Advancing Transportation Performance Management and Metrics with Census Data

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1. Background

The Census Transportation Planning Products (CTPP) program was funded by the State Departments of Transportation and administered by the American Association of State Highway and Transportation Officials (AASHTO). The purpose of this program, as a partnership among all states, is to support the development of census data products and their application in the field of transportation. Since the initial development of CTPP data, a number of transportation projects and studies have benefited from using the data. By introducing CTPP, the early stages of transportation project planning and development are being emphasized. The quality of the data is improved with the new formatting and access capabilities, and the CTPP application is free for the public use.

While previous studies extensively used CTPP data to inform practice and research about the characteristics of journey-to-work traveler behavior dynamics, data sampling issues, the implications for new travel demand models, and improving the data structure (1- 3), this research paper shifts the focus to performance management and metrics. Transportation system performance indicators have been driving decision making for decades, and as data availability improves, the range of metrics is becoming wider to accommodate the variety of users in the transportation system (4-5).

This research paper is divided into several sections. The introductory sections explain the purpose of CTPP, the research objectives, general approach to performance measurements selection, and the case study that serves as a demonstration. The core sections focus on three performance metrics: Safety, Mobility, and Accessibility, and demonstrate how these can be developed using the CTPP data. The final sections compare the performance metrics obtained by using CTPP data only, and the potential for fusing CTPP data with currently existing Open data platforms, and the summary of findings. With this type of setting, this research is aiming to identify: (1) The currently available data that can serve as the foundation for transportation decision making; (2) The performance metrics which can be developed using the currently available data, while primarily relying on CTPP data; (3) The way we can use the developed performance metrics to advance current performance management of transportation systems. While considering transportation as a system in the performance analysis conducted in the core sections, this paper also discusses the transferability and potential for future applications and improvements of CTPP data, particularly for the purpose of establishing long-range transportation performance management strategies.

2. Research Objectives

The main goal of this research is to demonstrate the application of CTPP for the purpose of advancing transportation performance management (TPM). The importance of developing transportation system performance measurements that can be adequately implemented in various stages of transportation project, ranging from programming and planning to operations and maintenance, has been increasing over the past two decades. This effort to improve TPM exists on the national level, as a strategic approach towards creating policy and infrastructure investment decisions that aim to achieve nationally established performance targets and goals (*6*). While earlier efforts in transportation research and practice have also been geared towards performance improvements, the current efforts, particularly in long-range transportation planning, have taken a much more systematic approach towards identifying transportation performance outcomes that should be prioritized. As previous TPM efforts scarcely consider the application of CTPP, this research is focused on exploring the potential of CTPP for the purpose of TPM development.

In addition to potential CTPP contributions in TPM field, the Era of Big Data and Open Data has brought tremendous opportunities in terms of the variety of data sources that are now available for transportation stakeholders. The past decision making in transportation has been highly dependent on the data collected and available from transportation agencies. The current decision making has a much broader range of data resources that can be utilized to not only improve transportation project-related decisions, but also reflect higher level of inclusion of various data generating platforms (*3*). For example, transportation agencies and transportation users are becoming more and more equal in terms of data provision, and thus transportation users are becoming more and more invested in transportation decision making. This is very significant, due to the fact that transportation is primarily a service, and whether it is provided by local, regional, or state agency, the outcomes and quality of this service need to prioritize and include users as much as possible.

This research brings the existing transportation data resources and performance metrics together, using CTPP data as the foundation, and performance metrics as the target outcome, with the purpose of exploring how CTPP can be used to advance the current TPM efforts.

3. Performance Measurements

The role of TPM is crucial for transportation decision making and policy formulation. A major shift in TPM begun during the past decade as performance metrics became more inclusive and started to account for the quality of transportation service for all users in the transportation system. In addition to being more inclusive, the metrics we now use are oriented towards enhancing the methodology used to evaluate the transportation service. The main goal of TPM improvement is to develop performance metrics that are transferable, data-driven, facilitate decision making, and enable communication between decision makers and transportation service users.

The TPM methods today go beyond the traditional metrics, which mostly focused on evaluating traffic congestion. The Federal Highway Administration has established six target groups of major transportation issues that need to be resolved through the development and implementation of adequate transportation performance metrics in the decision making process (*6*):

- improving safety
- maintaining infrastructure condition
- reducing traffic congestion
- improving efficiency of the system and freight movement
- protecting the environment and
- reducing delays in project delivery

These six "rules" for TPM development clearly distinguish six performance metrics for the transportation system evaluation: safety, infrastructure condition, traffic congestion, efficiency, environmental impact, and project delivery. This research paper will mainly focus on the metrics related to safety, congestion and efficiency, by demonstrating how CTPP data can be used to develop the following performance metrics:

- Safety
- Mobility
- Accessibility

These three areas of TPM are selected to capture both traditional and more recent approaches to performance measurement, with the capability to implement the developed metrics to private vehicle users, public transit users, pedestrians, and bicyclists. The goal is to demonstrate how CTPP data can be used to develop this set of metrics for various transportation users, and then demonstrate how the developed metrics could potentially be improved by fusing CTPP data with other data sources from transportation agencies and publicly available data platforms.

In the area of road safety, target-based, and result-oriented decisions towards reducing/eliminating the most severe crash types, are preferred when selecting the most effective countermeasures. This safety performance-based approach is already used in micro-level road safety analysis related to intersections and road segments. The macroscopic road safety analysis is gaining the momentum with the increasing need to incorporate road safety targets in the long-range transportation plans. This is where census-based data could play a major role in capturing the area-wide effects that are associated with crash frequencies and severities for multimodal transportation users.

Mobility-oriented performance metrics relate to speed and utilization of the available capacity of transportation infrastructure. Mobility is usually linked to intersections or roadway segments, but it is also an important element of long-range transportation planning. Census data has been used for decades to build travel demand models and evaluate the needs to invest in transportation infrastructure improvements. In certain parts of the country, Metropolitan Planning Organizations (MPOs) develop and conduct their own surveys to build travel demand models. The advantages and disadvantages of using local data with limited sample size versus CTPP need to be further explored.

Accessibility is dependent on the availability of multimodal infrastructure, and its integration with the land use patterns. It describes the ability of transportation users to reach desired destinations within the given time constraints. Accessibility as a transportation performance metric that recently became incorporated in transportation policies, particularly in the regional and city-level long-range transportation plans. The way accessibility is measured highly depends on data availability and the purpose of measurement.

The common thread for all three measures: safety, mobility, and accessibility, in this paper is the demonstration of the development of these metrics based on CTPP data only, and the comparison with the potential improvements that can be achieved when CTPP data are combined with data from alternative sources which are addressed in the following section.

4. Case Study and Data

City of Chicago is the case study. The most recent efforts that Chicago made to improve urban data collection make it a great candidate for future research efforts in this field. The possibility to transfer the findings of this research paper to other cities and regions will be discussed in the final section of the paper. The City of Chicago Department of Innovation and Technology maintains a very detailed database on transportation and urban environment features. Chicago's robust data portal was established in 2010 and hosts over 900 datasets with information on various services in the city, in tabular, GIS, and API formats. The portal is developed to enable residents to access government data and utilize them to develop tools that can improve the quality of life in the city. This is currently one of the "largest and most dynamic models of open government in the country" (*7*). In addition to improving the decision making process by merging various data sources and developing an Open Data platform, the City of Chicago is also invested into developing new ways to generate and collect urban data.

Apart from the major efforts to develop high fidelity open source data platforms, Chicago is also known for its extensive multimodal transportation system. The City has developed complete streets design guidelines (City of Chicago, 2013), with "Make Way for People" initiative that converts underutilized "excess asphalt" street spaces into active public spaces with purpose to increase safety, encourage walking, and support community development. Chicago has invested in bicycling infrastructure to become one of the best major U.S. cities for biking with over 200 miles of on-street bike lanes. The City of Chicago is also known for its active safety research, not only vehicles but bicyclists and pedestrians as well, and a very extensive transit system. Chicago is the first major city in the U.S. to adopt a city-wide policy for the investments in safety countermeasures that would reduce pedestrian crashes, as a part of the national "Vision Zero Network" initiative. All factors described above made Chicago a valid case study for the purpose of this research.

