Urban Air Mobility Flight Demand Modeling for Airports in New York City

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April 30, 2026

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Why is airport access in NYC a high-stakes problem?

- In NYC, **missing a flight is often caused by uncertainty, not distance**.
- Dense congestion makes airport trips **unpredictable**, especially during peak hours.
- Travelers do not plan for *average* travel time, they plan for **worst-case delays**.

Key question: How should we model demand when *reliability* matters as much as speed?

Urban Air Mobility as an airport-access solution

- Urban Air Mobility (UAM) offers:
  - **Shorter travel times**
  - **More predictable operations**
- Particularly suited for **airport shuttle missions**:
  - JFK, LGA, and EWR
  - Time-critical, reliability-sensitive trips

But adoption depends on more than average travel time.

What is missing in existing UAM demand models?

- Most prior studies compare modes using:
  - Mean travel time
  - Mean monetary cost
- **Travel time reliability is often ignored**, despite:
  - High congestion variability in NYC
  - Strong evidence that travelers value reliability

This gap limits our ability to predict who adopts UAM, when, and where.

Contributions of this work

1. Develop a **reliability-aware UAM demand framework** using 2023 NYC TLC data.
2. Extend the Generalized Cost of Trip (GCT) to include:
   - Travel time variability
   - Distance variability
3. Evaluate UAM adoption under **early, mid, and mature** operational scenarios.
4. Reveal **spatial** (zones/boroughs) and **temporal** (hourly) patterns of early adoption.

Study region and spatial resolution

- Study area: **New York City** and its three major airports.
- Spatial unit: **NYC taxi zones** (263 zones).
- Airport representation in TLC data:
  - Newark Liberty (EWR): Zone 1
  - John F. Kennedy (JFK): Zone 132
  - LaGuardia (LGA): Zone 138
- Taxi zones enable **OD-based modeling** while preserving user privacy.

Figure: Taxi Zones in New York City

How do we go from taxi trips to UAM demand?

- Start with **observed airport access behavior**:
  - Hourly taxi OD trips to JFK, LGA, and EWR (2023)
- Quantify what travelers experience today:
  - Monetary cost
  - Travel time
  - **Travel time reliability**
- Ask a counterfactual question:
  - *Would travelers switch if UAM were available?*

Modeling logic

- We model **two competing modes**:
  - Ground taxi (observed, variable, congestion-sensitive)
  - UAM (hypothetical, faster, more predictable)
- Each mode is represented by a **generalized cost of trip (GCT)**.
- Differences in GCT drive **probabilistic mode switching**.

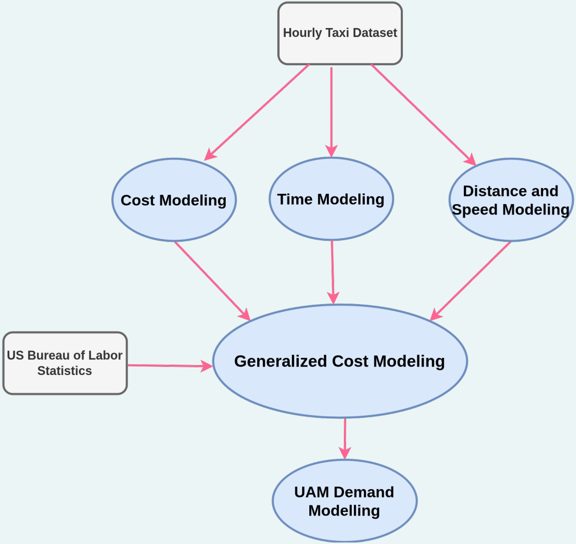


Figure: Approach for UAM demand modeling

From raw taxi records to airport OD demand

- Data source: **2023 NYC TLC trip records**
  - Yellow Taxi, Green Taxi, HV-FHV
- Pre-processing steps ensure realism:
  - Remove missing or implausible records
  - Exclude unknown taxi zones (264/265)
  - Retain only airport-related trips
- Final output:
  - **Hourly origin–destination demand** by taxi zone

Figure: Data Processing Pipeline

What makes a trip costly to travelers?

- Travelers experience three types of burden:
  - **Money** (fare)
  - **Time** (travel duration)
  - **Uncertainty** (variability)
- Reliability matters most for:
  - Airport access
  - Time-critical trips

We capture all three using a Generalized Cost of Trip (GCT).

