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Effect of weather on pedestrian trip count and duration: City-scale evaluations using mobile phone application data

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ABSTRACT

We examined the association between meteorological (weather) conditions in a given locale and pedestrian trips frequency and duration, through the use of locative digital data. These associations were determined for seasonality, urban microclimate, and commuting. We analyzed GPS data from a broadly available activity tracking mobile phone application that automatically recorded 247,814 trips from 5432 unique users in Boston and 257,697 trips from 8256 users in San Francisco over a 50-week period. Generally, we observed increased air temperature and the presence of light cloud cover had a positive association with hourly trip frequency in both cities, regardless of seasonality. Temperature and weather conditions generally showed greater associations with weekend and discretionary travel, than with weekday and required travel. Weather conditions had minimal association with the duration of the trip, once the trip was initiated. The observed associations in some cases differed between the two cities. Our study illustrates the opportunity that emerging technology presents to study active transportation, and exposes new methods to wider consideration in preventive medicine.

1. Introduction

In all, more Americans are walking: the CDC found the number of adults who walk for transportation, fun, or exercise went up 6% over 5 years (Center for Disease Control and Prevention, 2012). Walking, as the most common form of adult physical activity (United States Department of Health and Human Services, 1996), is an important lifestyle component for improving long term health (Stephens et al., 1985). Walkability and pedestrian activity have become major topics of conversation in urban planning (Talen and Ellis, 2015) and public health, with new interest in improving pedestrian facilities, improving safety, and improving the public's general quality of life (Heath et al., 2006).

These efforts, however, are moderated by the relationship between human mobility behavior and climate—namely, weather and environmental conditions when trip initiation decisions are made (Hoogendoorn and Bovy, 2004). A few earlier studies have largely concentrated on adverse conditions (Cools et al., 2010), but little is known about the everyday experience of pedestrians. Meteorological effects could influence travel demand and route choice in various ways, including diversion to other trip modes or paths, or deferring and canceling of trips. The severity of different conditions may also affect the characteristics of a trip—potentially slowing individuals down during heavy rain or a hot day.

While previous studies were often constrained to small spatial units of analysis, the increasing ubiquity of mobile devices offers opportunities to obtain new data to understand human activity. Leveraging these data offers an unprecedented opportunity to understand human mobility patterns at a substantial temporal and spatial scale, with a level of detail heretofore unavailable.

Most studies of the relationship between weather and travel tend to focus on network performance, such as velocities or disruptions rather than travel behavior at an individual level—the choices made as part of peoples' everyday routines (Böcker et al., 2013). Various studies have observed that higher temperatures (up to a certain threshold) were positively associated with outdoor activities in various cities including San Francisco (Zacharias, 2004) and Chicago (Dwyer, 1988). In Flanders, Belgium, temperature had significant positive effects on walking, although to a lesser degree than precipitation effects. The effect of

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temperature may be mediated or confounded by a trip's purpose (Cools et al., 2010; Aaheim and Hauge, 2005).

In addition to temperature, precipitation and wind have also been reported to play a role in travel behavior. Similar to the literature on temperature, precipitation studies have largely focused on road network performance at a system level rather than micro-level (Böcker et al., 2013). Precipitation is one of the most important weather factors influencing the occurrence of physical activity (Burke et al., 2006), and particularly walking (Cervero and Duncan, 2003). With respect to wind, some studies among pedestrians have not shown significant effects on walking (Murakami et al., 2004), while others observed that wind deterred physical activity (Aaheim and Hauge, 2005). These conditions have an impact on the distance traveled as well; strong winds were associated with a reduction in average total travel distance as compared with normal wind (Sabir et al., 2010) and precipitation was also associated with shorter trip distances (Aaheim and Hauge, 2005).

