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# AIMing for Equity in Aviation Accessibility: Development of the Aviation-accessibility Integrated Mobility (AIM) Metric

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**Abstract**
As federal spending and planning for air transportation infrastructure looks to prioritize access for disadvantaged populations, aviation systems planning metrics that measure accessibility at the individual level are necessary. Existing metrics, from the mobility-driven metrics focused on efficiency and on-time performance to geographic accessibility metrics focused on connectivity, lack the detail of the multiple, interlocking constraints that limit potential travelers (especially lower-income travelers) from executing their agency and accessing the aviation system. We seek to develop a methodology, resulting in new analysis metrics, to quantify accessibility on an origin–destination basis based on individual constraints, time- and cost-based impedance, and aviation travel supply. We develop and apply our Aviation-accessibility Integrated Mobility (AIM) metric to empirically model relative accessibility based on traveler-specific constraints, accounting for individual-level sensitivity to travel costs and propensity to travel by ground access modes. We illustrate how equity-focused variables can change the calculus and geographic distribution of accessibility by applying the AIM to our case study region: Philadelphia, Baltimore, and Newark metropolitan areas, a region with significant socioeconomic disparities, to diverse markets (Austin, Atlanta, Nashville). Our findings indicate that incorporating individual constraints greatly influences the calculation of accessibility; additionally, we find that transportation supply and service characteristics alter the distribution of accessibility. Our model supports a national map of accessibility and potential policy recommendations to expand traditional federal airport infrastructure projects, such as targeted air service enhancement.

**Keywords**
aviation, customer choice modeling, airport systems, airport planning

The 2021 $1.2 trillion federal bipartisan infrastructure bill included $25 billion for aviation infrastructure with a prioritization on projects that improve accessibility to the aviation system for historically disadvantaged populations. As accessibility captures "the fundamental difference between persons in terms of their freedom to engage in a range of activities and their ability to execute their agency" (*1*), focused spending on projects that improve accessibility could redefine how diverse populations are able to utilize the aviation system to travel. Yet, identifying the projects that improve accessibility for diverse populations is a significant, untested challenge. Existing accessibility measures tend to be narrowly defined by individual or locational impedance (i.e., time, cost). The multiple, interlocking constraints that limit potential travelers (especially lower-income travelers) from traveling by air—for example, individuals may have limited access to an automobile (*2*), airfare can be an access restriction to lower-income populations (*3*), and the uneven supply of routes to desired destinations can cause travelers to forgo travel or seek out very distant airports

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(*4*)—are not incorporated into existing accessibility modeling frameworks. Thus, the expenditure of federal transportation dollars is at risk of prioritizing infrastructure developments that expand services for the least constrained and the mobile travelers rather than improving accessibility for disadvantaged populations. To truly prioritize disadvantaged communities with the federal funding allocated for airports, the aviation planning community requires scalable methodologies that represent the true airport and aviation accessibility assessment for disadvantaged communities, incorporating equity considerations like affordability of airfare and ground transportation supply and constraints.

Across the distributed actors in air transportation, performance metrics have taken multiple perspectives skewing toward mobility and delay from a macroscopic level, rather than individual accessibility. Airlines, who are responsible for the allocation of flights and seat capacity, focus on optimizing for revenue as well as metrics such as on-time performance. The Federal Aviation Administration (FAA) and Department of Transportation (DOT), looking to ensure safety while managing capacity efficiently, also estimate and report on on-time performance and delay (*5*). Individual airports have numerous performance metrics, spanning from quality of customer service to ground congestion. Yet, metrics focused on accessibility, particularly accessibility to the aviation system for disadvantaged groups, have not been developed or adopted at a large scale. There are disparate examples of planning processes incorporating expanded views of accessibility, such as metropolitan planning organizations and regional planning coalitions studying regional physical accessibility to airports (*6*), and incentive programs like the federal Essential Air Service that focus on increasing accessibility to rural communities (*7*). However, these programs and studies stop short of developing and utilizing a method to quantify accessibility from the perspective of an individual that incorporates individual details and constraints.

In the following study, we develop a mathematical formulation of accessibility centering the constraints that individuals face in accessing the air transportation system. Our Aviation-accessibility Integrated Mobility (AIM) metric incorporates multiple impedance factors of intercity transport, including aviation supply and service characteristics of local ground access and long-distance travel. Using traditional accessibility variables like time and cost, we proactively assess the trade-offs inherent in a change in transportation supply during infrastructure development. We then build on the concept of the ability of different groups in executing their agency by taking a cohort-based approach. Using established parameters in utility modeling scholarship and income-based sensitivities, we jointly quantify individual constraints and preferences. The empirical portion of the method presents a case study that demonstrates the significance of incorporating individual constraint variables in an accessibility calculus from a spatial perspective. Findings indicate that individual constraints and transportation supply significantly change the landscape of accessibility and help redefine aviation accessibility both conceptually and methodologically as a planning metric. From this, we present several policy recommendations and motivate a new framework for mapping accessibility at a national scale.

## Literature Review

The relative maturity of aviation systems metrics such as on-time performance and the lack of metrics on the diversity of travelers who can access an airport is consistent with a broader struggle in transportation planning: planning for increased mobility, defined as efficiency and speed of movement (*8*) versus planning for increased accessibility, the ability of an individual to interact with social or economic opportunities (*9*). Planning for proximity to destinations, increased mobility, and higher accessibility often have conflicting objectives with competing political forces that shape people's ability to traverse space and reach desired destinations.

Part of what is creating this tension is the lack of an accepted framework around accessibility in the context of aviation to support equity-focused decision-making. Without a nuanced definition of accessibility that incorporates traveler constraints and specific traveler desires, intercity planners are unable to understand how potential infrastructure development may affect individual-level accessibility (*9*). Implicitly, we understand the criticality of evaluating accessibility in a detailed, individual-specific way. Consider that, before a change in infrastructure, the National Environmental Policy Act (NEPA) of the U.S. requires the full enumeration of social, economic, and environmental impacts for any large scale federal action, with a focus on different populations (*10*). Yet, with the NEPA process, changes in individual accessibility with respect to individual constraints are not measured, only how the environmental impact falls on different populations (*11*).

Foundational examples for a framework in measuring aviation accessibility include the small but rich literature focused on evaluating the air transportation system for accessibility. This literature largely measures a traveler's geographic proximity to air service, with air service defined as a function of variables such as flight seat availability, cost, and level of service. Scholars have used these measures to evaluate programs such as the Essential Air Service (EAS), a DOT program aimed at improving rural access by incentivizing airlines to increase services for smaller communities (*7*, *12*), and to evaluate the impact of exogenous economic shocks (*13*, *14*). These approaches quantify general impedance based on time and cost rather than parameterizing individual-level variables related to accessing opportunities by air travel, such as, for instance, affordability of airfare and vehicle availability in traveling to an airport. Without this focus on real-world constraints, existing accessibility models do not capture true accessibility in one's ability to access opportunities by transportation (*15*).

In the broader intercity transportation literature, there has been a call for considering more variables that describe the abilities and constraints of, and impacts on, the individual traveler in accessibility calculations. The intercity literature has attempted to measure accessibility with a dynamic, multi-dimensional set of factors including social costs that simultaneously weighs impacts of travel (*16*, *17*). While these scholars illustrate the importance of accounting for individual travel behavior and perceptions, these studies stop short of cohort-specific analysis of travelers and consideration of the constraints of low income and disadvantaged populations. Gosling (*11*) also outlines a framework pertaining to mobility and accessibility including travel time, delay, access to desired destinations, access to the airport system, reliability, cost effectiveness, safety, and equity, all of which have yet to be captured and weighed in an integrated quantitative assessment for intercity transportation. To seek a framework for incorporating individual constraints into accessibility analyses, we turn to the urban planning literature.

Scholars in transit planning have developed perspectives and methods to incorporate connectivity to opportunities for more vulnerable populations in accessibility models. In defining an approach in the early urban accessibility scholarship, Wachs and Kumagai (*18*) elevate the concept of constraints and the abilities of different individuals to reach certain destinations by presenting an approach that emphasizes constraints and balances the supply of travel opportunities with a demand-side impedance. To broadly incorporate equity, Wachs and Kumagai define cohorts based on income and employment and seek to capture accessibility as a weighted sum of the percentage of individuals in a cohort in a zone and the number of opportunities that can be reached in time thresholds. The study finds that an individual's accessibility is largely influenced by the availability of an automobile, location to urban areas or transit stops, and a host of other person-based variables that can pose restrictions on the ease with which individuals access opportunities.

