Big Data in Transportation Program Management: Findings and Interpretations from the City of Toronto

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Matthias N. Sweet
Assistant Professor
Ryerson University
School of Urban and Regional Planning
matthiassweet@ryerson.ca

Carly Harrison
Research Associate
McMaster Institute for Transportation and Logistics
School of Geography and Earth Sciences
McMaster University
c.harrison827@gmail.com

Stephen Buckley
General Manager
Transportation Services Division
City of Toronto
sbuckle@toronto.ca

Pavlos Kanaroglou
Director
McMaster Institute for Transportation and Logistics
School of Geography and Earth Sciences
McMaster University
pavlos@mcmaster.ca

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ABSTRACT

Among North American big cities, the Toronto experiences some of the worst traffic congestion (1). Traffic congestion remains the object of policy intervention across many cities, enabling public discourse about desired future transportation services and better transportation policy. Big Data and business analytics have emerged as a potentially critical group of analyses, technologies, and means of informing program management, but what does "Big Data" really mean for program management in big cities facing the effects of traffic congestion. In this study, *Big Data* is defined as the proliferation of new information on transportation flow, speeds, and trip information from probe data, global positioning data, and Bluetooth technology in near-real time, all in such volumes that make conventional computing methods unable to manage the challenge. Although "Big Data" appears to be a catch phrase with a somewhat ambiguous meaning, there are reasons to believe that it may have important benefits for program management. First, this is illustrated by conceptually discussing how Big Data is different than other established analytical methods for performance monitoring. Second, empirical results from this study using archived probe speed data purchased from Inrix, Inc. for 2011, 2013, and 2014 on are shown to illustrate one initiative taken on by the City of Toronto to more tightly integrate Big Data solutions into road surface program management and performance monitoring.

Keywords: Big Data, congestion, performance monitoring, program management, City of Toronto, traffic, transportation planning, policy

INTRODUCTION

New technologies are increasingly available with which to better understand the complexities of transportation system performance and combat congestion (2). This study explores how leveraging Big Data can be used to drive inform congestion and transportation program management. First, this paper discusses how Big Data analytics might be different from more conventional performance monitoring tools by reviewing the attributes of Big Data that make it different for big cities. Second, this study illustrates how Big Data is being integrated into transportation performance monitoring in the context of the City of Toronto, the fourth biggest city in North America.

In empirically illustrating how Big Data can be leveraged for better performance monitoring, select results are presented from a larger study of system performance which spans 2011-2014. Archived probe data from Inrix, Inc. are purchased from Inrix, Inc. for portions of 2011 and 2013 and all of 2014 to estimate metrics of system performance for Toronto arterials, Toronto freeways, and the downtown core. System performance is explored across multiple dimensions, including annual variations, monthly variations, day-to-day variations, and hourly variations in several categories of performance measures, including speed, delay, and unreliability. Only a select sub-set of results of this broader initiative are shown here. These probe data cover 88.7% of individual freeway links and 48.0% of all arterial links, on average, during any given 15-minute interval within the traffic network between 5am and 10pm. When coupled with a four-step travel demand model (TRAFFIC), City of Toronto count data, and Ontario Ministry of Transportation count data, this speed data is used to monitor road performance characteristics for different system components and at different times. In cases where the level of granularity may introduce sampling bias into metrics, multiple methods are employed, including conventional descriptive statistics, multilevel modeling, and simulation.

ABOUT CONGESTION

Congestion is a powerful cultural construct which has long informed transportation policymaking in big cities. Engineers define congestion as when road volumes exceed road capacity (3). Economists define congestion as occurring when incremental road use disproportionately impacts others (4). Sociologists define congestion as a cultural construct which varies from place to place based on normative perspectives (5). But underlying each perspective is the normative view that congestion is (or at least that it <u>can</u> be) a problem which can and should be alleviated. All three perspectives provide different guidance on identifying how policy should manage traffic congestion.

The shift towards Big Data has much potential to change how travel services are understood, delivered, and used. In this study, <u>Big Data</u> is defined as the *collection, analysis, and use of new travel data, e.g. transportation flow, speeds, and trip information, from technology in near-real time and in such volumes as to make conventional computing methods irrelevant.* In many cases, such data is constantly being generated but not always collected, and is often used for multiple purposes for which it was not explicitly intended. But to explore how such data may shape transportation service delivery, four of the chief approaches to measuring and assessing congestion are introduced, illustrating why gridlock continues to be badly understood and how Big Data may fill a gap. Which approach is "better" depends on the core objectives of estimating congestion, but choosing entails trade-offs between generalizing or focusing on unique user experiences and facility conditions, and between observing conditions or inferring conditions to simulate policy alternatives. A weakness underlying each of the four conventional study approaches is the dependence on deeply established methods which overly simplify trade-offs between different transportation service objectives. Perhaps most notably is the Bureau of Public Roads function (also called Davidson Equation) describing the relationships between speed, flow, and density. In reality, this function is quite different in different contexts (6). Big Data holds much promise in better understanding these trade-offs and understanding the uniqueness of facilities and user experiences.

There are many definitions and approaches to studying congestion, but four key techniques discussed in this paper include 1) travel demand modeling, 2) real-time traffic monitoring, 3) facility-specific traffic studies, and 4) empirical regionally-scaled congestion studies. Each of these methods has its own advantages and disadvantages, but they differ across two conceptual dimensions: whether they <u>generalize</u> or identify the <u>uniqueness</u> of congestion experiences, and whether they are based on <u>observed</u> data or based on <u>inferred</u> outputs using other inputs. Empirical data on transportation system performance is becoming increasingly available, reducing the need to infer based on established (but highly-generalized) speed-flow functions. As in this study, such data is expected to permeate congestion studies at all scales: regional, local, corridor or facility-specific, and user-specific.

