Analysing modal shift and induced demand for innovative air mobility: evidence from Catalonia

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SHORT SUMMARY

Innovative Air Mobility (IAM) is expected to enhance regional connectivity. However, its successful deployment depends on understanding who is willing to adopt IAM, how much demand it can realistically capture, and the extent to which it can generate new trips. To address this, this paper develops a hybrid behavioural–big data framework to model IAM demand. A stated preference survey is used to estimate a multinomial logit model. The behavioural model is then transferred to large-scale origin–destination flows derived from mobile network data. The methodology is applied to different OD pairs in the Catalonia region, Spain. Results show that IAM uptake varies significantly across corridors, reaching up to 22.6% in intra-regional trips but remaining below 7% in longer corridors, with demand primarily substituting car travel. Induced demand emerges only under low pricing scenarios and is concentrated among high-income, time-sensitive users, highlighting IAM's role as a premium, niche mobility service rather than a mass transport solution.

Keywords: Innovative Air Mobility, Regional Access, Demand Modelling, Discrete Choice Modelling, Mobile Network Data.

1. INTRODUCTION

Innovative Air Mobility (IAM) is rapidly transitioning from concept to implementation. Electric vertical take-off and landing (eVTOL) aircraft are expected to complement existing transport systems by providing fast, regional, and inter-urban connections. Several European initiatives are already preparing regulatory, operational, and infrastructural frameworks to enable early deployment. However, despite technological progress, one fundamental question remains insufficiently answered: how many travellers will actually use IAM once it becomes available? How many new induced trips will IAM generate? Accurate demand estimation is critical for infrastructure planning, vertiport placement, fleet sizing, airspace management, and investment decisions. Overestimation may lead to stranded infrastructure and inefficient allocation of public resources, while underestimation may result in capacity shortages and reduced system performance. Therefore, robust and scalable methods for forecasting IAM demand are urgently needed. Most existing IAM demand studies rely primarily on stated preference (SP) surveys to estimate behavioural responses to hypothetical IAM services (Brunelli et al., 2023; Long et al., 2023). While SP approaches allow detailed modelling of user preferences and sensitivity to travel time and cost, they typically suffer from limited sample sizes and do not directly provide population-level demand volumes. On the other hand, large-scale mobility datasets, such as mobile network data (MND), provide extensive origin–destination (OD) flows at high spatial and temporal resolution, but lack behavioural information regarding modal choice under new mobility alternatives (Andersson et al., 2024). This paper proposes a hybrid demand estimation framework that combines the behavioural richness of SP discrete choice modelling with the large-scale representativeness of mobile network data (Franco et al., 2023). First, a multinomial logit model is estimated using SP survey data to identify the determinants of mode choice, including generalised travel cost and socio-

demographic effects. Then, the estimated utility specification is transferred to OD flows derived from mobile network data. To ensure consistency with observed baseline modal shares, alternative-specific constants (ASCs) are recalibrated using revealed market patterns before introducing IAM into the choice set. Finally, IAM demand is forecast under defined service scenarios, and spatial–temporal adoption patterns are analysed. The methodology is applied to regional case studies where IAM is envisioned as a complementary mode to road and public transport services. The results provide (i) behavioural insights from the survey, (ii) validated baseline market consistency using large-scale mobility data, and (iii) scenario-based forecasts of IAM demand across OD pairs and time periods.

2. METHODOLOGY

Study Context and Data

This study is conducted within the framework of the PRIAM project and focuses on two regional European case studies selected to evaluate the potential of IAM for enhancing regional connectivity: (i) the Canary Islands case (Tenerife–La Gomera) and (ii) the Catalan Pyrenees case. In this paper the result of the second case study, Catalan Pyrenees case, is presented. The case focuses on three representative origin–destination pairs: Intra-Pyrenees, capturing trips within the mountain area itself; Barcelona–Pyrenees, representing long-distance access between the metropolitan core and the mountain region; and Lleida–Pyrenees, reflecting the role of Lleida as an intermediate access gateway through its airport and high-speed rail connections.