This study combined data from several sources, including Open data and data obtained from multiple transportation agencies, to develop a comprehensive framework for the analysis of the relationship between multimodal transportation features and safety in urban transportation systems. Data collection included crash data, multimodal transportation features, road network features and traffic conditions, land use data, socio-economic characteristics, and analysis of spatial features to select the adequate spatial units of analysis. The CTPP data packages are developed from the American Community Survey (ACS) data for the designated five-year periods. Thus, the most recent available CTPP data package is based on ACS data for the period from 2006-2010. The data includes residence tables, workplace based tables, and flow tables (home to work trips) with the capability to extract tabulated data in various formats and visualize them using the available map tool. Tables include means of transportation univariate and crossed with travel time, household income, vehicle availability, age, time leaving home, and (new) presence of children, minority status, the number of workers in household and median household income. The characteristics of CTPP data formatting, as well as the fact that the data are collected for the five-year periods, makes the data very flexible for transportation analysis

purposes. In addition to CTPP, data was obtained from the Illinois Department of Transportation (DOT), Chicago Metropolitan Agency for Planning (CMAP), Chicago Transit Authority (CTA), and the available Open data platform supported by the City of Chicago.

Determining the level of spatial data aggregation is an important step in this study, as the choice of spatial analysis units could significantly impact the outcomes of the study. Census tracts were the most appropriate for spatial analysis in this case due to the data coverage and availability, and the convenient link to socio-economic characteristics, which have proven to be relevant for safety outcomes. The ranges of spatial units numbers used in the available literature indicated that census tracts would be appropriate as well. Census tracts are small statistical county subdivisions with relatively permanent geography that are updated each decade under the initiative of the U.S. Census Bureau. Census tracts are supposed to be somewhat homogeneous and ideally have around 1200 households (perhaps 2000-4000 people), but, in Chicago, population varies from 0 up to 16,000. Census tracts in the City of Chicago have remained nearly constant since the 1920s, but the numbering system has changed. Census tracts in the suburbs have changed a great deal over the years, in most cases by splitting. There were 876 census tracts in Chicago according to the 2000 census. After merging the data needed for the analysis and eliminating some census tracts due to missing data in the geocoding process, a total of 801 census tracts remained in the dataset. Table 1 shows the summary statistics of data used to develop performance metrics described in the following sections of this paper.

Table 1: Descriptive Statistics (801 census tract observations)

Variable	Description	Mean	Std. Dev.	Min	Max
DOT Crash Data					
VehCrash	Vehicle-only Crashes	375.176	354.534	5	3920
Veh_KA	Vehicle-only Fatal and Severe Injury Crashes	8.004	8.465	0	71
PedCrash	Crashes Involving Pedestrians	17.750	22.528	0	481
Ped_KA	Fatal and Severe Injury Crashes Involving Pedestrians	2.131	2.555	0	41
BikeCrash	Crashes Involving Bicyclists	9.528	13.178	0	172
Bike_KA	Fatal, and Severe Injury Crashes Involving Bicyclists	0.783	1.293	0	12
CTPP Data					
Population	Population Size	3.402	1.741	0.000	15.740
Pop_Dens	Population Density per mile squared	18.203	20.206	0.000	485.019
Employed	Percent of Employed Population	6.759	18.955	0.000	86.000
Unemploy	Percent of Unemployed Civil Population	14.970	9.459	0.000	51.000
PerCapInc	Average Income per Capita	27,786.690	20,029.490	0.000	131,548.000
NoVeh	Households with no Vehicles, %	26.537	15.118	0.000	89.400
Veh1	Households with 1 Vehicle, %	43.589	9.508	0.000	81.300
Veh2	Households with 2 Vehicles, %	22.558	11.544	0.000	59.100
Veh3plus	Households with 3 or more Vehicles, %	6.814	5.648	0.000	26.900
DriveAlone	Drive-alone Trips to Work, %	50.186	15.522	0.000	86.300
Carpool	Carpool Trips to Work, %	9.511	6.560	0.000	39.500
Transit	Transit Trips to Work, %	27.506	12.956	0.000	79.100
Walk	Walk Trips to Work, %	0.603	3.156	0.000	35.000
OtherMeans	Trips to Work by Other Means, %	2.542	2.942	0.000	21.300
WorkHome	Work Home, %	4.058	3.296	0.000	21.300
TT_min	Average Travel Time to Work, minutes	34.019	6.303	0.000	56.500
Open Data					
Road	Total Length of Roads, miles	6.278	3.910	0.142	30.762
Art	Arterials, % of street network	0.924	0.790	0.000	7.675
BikeLane	Total Length of Bike Lanes, miles	0.679	0.723	0.000	6.163
BusRoute	Total Length of Bus Routes, miles	1.541	2.559	0.000	39.980
Ltrain	Total Length of L-Train Lines, miles	0.147	0.353	0.000	4.411
Sidewalk	Total Sidewalk Area, feet squared	287.382	198.201	0.000	1,131.373
Intersect	Total Number of Intersections	37.803	27.800	0.000	163.000
Connect	Connectivity Index, intersections/mile of road	5.798	1.531	0.000	16.232
Signal_P	Signalized Intersections, %	0.123	0.141	0.000	1.333
BusStops	Total Number of Bus Stops	13.104	9.099	0.000	75.000

LStops	Total Number of L-Train Stops	0.091	0.325	0.000	2.000
DVMT	Daily Vehicle Miles Traveled	40,563.580	57,246.750	8.057	522,024.400
Ped	Pedestrian Trips Generated	47.715	103.345	1.191	1581.315
Bike	Bicyclist Trips Generated	2.511	5.439	0.062	83.227

The following sections of the research paper focus on the application of CTPP data combined with other data sources in the City of Chicago, to develop transportation performance metrics of safety, mobility and accessibility for private vehicle users, pedestrians, and bicyclists.

5. Applying Census Data for Safety Evaluation

The main purpose of this section is to develop transportation safety evaluation methods based on census data. The question that safety evaluation metrics are attempting to answer is what the expected frequency of crashes is under the particular area-wide set of characteristics that can be described by using census data. Safety Performance Functions (SPFs) are developed to predict vehicle-only (vehicular), pedestrian-vehicle (pedestrian), and bicyclist-vehicle (bicyclist) crashes on the census tract level. Safety Performance Functions (SPFs) are statistical models developed to estimate the average crash frequency for the selected entity (intersection, segment, area) as a function of exposure measures (traffic volume and road segment length) and, if the data availability allows, other conditions that characterize transportation network design and operations, and its environment. The general formulation of SPFs follows negative binomial regression model form as the most common approach to representing count data with overdispresion. The general form of each SPF is the following (*9*):

$$\theta_i = e^{(\beta_0 + \beta_1 \ln(\text{Exp1}_i) + \beta_2 \ln(\text{Exp2}_i) + \sum_j \beta_j \, x_{ij} + \varepsilon_i)}$$

Where:

θ_i - expected number of crashes for census tract "i"
β_0 - intercept
β_i - coefficients quantifying the effect of the "j" explanatory variables characterizing census tract "i" on θ_i
Exp1 and Exp2 – measures of exposure in census tract "i"
x_i - a set of "j" explanatory variables that characterize census tract "i" and influence θ_i
ε_i - disturbance term corresponding to census tract "i"

We compared four SPFs for vehicular, pedestrian, and bicyclist crashes aggregated on the census tract level:

- Models based on CTPP data only, where exposure to road crashes is based on ACS commute trips
- Models based on CTPP data fused with Open data, where exposure to road crashes is based on ACS commute trips
- Models based on CTPP data, including exposure characteristics from regional travel demand models
- Models based on CTPP data fused with Open data, including exposure characteristics from regional travel demand models

This process of model development resulted in a total of twelve safety evaluation models for all three crash types (vehicular, pedestrian, and bicyclist) for all crash severities. The process enabled us to compare the SPFs based on CTPP data only, to SPFs developed by combining CTPP data with data from regional transportation agencies and Open data platforms. The

purpose of this process was to ensure that the advantages and disadvantages of using only CTPP data for safety evaluation methods, and to demonstrate the variety of options that transportation agencies may use to develop their own SPFs depending on data availability and desired complexity and level of information required in road safety performance management process.