Travel Demand Models

Travel demand models were pioneered in the 1950s and include the use of technology, survey data, and models to explore user travel experiences and how they are likely to travel under different policy alternatives. Generalization enables studies to explore the broad range of user experiences as a consequence of the travel conditions. As such, generalization is designed to not only estimate user experience and infrastructure performance at unique locations, but to extrapolate these experiences to reflect on the function of the entire system. The Chicago Area Transportation Study (CATS) of 1955 was among the first and most important travel demand models (6) in which the four-step process of travel demand modeling was pioneered (7). Trips are generated accordingly, distributed across space, modes are chosen, and routes are assigned to estimate user travel experiences, mode share, and changes in behavior due to alternative policies. Travel demand models have become more complex in reflecting transportation-land use dynamics (8). Nevertheless, such models have been critiqued on the basis of becoming more complex without fundamentally capturing the innate motivations of individuals to maximize utility (not minimize travel) (9), to retain relatively stable travel time budgets on aggregate (10; 11), and to adjust location decisions and travel behavior dynamically and over time in unpredictable or unexplained ways (12). Others have broadly critiqued the use of travel demand modeling on the basis of misunderstanding the relationships between traffic volumes and speeds (13) – leaving estimates of traffic congestion in question. In fact, according to Handy (14), these limitations of travel demand modeling has led many of the largest U.S. Metropolitan Planning Organizations to de-emphasize travel demand model results in favor of empirical estimates of change in a wide variety of performance metrics over time.

Regionally-Scaled Congestion Studies

Regionally-scaled congestion studies are generalized performance monitoring tools to reflect broader congestion experiences, but unlike travel demand modeling, they use observed road speed data and do not explicitly test links between congestion, policy, and other outcomes. These studies aggregate travel and road service data to estimate typical user experiences at different times of the day within a large geographic region. The Texas Transportation Institute`s Urban Mobility Report (UMR) series began in the 1980s, is federally funded in the United States, and is perhaps among the best-known such congestion study. But with the exception of recent congestion reports generated by private companies such as Inrix, Inc. (15) and TomTom (1), few equivalent regionally-scaled congestion studies consistently track change over sustained durations of time. In the case of the UMR, the report has long been both the standard for congestion studies and a lightning rod for critique (16; 17). Many have critiqued the use in the past of volume and capacity data to infer speeds (16), but beginning with the 2010 UMR, the authors began estimating speeds directly using speed data purchased from Inrix, Inc. While travel demand models continue to rely on inferred speeds, regionally-scaled congestion studies do not – enabling a more complete picture of observed changes in system function over time. The power of measuring speeds directly has greatly improved the potential to monitor speeds and performance over time, reducing the role of underlying assumptions in dictating findings.

Facility-Specific Traffic Studies

Facility-specific traffic studies have been a core skill of traffic engineers and are designed to use volume, capacity, and operating conditions information to identify how to improve the speed and efficiency of traffic flow on specific facilities. The Highway Capacity Manual (18) establishes the relationships between operating conditions (signalization, striping, and external factors) user conditions (volumes, movement, vehicle types, driver types), and physical conditions (roadway geometry, design, sight distances, and roadway alignment) and roadway performance. Such analyses assume given relationships between operating conditions and volumes, enabling traffic engineers to simulate alternate volume scenarios or operating conditions and identify current and future traffic conditions at intersections, arterial links, freeway links, merging sections, and weaving sections. Some localized traffic studies augment volume-capacity information with speed estimates with which the relationships between volumes, capacity, and speeds can be better calibrated, but legal practices have encouraged little deviation from universally-assumed relationships between volumes, capacities, and speeds on select facilities to establish the basis of analysis. Thus, while the previous means of studying congestion focus on general user experiences across the region, facility-specific traffic studies focus exclusively on specific facilities. As such, they are rooted in a relatively clear set of potential policy levers (improving operations or capacity) but ignore the dynamic nature of travel conditions – whereby users adjust to other routes, modes, destinations, and times of day. In fact, the dependence on volume-capacity relationships to estimates speeds and congestion on specific facilities is a critical assumption and weakness of the method (13) – stripping engineers of the potential to increase volumes while retaining speeds.

Real-time traffic monitoring systems

Real-time traffic monitoring systems are being deployed by both the public and private sectors and have emerged as a newer means of studying and disseminating traffic information on different system performance elements (e.g. speeds, volumes, travel times). Advanced Traveler Information Systems (ATIS) can inform users and lead them to adjust their expectations (19; 20; 21) or change their travel behavior (22; 23; 24). ATIS have become attractive for sub-markets of transportation system users (22) to search online traffic updates from their computers, listen to radio traffic reports, employ smart phone mapping applications, or sign up for real-time information on specific links to get information on current traffic conditions (25). Real-time traffic monitoring could thus shape not only service supply – insofar that public entities may employ real-time information to change operations, but also to shape travel demand if the users respond to ATIS. Real-time traffic monitoring is common in public and private applications (25), but users' consumption of information through ATIS is relatively slower (26; 27). Thus, real-time traffic monitoring and communication through ATIS remains largely descriptive and behavioral change en masse remains elusive while the largest benefits may be simply that users' stress levels go down because they better understand what to expect (22). But unlike other methods of studying congestion, real-time traffic monitoring focuses on users' own unique potential needs by describing the conditions on select routes on select days using streamed empirical traffic data (28; 29). Real-time traffic monitoring is highly-localized, relies on empirical data, and is not designed to forecast future conditions for policymaking (30). In short, while information from real-time traffic monitoring systems and ATIS are still penetrating the market of transportation system users, they can inform the public of transportation conditions and can better link real-time conditions with both capacity (the domain of service providers) and demand (the collective actions of system users).

Will Big Data Meaningfully Change Congestion Management?

Big Data holds much promise in better understanding trade-offs between different transportation output objectives (e.g. flow, speed, reliability) and understanding the uniqueness of facilities and user experiences. With the exception of four-step travel demand models, we might expect the proliferation of probe data to significantly change how each of the other three types of congestion study can be conducted. Real-time monitoring and information provision can be significantly improved and both regional and localized facility-specific congestion studies can be conducted more regularly with direct comparisons between areas and over time.