Incorporating demand-side travel impedances that reflect individual-level constraints is critical to account for the limitations in accessing opportunities, as opposed to quantifying accessibility through supply (*19*). To better quantify the interaction between individuals' constraints and accessibility, classic urban accessibility scholarship suggests the integration of utility-based frameworks into location-based models (*15*). Bills and Walker (*20*) do this by creating a log sum equity indicator, an established metric to capture utility and accessibility, to compare distributions of travel changes across planning scenarios in demonstrating a method for examining the impacts of transportation investment across population groups. Based on these considerations, we now construct an aviation-accessibility model that incorporates individual-level preferences and constraints.

## Model Formulation

We propose a novel methodology to model accessibility to the aviation system in the AIM metric. In this section, we explain the conceptual and mathematical foundations of the AIM methodology. Our choice of model functional form and the robustness of our formulation is discussed below, under Spatial Analysis and Discussion.

### *Conceptual Framework*

Previous literature encourages—but stops short of developing—an accessibility model that more accurately characterizes the complexities of the aviation system based on individual-level ability to reach desired destinations. The AIM metric adopts a multi-modal modeling approach for measuring aviation accessibility between an origin–destination pair, outputting a single, comprehensive metric that captures the trade-offs between air service characteristics and individual traveler behavior. The AIM metric balances the supply of travel opportunities between an origin airport $i$ and destination airport $j$ for origin census tract $q$ with a demand-side, "impedance" measure that reflects the barriers in how individuals reach these opportunities as a function of airfare, time, reliability, and individual constraints for both local airport and long-distance access. This approach in aviation accessibility will ultimately allow planners to understand and assess the accessibility impacts of a potential infrastructure development on disparate socioeconomic groups.

A major innovation of the AIM metric is the development of priority area indicators (PAIs), a novel mechanism to quantify accessibility from the individual perspective through several "modules." Each PAI in the AIM represents a module or major component of aviation accessibility: mobility, affordability, time and reliability, and local airport access. Both aviation and urban planning scholars have acknowledged the need for PAIs from a qualitative perspective; we seek to parametrize these PAIs with multiple variables that integrate individual constraints as well as transportation system characteristics. The concept of priority area indicators allows presentation of the model in a modular format that permits examination of the impact of each PAI individually on the aggregated accessibility metric. The construction of the model in this manner allows for further mathematical expansion in future iterations of the AIM.

Throughout these PAIs, we integrate variables that correspond to the constraints of individuals across income groups. The AIM incorporates individual constraints by defining cohorts, parameterized by $v$, which represent a grouping of census tracts based on socioeconomic and demographic variables. Cohort-based variables account for individual traveler behavior and preferences and down weight the impedance measure based on the constraints of a particular cohort, which we define at the census tract level. We capture sensitivity to airfare based on cohort-level income, as well as the propensity for a cohort to travel by a local access mode $k$, quantified through private vehicle availability and public transit usage. This cohort-based approach in modeling aviation accessibility departs from methods of accessibility that focus heavily on supply-side metrics; our demand-side modeling perspective accounts for the individual constraints that pose limitations to individuals in qualifying for the total available supply of opportunities.

Within the impedance measure, we account for the impact of each PAI variable on the individual traveler. Quantifying individual valuation is critical in measuring the total cost of a variable which integrates both the objective cost and individual perception and utility (*16*). To this end, we adapt coefficients from airport choice utility models that quantify the effects of air service characteristics on a general traveler's utility. In adapting these coefficients, we account for the diminishing marginal returns in utility for each unit increase in the variable, modeling travel behavior theory as in previously used negative exponential forms (*21*). In accordance with established literature, individuals do not face a constant decrease in utility for increases in time and cost, and our coefficient estimates capture these diminishing returns to utility. We further review the airport choice literature and model specifications below under Estimating Individual Utility of PAI Variables.

In the following section, we apply this conceptual framework to develop the set of equations in the AIM methodology.

## Mathematical Framework

Let $s_{ij}$ refer to the travel opportunities calculated as the number of flight seats flown over the course of a year from origin airport $i$ to destination airport $j$. This concept of supply is also discussed in Reynolds-Feighan and McLay (*14*), who denote the supply of air travel opportunities as the number of nonstop seats over the course of a year to account for both frequency and size of aircraft. For each census tract $q$, we compute an AIM score for origin airport $i$, destination airport $j$, and local access mode $k$. We then assign the census tract $q$ its maximum AIM value over all $i$ and $k$ with a fixed destination airport $j$.

$$\mathrm{AIM}_{qj} = \max_{ik} \left(s_{ij} * M_{qijk}\right) \tag{1}$$

The PAIs notated explicitly in the model are affordability ($C_{ij}$), travel time and reliability ($T_{ij}$), and airport access ($A_{iqk}$). Combining these PAIs, we define the aggregated impedance measure $M_{qijk}$ between origin airport $i$, destination airport $j$, and origin census tract $q$ by normalizing $C_{ij}$, $T_{ij}$, and $A_{iqk}$ across an origin–destination pair. We express the aggregated impedance measure as a combination of each PAI similar to Bao et al. (*22*), who express the total cost of airport access as a summation of convenience, time, and affordability. We further define the variables within each PAI below.

$$M_{qijk} = C_{ij} + T_{ij} + A_{iqk} \tag{2}$$

The affordability PAI $C_{ij}$ includes both air transportation and cohort-specific components: the median airfare per seat ($c_{ij}$) from origin airport $i$ to destination airport $j$, and $w_v$, a traveler's sensitivity to airfare specific to cohort $v$. We define cohorts as groupings of census tracts based on socioeconomic and demographic variables. Recall from the above Conceptual Framework section, we weight each PAI with coefficients adapted from existing airport choice models; the values of these coefficients ($\sigma$, $\tau$, $\theta_v$, $\zeta$, $\lambda_k$) are further described below under Estimating Individual Utility of PAI Variables.

$$C_{ij} = \sigma * w_v * \log(c_{ij}) \tag{3}$$

The time and reliability PAI includes schedule delay ($w_{ij}$), average arrival and departure delay ($d_{ij}$), average airborne time ($t_{ij}$), and processing time ($p_i$) between origin airport $i$ and destination airport $j$ across flights for a year.

$$T_{ij} = \tau * \log\left(w_{ij} + d_{ij} + t_{ij} + p_i\right) \tag{4}$$

The access to airports PAI $A_{iqk}$ quantifies accessibility between census tract $q$ and airport $i$ by mode $k \in K$, where $K$ is a discrete choice set of all possible airport access modes. We include traveler time ($t_{iqk}$) and traveler cost ($c_{iqk}$) between census tract $q$ and origin airport $i$ for mode $k$. The propensity to travel by mode parameter, denoted by $e_{kv}$, represents the ability of cohort $v$ to travel by mode $k$ from census tract $q$ to airport $i$. The

**Table 1.** Cohort-Based Coefficient Values

| Coefficient | Low income | Middle income | High income |
|---|---|---|---|
| $w_v$ (airfare sensitivity) | 0.57 | 0.30 | 0.13 |
| $e_{k=\text{car}, v}$ (propensity to travel by car) | 0.77 | 0.16 | 0.06 |
| $e_{k=\text{transit}, v}$ (propensity to travel by transit) | 0.36 | 0.81 | 0.81 |

parameterization of is further discussed in the next section, under Parameterizing Cohort-based Coefficients.

$$A_{iqk} = e_{kv}\left[\frac{\zeta}{\lambda_k}{}^* \ \log(t_{iqk}) + \frac{\theta_v}{\lambda_k}{}^* \ \log\left(c_{iqk}\right)\right] \tag{5}$$

## Definition of Model Coefficients

In this section, we discuss data and methods used to parameterize PAI coefficients in the AIM impedance measure.