Results of the statistical modeling process are provided in Tables 2-4. Table 2 shows the results for SPFs developed to predict vehicular crashes on the census tract level. The basic SPF developed using CTPP data to predict vehicular crashes, has the following form:

$$Vehicular\ crashes_i = e^{(5.55+3.64\times10^{-4}\times\text{Workers Driving}+4.00\times10^{-6}\times\text{Income}-2.99\times10^{-3}\times\text{Median Age})}$$

To further improve CTPP data-based SPFs, crash exposure variables from the CMAP's travel demand model were used to replace the commuter trips and see how this change in exposure data reflects on the statistical models. The resulting SPF obtained by including CMAP exposure measure of DVMT for predicting vehicular crashes on the census tract level is:

$$Vehicular\ crashes_i = e^{(0.23+0.54\times\ln(\text{DVMT})+1.00\times10^{-6}\times\text{Income}-1.33\times10^{-3}\times\text{Median Age})}$$

The SPFs can be developed using CTPP data only, in the absence of other data resources. However, the primary advantage of using DVMT as the measure of exposure in the developed SPFs is the possibility of making the assumption of the expected zero crashes in census tracts where DVMT value is zero. Further, SPFs based on CTPP data only show that the expected increase in vehicular crashes is associated with the increase in exposure measures (workers driving or DVMT), increase in income per capita, and decrease in median age. Census tracts with higher average income are expected to have higher vehicle ownership, as cars would be more affordable in these areas, which could explain the estimated relationship between income per capita and the expected number of vehicular crashes. More complex SPFs developed by combining CTPP data with data from other transportation agencies and Chicago Open data platform are also given in Table 1, using exposure expressed as the workers driving (from CTPP) and exposure expressed as the measured DVMT (from CMAP). The addition of Open data makes the SPFs much more informative, as it allows better prediction of the expected number of vehicular crashes on the census tract level, through association with the increase of arterial roads mileage, intersection density, and the number of bus stops. Arterial roads are characterized by higher speeds than the local roads, and less uniform speeds than the freeways, which could explain the statistical significance of this variable in the SPF developed for predicting the expected number of vehicular crashes. The relationship between the intersection density and conflict points, as well as the presence of speed-changing behavior around bus stops, explains the association between these two variables and vehicular crashes.

Table 2: Vehicle-only Statistical Crash Models

CTPP Data						CTPP Data with CMAP Exposure					
Coefficients:	Estimate	Std. Error	Z value	P value		Coefficients:	Estimate	Std. Error	Z value	P value	
Intercept	5.552000	0.144700	38.382	0.000	***	Intercept	0.234100	0.192200	1.218	0.223	
Workers Driving	0.000364	0.000042	8.601	0.000	***	ln(DVMT)	0.545300	0.017760	30.711	0.000	***
Income per Capita	0.000004	0.000001	2.995	0.003	**	Income per Capita	0.000000	0.000001	-0.099	0.921	
Median Age	-0.002998	0.004373	-0.686	0.493		Median Age	-0.001337	0.003114	0.429	0.668	
AIC	10921.63					AIC	10296.14				
CTPP Data + Open Data						CTPP Data + Open Data with CMAP Exposure					
Coefficients:	Estimate	Std. Error	Z value	P value		Coefficients:	Estimate	Std. Error	Z value	P value	
Intercept	4.726000	0.121800	38.790	0.000	***	Intercept	1.215000	0.227300	5.348	0.000	***
Workers Driving	0.000255	0.000033	7.848	0.000	***	ln(DVMT)	0.403200	0.022540	17.886	0.000	***
Income per Capita	0.000004	0.000001	3.807	0.000	***	Income per Capita	0.000000	0.000001	0.472	0.637	
Median Age	-0.005388	0.003269	-1.648	0.099	.	Median Age	-0.001696	0.002899	-0.585	0.559	
Arterial Network	0.249600	0.021620	11.547	0.000	***	Arterial Network	0.033860	0.022240	1.523	0.128	
Intersection Density	0.001062	0.000338	3.143	0.002	**	Intersection Density	0.000907	0.000302	3.006	0.003	**
Bus Stops	0.032590	0.002651	12.297	0.000	***	Bus Stops	0.025420	0.002394	10.618	0.000	***
AIC	10363.79					AIC	10167.14				

*** - 99.9% statistical significance; ** - 99% statistical significance; * - 95% statistical significance; . – 90% statistical significance

Table 3 shows the results for SPFs developed to predict pedestrian crashes on the census tract level. The basic SPF developed using CTPP data to predict pedestrian crashes, has the following form:

$$Pedestrian\ crashes_i = e^{(3.42+1.47\times10^{-4}\times\text{Workers Driving}+1.76\times10^{-3}\times\text{Workers Walking}+\cdots)}$$

The resulting SPF obtained by including CMAP exposure measure of DVMT for predicting pedestrian crashes on the census tract level is:

$$Pedestrian\ crashes_i = e^{(0.98+0.17\times\text{ln(DVMT)}+0.41\times\text{ln(Ped.Trips)}+\cdots)}$$

The SPF developed to predict pedestrian crashes based on CTPP data only uses drive and walk trips to work as exposure measure, with the disadvantage that commuter trips to work make less than one quarter of total daily trips for transportation users in major cities. The SPF estimated using the measured DVMT and pedestrian trips based on CMAP's travel demand model enables to predict pedestrian crashes with the assumption that census tracts with zero vehicular trips or zero pedestrian trips are likely to have no crashes involving pedestrian, which is a more realistic model specification. Further addition of Open data demonstrates that variables such as intersection density, L-train stops, and bus stops are statistically significant in pedestrian crash SPFs. Intersection density and bus stops are associated with the increase in pedestrian crashes, due to higher exposure to pedestrian-vehicle conflicts in these areas. The L-train stops, as low-speed areas, are associated with the decrease in the expected pedestrian crash frequency. The statistically significant variables in pedestrian crash models show area-wide effects that influence pedestrian crash frequency, and capturing the impact of these variables on the corridor-level or intersection-level analysis would be challenging to capture. Whether the SPFs are based on CTPP data only, or CTPP data merged with Open data, SPFs developed to predict crashes on the census tract level in general prove to be informative for road safety managers in the manner that is complementary to microscopic-level statistical models.