The survey, conducted online in July 2025 in English and Spanish, gathered 211 responses, providing a dataset suitable for analysing mode choice behaviour, estimating value of time and price sensitivity, and assessing potential IAM adoption and modal shift. The survey was designed as a structured stated preference experiment consisting of 48 questions grouped into four sections covering socio-demographics, current travel behaviour, perceptions of IAM (referred to as “air taxis”), and hypothetical travel choices. Respondents were presented with realistic choice scenarios based on the case studies (including the Catalan Pyrenees), where IAM attributes such as cost and travel time were systematically varied. To ensure robust estimation of behavioural parameters, eight survey versions were developed combining two travel purposes (work and leisure) with different cost–time configurations, and these were randomly distributed among participants. Each respondent evaluated both their current travel mode and their preferred mode under IAM scenarios, allowing the collection of both revealed and stated preference data. IAM is represented as a passenger “air taxi” service, consistent with the terminology used in the PRIAM survey to ensure respondent clarity. The IAM concept assumes point-to-point regional services designed to significantly reduce travel time relative to surface transport, particularly in corridors affected by geographical barriers.

To scale behavioural predictions to population level, anonymized and aggregated MND were used to reconstruct OD flows across the study regions. Two representative “typical” weeks of 2024 were selected. The MND dataset provides hourly trip records (P00–P23) including origin zone, destination zone, main travel mode (car/taxi, bus, train), trip purpose (home, work, frequent, non-frequent, other), and aggregated socio-demographic attributes (age bracket, income bracket, nationality, sex). Spatial disaggregation is performed at district level (7-digit zoning system), enabling detailed OD matrix construction.

For each OD pair, travel time and cost for existing modes were computed using harmonised assumptions. Road travel times were calculated using OpenStreetMap network. For public transport modes, total travel time includes access time, dwell time, in-vehicle travel time, and egress time. Travel cost assumptions were derived from publicly available fare structures and €/km values for car and taxi. These inputs enable consistent computation of generalized cost across modes prior to applying the behavioural model.

Hybrid Behavioural–Big Data Methodology

This section presents the hybrid modelling framework developed to estimate demand for IAM, including both mode choice behaviour and induced travel demand. The approach integrates behavioural estimation based on stated preference (SP) data with large-scale mobile network data (MND), followed by market-consistent calibration and out-of-sample validation.

In the first stage, behavioural sensitivities are estimated using the SP dataset. A multinomial logit (MNL) model is specified in generalised cost space, where travel time and travel cost are combined through the value of time (VoT). This formulation avoids collinearity between time and cost while preserving behavioural interpretability.

Generalised cost for each alternative is defined as:

$$GC_i = TC_i + VoT \cdot TT_i$$

The VoT is inferred from an initial preference-space estimation using separate time and cost coefficients. The estimated VoT is approximately 129.6 €/hour, indicating a relatively high sensitivity to travel time .The analysed choice set consists of four alternatives: IAM (air taxi), train, road (car/taxi), and bus. The utility functions are specified as follows:

$$V_{\text{bus}} = ASC_{\text{bus}} + \beta_{GC} \cdot GC_{\text{bus}}$$

$$V_{\text{train}} = ASC_{\text{train}} + \beta_{GC} \cdot GC_{\text{train}}$$

$$V_{\text{road}} = \beta_{GC} \cdot GC_{\text{road}} + \gamma_{\text{road,income}} \cdot income_z + \gamma_{\text{road,purpose}} \cdot purpose_1$$

$$V_{\text{IAM}} = ASC_{\text{IAM}} + \beta_{GC} \cdot GC_{\text{IAM}} + \gamma_{\text{IAM,income}} \cdot income_z + \gamma_{\text{IAM,purpose}} \cdot purpose_1$$