### *Parameterizing Cohort-Based Coefficients*

A fundamental contribution of the AIM metric is that we incorporate the individual constraints of travelers through a cohort-based approach. We do this by defining two parameters in which constraints associated with one's socioeconomic status may affect one's accessibility: the sensitivity to airfare parameter, which we scale by $w_v$, and the propensity to travel by mode $k$ parameter, $e_{kv}$. Both values are specific to the cohort $v$, which represents a grouping of individuals based on socioeconomic variables. Table 1 refers to the coefficient values used in this study.

Our methodological approach in modeling these parameters considers the travel impedances arising from an individual's income. The cohort parameter $v$ can be refined to include any number of socioeconomic definitions; to pilot this concept, we employ three cohorts based on income (low, middle, and high income). Certainly income level directly affects one's ability to pay for airfare (*3*); income levels can also serve as a proxy for vehicle ownership and public transit usage to account for individual means to access airports by auto and transit (*23*, *24*). We collect median income by each census tract from the open-source, publicly available 2019 5-year American Community Survey (ACS) data and categorize census tracts into low-, middle-, and high-income cohorts based on break points from national data sources for each parameter.

To parameterize $w_v$ as a traveler's sensitivity to pay for airfare, we utilize survey data that correlates percentages of individuals who have never flown by low (<\$40,000), middle (<\$80,000), and high (>\$80,000) income brackets. We interpret these percentages as a likelihood that an individual can afford airfare based on their income, thus estimating an individual's sensitivity to airfare. The percentages are normalized to construct the values of $w_v$ that map to each census tract, accounting for the individual impact of airfare based on traveler economic status. While we often parameterize models for sensitivity to airfare based on leisure and business travelers, dividing travelers based on their income classes is less considered (*25*, *26*). However, the lack of quantitative data on cohort-specific preferences based on airfare prevents in-depth, nuanced analysis of airfare sensitivity across socioeconomic cohorts and fare values: in our pilot study, we model this factor as dependent on income. We therefore focus on demonstrating the functionality of the cohort-based model rather than precisely estimating accessibility.

The propensity to travel by mode parameter $e_{kv}$ specified for mode $k$ and cohort $v$ captures the constraints by income in utilizing ground access modes; in defining this parameter, we account for individual-level ability to travel via private vehicle and public transit across income groups. Data from the DOT's study on National and Household Travel Trends correlates zero vehicle access with percentages of low (<\$22,050), middle (<\$100,000), and high (>\$100,000) income brackets (*24*). Similarly, for the transit mode, we parameterize $e_{kv}$ based on the same DOT study that calculates frequency of transit use for individuals across income groups. In normalizing these values to parametrize $e_{kv}$ for income cohorts, we correlate a larger magnitude of the $e_{kv}$ parameter with greater airport access impedance, and thus lower overall accessibility. Similar to the airfare sensitivity coefficient, we emphasize the functional form of this equity consideration and encourage additional ways to parametrize this coefficient, including vehicle ownership as well as more location-specific metrics of public transit service characteristics.

### *Estimating Individual Utility of PAI Variables*

To further incorporate individuals' preferences and the trade-offs between different accessibility components, we scale the PAIs within the impedance measure with traveler coefficients. Disutility has been modeled extensively in the airport access literature and developed in theoretical frameworks, yet has not been integrated into supply-based aviation-accessibility models. In crafting individual-focused definitions of accessibility, urban accessibility scholars encourage incorporating utility modeling frameworks into supply-based accessibility perspectives (*15*). Borrowing from the airport choice literature, our modeling approach captures the approximate relationships between the trade-offs individuals make for different variables (*4*, *27*). We adapt the coefficients from Hess et al. (*28*) and Hess and Polak's (*29*) multinomial and nested logit models to capture individual impact of airfare ($\sigma$), travel time ($\tau$), access cost ($\theta_v$), and access time ($\zeta$). Access cost and time variables are also specified by mode $k$ with the coefficient $\lambda_k$ . Further, we parameterize the coefficient for access cost based on income groups to reflect varying cost sensitivity.

Hess et al. (*28*) present a discrete choice model of air traveler behavior using stated preference survey data. Their study extends the work of Adler et al. (*25*) to model the effects of air service and supply characteristics in airport and airline choice behavior. To estimate these effects, the authors build a multinomial logit model as a function of access time, airfare, and flight time for business, holiday, and VFR (visiting friends and relatives) travelers. We apply a log-transform of the airfare and travel time variables and scale by $\sigma$ and $\tau$ values (Table 2). In the study by Hess and Polak (*29*), the authors model air traveler choice for both residents and non-residents through a nested logit model, nesting by airport access mode, airline, and airport. The study quantifies the impact of access time and access cost by mode, and, for access cost, additionally by income group, in the overall calculation of utility. We adopt Hess and Polak's coefficients ($\lambda_k$) for car and public transit, along with the access cost coefficient ($\theta_v$) for low- and high-income groups (threshold at $44,000) and access time ($\zeta$) coefficient.

We utilize the coefficients for the models that capture sensitivities of business travelers, which we justify as follows. A critical difference between our research and that of discrete choice modeling scholarship is that we illustrate accessibility, while Hess and others seek to estimate choices. By choosing to weigh our accessibility components in a way that reflects the traveler with the greatest sensitivity to time and cost, we are not unnecessarily "discounting" the value of accessibility to any particular group. The goal of our model is to measure equity in accessibility; presuming that certain populations with lower values of time do not value accessibility in the same way would embed bias against vulnerable populations. Additionally, the nature of our model allows for different parameters to be input; thus, our choice of coefficient is for illustration purposes only and does not limit the future use of the model.

These coefficients help to provide intuition on the general trade-offs individuals make across variables in an aggregated accessibility calculation. The coefficients we present, while derived from established utility models, can also be calculated from travel survey data. However, similar to the approach of Ryerson and Kim (*4*) we do not conduct our own survey: the contribution of this study is methodological as we provide a mathematical framework of capturing accessibility. Rather, we motivate the usage of a utility modeling approach in integrating individual impact and valuation of accessibility variables into a single metric. Thus, the coefficients can be adapted to the changing utility distributions for different variables. Consequently, we emphasize the framework of the model and relationships between the trade-offs, as opposed to the precise values of the coefficients.

**Table 2.** Priority Area Indicator (PAI) Coefficient Values

| Coefficient | Value |
|---|---|
| $\sigma$ (airfare) | −3.534 |
| $\tau$ (travel time) | −1.628 |
| $\theta_{\text{low-income}}$ (access cost for low-income) | −0.036 |
| $\theta_{\text{high-income}}$ (access cost for high-income) | −0.024 |
| $\zeta$ (access time) | −0.052 |
| $\lambda_{car}$ | 0.179 |
| $\lambda_{transit}$ | 0.312 |

## Case Study Definition and Data

This section describes the empirical implementation of the AIM. We define our case study (Selection of Study Airports and Geography), data for parameterizing PAI variables (Data Collection for PAI Variables), and analytical intuition (Summary Statistics of Accessibility Variables) before presenting our findings.

### *Selection of Study Airports and Geography*

Our case study region is set to illustrate the power of our method; if our results indicate that incorporating the constraints of disadvantaged travelers changes the nature of accessibility estimates, we motivate a field of models that focus on individualized accessibility. Recall that our model optimizes for the maximum accessibility for each census tract; that is, we compute AIM scores for each origin airport and each local access mode and select the maximum score (Equation 1). To illustrate the AIM, we choose to examine a regional airport market as opposed to a single airport or catchment area; in doing so, we capture the complexity of choices facing a potential traveler in making trade-offs between ground access and aviation system variables based on their socioeconomic status. For instance, certain travelers may be able to maximize their accessibility by traveling to a relatively distant airport with more frequent service or lower airfare (*4*). Or, similarly, one airport may be more accessible via transit than another, and, as a less expensive mode, may be more attractive to lower-income travelers (*30*). Our model captures these trade-offs that individuals make based on their constraints and service characteristics.

As the AIM incorporates air service variables as an important component, our case study implementation involves a hypothetical traveler as defined by the variables reflective of their census tract of origin, bound for a specific destination airport, and considering a potential set of origin airports across a region. By considering airport-to-airport scenarios, we can collect service-level variables of which accessibility is a function. Accessibility is at the metropolitan statistical area (MSA) level, focusing on all census tracts within an MSA; each hypothetical traveler from a census tract has the possibility of originating their travel at one of the three major airports in our study conurbation. We choose the region of the Northeast Corridor of the U.S., home to the major metropolitan areas of Philadelphia, Pennsylvania (with Philadelphia International [PHL]), Baltimore, Maryland (with Baltimore/Washington International Airport [BWI]), and Newark, New Jersey (with Newark Liberty International Airport [EWR]).