Table 3: Pedestrian-Vehicle Crash Models

CTPP Data						CTPP Data with CMAP Exposure					
Coefficients:	**Estimate**	**Std. Error**	**Z value**	**P value**		**Coefficients:**	**Estimate**	**Std. Error**	**Z value**	**P value**	
Intercept	3.426000	0.290900	11.777	0.000	***	Intercept	0.989200	0.337000	2.936	0.003	**
Workers Driving	0.000147	0.000045	3.243	0.001	**	ln(DVMT)	0.172200	0.025360	6.789	0.000	***
Workers Walking	0.001764	0.000143	12.340	0.000	***	ln(Pedestrian Trips)	0.524300	0.035860	14.621	0.000	***
Income per Capita	-0.000007	0.000002	-4.111	0.000	***	Income per Capita	-0.000008	0.000001	-5.919	0.000	***
Male Population	-0.009973	0.005547	-1.798	0.072	.	Male Population	-0.024110	0.005168	-4.665	0.000	***
Median Age	-0.008215	0.004626	-1.776	0.076	.	Median Age	-0.010170	0.004208	-2.416	0.016	*
AIC	6008.585					**AIC**	5853.124				
CTPP Data + Open Data						**CTPP Data + Open Data with CMAP Exposure**					
Coefficients:	**Estimate**	**Std. Error**	**Z value**	**P value**		**Coefficients:**	**Estimate**	**Std. Error**	**Z value**	**P value**	
Intercept	3.130000	0.268100	11.672	0.000	***	Intercept	1.976000	0.340600	5.803	0.000	***
Workers Driving	0.000052	0.000043	1.206	0.228		ln(DVMT)	0.068300	0.028060	2.435	0.015	*
Workers Walking	0.001080	0.000134	8.075	0.000	***	ln(Pedestrian Trips)	0.418600	0.035870	11.670	0.000	***
Income per Capita	-0.000003	0.000001	-1.876	0.061	.	Income per Capita	-0.000006	0.000001	-4.329	0.000	***
Male Population	-0.011200	0.005093	-2.198	0.028	*	Male Population	-0.025210	0.004999	-5.044	0.000	***
Median Age	-0.016850	0.004265	-3.951	0.000	***	Median Age	-0.014870	0.004028	-3.691	0.000	***
Intersection Density	0.000890	0.000435	2.048	0.041	*	Intersection Density	0.001190	0.000416	2.858	0.004	**
L Train Stops	-0.165000	0.072360	-2.280	0.023	*	L Train Stops	-0.229600	0.070390	-3.262	0.001	**
Bus Stops	0.040490	0.002942	13.763	0.000	***	Bus Stops	0.029360	0.003189	9.208	0.000	***
AIC	5854.43					**AIC**	5773.997				

*** - 99.9% statistical significance; ** - 99% statistical significance; * - 95% statistical significance; . – 90% statistical significance

Table 4 shows the results for SPFs developed to predict bicyclist crashes on the census tract level. The basic SPF developed using CTPP data to predict bicyclist crashes, has the following form:

$$Bicyclist\ crashes_i = e^{(-0.02+4.36\times10^{-4}\times \text{Workers Driving}+5.26\times10^{-2}\times \text{Workers Biking}+\cdots)}$$

The resulting SPF obtained by including CMAP exposure measure of DVMT for predicting bicyclist crashes on the census tract level is:

$$Bicyclist\ crashes_i = e^{(-2.77+0.27\times \ln(\text{DVMT})+0.50\times \ln(\text{Bike Trips})+\cdots)}$$

Similar to vehicular crash and pedestrian crash models, the SPF for predicting the expected number of bicyclist crashes can be estimated using CTPP data only, and the number of driving and biking commute trips to work as the measure of exposure. When CMAP exposure measures are incorporated in the SPFs for predicting bicyclist crashes, the assumption holds that no bicyclist crashes are expected to occur in census tracts where either DVMT or the number of bike trips have the value of zero. After fusing CTPP data with Open data, additional variables show statistical significance in SPF specification for the expected number of bicyclist crashes: intersection density, bus stops, and bike lanes. In this case, bike lanes serve as a proxy for bicyclist exposure to crashes, so this variable should not be interpreted as the cause for the increase in bicyclist crashes. The presence of bike lanes may be associated with higher volumes of bike traffic. However bike traffic is expected to be present on the parts of the roadway network where bike lanes are unavailable, so including this variable is a form of a surrogate for bike miles traveled on the census tract level. Just as in the case of pedestrian crashes, these system-wide effects can be easily captured as the analysis is conducted on the census tract level. Four SPFs for predicting bicyclist crashes provided in Table 4 demonstrate how combining CTPP data with other data resources can provide relevant information about the expected crash frequency due to investment in multimodal infrastructure.

Table 4: Bicyclist-Vehicle Crash Models

CTPP Data						CTPP Data with CMAP Exposure					
Coefficients:	Estimate	Std. Error	Z value	P value		Coefficients:	Estimate	Std. Error	Z value	P value	
Intercept	-0.021680	0.394100	-0.055	0.956		Intercept	-2.778000	0.412500	-6.734	0.000	***
Workers Driving	0.000436	0.000049	8.920	0.000	***	ln(DVMT)	0.277500	0.026650	10.411	0.000	***
Workers Biking	0.052640	0.010440	5.044	0.000	***	ln(Bike Trips)	0.506700	0.042970	11.794	0.000	***
Income per Capita	0.000018	0.000001	11.907	0.000	***	Income per Capita	0.000010	0.000001	7.296	0.000	***
Male Population	0.046220	0.007155	6.460	0.000	***	Male Population	0.047710	0.006134	7.779	0.000	***
Median Age	-0.034730	0.005338	-6.506	0.000	***	Median Age	-0.025950	0.004781	-5.429	0.000	***
AIC	4919.062					AIC	4719.006				
CTPP Data + Open Data						CTPP Data + Open Data with CMAP Exposure					
Coefficients:	Estimate	Std. Error	Z value	P value		Coefficients:	Estimate	Std. Error	Z value	P value	
Intercept	-0.535500	0.364800	-1.468	0.142		Intercept	-2.200000	0.419800	-5.240	0.000	***
Workers Driving	0.000312	0.000045	7.013	0.000	***	ln(DVMT)	0.177900	0.029970	5.937	0.000	***
Workers Biking	0.045400	0.009210	4.929	0.000	***	ln(Bike Trips)	0.423600	0.043310	9.781	0.000	***
Income per Capita	0.000015	0.000001	11.176	0.000	***	Income per Capita	0.000010	0.000001	6.894	0.000	***
Male Population	0.044540	0.006474	6.880	0.000	***	Male Population	0.045690	0.006099	7.492	0.000	***
Median Age	-0.037880	0.004829	-7.843	0.000	***	Median Age	-0.028440	0.004688	-6.066	0.000	***
Intersection Density	0.002053	0.000440	4.666	0.000	***	Intersection Density	0.002344	0.000424	5.534	0.000	***
Bus Stops	0.028030	0.003338	8.397	0.000	***	Bus Stops	0.011130	0.003662	3.039	0.002	**
Bike Lanes	0.230700	0.041410	5.571	0.000	***	Bike Lanes	0.201900	0.040200	5.021	0.000	***
AIC	4712.349					AIC	4655.8				

*** - 99.9% statistical significance; ** - 99% statistical significance; * - 95% statistical significance; . – 90% statistical significance

Further comparison of the developed SPFs for vehicles, pedestrians and bicyclists can be conducted based on the results from the Tables 2-4. The CTPP data based variables that serve as the measures of exposure for these three modes of transportation include: workers driving, workers walking, and workers biking. Although the work commute trips represent only a portion of total trips in each census tracts, in the absence of other exposure variables, commute trips can still provide logical relationship between the increase in travel demand and increase in road crashes. These exposure variables proved to be statistically significant in all three CTPP data based SPFs. It was important to explore whether some other socio-economic variables coming from CTPP datasets may be used to estimate the number of crashes for various transportation users. Median age in census tract is associated with decrease in vehicle-only, pedestrian, and bicyclist crashes. This finding could be the consequence of lower driving populations in census tracts with higher percentage of seniors. Variable describing gender (percent of male population) was not statistically significant in vehicle crash models, while it was negatively associated with pedestrian crashes, and positively associated with bicyclist crashes. This could lead to further exploration of the expected vulnerability levels of vehicle-pedestrian crash victims, or recently explored gender gap in biking studies. However, the authors emphasize that further research is required before gender-related variables are used to develop census tract level SPFs, and that the presented models are stable even without these variables. Another important socio-economic characteristic presenting income per capita was associated with increase in vehicle-only crashes, potentially due to higher level of driving affordability in census tracts with higher income. Similar is the finding for bicyclist crashes, and it could be explained with higher investments in biking infrastructure in higher income neighborhoods. The income per capita is associated with decrease in pedestrian crashes, potentially indicating that people are more likely to walk in lower income neighborhoods.