This specification captures heterogeneity in mode choice behaviour, particularly for IAM adoption, which is influenced by income level and trip purpose. To ensure consistency with observed travel behaviour, the model is calibrated using MND, which serves as the training dataset. Rather than re-estimating behavioural parameters, alternative-specific constants (ASCs) are adjusted to reproduce observed modal shares. Only the ASCs of bus and train are recalibrated, while IAM and road remain fixed:

$$ASC_{\text{bus}}^{cal} = ASC_{\text{bus}} + \delta_{\text{bus}}$$

$$ASC_{\text{train}}^{cal} = ASC_{\text{train}} + \delta_{\text{train}}$$

The calibration parameters are estimated by maximising the likelihood of observed MND mode choices. This step aligns the behavioural model with real-world travel patterns and ensures that baseline modal shares are accurately reproduced prior to IAM introduction .

To assess robustness and generalisation performance, the calibrated model is applied to MND data from a different day, treated as an independent test dataset. Using the SP-estimated behavioural parameters and calibrated ASCs, modal shares are predicted without re-estimation.

Predicted modal distributions are then compared with observed MND data to evaluate out-of-sample performance and mitigate the risk of overfitting.

Following calibration and validation, IAM demand is forecast under a defined service configuration. IAM travel time is computed assuming: 1- a cruise speed of 120 km/h, and 2- an additional 15 minutes for access, waiting, and boarding. IAM cost is assumed to be: 3 €/km, representing a premium mobility service. In addition, IAM is assumed to be available in all zones within the study area. While this assumption is not fully realistic, it provides an upper-bound estimate of potential IAM demand by removing infrastructure constraints such as vertiport availability.

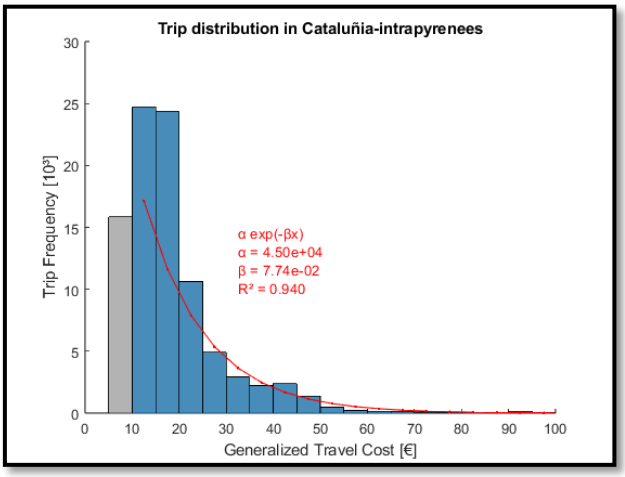
For each origin–destination (OD) pair in the test dataset: 1- Travel time and cost are computed for bus, train, and road modes. 2- IAM travel time and cost are derived based on the scenario assumptions. 3- Generalised costs are calculated using the estimated VoT. 4- Utilities are evaluated using calibrated ASCs and behavioural parameters. 5- Mode choice probabilities are computed using the multinomial logit formulation. IAM demand is obtained by aggregating the predicted choice probabilities across all OD pairs. The calibrated parameters of the mode choice model are provided below:

Table 1: mode choice model estimated parameters

Parameter	Estimate	p-value
ASC_IAM	-0.3529	0.038
ASC_Bus	-1.1853	<0.001
ASC_Train	0.6494	<0.001
ASC_Road	0.0000	—
β_GC	-0.01380	<0.001
γ_IAM_income	0.3002	0.0047
γ_IAM_purpose	-0.7620	<0.001
γ_Road_income	0.2716	0.018
γ_Road_purpose	-0.6939	0.002
Log-likelihood (final)	-12,102.56	
Log-likelihood (null)	-34,410.63	
McFadden ρ^2	0.648	