The selected geographies provide a highly diverse socioeconomic region that presents a relevant case study for measuring equity-based accessibility. Significant wealth disparities exist across these areas: the Philadelphia and Baltimore metropolitan areas rank in the top four for largest income disparities and are cities with large minority populations in inner-city areas (*31*). Comparatively, the Newark area has higher incomes than the Baltimore and Philadelphia regions. Moreover, the three major airports in each urban center are ranked within the top 25 of busiest airports in the U.S. We recognize that in assigning each census tract the airport and local mode that provides them with the greatest accessibility, the traveler may or may not choose that airport or mode in reality. While it is possible that a hypothetical traveler from our case study census tracts could, in theory, choose to travel from an airport other than the three origin airports in our case study, our three airports represent those with the maximum service and most competitive pricing; thus, our three airports are likely to offer the highest overall accessibility, which is what the AIM intends to measure. For the purposes of this study, we select the geographic bounds to illustrate our methods and highlight the disparities in accessibility across socioeconomic groups, thus justifying the bounding.

To illustrate our accessibility method across a variety of destination airport service and spatial characteristics, we select several destination airports based on market size, proximity to the origin census tracts, and data availability. The destinations we use for illustration purposes only are Austin–Bergstrom International Airport in Austin, Texas (AUS, distant, medium market), Atlanta (Georgia) Hartsfield-Jackson International (ATL, proximate, large market), and Nashville (Tennessee) International (BNA, proximate, medium market).

### *Data Collection for PAI Variables*

In the implementation of the AIM metric, we focus on specific case study destination airports and the domestic airlines that serve these routes using empirical data from 2019, thus representing the most recent pre-COVID data (Table 3). In Table 3, note that we enumerate equity as a PAI for clarity purposes in documenting the data definitions and sources associated with modeling equity. Equity is not explicitly notated as a PAI in the above, but rather mathematically integrated throughout the modeling framework.

We use Bureau of Transportation Statistics (BTS) Air Carrier Statistics (T-100) to determine the number of nonstop seats in 2019. Airfare data is collected from the BTS Airline Origin and Destination Survey (DB1B market data, 10% sample of airline tickets in the U.S.). Flight times, delay statistics, and schedule delay are computed for each origin–destination pair based on 2019 BTS on-time performance data. We parameterize these statistics based on the “design day” perspective from the Port Authority of New York and New Jersey and select a weekday in the month of August to represent the optimal month for air passenger activity in airports (not necessarily peak demand) (*36*). Per the DOT Federal Highway Administration recommendation, we take averages for arrival and departure delays and airborne time at the 90th percentile (*37*). Schedule delay and processing time data is specific to the morning peak period from 6 a.m. to 10 a.m.; if no flight data was available for the origin–destination pair, the average across the evening peak from 4 p.m. to 8 p.m. was used (*36*). Schedule delay represents the average headway of flights in the peak period (*38*); according to Borenstein and Netz (*39*), travelers’ preferred departures depend on the spread of flights across a day, which is determined by airport competition. Taking the schedule delay at peak time intervals accounts for this demand-side effect. Processing times for the PHL, BWI, and EWR airports are the average Transportation Security Administration (TSA) wait times for these peak periods (*32*).

In modeling local airport access, we estimate time and cost for the local transportation modes of public transit and private vehicle. Travel durations are calculated through the Google Maps API between each origin census tract centroid and destination airport pair; we utilize the fastest travel time contingent on traffic and wait time estimates (*40*). For the public transit mode, we assign to each census tract the mode across bus, trolley, regional rail, light rail, subway, and Amtrak that corresponds to

**Table 3.** Description of Priority Area Indicators (PAIs), Variables, and Data Sources

| PAI | Description | Variable description | Data source |
|---|---|---|---|
| Mobility ($s_{ij}$) | Mobility is defined as efficiency and speed of movement (*8*) | • Supply of nonstop seats between origin and destination airports | • 2019 T-100 Segment data |
| Affordability ($C_{ij}$) | Affordability includes air travel costs for passengers | • Median airfare | • DB1B Market 2019 data (10% sample of airline's tickets) |
| Time and reliability ($T_{ij}$) | Time and reliability accounts for temporal elements of air travel | • Average arrival and departure delay<br>• Average airborne time<br>• Schedule delay of flights for a.m./p.m. peak<br>• Processing times for a.m./p.m. peak | • BTS August 2019 on-time performance data<br>• TSA Wait Times data (*32*) |
| Airport access ($A_{iqk}$) | Airport access constitutes travel-related impacts between census tract and origin airport | • Traveler time (in-vehicle and wait time)<br>• Traveler cost | • Google Maps API<br>• Amtrak 2019 Performance Report (*33*) |
| Equity ($w_v$, $e_{kv}$) | Equity is defined as the degree of fairness to which disbenefits of transportation impacts are distributed across social groups (*34*) | • Sensitivity to pay for airfare as a percentage of travelers in income groups who have never flown<br>• Propensity to travel by private vehicle as a percentage of zero-vehicle households by income<br>• Propensity to travel by public transit as frequency of transit usage by income | • 2019 American Community Survey 5-year data<br>• 2015 YouGov Air Travel Frequency Poll (*35*)<br>• U.S. Department of Transportation National and Household Travel Trends (*24*) |

*Note*: BTS = Bureau of Transportation Statistics; T-100 = BTS Air Carrier Statistics (T-100); DB1B = BTS Airline Origin and Destination Survey (DB1B); TSA = Transportation Security Administration. Note that we enumerate equity as a PAI for clarity purposes in documenting the data definitions and sources associated with modeling equity. Equity is not explicitly notated as a PAI in the text, but rather mathematically integrated throughout the modeling framework.

the fastest travel time. Traveler cost for private vehicles is based on national averages of gas prices, \$3.09 per gallon, and a car mileage rate of 24.9 miles per gallon, with an additional \$15 airport parking cost. Traveler cost for public transit is either extracted from the local transit agency information available with the Google Maps API or, if this data is unavailable, calculated using the national average Amtrak costs of \$ 0.35 per passenger mile (*33*).

In our case study implementation, we limit the airport access modes to automobile and public transit. While in practice each individual has a likelihood of choosing across many modes (e.g., ride-hailing, securing a ride from a friend or family member, etc.), we assert that auto and transit encompass the largest range of possibilities here in just two options given their modal characteristics and their individual constraint coefficients, thus helping to illustrate the power of the AIM. For individuals with access to an automobile, the accessibility provided by the auto mode is roughly equivalent to (or even higher than) the accessibility provided by ride-hail or taxi. For individuals without access to an automobile, their accessibility is based on the accessibility through transit. While it is possible that a person without an automobile can choose to take ride-hail, ride-hailing modes are not preferred among low-income travelers who often rely more on transit or other lower-cost modes (*40*, *41*). Because of the greater cost sensitivities of taxis or nonavailability of private cars, lower-income travelers are more likely to take transit in ground access to the airport (*30*). Ride-hailing poses additional challenges for lower-income people because of their lack of credit or debit card, the predominant payment method used for ride-hailing in the U.S. (*42*, *43*). Estimating accessibility wherein individuals get a ride from a relation does not contribute to our perspective of accessibility where we model the interaction between individual impedance and accessibility, rather than individual preferences. Toward illustrating accessibility rather than precisely modeling the exact mode of travel for each traveler, we utilize the assumptions here.

## *Summary Statistics of Accessibility Variables*

The distribution of air service and airfare, as well as the spatial distribution of individual constraints, influence overall accessibility; in this section, we evaluate their overall influences in our accessibility equation. Service differences specific to origin–destination pairs show variation in supply of nonstop seats, while median airfare relationships remain more constant across destination airports with varying degrees of magnitude.