In contrast to the common four techniques in congestion monitoring discussed above, Big Data can focus on the unique and the general - both in describing the smaller or larger elements of the transportation system and in estimating unique or general functions whereby different elements of traffic flow influence one another (e.g. speed and flow). Moreover, Big Data - by definition - focuses much more explicitly on observed system characteristics without needing to infer outputs based on deterministic and generalized functions estimated elsewhere (which may or may not adequately characterize facility-specific function). The need to infer system outputs which cannot reasonably be measured will not disappear, but if the need for inferring based on generalized functions can be reduced, the complexity of system function can more fully be understood.

RESEARCH DESIGN

Integrating Big Data into transportation performance monitoring relies on combining various sources and types of data, validating results, and streamlining analyses for reproduction. This study focuses on three elements of the road system in the City of Toronto: city-wide arterials, city-wide freeways, and arterials in the downtown core (see FIGURE 1). This study employs two basic types of data inputs: link-specific and time-specific speed estimates (from Inrix, Inc.) and link-specific and time-specific volume estimates (from four-step travel demand modeling output, City of Toronto count data, and Ontario Ministry of Transportation count data). All analyses are conducted using the software R. Several sets of count estimates based on different assumptions are employed to scale up the speed data to reflect experiences of road users. As traffic counts are not continuously collected at all locations at all times, assumptions are necessary to estimate seasonal, weekly, and hourly fluctuations in traffic volumes. First, the method for estimating traffic volumes is described using TRAFFIC, the McMaster Institute for

Transportation and Logistics (MITL) four-step travel demand model, City of Toronto traffic count data, and Ministry of Ontario traffic count data. Second, methods are discussed for using speed data in combination with volume estimates for extracting performance indicators for system components.

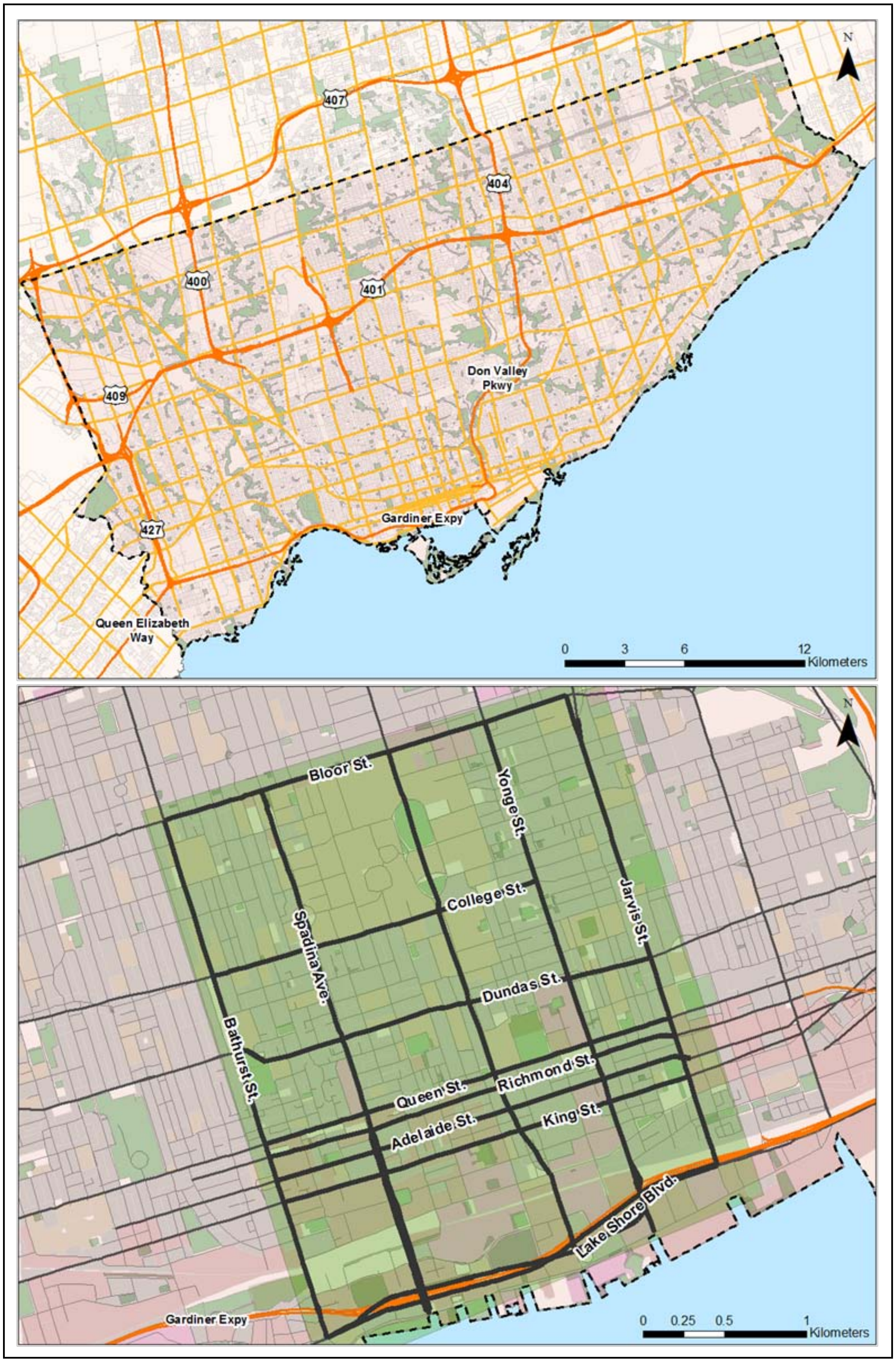

FIGURE 1. City of Toronto and Downtown Core Study Areas.

Traffic Volumes

Traffic volumes are key inputs into this method for transportation system performance monitoring because they enable performance measures to be interpreted in light of user impacts. As such, metrics can be estimated on a per user basis and aggregated to the level of the transportation system and its sub-components. Traffic volumes on the study area roadways use three sequential traffic volume estimates and adjustments: first, from the four-step model; second, additional adjustments (including seasonal and weekday differences) are estimated using continuous count data collected on the Gardiner Expressway (managed by the City of Toronto); finally, additional adjustments are estimated for several of the 400-series freeways (managed by the Ontario Ministry of Transportation).