Methodologically, previous studies of weather conditions and pedestrian mobility have usually relied upon self-report surveys or trip diaries (Lee and Moudon, 2006), for example). Such approaches tend to limit a study's spatial and temporal breadth, as recalled information may lose detail regarding travel modes and locations. Often, there is a loss of actual paths traveled, and a limited capability to collect precise data on travel start and end times, trip duration, and destination location (Murakami et al., 2004). Respondents may also omit trips because they do not consider them to be “transportation” or simply forgot to log them; individuals may consider some activities and short trips to be below the threshold of reporting (Agrawal and Schimek, 2007). Nikolopoulou and Lykoudis (2006)), to understand thermal comfort in key locations in 14 cities, focused their instrument to the felt experiences in specific spaces and a narrow set of questions to survey of 10,000 respondents.

Some studies have attempted to resolve this issue through technological means of data collection, including automated pedestrian counters in select points (Altman et al., 2010) or web-connected cameras, which have allowed for studies across multiple sites (de Montigny et al., 2012). These studies, while providing a more granular, but highly localized, alternative to survey methods, cannot readily infer trip purpose. The limited spatial resolution does not account for the microclimatological diversity that exists across a city outside of the sensors' range of view, and could not continually track the same individual longitudinally over time. As an understanding of the increasingly varied patterns of human activity becomes more important, longer periods of observation are needed (Lee-Gosselin, 2005).

One approach to addressing these challenges is to leverage the increasing pervasiveness of mobile devices (Hazas et al., 2004). Location-based tracking from these devices has progressed forward our understanding where persons are in space and the description of their activities. These spatiotemporal data have created new opportunities to describe human mobility. While the use of anonymized call detail records from mobile phones has permitted improved analyses of individuals (Ratti et al., 2006), the inclusion of geolocation capabilities with active mobile-phone tracking permits a more granular level of analysis (Asakura and Iryo, 2007). GPS technologies, in the automated collection of activity data, have been found to provide high-resolution spatial and temporal records, enabling the mass participation of subjects and the collection of enormous amounts of data in the long term (Shoval, 2008). This has the added benefit of higher accuracy and reliability than when the user is asked to recall their past activities (Forrest and Pearson, 2005).

The newly-available breadth and depth of the empirical data present new research opportunities, and we set out to implicitly test the use of these locative, digital data as a means of describing human behavior in space. In particular, to our knowledge this study is unique to evaluate these effects, concurrently, 1) over a one-year period, 2) at the city or regional scale rather than at a limited spatial scale such as an intersection or block, 3) longitudinally, with a population of specific users over time, and 4) across two cities. Hence, our study focused on evaluating the associations between meteorological conditions and pedestrian activity—count[1] and duration at the city-scale.

2. Methods

To understand general mobility patterns, trip data were collected from a free, commercially-available, proprietary activity-oriented mobile application (AOMA). This application utilized the devices' motion co-processor to record the time and movements of the phone. Generally, the AOMA assigned geographic information to those activities through the use of a device's geolocation services including assisted-GPS (A-GPS) which triangulates proximate Wi-Fi and satellite-based systems providing the highest precision with minimal battery draw; traditional satellite based GPS; and carrier-based signals, providing the coarsest resolution. A-GPS allows locationing even when full line-of-sight to sky is not available, such as in downtown areas. In the georeference data, we calculated the velocity between two points and changes in spatial resolution to further filter the data for errant records resulting in a loss of 8.81% Boston, and 16.06% of San Francisco records.

A new trip record was generated when the user moved outside of a geo-fenced area of approximately 10-meters radius from their previous location. Therefore, we defined a trip as departing one geo-fenced area and the user's journey until s/he remained in another location for a duration of time, thereby creating a new geo-fenced area using the application's own proprietary “stay-detection” algorithm and the device's motion coprocessor. As this process occurred in the background, information on the user's movement was passively recorded. The data were provided by the developer to the researchers as one historic dataset after censoring of the origins and destinations to preserve anonymity.