In Figure 1*a*, we observe an overall high frequency of air service to ATL and low frequency to AUS from our case study region. However, the number of nonstop seats to our destination airports is unevenly distributed, with EWR, BWI, and PHL providing varying relative degrees of service to ATL, AUS, and BNA. In Figure 1*b*, across all possible destinations, EWR consistently has the highest airfare. Based on these trends, we might expect to see a relatively strong accessibility measure in the Baltimore region for the destination of ATL, an airport with both the greatest supply and lowest airfare from BWI. Considering the destination airport of AUS, BWI has the lowest airfare while EWR has the largest number of seats. A classical (impedance-based) accessibility calculation for a hypothetical traveler traveling to AUS may see areas around Baltimore and Newark with the highest accessibility.

As the AIM considers not just supply and service-based variables but also individual variables, summaries of our more urban focused variables help frame what to expect in the AIM case study. Consider Figure 2, which shows a map of median incomes across census tracts. We observe a concentration of lower-income populations in core inner-city areas near airports, with higher incomes in suburban areas. Geographic areas west of EWR, far north of PHL, in-between EWR and PHL, and far west of BWI show the wealthiest suburbs in our case study. In the urban core, inner suburbs, and far rural areas, we find a more mixed economic profile. Contrary to accessibility measures of supply-based impedance, we expect to find greater accessibility in suburban areas in respect of economic ability, while areas immediately proximate to the airports with severely low income may experience lower accessibility.

## Spatial Analysis and Discussion

Based on the specifications of the AIM metric, we present a case study of accessibility across our sample MSAs for origin census tracts to three possible destination airports (AUS, ATL, BNA). In this section, we present and discuss our spatial analysis of the AIM metric, summarize key takeaways, and comment on the functional form and robustness of our model.

### *Case Study Results and Interpretation*

The spatial maps discussed below demonstrate the changes in accessibility when considering equity variables

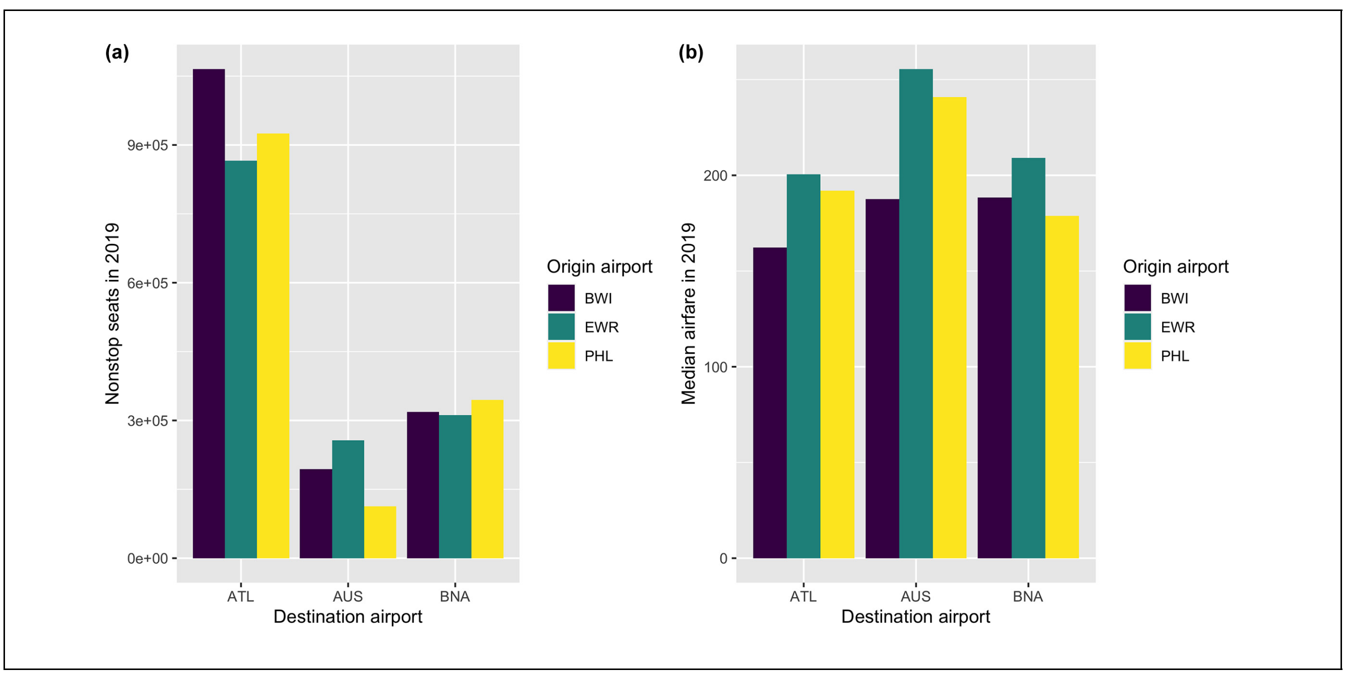


**Figure 1.** Comparison of origin and destination airports for (*a*) supply of total nonstop seats in 2019 and (*b*) median airfare in 2019.
*Note*: Destination airports: ATL = Atlanta Hartsfield-Jackson International, Georgia; AUS = Austin–Bergstrom International, Austin, Texas; BNA = Nashville International, Tennessee. Origin airports: BWI = Baltimore/Washington International, Maryland; EWR = Newark Liberty International, New Jersey; PHL = Philadelphia International, Pennsylvania.

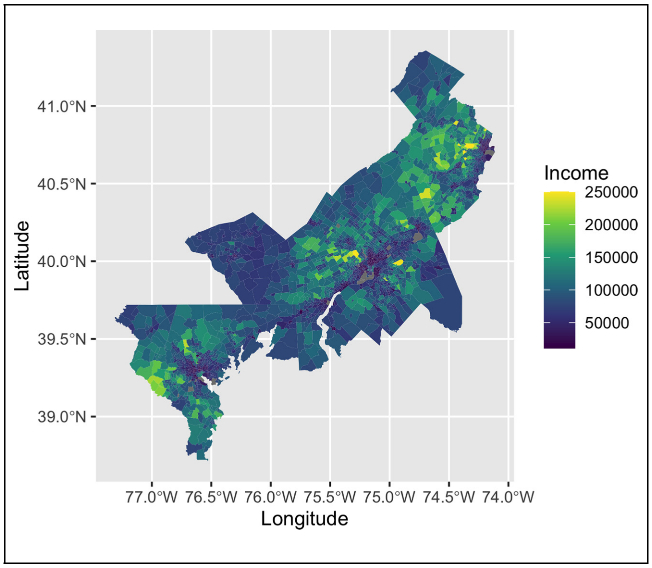


**Figure 2.** Median income across the Newark, Philadelphia, and Baltimore area by census tract.

and potential changes in transportation supply. It is important to note that the model does not force a hypothetical traveler to utilize a specific airport when traveling to destination *j*; instead, we construct a matrix with the AIM scores for EWR, BWI, and PHL to each destination airport for each census tract for each mode, and select the largest AIM associated with each census tract. Thus, each census tract's accessibility corresponds with its maximum possible accessibility. In creating the plots, we normalize the long-distance and airport access impedance factors to a range relative to each other. The scale for each plot is normalized to a range of 0 to 1 for visual purposes.

Figures 3–5 represent spatial distributions of the AIM metric for the destination airports of AUS, ATL, and BNA. Figures 3*a*, 4*a* and 5*a* are a traditional representation of accessibility that accounts for time, cost, and locational impedance, where accessibility is relatively higher in the catchment areas proximate to the airports. This is achieved by encoding the cohort-specific variables ($w_v$, $e_{kv}$) as constants by setting these parameters equal to one (recall that $w_v$ contributes to individuals' ability to afford the price of airfare and $e_{kv}$ influences individuals' ability to travel to the airport by private vehicle and transit modes). Figures 3*b*, 4*b* and 5*b* show the spatial analysis when we parameterize the equity variables ($w_v$, $e_{kv}$) as specified above under Parameterizing Cohort-based Coefficients.

Figure 3*a* displays greater accessibility to Austin for the geographic areas around Baltimore and Newark. This is largely a result of, first, the higher magnitude of seats from EWR, and, second, the more favorable traveling conditions with BWI's lowest airfare factor (Figure 1*b*). Once income-specific constraints are accounted for in Figure 3*b*, the higher accessibility areas are more concentrated in the suburbs surrounding EWR. The higher concentration of low-income populations in Baltimore down weight the AIMs in that area, resulting in relatively lower accessibility than the areas surrounding EWR despite similar supply levels and lower airfare. Correspondingly, the high accessibility in the EWR region in Figure 3*b* can be largely attributed to the affluent suburbs of Newark where income-related weights are considered more of an inconvenience than an impedance to travel (Figure 2).