Generalized Cost of Trip (GCT)

Taxi (congested and variable)

$$GCT_{Taxi} = \mu_c + VOT \cdot \mu_T + VOR \cdot \sigma_T + VOR \cdot \left(\frac{\sigma_D}{\mu_v} \right)$$

- Captures both **average conditions** and **variability**
- Reliability penalty increases with congestion

UAM (faster and more predictable)

$$GCT_{UAM} = C_m \cdot D + VOT \cdot \left(\frac{D}{S} \right)$$

- No reliability penalty assumed
- Reflects structured air operations

From cost comparison to traveler behavior

$$P_{UAM} = \frac{1}{1 + \exp^{(GCT_{\text{Taxi}} - GCT_{\text{UAM}})}}$$

- Travelers are **not deterministic**:
  - Same cost does not imply same choice
- Multinomial Logit captures:
  - Unobserved preferences
  - Perception and decision noise

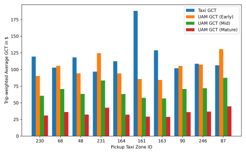
UAM development scenarios

- Early: $C_m = 15/\text{mile}$, $S = 125$ mph
- Mid: $C_m = 10/\text{mile}$, $S = 150$ mph
- Mature: $C_m = 5/\text{mile}$, $S = 175$ mph

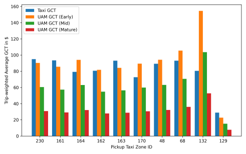
Result 1: Where does UAM become competitive first?

- Compare **trip-weighted average GCT** for top pickup zones serving each airport.
- Early insight:
  - **Highly congested Manhattan zones** favor UAM even in the early phase.
  - Outer borough zones become competitive as UAM cost and speed improve.

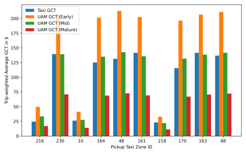
Key message: Reliability can outweigh cost in dense urban cores.



(a) EWR



(b) LGA



(c) JFK

Figure: GCT of Top Ten Pick Up Taxi Zones by Trip Volume for Airports

Result 2: When does travelers' switching behavior emerge?

- Switching probability evaluated **hour-by-hour** for top pickup zones.
- Early phase:
  - Switching concentrates in **peak and reliability-sensitive hours**.
- Mid to mature phases:
  - Switching expands across the day
  - Near-saturation in the most congested zones

Interpretation: Reliability drives early adoption; cost drives scale.

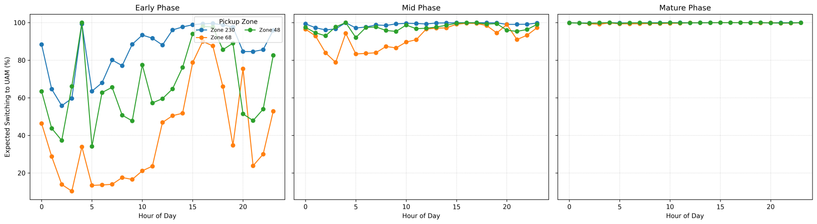


Figure: Hourly Switching Probability of Trips From Top Three Pick Up Taxi Zones for EWR

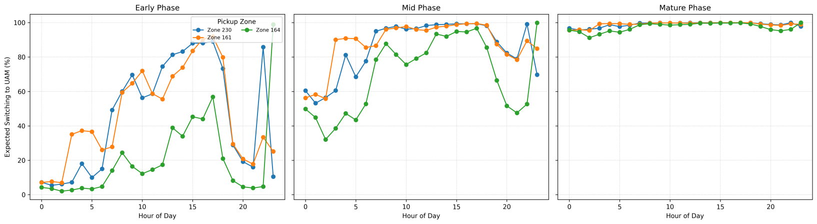


Figure: Hourly Switching Probability of Trips From Top Three Pick Up Taxi Zones for LGA

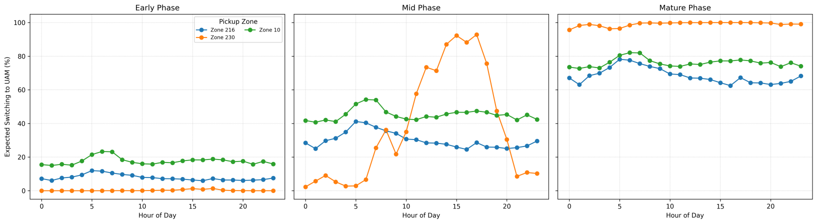
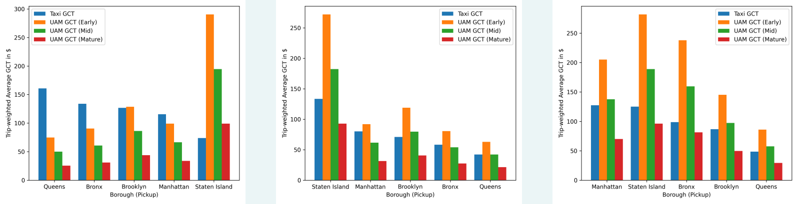