Statistical models are validated using bootstrapping method. Ordinary nonparametric bootstrapping allowed to fit the model repeatedly by selecting data subsets randomly with replacement (*8*). The bootstrapping was conducted for 2000 resamplings of the given dataset.

After reaching the final model specifications the model goodness of fit is assessed using the Akaike Information Criterion (AIC), calculated as:

$$AIC = 2k - 2\ln(\hat{L})$$

Where k is the number of estimated parameters in the model, while $\hat{L}$ is the maximized value of the likelihood function of the estimated model.

The comparison of SPFs that use commuter trips as exposure variables and SPFs that use travel demand estimates as exposure variables, shows a better model with a lower AIC value for CTPP data based model with CMAP exposure. The new model that uses CMAP exposure information also shows that the SPFs based on CTPP data only tend to overestimate the association of socio-economic variables with estimated crash frequencies in the case of vehicle-only crashes. This could indicate that socio-economic variables are more influential in census tracts with higher percentage of population (including workers) walking and biking.

The SPFs for vehicle-only, pedestrian, and bicyclist crashes were developed based on CTPP data combined with data from Chicago transportation agencies and City's Open data platform. These SPFs were developed based on CTPP exposure variables and CMAP exposure variables. They show how characteristics of roadway network (e.g., presence of arterials and intersection density), and multimodal transportation infrastructure (bus stops, L train stops, and bike lanes) are associated with multimodal crashes.

6. Applying Census Data for Mobility Evaluation

Performance metrics that describe mobility are developed to primarily indicate how congested the transportation system is. Metrics traditionally used to evaluate mobility/congestion level rely on the fundamental traffic flow theory characteristics, including volume, speed, and density (*10*). The resulting indicators of mobility are usually expressed as Level of Service (LOS) and travel time. The main question these metrics are aiming to answer is how efficient travel is under a particular set of area-wide characteristics. In order to remain consistent with the safety evaluation metrics described in the previous section, mobility metrics in this section are also developed on the census tract level, for the City of Chicago's case study, using both CTPP data and data from alternative sources.

The simplest mobility metric that can be extracted from CTPP data is the average commuter travel time for each census tract. Further, CTPP data provide the information on the mode of transportation used by workers in each census tract. Figures 1 and 2 represent some of these mobility and quality of service indicators that can be developed by only using CTPP data or open data.
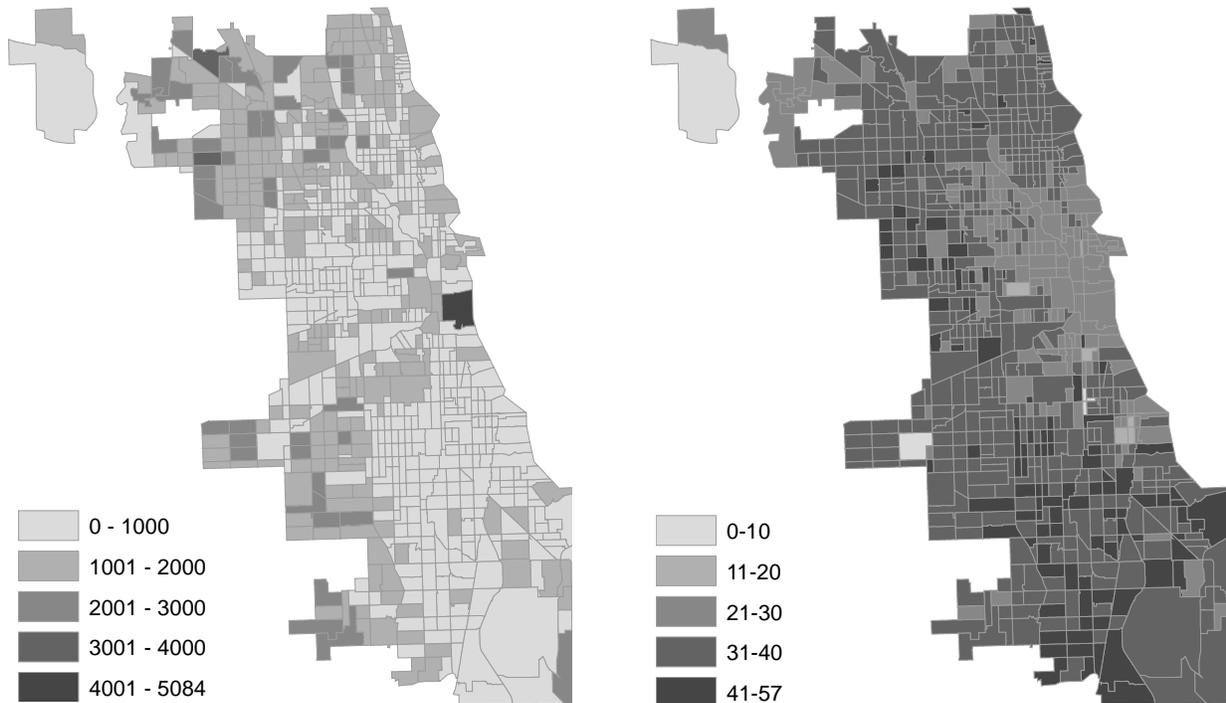

Figure 1: CTPP-based Mobility Metrics: Number of Workers Driving (left) and WTT (right)

It is expected that census tracts with higher number of workers driving would have higher congestion and more limited mobility. As noted in Figure 1, the highest number of driving commuter trips comes from the very core of the City of Chicago, the Loop. In addition, broader ring of census tracts surrounding the City's center form an area where travel time to work seems to be lower than in other areas of the City. This implies that the areas with the highest share of driving trips are also the areas with the shortest commute time to work. Further, this could indicate that for those transportation users living in the city center, their origin-destination distances are shorter when compared to the outside of the Loop area, and most of their daily transport needs can be met within a close proximity to their residences, which is due to a good mix of land uses in the city center. Based on the Figure 1, higher congestion levels are present in the downtown area, and this issue was not completely resolved by multi-level transportation infrastructure solutions present in Chicago. In addition, the major congestion generator in the City of Chicago, the Loop, is an area characterized by a very extensive multimodal network, which could provide a viable alternative if driving limitations (e.g., congestion pricing ring) are implemented in the City core. A simple visualization based on CTPP data indicates workers mode share spatial distribution and census tracts with the highest share of long-distance trips. However, it is challenging to assess city-wide mobility in a more detailed manner using CTPP data only.

The Open data from the City of Chicago can form their own indicators of mobility. For example, CMAP and City's Open data can be used to calculate Daily Vehicle Miles Traveled, as shown in Figure 2.
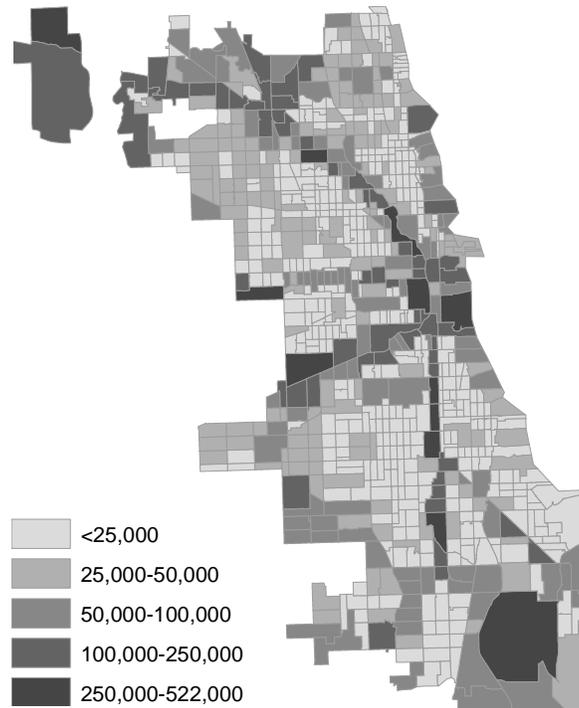