In addition to mode choice and demand redistribution, the framework explicitly estimates induced demand, i.e. new trips generated as a result of improved travel conditions. The induced demand model is constructed using MND by first developing a simplified trip distribution model. The dataset provides observed trip flows between OD pairs, including modal information and socio-demographic segmentation. For each OD pair, a generalised travel cost is computed as the sum of monetary cost and travel time, with time converted using the estimated VoT. Based on these costs, a gravity-type model with an exponential impedance function is specified, in which trip frequency decreases as generalised cost increases. The parameters of this relationship are estimated through regression on aggregated trip data grouped by cost levels. This establishes the sensitivity of travel demand to generalised cost. Induced demand is then derived by simulating a reduction in generalised cost due to the introduction of IAM. The model assumes that lower travel costs lead to increased trip frequencies. The proportional change in demand is calculated using the estimated cost elasticity and is applied to baseline OD flows. This process yields an estimate of additional (induced) trips attributable to IAM, complementing the mode shift captured by the discrete choice model. Together, the framework provides a comprehensive assessment of IAM demand, including both modal substitution and newly generated travel demand. The relationship between trip frequency and generalised travel cost, illustrated in Figure 1, shows a clear exponential decay pattern, where higher travel costs are associated with significantly lower trip frequencies; the fitted exponential function ($R^2 = 0.94$) confirms a strong and well-defined cost–demand relationship that underpins the induced demand estimation.

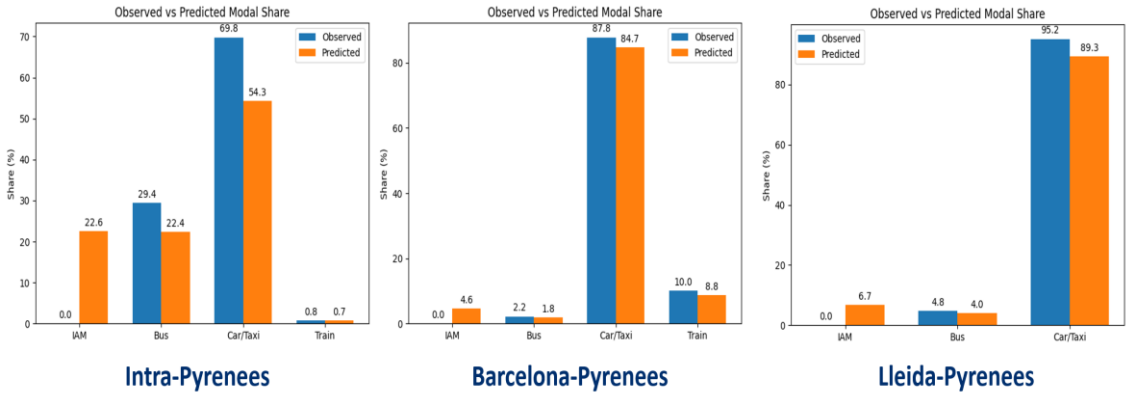
Figure 1: Trip frequency vs generalized travel cost relationship



3. RESULTS AND DISCUSSION

The predictive performance of the calibrated model is assessed by comparing observed and predicted modal shares across the three corridors: intra-Pyrenees, Lleida–Pyrenees, and Barcelona–Pyrenees.