Figure: Hourly Switching Probability of Trips From Top Three Pick Up Taxi Zones for JFK

Result 3: Borough-level competitiveness (planning view)

- Aggregate results to the **borough level**.
- Reveals **phased roll-out logic**:
  - Manhattan benefits earliest
  - Queens and Brooklyn become competitive as UAM matures
- Useful for:
  - Fleet sizing
  - Pricing strategies
  - Vertiport prioritization



(a) EWR (b) LGA (c) JFK

Figure: Average GCT of Trips from Borough to each airport

Result 4: Borough-level switching dynamics (operations view)

- Switching probability by hour for:
  - Manhattan
  - Brooklyn
  - Queens
- Early phase:
  - Strong **peak-hour amplification**
- Mature phase:
  - **Near-saturation** across boroughs

Operational insight: Peak demand arrives before full market maturity.

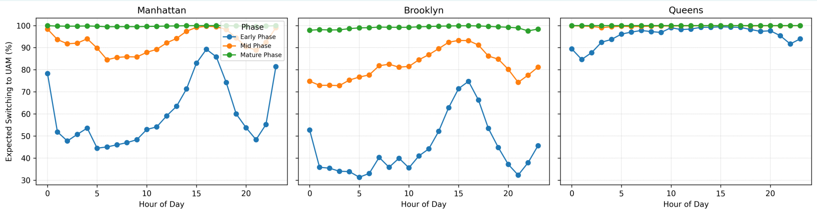


Figure: Hourly Switching Probability of Trips from Borough to Airports for EWR

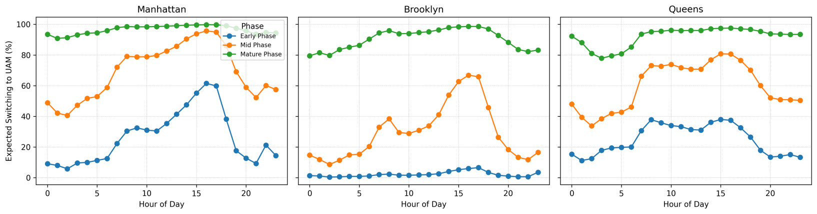


Figure: Hourly Switching Probability of Trips from Borough to Airports for LGA

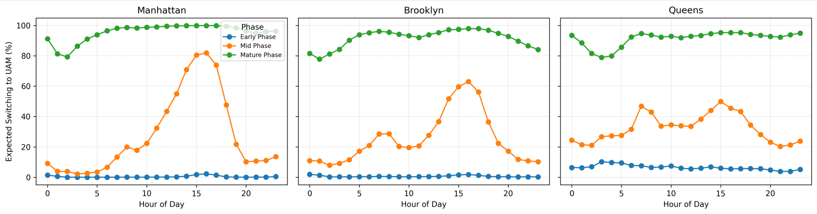


Figure: Hourly Switching Probability of Trips from Borough to Airports for JFK

So what does this mean for NYC airport UAM?

Implications for deployment

- Early UAM adoption is driven by **reliability, not just speed**.
- Initial services should target:
  - Highly congested zones
  - Peak, time-critical airport trips
- As cost and performance improve, UAM demand expands **spatially and temporally**.

What this enables for planners and operators

- **Fleet sizing**: anticipate sharp peak-hour demand.
- **Vertiport siting**: prioritize high-reliability-value zones.
- **Pricing**: align fares with phase-specific willingness to pay.

Who adopts first, and why?

Who?
Reliability-sensitive travelers

↓

When?
Peak congestion periods

↓

Where?
Manhattan → Queens / Brooklyn

Interpretation: UAM adoption follows reliability pressure before cost efficiency.

Modeling scope and limitations

Limitations

- Airport access demand is inferred from **revealed taxi behavior**; UAM stated-preference data are not directly observed.
- UAM cost and speed are modeled through **phase-based scenarios**; real-world values may vary by operator and infrastructure.
- Mode choice is represented using **Multinomial Logit**; richer models could capture traveler heterogeneity (income, purpose, luggage, party size).

Where does this framework go next?

Next steps

- **Vertiport siting optimization** using predicted zone–hour adoption surfaces.
- **Sensitivity analysis** on reliability valuation: VOR, VOT, pricing, and access/egress time.
- Extend to **multimodal competition**: subway, ride-share, airport shuttles, and weather-induced reliability effects.

Key takeaway

When **reliability is priced explicitly**, Urban Air Mobility becomes most attractive for **congested, time-critical airport trips**, with adoption expanding outward as technology matures.

Thank You