First, the MITL four-step travel demand model, TRAFFIC, is estimated using the 2006 Transportation Tomorrow Survey. Trip generation, attraction, distribution, mode choice, and route assignment are each performed according to conventional industry standards. Traffic volumes are estimated for specific links on the Traffic Message Channel (TMC) network and matched with the TMC links for other sources of data, principally Inrix, Inc. speed estimates.

Second, traffic volumes estimated using the four-step model are compared with volume estimates from the City of Toronto Transportation Services Division's ongoing traffic count program. The best comparisons are available on the Gardiner Expressway and these volumes are compared with TRAFFIC volumes to estimate monthly, weekday, and hourly volume adjustment factors which are expanded to the balance of the network. Continuous count locations on the Gardiner Expressway in 2011 are used to adjust TRAFFIC model output for 2011, 2013, and 2014. Count data for 2011 is employed due to significant closures and maintenance on the Gardiner Expressway began in late April 2014 – making the seasonal volume adjustments invalid when expanded to the rest of the road system. Adjustment factors are estimated using regression in which month-specific, and weekday vs. weekend-hour-specific adjustment factors are estimated.

Finally, traffic volume estimates are further adjusted using cross-sectional data from the Ministry of Transportation for the 400-series freeways for 2013 and 2014. Because 400-series freeway volumes are such a critical component of overall traffic flow, the precision of seasonally-adjusted TRAFFIC model output with daily and seasonal adjustments are tested. A regression model is estimated in which the city count-adjusted hour and day-specific counts are used to predict the observed hourly traffic counts collected by the Ontario Ministry of Transportation along 400-series highways. Corridor-specific adjustment factors are estimated, such that adjustments overcome systematic biases, for example, if the existing count estimates overestimate volumes on one freeway but not another. Beyond corridor-specific adjustment factors, other 400-series links which are badly represented by the count locations below (e.g. the 427 between the Gardiner and the 401) are adjusted using a regression model of the pooled adjustment factor (with no corridor-level differentiation).

Speed Estimates

To estimate road system performance, archived road speed data are purchased from Inrix, Inc. Data are provided using TMC links as the unit of observation and cover parts of 2011 (August 8 - December 31), 2013 (July 1 - December 31), and all of 2014 (January 1 - December 31). There are 1,911

TMCs included in the full City of Toronto network, on which Inrix, Inc. traffic data is collected by numerous types of floating probe vehicles, many of which represent heavy vehicle operators.

Although the Inrix, Inc. data is available to depict link-specific speeds during specific seconds during the day, to generalize performance metrics, data are aggregated - as needed - to reflect typical speeds for 15-minute intervals (on each individual day) or to reflect speeds for specific 15-minute intervals or hours during the typical weekdays, months, or years. As such, the core methodological challenge is to appropriately adjust data to eliminate sampling bias. In short, the finer the data is sliced, the larger the potential for sampling bias to significantly bias results. Specific methods fall into three categories.

Descriptive Statistics

To extract performance measures in their most basic form, raw data are first extracted and preprocessed for use in specific analyses. Two types of preprocessed data are extracted: 1) data which is specific for 15-minute intervals between 5am and 10pm for each specific link on each specific day for which data is collected and 2) data which captures average speeds for each pair of 15-minute intervals (17 hours * 4 15-minute intervals = 68 intervals), weekdays (7 days of the week), and months (12 months in the year) for each of the study time periods: August - December 2011, July - December 2013, and January - December 2014. When estimating performance measures, differences between days of the week, months, and time periods are restricted to two full dimensions at a time when extracting results: e.g. all seven weekdays for all time periods, but for a typical year (not based on seasonal variations) or all months of the year for all time periods, but only for a typical weekday.

Multilevel Modeling

For analyses requiring more than three full dimensions (e.g. weekday by month by time of day), multilevel modeling is employed to ensure that sampling bias is not a source of error. Multilevel modeling is primarily employed when year-over-year differences are estimated in order to ensure that differences in sample size do not drive the differences in year-over-year performance measure changes. For example, to estimate year-over-year differences in transportation system performance, hourly data for each link for 2011, 2013, and 2014 are pooled, focusing exclusively on the months of September, October and November. Speeds are estimated as a function of the year (2011, 2013, or 2014) and the hierarchical groups defined by the interactions of hour of the day, day of the week, and link of interest. In some cases, as many as64,974 coefficients (1,911 links * 17 hours in the day * 2 day of the week types) are estimated exclusively for the purposes of controlling for background characteristics which are unique to each link. Thus, if conditions are different from one year to another - independently of differences in sampling density - this is estimated.

Simulation and Sampling

Sampling is employed as a method for extracting travel time unreliability measures. When estimating unreliability, conventional descriptive statistics would ignore that transportation system users' perceptions of unreliability rely on their trip experiences which are made up of several road links. Thus, while there may be atypically slow travel conditions on a given link, adjacent or proximate links which could make up a trip may have different characteristics at any given point in time. Understanding the unreliability of trips (as opposed to specific links) rests on considering the joint distributions of travel speeds on a simulated set of links which could comprise a trip.

Potential trips of set lengths (5 kilometers, 10 kilometers, 15 kilometers, and 20 kilometers) are sampled to simulate the distribution of travel speeds associated with these trip lengths. The volume-adjusted mean link length is approximately 1.25 kilometers, so four links are selected for five-kilometer trips, eight links are selected for ten-kilometer trips, 12 for 15-kilometer trips, and 16 for 20-kilometer trips. Links are sampled using the probability of traveling on a specific link based on its length and volume such that the sum of the probabilities of selecting each link add up to one. While each simulated trip is not precisely the mean trip length, on average, the mean trip length (five, 10, 15, or 20 kilometers) is retained and the mean speeds for each simulated trips are used to estimate unreliability metrics. At least 10,000 simulated trips are used to estimate the distributions of travel speeds for simulated trips - from which both typical and atypical performance indicators can be generated to explore unreliability.