Figure 2: Observed vs predicted modal shares



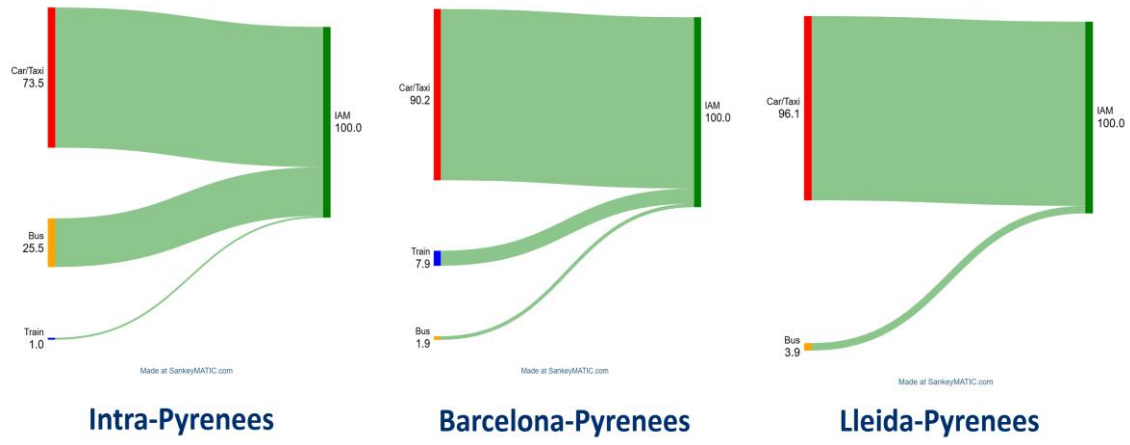
Overall, the model demonstrates strong predictive accuracy, particularly for the Lleida–Pyrenees and Barcelona–Pyrenees corridors, where predicted modal shares closely match observed values. In the intra-Pyrenees case, some deviations are observed, notably an underestimation of car/taxi share, which is partly redistributed towards IAM due to its introduction in the simulation.

These results confirm that the hybrid SP–MND framework provides a reliable basis for forecasting IAM demand, while also highlighting the sensitivity of results to the introduction of a new alternative.

The introduction of IAM leads to markedly different levels of market penetration across the three corridors: Intra-Pyrenees: ~22.6% ; Lleida–Pyrenees: ~6.7% ; Barcelona–Pyrenees: ~4.6% . The intra-Pyrenees corridor shows a significantly higher IAM uptake compared to the other two corridors. This result is particularly noteworthy given that it does not correspond to the longest trips, suggesting that shorter regional trips can exhibit higher IAM adoption, while longer distances do not necessarily guarantee higher uptake.

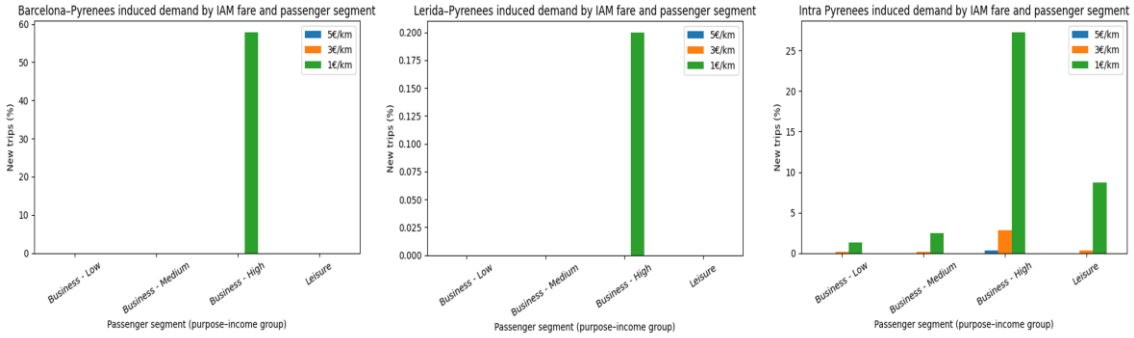
Figure 3 provide the modal shift towards IAM in different O-D pairs. Across all corridors, IAM demand is primarily drawn from car/taxi users, confirming that IAM acts mainly as a substitute for private and flexible modes. In the Lleida–Pyrenees corridor, this effect is almost exclusive, with over 95% of IAM users originating from car travel. In the intra-Pyrenees corridor, car remains the dominant source, followed by a secondary shift from bus, while train contributes minimally.