Boston, Massachusetts and San Francisco, California served as study sites. These cities were chosen for their general regional similarities in size, population numbers and density, and car-ownership rates. The Boston data collection area was bounded by 42.2284°N, 71.1895°W and 42.3979°N, 70.9852°W, which encompassed 317.06 km^2 and included Boston and Cambridge, and portions of Somerville, Brookline, Newton and Chelsea. The San Francisco area was bounded by 37.8064°N, 122.5444°W and 37.6016°N, 122.3472°W, which encompassed 394.38 km^2 and included San Francisco, Broadmoor, Brisbane, Daly City, Colma, South San Francisco and portions of Pacifica and San Bruno. In total, 246,814 trips from 5432 users were recorded in Boston and 257,697 from 8256 users in San Francisco. The average trip density was 778.45 trips per square kilometer in Boston and 653.42 in San Francisco. The average trip length was 889.11 m in Boston and 1017.7 m in San Francisco, with average durations of 1237.48 s and 1371.74 s, respectively. The data covered a period from May 15, 2014 through May 1, 2015.

To protect the privacy of the AOMA's users, the application developer assigned a hashed unique identifier to each individual. No biographical information was collected by the developer, and no personally-identifiable information was provided to the researchers. Further, a random distance of 0–100 m was removed from the start and end of each trip to mask a user's common locations to further anonymize the data.

Data were filtered to eliminate errant activity traces due to errors in the mobile phone's geo-locationing functionalities, which resulted in a loss of 8.81% of Boston, and 16.06% of San Francisco records. (This type of error creates incorrect trip details in the data due to the inherent errors of each locationing method; see Zandbergen and Barbeau, 2011). Further, periods from 01:00 am–05:00 am were excluded due to low or zero trip counts, which resulted in the omission of 2351 trips (0.9%) in Boston and 4052 (1.6%) trips in San Francisco.

[1] We use the terms “count” and “volume” interchangeably as a measure of the number of trip originations within a specified hour.

Hourly weather conditions were collected from several weather stations within the study areas via a web-based meteorological service. Weather attributes were assigned to each trip based on the nearest station to the trip origin point based on Euclidian distance—eleven in Boston and ten in San Francisco—to account for microclimatic differences within each case study area. The median coverage area of a weather station in Boston was 32.64 km^2, and in San Francisco was 39.62 km^2. Wind speed, humidity, precipitation rate, visibility and the dry-bulb air temperature measurements were coded as continuous variables. Sky conditions were documented as dichotomous variables, and snowfall as an interaction with precipitation rate. More information on the patterns of weather can be found in the Descriptive Table in Supplemental Material 1.

To determine how meteorological conditions impacted pedestrian activity, a log-linear regression model was employed (Washington et al., 2010). A multilevel, hierarchical model allowed us to account for varying numbers of trips observed for each voronoi area defined by the nearest weather station and for dependence of observations (Purser et al., 2005). This approach accounts for the potential underestimation of standard errors of the regression coefficients measured at the community-level (Bryk and Raudenbush, 2002).

In considering the hourly count of trips, we defined the first level (weather station voronoi) model considering within-voronoi magnitudes of effect of trip i of within voronoi j at time unit (hour, day, month) t in each city as:

$$\log\left(\hat{Y}_{tij}\right) = \beta_{0j} + \Sigma_{k=1}^{n}\beta_k X_{tij} + \mu_t + r_{tij}$$

where $\hat{Y}_{tij}$ is the trip start count dependent variable, measured in number of trips; β_{0j} is the intercept for user j; β_k is the regression coefficient associated with predictor variable X_{tij} for user j; and $r_t(i,j)$ is the random error associated with the trip i nested within voronoi j.

We defined the level 2 (trip) analysis as:

$$\beta_{0j} = \gamma_{00} + U_{0j}$$
$$\beta_{kj} = \gamma_{k0} + U_{kj}$$

where γ_{00} is the mean of the intercepts across trips for weather station voronoi j; γ_{n0} is the mean of the slopes across trips for voronoi j; U_{0j} is the variance in the intercepts for voronoi j; and U_{nj} is the variance in the slopes for voronoi j.

Table 1
Impact of weather factors on hourly trip counts in Greater Boston.