Figures 4 and 5 showcase AIM spatial distributions for the destination airports of ATL and BNA respectively where large aviation supply and low effects from airfare and travel time influence accessibility. Similar to Figure 3, individual constraints and sensitivities related to income affect the distribution of accessibility, particularly in areas proximate to airports. The higher supply of seats from PHL–BNA and BWI–ATL, as well as both PHL–BNA's and BWI–ATL's low airfare (Figure 1*b*) produce regions of high accessibility in the surrounding Philadelphia and Baltimore areas.

In Figures 4 and 5, we also demonstrate how a change in aviation supply and service characteristics influences spatial accessibility scores. From Figure 1*a*, ATL has an overwhelmingly higher number of nonstop seats across EWR, BWI, and PHL when compared with AUS and BNA. Yet, comparing the spatial distributions of accessibility across destination airports, lower-income inner-city populations and far rural areas consistently experience relatively lower accessibility, despite an increase in flight seat availability to ATL. Accessibility remains higher for wealthier suburban areas with both the ability and proximity to access air transportation supply.

## *Summary of Key Findings*

The analysis and interpretations in the previous section present several critical advances in understanding the relationship between equity and accessibility; these key findings are summarized below.

*Proximity to Airports Does Not Imply High Long-Distance Accessibility.* In Figures 3–5, low-income areas near EWR, BWI, and PHL consistently produce a severe concentration of low accessibility across destinations. The AIM down weights their accessibility based on their low income, and thus greater sensitivity to airfare and unstable access to a vehicle. Accessibility peaks just outside the inner-city region in wealthier suburbs where people have both the socioeconomic means and proximity to airports to travel long-distance. Thus, a major finding of this study is in the integration of cohort-specific variables

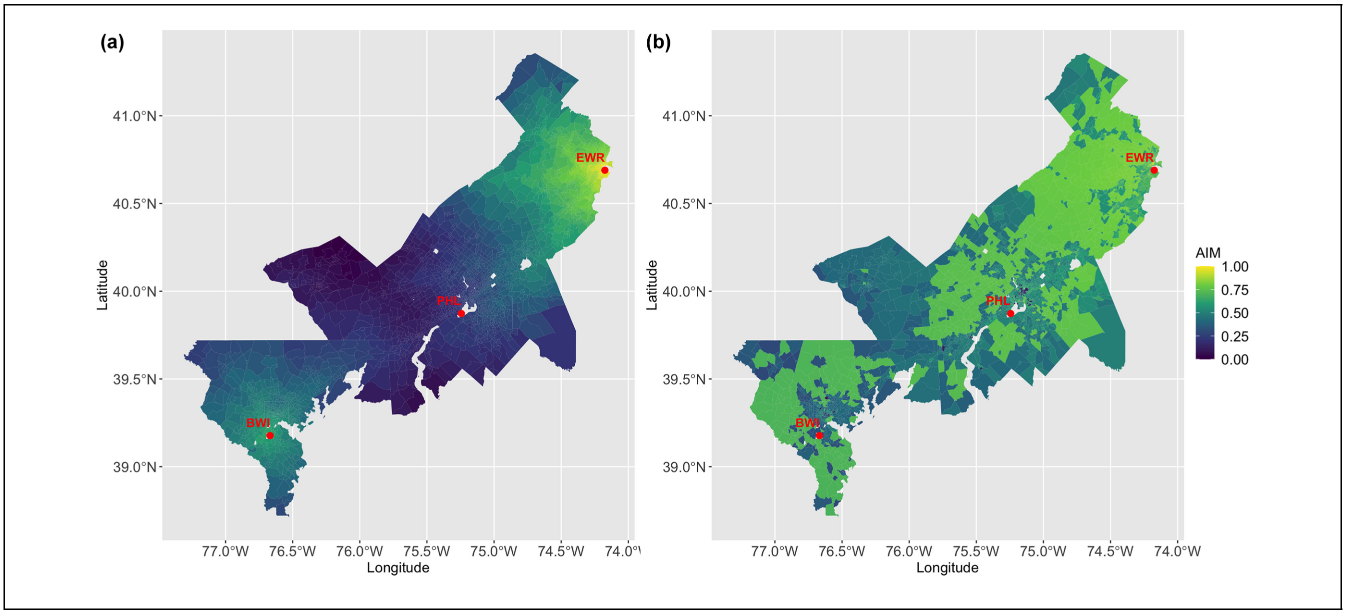


**Figure 3.** AIMs for AUS for (*a*) base and (*b*) cohort accessibility.
*Note*: AIM = Aviation-accessibility Integrated Mobility; AUS = Austin–Bergstrom International Airport, Austin, Texas.

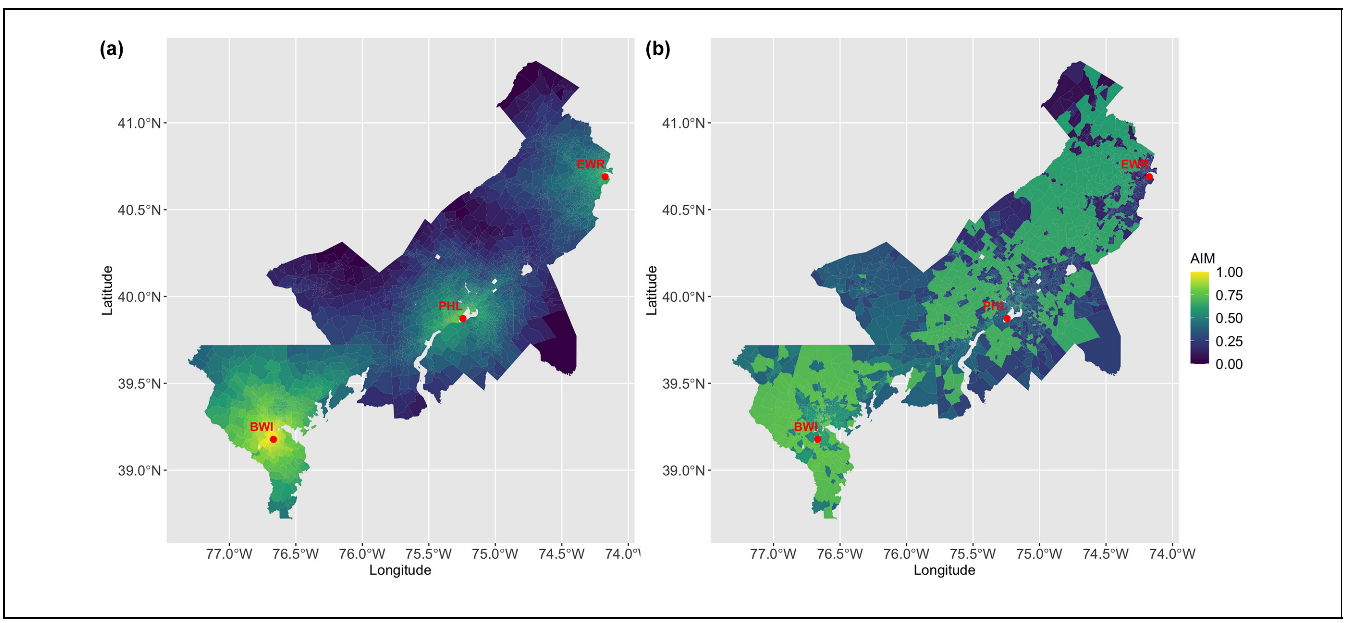


**Figure 4.** AIMs for ATL for (*a*) base and (*b*) cohort accessibility.
*Note*: AIM = Aviation-accessibility Integrated Mobility; ATL = Hartsfield-Jackson International Airport, Atlanta, Georgia.

in accessibility modeling: traditional accessibility models do not capture the disparities in accessibility across socioeconomic groups.

