT authorship contribution statement

Tao Guo: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Formal analysis, Conceptualization. **Hao Wu:** Writing – review & editing, Writing – original draft, Validation, Software, Methodology, Conceptualization. **Shahriar Iqbal Zame:** Writing – review & editing, Visualization, Formal analysis. **Constantinos Antoniou:** Writing – review & editing, Supervision, Resources, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix. Results of ANOVA tests

This appendix presents the results of 2-by-2 one-way ANOVA test between each two scenarios regarding the r_{tts} and r_{ai} (see Tables A.1 and A.2).

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