Figure 3: Mode shift towards IAM



In the Barcelona–Pyrenees corridor, IAM also competes with rail to a limited extent, reflecting the presence of an existing high-quality public transport alternative. However, even in this case, the modal shift from train remains modest.
These results indicate that IAM does not significantly replace mass public transport, but rather competes with car-based travel, particularly where time savings are substantial.
In addition to modal substitution, IAM introduction generates induced demand, which varies significantly across corridors and user segments.

Figure 4: Induced demand by fare and segment



Intra-Pyrenees **Barcelona-Pyrenees** **Lleida-Pyrenees**

Induced demand is strongly dependent on pricing. It becomes significant only under low-cost scenarios (approximately ≤1 €/km), while remaining negligible at higher fares (3 €/km and above). The intra-Pyrenees corridor shows the strongest induced demand effects, particularly for high-income business travellers and, to a lesser extent, leisure trips. In contrast, induced demand in the Lleida–Pyrenees corridor is minimal, even under low-cost conditions, indicating a relatively inelastic market. For the Barcelona–Pyrenees corridor, induced demand is highly concentrated and occurs almost exclusively among high-income business users.
These findings highlight that induced demand occurs primarily when two conditions are met: low IAM prices, and limited attractiveness of existing transport options. Furthermore, induced demand is consistently strongest among high-value users (i.e. travellers with high value of time) and is more pronounced for short regional trips.

4. CONCLUSION

The results of this study provide several important cross-cutting insights into the potential role of IAM across different regional contexts. First, IAM adoption does not scale linearly with distance. While longer trips may offer greater absolute time savings, the findings show that shorter regional trips can exhibit significantly higher IAM uptake, as observed in the intra-Pyrenees corridor. In contrast, longer corridors such as Barcelona–Pyrenees do not necessarily lead to higher adoption, primarily due to stronger competition from existing modes, particularly rail. This suggests that relative competitiveness, rather than distance alone, is the key determinant of IAM attractiveness.
Across all corridors, IAM demand is found to be primarily drawn from car and taxi users, with only limited substitution from train and bus. This consistent pattern indicates that IAM functions mainly as a premium alternative to private and flexible transport modes, rather than as a direct competitor to mass public transport. As such, IAM is more likely to complement existing public transport systems than to replace them.
The analysis of induced demand further highlights that IAM does not uniformly generate additional travel, but does so only under specific conditions. Induced demand becomes significant when IAM prices are sufficiently low—around 1 €/km or below—and when existing transport options are relatively weak or constrained. Moreover, the strongest induced demand effects are

observed among high-income and time-sensitive users, particularly for business travel. This indicates that IAM demand is highly elastic only within specific market segments, rather than across the broader population.

Taken together, these insights suggest that IAM should not be interpreted as a mass transport solution. Instead, it is best understood as a premium, niche mobility service, primarily targeting high-income and time-sensitive users. Its main contribution lies in providing faster alternatives to car travel, improving accessibility in geographically constrained areas, and generating additional demand under favourable pricing conditions. However, its overall impact remains limited in corridors where existing transport systems are already efficient or highly competitive.

From a policy and deployment perspective, the results indicate that successful IAM implementation will require a targeted and context-sensitive approach. IAM services should focus on corridors where geographical and infrastructural constraints create a clear competitive advantage. Pricing strategies will play a crucial role in determining both adoption and induced demand, and early deployment is likely to rely on high-value user segments. Furthermore, IAM should be integrated as a complementary component within the broader transport system, rather than positioned as a standalone or disruptive replacement.

Finally, it is important to acknowledge that the assumption of IAM availability in all zones represents an upper-bound scenario. In practice, infrastructure constraints, particularly related to vertiport placement and network design, are likely to limit actual demand. Future research should therefore incorporate spatial optimisation of IAM infrastructure and more realistic operational constraints to refine demand estimates and support practical implementation strategies.

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