Figure 2: City Open Data Based Mobility Metrics: DVMT

The DVMT is calculated on the census tract level, for each census tract, by adding up the products of the average Annual Daily Traffic volume (data available from CMAP) and their corresponding road segment lengths computed in ArcGIS:

$$DVMT_i = \sum_{ij} AADT_{ij} \times L_{ij}$$

Where:
$DVMT_i$ - the total daily vehicle miles traveled in census tract "i"
$AADT_{ij}$ – the estimated AADT on road segment "j" within census tract "i"
L_{ij} – the length of road segment "j" within census tract "i" in miles
The DVMT is a slightly better indicator of congestion that can be calculated from the available City data and CMAP data. Figure 2 shows how census tracts with the highest congestion levels are those near the major freeway routes, including: I-90, I-290, and I-55. These congested corridors are intersecting in the downtown area that shows the highest DVMT values in the city. The DVMT calculated on the census tract level for the entire City of Chicago shows relatively balanced mobility services distribution throughout the entire city.

More comprehensive indicators of congestion/mobility can be derived if CTPP data are combined with alternative data sources. These combined metrics are derived from the traditional congestion measures such as travel time index and total delay, commonly used in Urban Mobility Report (*10*). These metrics refer primarily to working population within census tracts, as CTPP data include mode share for work trips and average travel time for work trips. Travel

time index is the ratio between the average peak hour travel time and the free flow travel time in the observed roadway network (*10*). This index is adjusted to measure the commuter travel time index (CTTI) as the ratio between the average travel time to work by a specific mode (e.g., drive or transit) and the total average travel time to work in each census tract:

$$CTTI_i = \frac{TTI_{ij}}{WTT_i}$$

Where:
TTI_{ij} - the average travel time to work for census tract "i" and mode "j"
WTT_i – total average travel time to work in census tract "i"

Figure 3 shows the results for the calculated CTTI on the census tract level, for "drive alone" mode in Chicago. It should be noted that the fields valued as "zero" are the census tracts where travel time data are currently unavailable for "drive alone" mode. The downtown area appears to have less competitive travel times by private vehicles when compared to other modes such as public transit, indicating that transportation users could be more likely to select other modes over private vehicle.

☐	0.00
	0.00 – 1.25
	1.26 – 1.50
	1.51 – 1.75
■	> 1.75

Figure 3: Travel time by car ("drive alone" mode) relative to the average travel time to work

Figure 4 shows the results for the calculated CTTI on the census tract level, for "public transit" mode in Chicago. It should be noted that the fields valued as "zero" are the census tracts where travel time data are currently unavailable for public transit mode. When compared to the average travel time, for those census tracts where transit travel time data are available, there is a significant number of areas where traveling by transit almost doubles the commute time to work. The metrics presented in Figures 3 and 4 show how competitive public transit is as a mode choice when compared to private vehicles and all transportation modes together. The downtown area of Chicago appears to have the most efficient public transit services with the most competitive travel times when compared to other modes of travel. City's Open data on multimodal infrastructure can be used to calculate the percentage of multimodal street network

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as an indicator of quality of transit service related to the accessibility metrics presented in the following section.
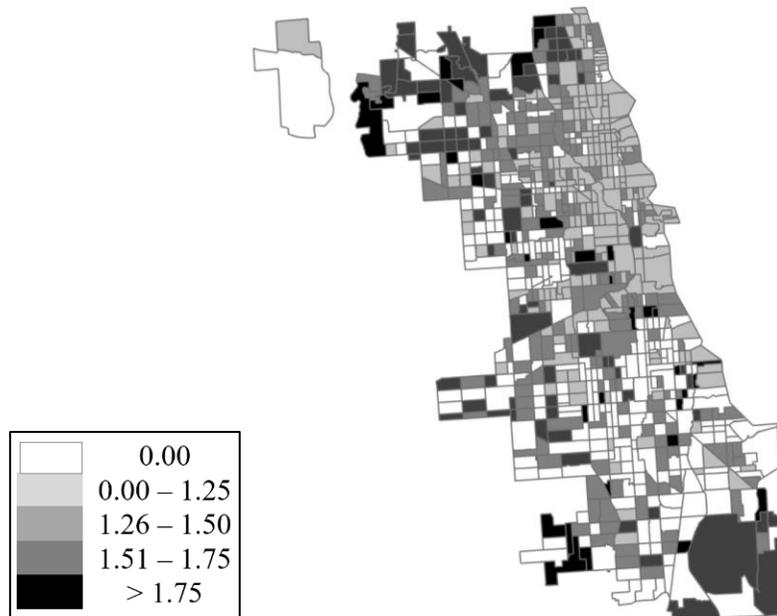

☐	0.00
☐	0.00 – 1.25
☐	1.26 – 1.50
▨	1.51 – 1.75
■	> 1.75

Figure 4: Travel time by public transit relative to the average travel time to work

7. Applying Census Data for Accessibility Evaluation

Accessibility is a relatively new addition to the current transportation performance measurement efforts. It describes the ability to reach desired destinations within the given spatial and temporal constraints (*11*). While mobility as a transportation performance metric relates to users need to reduce travel time to desired destination by ensuring that at least one option of travel is available; accessibility relates to reaching as many destinations as possible while using all available modes of travel.

Mobility is prioritized in areas where land use and transportation are highly disintegrated, with residential areas very distant from opportunities such as jobs, schools, hospitals, and shopping centers. Accessibility is prioritized in mixed land use areas with multimodal transportation infrastructure, where trip origins are in relative proximity to trip destinations and transportation users have diverse travel options with the opportunity to meet a broad range of travel needs within relatively short amount of time.

Accessibility is considered when more sustainable transportation solutions are incorporated in long-range transportation plans (*12*). Unlike mobility, which is essential for determining the capacity of the planned transportation network, accessibility is a measure crucial for spatio-temporal allocation of transportation resources while ensuring that freeways, transit lines, bike lanes, and sidewalks are layered in a manner that effectively connects transportation users to their trip destinations.

The first step towards evaluating accessibility using Chicago as a case study was to determine which transportation options are available and accessible on various parts of the entire transportation network. A simple network completeness analysis can provide this information by showing which network segments allow movements for all transportation user types (which

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segments can be considered "complete"). Figure 5 shows the percentage of roadway network that provides mobility opportunities for all four modes of transportation in Chicago (e.g., driving, transit, walking, and biking). The majority of the inner city area has more than 25% of street network that can be considered as "complete", while the very core of the city and some regions near lake Michigan have significantly higher presence of multimodal network when compared to the outer areas of the city. This further supports the findings related to mobility evaluation (Figure 1 from the previous section), which implies that the City center is the main car trip generator but with a high concentration of short car trips due to better land use mix that also contributes to better presence of the alternative and more sustainable modes of transportation. Based on the results from Figure 5, complete streets presence is higher along the major public transit (rail) corridors, indicating that areas around L-train stations facilitate access for pedestrians and bicyclists. As the distance from the City center increases, the presence of complete streets that provide access for all users decreases, as does accessibility to opportunities, which will further be discussed in this section.
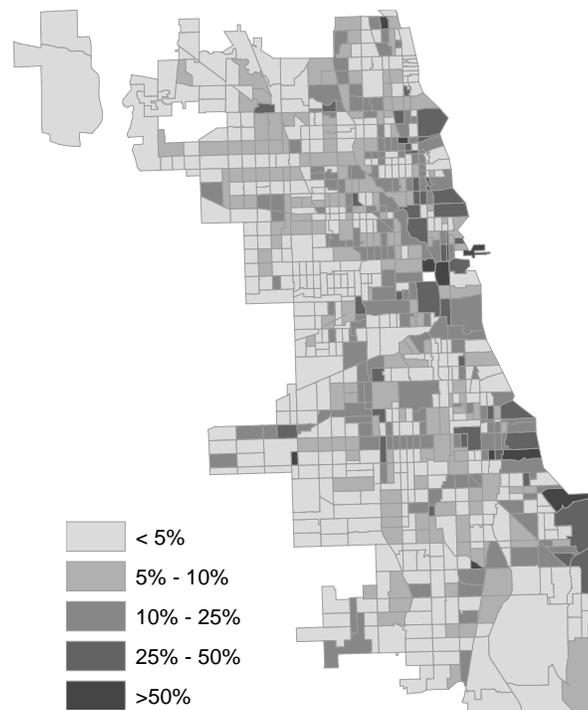