*Equity and Cohort Variables Can Influence the Relative Accessibility Scores.* The integration of cohort-level variables can alter the spread of accessibility and capture finer details within accessibility. For example, with the Austin AIM, when we account for airfare sensitivity among low-income groups, the higher-income suburbs of Newark are able to afford higher prices of airfare and benefit from reliable vehicle access despite the greater impedance from EWR resulting from airfare. This finding indicates that previous accessibility models that largely depend on factors like supply, cost, and time,

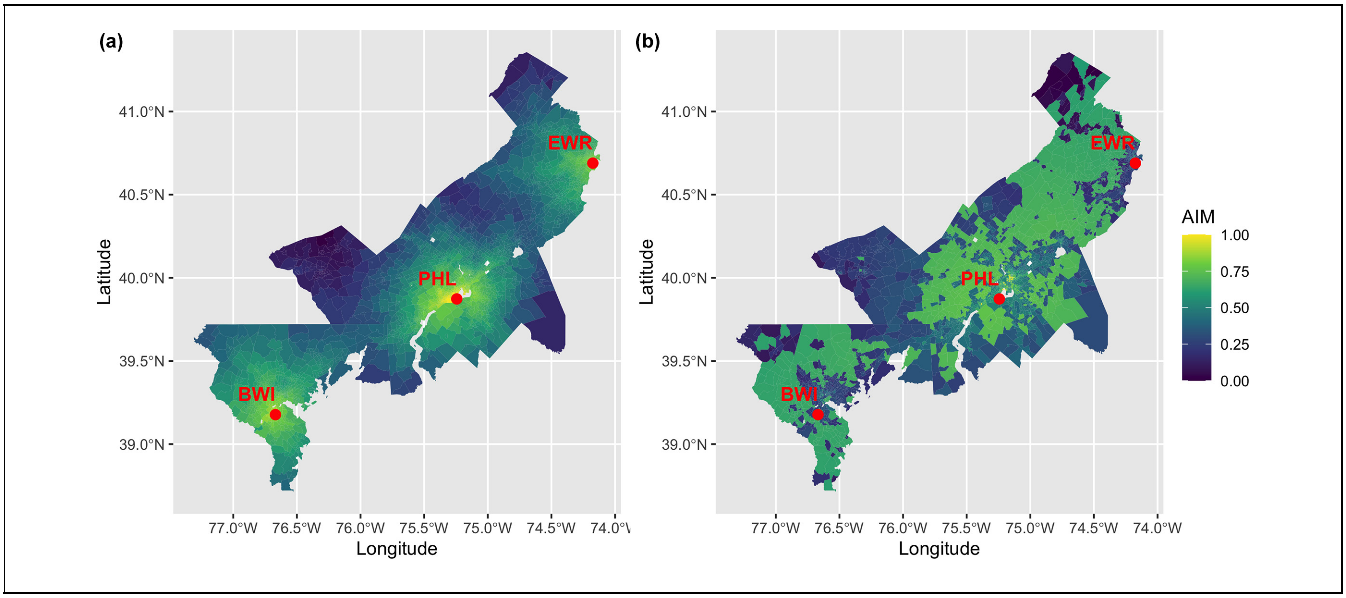


**Figure 5.** AIMs for BNA for (*a*) base and (*b*) cohort accessibility.
*Note*: AIM = Aviation-accessibility Integrated Mobility; BNA = Nashville International Airport, Tennessee.

rather than individual-level variables, miss out on key features of accessibility, while models that consider equity capture the needs and constraints of lower-income and disadvantaged populations.

*Accessibility Varies Significantly Because of Differences in Air Transportation Supply and Service Characteristics across Origin–Destination (OD) Pairs.* The differences across destination airports and the spread of accessibility across a region can be attributed to the supply of nonstop seats and the relative weights of airfare and travel time as illustrated by the impedance measure. Comparing the relative AIMs across census tracts and origin–destination pairs in Figures 3–5, differences in air service characteristics across OD pairs influence individuals' best accessibility. Increasing the supply of nonstop seats from AUS to ATL increases accessibility for higher-income suburban areas with the physical and financial means to take advantage of supply, while accessibility for lower-income inner-city areas remains low. This is a critical finding from the study: expanding aviation supply exacerbates disparities in access, rather than increasing access for all populations.

### Choice of Functional Form

Before outlining policy implications based on our case study findings, we want to address the choice of the functional form of the model and the spatial implications of the model findings. We tested several model structures, including one in which we exponentiated the impedance measure ($M_{qijk}$) and considered logarithmic utility coefficient curves. In doing so, our results captured similar trends in the distribution of accessibility, reaffirming the robustness of our model results. This indicates that multiple functional forms of models can capture the disparities in accessibility we seek to illustrate. Thus, this reinforces and solidifies our cohort-based approach; one can perturb the model structure yet achieve the same conclusions about the role of equity in measuring accessibility. We do not assert necessarily that our methodology is the sole way to model accessibility; rather, our contribution is in implementing a cohort-based approach that incorporates individual constraints and preferences into a single accessibility metric.

## Policy Implications

This study's methodology contributes a novel perspective in defining accessibility both mathematically and conceptually in an individual-specific analysis. Considering individual means and constraints is necessary in capturing accessibility wherein low-income populations near airports are more sensitive to airfare and experience lower vehicle availability. The empirical spatial analysis for a socioeconomically and demographically diverse region with large airport markets challenges commonly used isochrone and supply-based accessibility assessments. Because we showcase the nuances of accessibility through our cohort-based approach, we motivate a field of accessibility models that capture individual constraints and encourage implementing the AIM model at a national level.

The AIM metric also serves as a planning tool to study how infrastructure investments affect accessibility; thus, we identify projects that help guide the federal funding's prioritization for aviation infrastructure improvements that seek to improve access for disadvantaged populations. In the application of our model, we consider how changes in transportation supply can influence accessibility across socioeconomic groups. We find that expanding air services does not affect all populations equally; rather, when considering the perspective of vulnerable travelers, the accessibility benefits are dispersed across socioeconomic groups. By incorporating these constraints into an accessibility modeling framework, simply building more runways or expanding aviation supply will not improve accessibility for low-income individuals and will only benefit those in wealthier communities.

Since our findings indicate that incorporating the constraints of disadvantaged travelers changes the distribution of accessibility, we can use the AIM to model accessibility across a wider range of geographic regions at a national scale. In doing so and in addressing the limitations of the study, we would want to build a national map of accessibility and move beyond our initial case study geography. We further encourage building on the model and adding additional variables that capture the nuances within accessibility; for example, additional ground access modes of transportation, convenience-related features of air travel, and cohorts beyond income groups. In doing so, qualitative travel surveys of low-income populations would more precisely model the PAI and cohort-based coefficients. These methodological improvements could also provide evidence toward more nuanced policy recommendations—for example, highlighting the need for expanding access through intermodal and interregional transportation systems.

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## Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: S. Karam, S. J. Nam, M. S. Ryerson; data collection: S. Karam, S. J. Nam; analysis and interpretation of results: S. Karam, S. J. Nam, M. S. Ryerson; draft manuscript preparation: S. Karam, S. J. Nam, M. S. Ryerson. All authors reviewed the results and approved the final version of the manuscript.

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The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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## References

1. Martens, K., and F. Di Ciommo. Travel Time Savings, Accessibility Gains and Equity Effects in Cost–Benefit Analysis. *Transport Reviews*, 2017, Vol. 37, No. 2, pp. 152–169.
2. Bureau of Transportation Statistics. *Household, Individual, and Vehicle Characteristics, Bureau of Transportation Statistics*. Bureau of Transportation Statistics, 2011. https://www.bts.gov/archive/publications/highlights_of_the_2001_national_household_travel_survey/section_01. Accessed July 30, 2021.
3. Bhadra, D. Air Travel in Small Communities: An Econometric Framework and Results. *Journal of the Transportation Research Forum*, Vol. 43, No. 1, 2010. https://doi.org/10.5399/osu/jtrf.43.1.711.
4. Ryerson, M. S., and A. M. Kim. A Drive for Better Air Service: How Air Service Imbalances across Neighboring Regions Integrate Air and Highway Demands. *Transportation Research Part A: Policy and Practice*, Vol. 114, 2018, pp. 237–255.
5. Kim, A., and M. Hansen. Deconstructing Delay: A Non-Parametric Approach to Analyzing Delay Changes in Single Server Queuing Systems. *Transportation Research Part B: Methodological*, Vol. 58, 2013, pp. 119–133.
6. Ryerson, M. S. Incentivize It and They Will Come? How Some of the Busiest U.S. Airports Are Building Air Service with Incentive Programs. *Journal of the American Planning Association*, Vol. 82, No. 4, 2016, pp. 303–315.
7. Grubesic, T. H., T. C. Matisziw, and A. T. Murray. Assessing Geographic Coverage of the Essential Air Service Program. *Socio-Economic Planning Sciences*, Vol. 46, No. 2, 2012, pp. 124–135.
8. Grengs, J., J. Levine, Q. Shen, and Q. Shen. Intermetropolitan Comparison of Transportation Accessibility: Sorting Out Mobility and Proximity in San Francisco and Washington, DC. *Journal of Planning Education and Research*, Vol. 29, No. 4, 2010, pp. 427–443.
9. Miller, E. J. Accessibility: Measurement and Application in Transportation Planning. *Transport Reviews*, Vol. 38, No. 5, 2018, pp. 551–555.
10. Ryerson, M. S., and A. Woodburn. Build Airport Capacity or Manage Flight Demand? How Regional Planners Can Lead American Aviation into a New Frontier of Demand Management. *Journal of the American Planning Association*, Vol. 80, No. 2, 2014, pp. 138–152.
11. Gosling, G. D. Aviation System Performance Measures for State Transportation Planning. *Transportation Research Record: Journal of the Transportation Research Board*, 2000. 1703: 7–15.