RESULTS

Results from this study indicate that road transportation system performance is a highly-dynamic across the City of Toronto's arterial and freeway systems and in the downtown core. Transportation system performance estimates are performed for two geographies: the City of Toronto as a whole and Downtown Toronto, bounded by Lake Ontario, Jarvis Street, Bloor Street, and Bathurst Street (see FIGURE 1). Results from each are discussed simultaneously to explore transportation system performance across two broad dimensions: change over time and hourly variations within the day.

Peak-Hour Changes in System Performance

Using multilevel modeling, changes in transportation system performance are estimated between 2011, 2013, and 2014. To increase comparability, only data for September, October, and November are used to estimate differences between the three years. This restriction is preferred for several reasons: 2011 (August 8-December 31) and 2013 (July 1 - December 31) only have partial data and second and while December is available in all three years, many severe weather events occur at this tim which significantly impact weather-induced differences in congestion which are not strictly functions of annual differences in background congestion.

City-Wide Annual Changes

Differences between each of the years are first estimated for the entire city as a whole (see FIGURE 1). Four core performance measures are estimated: two which reflect recurring congestion (speed and delay) and two which reflect the unreliability of the system (planning time index and buffer time index). City-wide delay is estimated using both the 85th percentile fastest travel speeds and the mean night speeds (between 11pm and 5am), illustrating the importance of the free-flow speed as a reference point. Each metric indicates that congestion decreased (or remained stable) between 2011 and 2013 but that it grew in 2014 - particularly on the arterial system. The largest shifts in recurring congestion occurred during the PM peak hour (5pm - 6pm) and the largest increases in congestion occurred on the arterial system (on average, 7kph slower during the evening hour). Results indicate that delay on the arterial system increased by 6,453 and 6,721 hours (using night speeds as free-flow) or by 7,236 and 7,398 hours of delay per hour (using 85th percentile speeds as free-flow) during the morning and evening peak hours respectively. Both speed-based measures of congestion and delay-based measures indicate that changes on the arterial system between 2011 and 2014 are more severe than on the freeway system. An increase of approximately 7,000 hours of delay per peak hour translates into approximately (52*5*7000 + 52*5*7000) = 3.64 million hours of delay annually during the morning and evening peak periods alone.

Measures of unreliability similarly indicate that city-wide travel conditions become less reliable over time - in this case for a simulated 5-km trip during the 5pm hour. Unreliability is measured using two indices: the planning time index (PTI), which represents the ratio of the 95th percentile slowest travel times to the free-flow travel times, and the buffer time index (BTI), which represents the ratio of the 95th percentile slowest travel times to the average time-specific travel times. While PTI reflects unreliability relative to free-flow expectations, BTI reflects unreliability relative to mean time-specific expectations, which also change.

Results are only shown for the PM peak hour and indicate that PTI increases by 0.4 units between 2011 and 2014. For a hypothetical ten-minute trip, this would indicate that for one to arrive on-time 95% of the time in 2011, one would need to allow 21.9 minutes in 2011 but 25.9 minutes in 2014 - an additional four minutes. Changes in buffer time index are much more modest: buffer time index increases only by 0.16 units between 2011 and 2014. Changes in buffer time index must be interpreted relative to changes in background speeds, which decrease. As such, a 0.16-unit increase in BTI between 2011 and 2014 means that the 95th percentile longest travel times increase 16% faster than the increase in mean travel times for simulated 5-kilometer trips during the evening peak period.

TABLE 1. City of Toronto Changes in Congestion (2011-2014).

Key Performance Indicators		2011		2013		2014		Change (2011-2014)	
		Arterials	Freeways	Arterials	Freeways	Arterials	Freeways	Arterials	Freeways
Speed (km/h)	AM Peak	42	75	43	75	37	73	- 5	- 2
	PM Peak	42	72	42	74	35	70	- 7	- 3
Delay Hours (ff = 85th pct.)	AM Peak	4,761	9,066	3,872	10,129	11,997	11,791	+ 7,236	+ 2,725
	PM Peak	4,346	9,776	3,994	9,522	11,744	11,838	+ 7,398	+ 2,062
Delay Hours (ff = night)	AM Peak	4,919	8,036	4,324	9,139	11,371	10,779	+ 6,453	+ 2,743
	PM Peak	4,352	8,786	4,193	8,583	11,073	10,857	+ 6,721	+ 2,071
Planning Time Index		2.19		2.11		2.59		+ 0.40	
Buffer Time Index		1.6		1.6		1.76		+ 0.16	

Downtown Annual Changes

The downtown study area (see FIGURE 1) reflects all arterials covered by Inrix, Inc. data between Jarvis, Bathurst, Bloor, and Lake Ontario. Although the Gardiner Expressway crosses through this study area, it is not included as part of the downtown core because, as a freeway, its function is significantly different than the downtown arterials. Similarly to annual changes in road system performance city-wide, downtown congestion increased significantly between 2011 and 2014, while congestion drops slightly or remains stable between 2011 and 2013. Downtown delay is estimated exclusively using 85th percentile speeds as free-flow speeds (and not using night speeds) because night speeds in the downtown core are already very slow, yielding unreasonably low estimates of travel delay.

Changes in mean downtown vehicle speeds are similar to those for the City of Toronto: 4kph and 7kph slower in the morning and evening peak hours. However, as the mean base speeds in 2011 are approximately 10kph slower in the downtown in 2011 than in Toronto as a whole, this represents a larger proportional decrease in speeds in the downtown core. In contrast to the city as a whole, travel conditions during the PM peak hour are somewhat more reliable (reliably slow) during both 2011 and 2014, but the planning time index increases by 0.64 units between 2011 and 2014 while the PTI for the city as a whole increased by 0.4 units. As discussed above, the 0.4-unit increase in PTI translates into an additional 4 minutes of time between 2011 and 2014 to arrive on time 95% of the time for a 10-minute trip under free-flow conditions. The 0.64-unit increase in PTI in the downtown unreliability translates into an additional 14 minutes of time between 2011 and 2014 to arrive on time 95% of the time. Thus, while unreliability remains higher in the City as a whole and reliably slower in the downtown, the changes in unreliability between 2011 and 2014 have the highest implications for downtown travel experiences.