Figure 5: Network Completeness

Deriving accessibility measures based on CTPP data only would be challenging due to lack of information on multimodal infrastructure. For this particular metric, using CTPP as a standalone data source would not be a feasible solution. The combination of CTPP data and Open Data however, may result in more comprehensive indicators of accessibility. A more comprehensive review of different categories of accessibility measures may be found in the literature (*11*). For demonstration purposes in this study, CTPP data with the addition of Open Data are used to compute cumulative accessibility measures which indicate the total number of opportunities which may be reached by a specific mode of travel within the given time frame.

The *first step* in cumulative accessibility analysis is identification of the potential origins and destinations. For this purpose CMAP land use parcel-based inventory was used to define residential parcels as origins, and all other parcels as destinations (including the mixed land use parcels). In this manner, all census tracts were disaggregated into purely residential parcels representing the trip origins and all other parcels representing the potential trip destinations coupled with CTPP data on socio-economic characteristics. An example of an area from Chicago split into parcels is provided in Figure 6, which shows how parcel-based separation increases the accuracy about the information on land use type and spatial coverage. The main limitation in this process is that while the information about the spatial allocation of opportunities is fully available (e.g., CTPP information on where jobs are located), the total number of opportunities within each parcel is not counted and should be a subject of future research efforts.
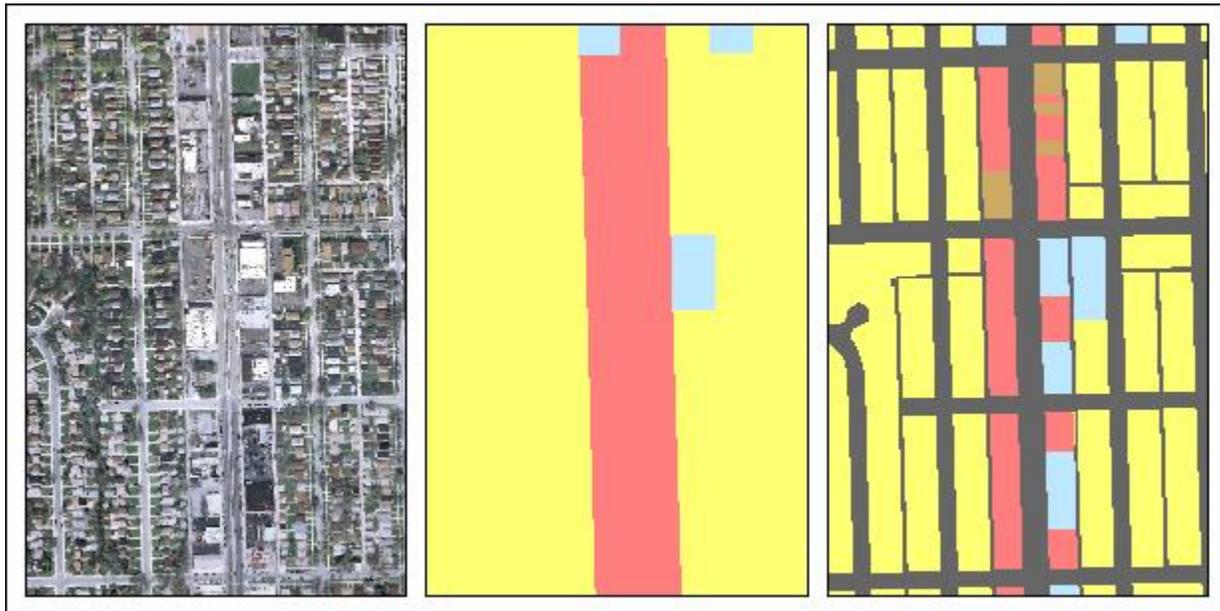

Figure 6: Polygon-based (center) versus parcel-based (right) land use inventory in Chicago (CMAP)

The *second step* in accessibility calculation was to connect the defined origins and destinations by the existing transportation network links using the information on roadway infrastructure, sidewalks, bike lanes, and transit lines. Multimodal infrastructure is overlaid on top of the defined origins and destinations to determine whether a feasible path by a specific mode exists between each origin and destination. If a feasible connection can be found, then the following *third step* is to compute travel time between each origin-destination (OD) pair. Using ArcGIS Network Analyst, travel time was computed for each mode of travel. In the case of public transit, only walking travel time was computed to the stations no further than 15-minute walk from the defined origins. The final step of the analysis is a simple count of accessible destinations from each origin within the defined time budget (e.g., 5, 10, 15,…120 minutes), and the summation of accessible destinations on the census tract level.

The following general framework may be used to calculate cumulative accessibility measure for each travel mode of interest:

$$A_{ik} = \sum_i \sum_j \{d_{ij} \in N | T_{ij} \leq T\}$$

Where:

A_{ik} – total number of destinations accessible from origin i within time T, using mode k

d_{ij} – destination j accessible from origin i within time T_{ij}

N – total number of available destinations

T_{ij} – time needed to reach destination j from origin i

T – available time budget $(5, 10, 15 \dots 120 \text{ minutes})$

Figure 7 can serve as a simple example of cumulative accessibility calculations for public transit mode. If we assume that average transit speeds are available for each link in the example network and that the link length is known, then travel time calculation for each link is computed simply as "Link Length/Distance". Further, if we assume that node "1" is origin, while all other nodes are destinations, we can then compute the cumulative number of destinations reachable from node "1" within the defined travel time budget. Based on the information given in the example in Figure 7, the total number of destinations accessible from node "1" within the 30-minute time budget is 5.

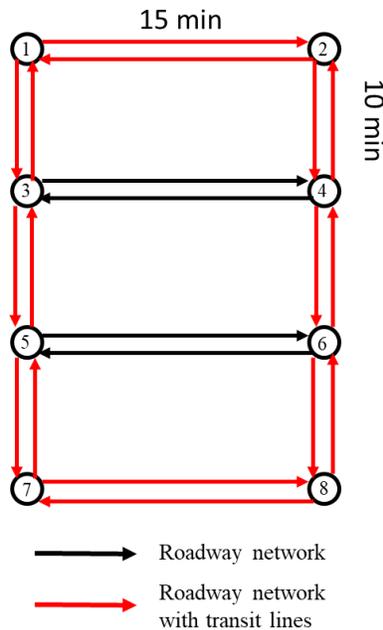$$A_{1,transit} = d_{12} + d_{13} + d_{14} + d_{15} + d_{17}$$

Figure 7: An example of a simple roadway network for cumulative accessibility calculations