12. Grubesic, T. H., and T. C. Matisziw. A Spatial Analysis of Air Transport Access and the Essential Air Service Program in the United States. *Journal of Transport Geography*, Vol. 19, No. 1, 2011, pp. 93–105.
13. Matisziw, T. C., and T. H. Grubesic. Evaluating Locational Accessibility to the US Air Transportation System. *Transportation Research Part A: Policy and Practice*, Vol. 44, No. 9, 2010, pp. 710–722.
14. Reynolds-Feighan, A., and P. McLay. Accessibility and Attractiveness of European Airports: A Simple Small Community Perspective. *Journal of Air Transport Management*, Vol. 12, No. 6, 2006, pp. 313–323.
15. Geurs, K. T., and B. van Wee. Accessibility Evaluation of Land-Use and Transport Strategies: Review and Research Directions. *Journal of Transport Geography*, Vol. 12, No. 2, 2004, pp. 127–140.
16. Levinson, D. M., D. Gillen, and A. Kanafani. The Social Costs of Intercity Transportation: A Review and Comparison of Air and Highway. *Transport Reviews*, Vol. 18, No. 3, 1998, pp. 215–240.
17. Janić, M. Aviation and Externalities: The Accomplishments and Problems. *Transportation Research Part D: Transport and Environment*, Vol. 4, No. 3, 1999, pp. 159–180.
18. Wachs, M., and T. G. Kumagai. Physical Accessibility as a Social Indicator. *Socio-Economic Planning Sciences*, Vol. 7, No. 5, 1973, pp. 437–456.
19. Grengs, J. Nonwork Accessibility as a Social Equity Indicator. *International Journal of Sustainable Transportation*, Vol. 9, No. 1, 2015, pp. 1–14.
20. Bills, T. S., and J. L. Walker. Looking Beyond the Mean for Equity Analysis: Examining Distributional Impacts of Transportation Improvements. *Transport Policy*, Vol. 54, 2017, pp. 61–69.
21. Handy, S. L., and D. A. Niemeier. Measuring Accessibility: An Exploration of Issues and Alternatives. *Environment and Planning A: Economy and Space*, Vol. 29, No. 7, 1997, pp. 1175–1194.
22. Bao, D., S. Hua, and J. Gu. Relevance of Airport Accessibility and Airport Competition. *Journal of Air Transport Management*, Vol. 55, 2016, pp. 52–60.
23. Garasky, S., C. N. Fletcher, and H. H. Jensen. Transiting to Work: The Role of Private Transportation for Low-Income Households. *The Journal of Consumer Affairs*, Vol. 40, No. 1, 2006, pp. 64–89.
24. *Chapter 3: Travel—Policy, Federal Highway Administration*. U.S. Department of Transportation Federal Highway Administration, 2020. https://www.fhwa.dot.gov/policy/23cpr/chap3.cfm. Accessed July 30, 2021.
25. Adler, T., C. S. Falzarano, and G. Spitz. Modeling Service Trade-Offs in Air Itinerary Choices. *Transportation Research Record: Journal of the Transportation Research Board*, 2005. 1915: 20–26.
26. Merkert, R., and M. Beck. Value of Travel Time Savings and Willingness to Pay for Regional Aviation. *Transportation Research Part A: Policy and Practice*, Vol. 96, 2017, pp. 29–42.
27. de Luca, S. Modelling Airport Choice Behaviour for Direct Flights, Connecting Flights and Different Travel Plans. *Journal of Transport Geography*, Vol. 22, 2012, pp. 148–163.
28. Hess, S., T. Adler, and J. W. Polak. Modelling Airport and Airline Choice Behaviour with the Use of Stated Preference Survey Data. *Transportation Research Part E: Logistics and Transportation Review*, Vol. 43, No. 3, 2007, pp. 221–233.
29. Hess, S., and J. W. Polak. Airport, Airline and Access Mode Choice in the San Francisco Bay Area. *Papers in Regional Science*, Vol. 85, No. 4, 2006, pp. 543–567.
30. Gupta, S., P. Vovsha, and R. Donnelly. Air Passenger Preferences for Choice of Airport and Ground Access Mode in the New York City Metropolitan Region. *Transportation Research Record: Journal of the Transportation Research Board*, 2008, 2042: 3–11.
31. Delaware Valley Regional Planning Commission. *Rating the Region: Metropolitan Indicators Report*. https://www.dvrpc.org/Reports/16010.pdf.
32. *TSA Wait Times*. https://www.tsawaittimes.com/.
33. *Amtrak Monthly Performance Report*. https://www.amtrak.com/content/dam/projects/dotcom/english/public/documents/corporate/monthlyperformancereports/2019/Amtrak-Monthly-Performance-Report-FY2019-Final.pdf.
34. Martens, K., and J. Bastiaanssen. 3—An Index to Measure Accessibility Poverty Risk. In *Measuring Transport Equity* (Lucas, K., K. Martens, F. Di Ciommo, and A. Dupont-Kieffer, eds.), Elsevier, Cambridge, MA, 2019, pp. 39–55. https://www.sciencedirect.com/science/article/pii/B9780128148181000032. Accessed February 6, 2021.
35. *2015 YouGov Air Travel Frequency Poll*. YouGov. http://d25d2506sfb94s.cloudfront.net/cumulus_uploads/document/ccrem93qj2/tabs_OPI_tsa_20150604.pdf.
36. 2018 Airport Planning Standards. Aviation Department—Port Authority of New York and New Jersey. 2018.
37. Federal Highway Administration. *Travel Time Reliability: Making it There on Time, All The Time*. https://ops.fhwa.dot.gov/publications/tt_reliability/ttr_report.htm.
38. Ball, M., C. Barnhart, M. Dresner, M. Hansen, K. Neels, A. Odoni, E. Peterson, et al. *Total Delay Impact Study: A Comprehensive Assessment of the Costs and Impacts of Flight Delay in the United States*. 2010. https://rosap.ntl.bts.gov/view/dot/6234.
39. Borenstein, S., and J. Netz. Why Do All the Flights Leave at 8 am?: Competition and Departure-Time Differentiation in Airline Markets. *International Journal of Industrial Organization*, Vol. 17, No. 5, 1999, pp. 611–640.
40. Greig, H. Study of Airport Access Mode Choice. *Journal of Transportation Engineering*, Vol. 112, No. 5, 1986, pp. 525–545.
41. Pasha, M. M., M. D. Hickman, and C. G. Prato. Modeling Mode Choice of Air Passengers' Ground Access to Brisbane Airport. *Transportation Research Record: Journal of the Transportation Research Board*, 2020. 2674: 756–767.
42. Littwin, A. Beyond Usury: A Study of Credit-Card Use and Preference among Low-Income Consumers. *Texas Law Review*, Vol. 86, No. 3, 2008, pp. 451–506.
43. Sikder, S. Who Uses Ride-Hailing Services in the United States? *Transportation Research Record: Journal of the Transportation Research Board*, 2019. 2673: 40–54.