TABLE 2. Downtown Toronto Changes in Congestion (2011-2014).

Key Performance Indicators		2011	2013	2014	Change (2011-2014)
Speed (km/h)	AM Peak	31	32	27	- 4
	PM Peak	28	28	21	- 7
Delay Hours	AM Peak	183	172	605	+ 422
	PM Peak	353	332	1,035	+ 682
Planning Time Index		1.51	1.5	2.15	+ 0.64
Buffer Time Index		1.15	1.15	1.21	+ 0.06

Hourly Variations and Changes Over Time

Hourly variations in transportation system performance within a typical day in 2014 are shown for both the city as a whole and the downtown. Results indicate significant morning and evening peak periods on the freeway system, but both the city-wide arterials and the downtown arterials have peaks which have spread so much as to make peak/off-peak differences challenging to interpret.

City-Wide Hourly Variations

While speeds decrease and delay increases across the city between 2011 and 2014, the changes on the arterial system are most pronounced. First, focusing on the metric of travel speeds during typical weekdays, hour-specific differences between 2011, 2013, and 2014 illustrate when changes in system performance occurred. For the freeway system, see FIGURE 2, speeds in 2014 are lower at all times of day while 2013 speeds are somewhat higher than those in 2011 - particularly after approximately 10 am. Likewise, 2014 speeds on the full city arterial system are significantly lower at all times but particularly in the afternoon (see FIGURE 2). In fact, while the morning and evening peak periods are very clear on the freeway system, the speeds on the arterial system never recover over the course of the day to their levels before the morning rush until after 9pm. In short, peak spreading is evident on both systems, but the significant drop in arterial speeds between 2011 and 2014 make distinguishing peak from off-peak arterial conditions challenging.

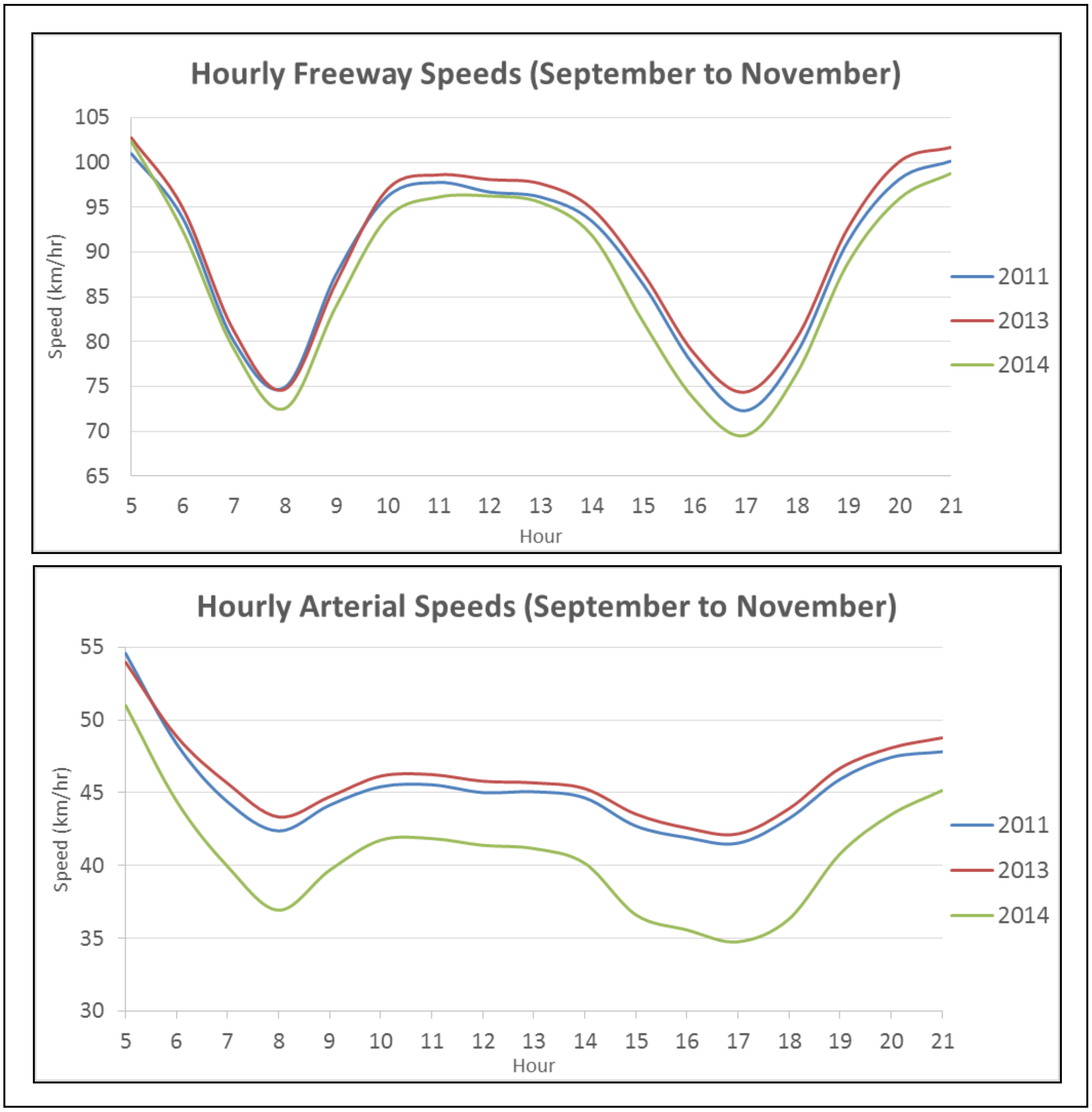

FIGURE 2. Hourly Mean Speeds for Freeways and Arterials in City of Toronto (2011, 2013, and 2014).

Finally, when focusing on differences between typical weekdays and weekends on freeways and arterials in the City of Toronto, results confirm weekday arterial and freeway trends, but illustrate that weekend speeds are much more static: speeds generally decrease in the course of the day, reaching their lowest in late afternoon. As such, while congestion significantly contributes to travel experiences on some links at some times on weekends, at the scale of the entire city, the magnitude of the weekend congestion "problem" is small in comparison with weekdays.