Using the principle shown in the Figure 7, cumulative accessibility can be calculated on a large scale for each census tract in Chicago. A sample of this cumulative accessibility measure for destinations accessible by walking or transit within the 30-minute travel time budget in Chicago is provided in Figure 8. Based on the results presented in Figure 8, the nature of the selected travel mode has a major influence on the overall destination accessibility. The other factors influencing accessibility include the availability of transportation infrastructure and its proper integration within the land use context. As the number of origins and destinations increases, the

computational complexity related to travel time calculation also increases, and the resulting accessibility metrics may become more challenging to calculate. It is, however, important to provide indicators of accessibility whenever possible, particularly in long-range transportation planning, as they influence both land use and transportation policies.
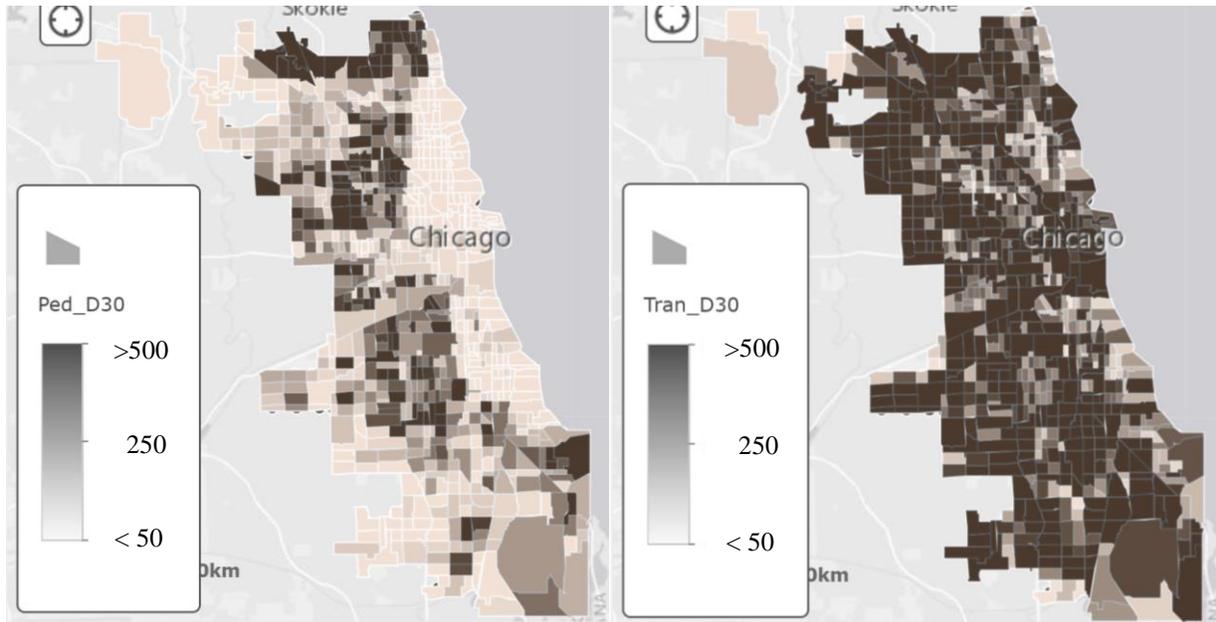

Figure 8: Cumulative accessibility within 30 minutes by walk (left) and public transit (right)

8. Summary of Findings and Implications for Research and Practice

This research paper focused on demonstrating how CTPP data can be used to develop and advance TPM, and what challenges may arise when developing TPM based on CTPP data only, versus the possibilities that result from fusing CTPP data with other available transportation data sources. Three groups of measures were developed using CTPP data combined with alternative data sources with City of Chicago as the case study: safety, mobility, and accessibility measures. These measures were presented for a broad range of transportation users, including private vehicle, public transit, pedestrian and bicyclist users.

The results of the developed safety metrics show how the SPFs based on more comprehensive datasets that combine CTPP data with alternative data sources outperform the SPFs that are based on CTPP data only. This is the case for all three examined crash types, showing the promising potential of harnessing data from multiple sources and platforms to improve crash predictions, and further investing transportation data infrastructure and multi-agency collaborations.

Both simple mobility metrics (Figure 1) and combined mobility metrics (Figures 2 - 4) can be used to derive conclusions about transportation service efficiency. These metrics may serve as indicators of spatial allocation of mobility services for various modes of transportation, and reveal the hotspots where there could be a potential need to invest in operational improvements in order to achieve desired mode share. Combining CTPP and Open data may serve to compute DVMT and travel time indices on the census tract level. Data sources other than CTPP data

currently provide better indications of mobility, but this may improve as CTPP flow data become available at a finer level.

The results of accessibility evaluation show how the exploration of accessibility measures can be combined with mobility metrics to inform practitioners about the overall availability of transportation service for various modes on the city-wide level. These metrics are also calculated by fusing CTPP and Open data, or data from transportation agencies. Accessibility evaluation clearly shows the distinction between modes of travel in terms of the ability to reach destinations of travel. Accessibility metrics can further be expanded beyond cumulative accessibility to incorporate the weighting factors for destination attractiveness and spatio-temporal variations for different modes.

Table 5 provides a summary of developed performance metrics for each group of measures, including the supporting data used to develop these metrics and whether these data can or cannot be obtained from the CTPP database. Based on the conducted analysis, the three groups of metrics developed here cannot rely on CTPP data only for the following reasons:

- In the case of safety performance measurement, the access to crash data is required in addition to CTPP data to develop the simplest form of SPFs. Further, the developed SPFs are improved if exposure metrics from sources other than CTPP are used.
- For mobility performance measurement, CTPP data can be used to derive conclusions about city-wide mobility, however, the metrics based on data combined from different sources are more informative when it comes to comparing different modes of transportation.
- The accessibility performance measurement requires multimodal network infrastructure data and basic information about speeds for different modes to enable the computation of accessible opportunities available from CTPP datasets.

In addition, while the exposure information based on CTPP and used to develop safety metrics can be replaced by using exposure data from transportation agencies, the mobility and accessibility metrics rely on CTPP data based information more strongly. The general role of CTPP data integration in all three groups of developed metrics remains significant, due to the fact that everyone can access and use CTPP data, which facilitates transferability of these metrics. Even though City of Chicago, which served as a case study here, is unique in terms of the broad range of transportation data sources, the metrics developed here, if relying on CTPP database, can be developed as long as information on crash data and transportation infrastructure is available to local and regional transportation agencies. This demonstration opens new possibilities for TPM development in regions with limited transportation data availability, particularly for the purpose of decision making related to long-range transportation planning for infrastructure investments.

Table 5: Summary of Data for Performance Metric Development from CTPP and Alternative Data Sources

Performance Measurements	Required Data Input	Available from CTPP Database	Available from Other Data Sources
Safety	Crash data	No	Yes
	Exposure data	Yes	Yes
Mobility	Travel time by mode	Yes	Yes
	Travel demand by mode	Yes	Yes
Accessibility	Multimodal infrastructure	No	Yes

	Trip origins and destinations	Yes	Yes

Based on the summary given in Table 5 and the performance analysis conducted on the census tract level, following conclusions and recommendations can be derived to guide researchers and practitioners attempting to use CTPP data for transportation performance measurement purposes:

1) Census tracts can be adequate units of analysis for the purpose of "big-picture" performance management and analysis, as they provide compatibility between CTPP and other data sources, while the metrics developed on this macroscopic level are suitable for the purpose of long-range transportation planning.
2) The independent use of CTPP data for TPM development is not feasible. However, if crash data and transportation infrastructure data are available, all local and regional agencies can rely on CTPP database to develop census-based transportation performance metrics, including: safety, mobility, and accessibility evaluation for multimodal user types.
3) In the case of all three groups of performance measures (safety, mobility, and accessibility), combining CTPP data with alternative data sources is recommended whenever possible to advance the decision making based on the developed performance metrics.

The TPM process is improving as better data and methods become available to transportation practitioners. The CTPP data based transportation performance measures are particularly important for transportation agencies in cities and regions where alternative data sources are still scarce or unreliable. The integration of CTPP data, with the constantly improving transportation data sources and platforms, has a promising potential to improve the efficiency and the quality of the decision making related to the investments in transportation infrastructure on all scales and in different environmental contexts.

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