			Weekday				Weekend
Season	Variable	All trips	All weekday	Commute	Transit (commute)	Non-commute	
All	Temperature (°C)	1.009 *	1.008 *	1.006 *	1.005 *	1.011 *	1.013 *
	Humidity (%)	0.995 *	0.996 *	0.998 *	0.998 *	0.995 *	0.993 *
	Wind speed (km/h)	1.004 *	1.003 *			1.004 *	1.005 *
	Precipitation (mm/h)	1.023 *	1.029 *			1.041 *	
	Snow	0.845 *	0.730 *	0.708 *	0.773	0.728 *	
	Thunder		2.071 *	1.527			
	Cloud cover	1.120 *	1.129 *			1.126 *	1.063 *
	Heavy cloud cover	1.045 *	1.069 *	1.079 *	1.085 *	1.076 *	
	Fog	1.083	1.121			1.188	1.191
Winter	Temperature (°C)	1.017 *	1.015 *	1.004		1.026 *	1.027 *
	Humidity (%)	0.996 *	0.997 *			0.995 *	0.994 *
	Wind speed (km/h)	0.998 *	0.998	0.994 *			0.997
	Precipitation (mm/h)						0.861 *
	Snow	0.890 *	0.844 *	0.783 *		0.801 *	1.141
	Thunder						
	Cloud cover	1.139 *	1.179 *	1.117 *		1.078	
	Heavy cloud cover						
	Fog				0.486 *	1.192	
Spring	Temperature (°C)	1.025 *	1.021 *	1.018 *	1.018 *	1.022 *	1.043 *
	Humidity (%)	0.997 *	0.997 *	0.998 *		0.997 *	
	Wind speed (km/h)	1.004 *	1.003			1.003	1.007 *
	Precipitation (mm/h)		0.929			0.869 *	
	Snow						
	Thunder	0.311 *					0.261 *
	Cloud cover	1.078 *				1.112 *	1.198 *
	Heavy cloud cover	1.080 *	1.138 *	1.143 *	1.214 *	1.106 *	0.869 *
	Fog		2.291 *				
Summer	Temperature (°C)	1.012 *				1.014 *	1.021
	Humidity (%)	0.993 *	0.993 *	0.997		0.992 *	0.994 *
	Wind speed (km/h)	1.008 *	1.004	1.011 *	1.010		1.017 *
	Precipitation (mm/h)						
	Snow						
	Thunder						
	Cloud cover	1.070 *				1.089	1.108
	Heavy cloud cover	1.094 *	1.145 *	1.116 *	1.169	1.114 *	
	Fog						
Autumn	Temperature (°C)	1.019 *	1.015 *	1.010 *	1.008 *	1.018 *	1.025 *
	Humidity (%)	0.993 *	0.995 *	0.997 *	0.997 *	0.994 *	0.986 *
	Wind speed (km/h)	1.005 *	1.006 *	1.003 *		1.007 *	1.005 *
	Precipitation (mm/h)	1.087 *	1.070 *			1.079 *	1.151 *
	Snow	0.862	0.340 *	0.012 *		0.448 *	
	Thunder		1.828				0.624
	Cloud cover	1.190 *	1.232 *			1.214 *	
	Heavy cloud cover						
	Fog	1.674 *	1.465 *				2.604 *

Note: Coefficients indicated with no asterisk are significant at $\alpha = 0.05$ and coefficients indicated with an asterisk (*) are significant at $\alpha = 0.01$. Variables corresponding to all insignificant coefficients were omitted during the model estimation process.

We employed a similar approach in considering trip duration as the outcome, where the first level analysis considers the user, so that the model considers within-user magnitudes of effect of trip i of user j at time unit (hour, day, month) t in each city.

As seasonality and trip type interacted with each variable, trips were categorized and analyzed separately for each meteorological season and by time category by weekday or weekend, and time of day (such as commuting hours, from 07:00–09:59 and 16:00–18:59). Trips were defined as transit trips if either the start or end location was within 50 m of light rail and rapid transit stations.

3. Results

The results of the multivariate, multilevel analysis which identified the magnitude of weather effects on the hourly volume of trips are presented in Tables 1 and 2, and on trip duration in Tables 3 and 4. To enable interpretation of these effects, the model coefficients were exponentiated to obtain the linear effects on the unlogged outcome variables. These coefficients reflect the multiplicative effect for a one-unit change in the independent weather variable on the number of trips begun in the first analysis, and the duration of trips in minutes in the second (Washington et al., 2010). The results in each table were divided into the different meteorological seasons, with each further subdivided into trip classifications.