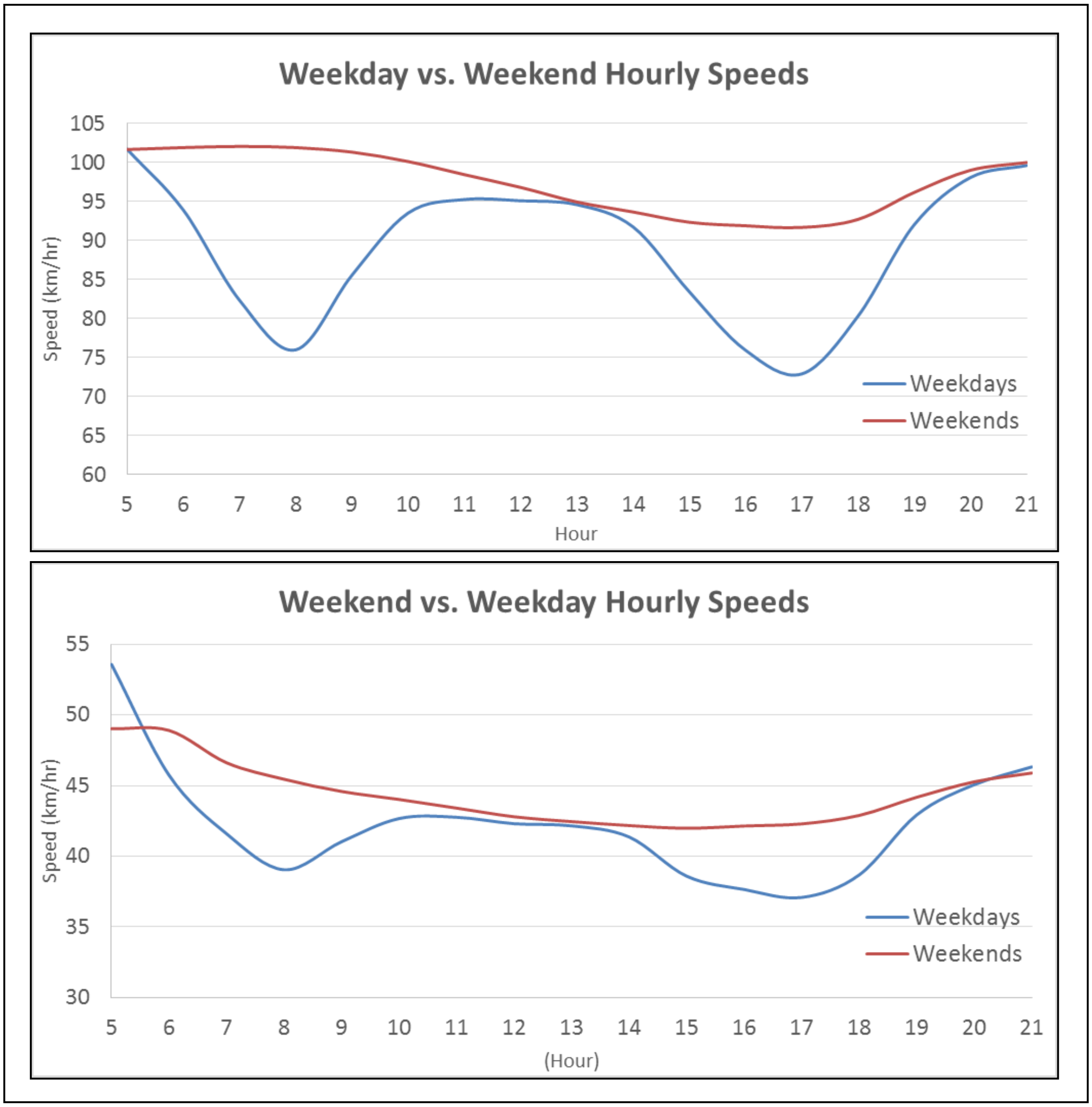

FIGURE 3. City-Wide Mean Freeway Speeds for Typical Weekday and Weekend (2014).

Downtown Hourly Variations

While analyses of city-wide freeways indicate significant peaks, hourly variations in transportation system performance exclusively for arterials within the downtown core suggest a very different daily congestion pattern. As shown in FIGURE 4, vehicle speeds decrease in the course of the day, reaching their lowest levels during the evening peak period. Although speeds during the morning peak period are somewhat lower (particularly during the 8 o'clock hour in 2014), the trend of decreasing speeds in the course of the day is much stronger than the impacts of the morning rush hour. Speeds are significantly slower at all times of day in 2014 and the evening peak period with the lowest speeds lasts longer than in 2011 or 2013.

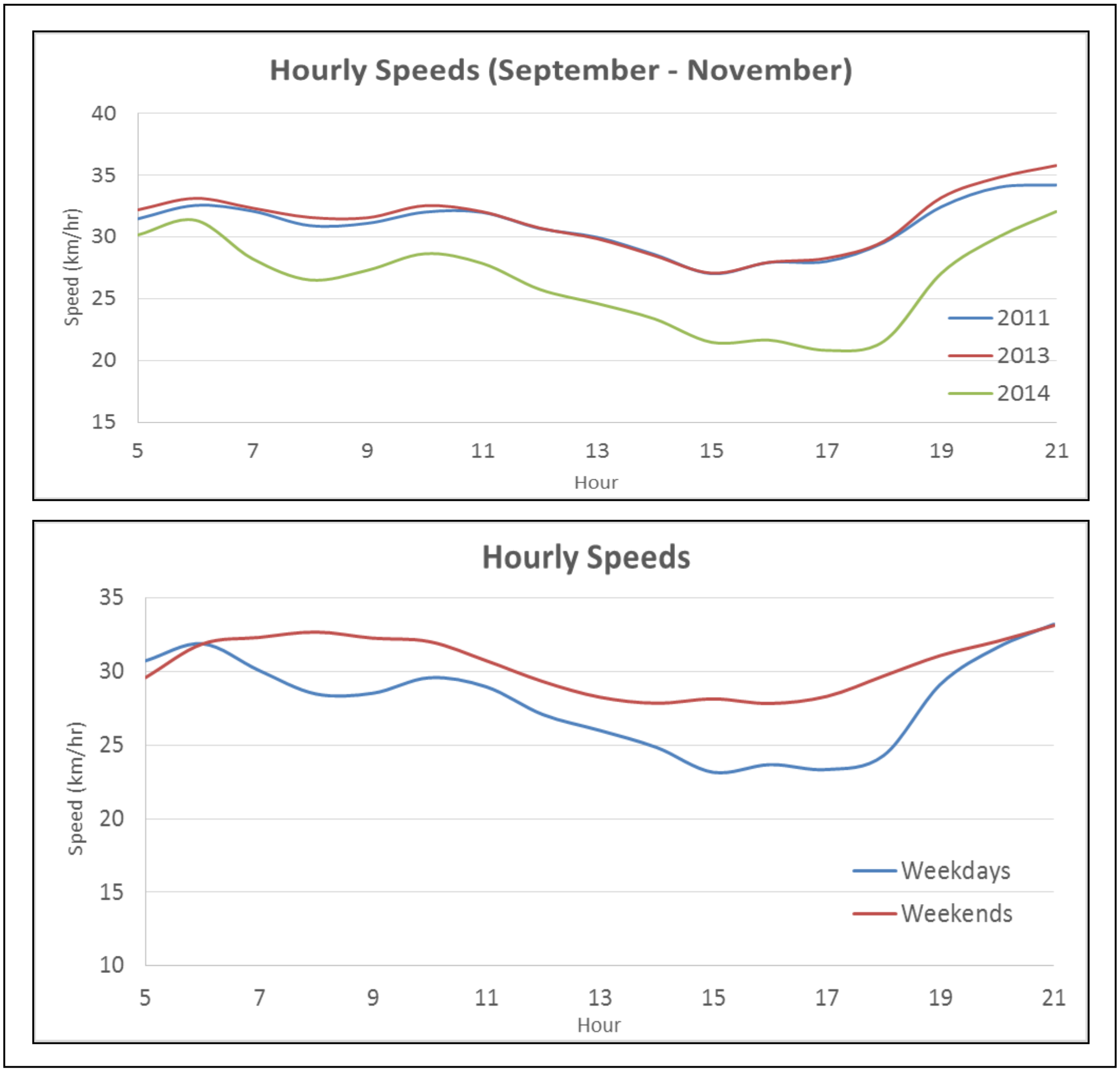

FIGURE 4. Hourly Mean Speeds for Arterials in Downtown Toronto (2011, 2013, and 2014) and on Weekdays and Weekends (2014).

Finally, when focusing on differences between a typical weekday and typical weekend in the downtown in 2014, results indicate that road speeds on downtown arterials are only moderately higher on weekends than during weekdays. During both weekdays and weekends, speeds decrease in the course of the day, but while they reach their lowest levels during the 3pm-7pm peak period on weekdays, road speeds already begin to increase by the 6pm hour on weekends. Differences between weekends and weekdays are at most 5kph (during the evening period), indicating that - in contrast to the city as a whole (and particularly on freeways) - downtown roadways face congestion challenges during all days of the week.

CONCLUSION AND LESSONS

This study illustrates how Big Data can be employed to monitor road system performance over time in the City of Toronto. Conclusions from this study address two issues: 1) the empirical findings of this study and 2) how Big Data could be used in the future for transportation program management in big cities.

Toronto congestion grew significantly between 2011 and 2014, but remained relatively stable between 2011 and 2013. Increases in congestion were not equal across the road system. Congestion on the arterial system grew much faster than on the freeways both in terms of typical intensity and transportation system unreliability. Road speeds on city-wide and downtown arterials decreased by 7kph during the peak period, while freeway speeds in the PM peak decreased by 3kph. Typical unreliability grew by 0.4 PTI units across the city and unreliability in the downtown core grew by 0.64 PTI units.

Although freeway congestion is consistent with a "peak-period" problem, city-wide arterials and downtown arterials are congested throughout much of the week. Results indicate significant peak spreading and gross decreases in vehicular speeds between 2011 and 2014. While the freeway system exhibits conventional morning and peak periods of vehicular delay, both the city-wide and downtown arterial systems have congestion throughout the day in which speeds generally decline as the day continues. These findings suggest very different policy measures for each of the system components.

Leveraging Big Data for transportation system performance monitoring holds much promise for better managing the use of scarce transportation system resources. However there are four critical challenges in how Big Data can be deployed to guide big city policy decisions. First, results must be intuitive, credible, and sufficiently interpretable to be easily understood by decision-makers with a range of expertise. While temporal and geographic granularity of a Big Data program should be able to assess, interpret, and inform rapid changes for certain applications, its core capabilities should not function at such a fine granularity across the board as to lead to "information overload." Second, if pairing multiple sources of data which are dynamically collected, this can enable explicit assessments of policy trade-offs to be made and judged by policymakers. In this study, traffic volumes and road capacities are largely static and variations in performance are primarily driven by speed data. Speeds are not the only potential output meriting policy intervention, so better understanding trade-offs among outputs is critical. Third, even to reasonably use static volume estimates and dynamic speed estimates, as in this study, the secondary data collection and management tasks rely on combining multiple sources of data which cover very different temporal and spatial extents. Inter-agency coordination to improve the comparison of different data sources should be encouraged. Finally, a path towards integrating Big Data into performance monitoring should be prepared to discover, explain, and leverage newly generalizable information on unique system attributes. Probe data, such as those purchased from Inrix, Inc., provide sufficient coverage to explore link-specific dynamics in speed, travel times, and unreliability which can be merged with link-specific policymaking characteristics from other data sources (e.g. on street parking policies and prices, changes in off-street parking supply/demand, lane configurations, bicycle facilities, sidewalk characteristics, or on-street transit services). Thus, unique user experience and volume-speed dynamics can be assessed not just by generalized functions, but based on context-specific characteristics.

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