Trip purpose had a substantive impact on the magnitude or significance of weather effects as well. Commuting trips were less flexible than those assumed to be discretionary such as weekend trips. These varying effects can also be seen with snow. For commuting hour trips in the autumn and winter, there was a statistically significant negative effect, yet there were no significant effects on transit-oriented trips. In the same period, effects were significant for elective non-commuting hour, weekday trips.

We also observed differences in effects between the two cities. For instance, San Francisco generally saw larger positive effects of a degree change in air temperature for elective travel—an increase of 8.0% in overall weekend trip counts for a 5 °C increase in San Francisco versus 6.5% in Boston. A degree increase during the winter was associated with a much larger effect in Boston—a 13.5% versus 2.5% increase (SF) in weekend trip counts for a 5 °C increase in air temperature. The effect of precipitation was always negative and stronger in San Francisco. The effect of a moderate rainfall of 5.0 mm per hour is associated with a 29.0% decrease in weekend trip counts.

Table 2
Impact of weather factors on hourly trip counts in the San Francisco Bay area.

			Weekday				Weekend
Season	Variable	All trips	All weekday	Commute	Transit (commute)	Non-commute	
All	Temperature (°C)	1.011 *	1.009 *	1.008 *	1.011 *	1.009 *	1.016 *
	Humidity (%)	0.993 *	0.994 *	0.994 *	0.99 *	0.994 *	0.989 *
	Wind speed (km/h)	1.007 *	1.004 *	1.009 *		1.003 *	1.022 *
	Precipitation (mm/h)	0.978 *		0.954			0.942 *
	Snow	–	–	–	–	–	–
	Thunder	1.868 *					1.707 *
	Cloud cover	1.224 *	1.214 *	1.225 *	1.565 *	1.200 *	1.157 *
	Heavy cloud cover		1.023			1.023	
	Fog	1.473 *	1.317 *	1.611 *	2.651 *	1.165	1.770 *
Winter	Temperature (°C)	1.005 *	1.004 *			1.005 *	1.005 *
	Humidity (%)	0.993 *	0.995 *	0.997 *	0.994 *	0.994 *	0.988 *
	Wind speed (km/h)	1.007 *	1.005 *			1.008 *	1.015 *
	Precipitation (mm/h)	0.975 *	0.979	0.945			
	Snow	–	–	–	–	–	–
	Thunder	1.842 *					1.540
	Cloud cover	1.191 *	1.245 *	1.240 *	1.774 *	1.242 *	
	Heavy cloud cover	1.077 *					1.252 *
	Fog	1.505 *	1.357 *	1.565 *	2.757 *		1.818 *
Spring	Temperature (°C)	1.062 *	1.043 *	1.042 *	1.107 *	1.045 *	1.095 *
	Humidity (%)	0.998 *	0.997 *	0.996 *		0.997 *	
	Wind speed (km/h)	1.014 *	1.009 *	1.013 *		1.008 *	1.026 *
	Precipitation (mm/h)		0.733				
	Snow	–	–	–	–	–	–
	Thunder						
	Cloud cover	1.283 *	1.265 *	1.301 *	1.411 *	1.240 *	1.197 *
	Heavy cloud cover	0.958					0.924
	Fog						
Summer	Temperature (°C)	1.025 *	1.021	1.034			1.051 *
	Humidity (%)	0.995					
	Wind speed (km/h)	1.016 *	1.011 *	1.018 *	1.031	1.010 *	1.027 *
	Precipitation (mm/h)					0.004	
	Snow	–	–	–	–	–	–
	Thunder						
	Cloud cover	1.151 *	1.104	1.208 *			1.156
	Heavy cloud cover						
	Fog						
Autumn	Temperature (°C)	1.033 *	1.032 *	1.051 *	1.062 *	1.026 *	1.037 *
	Humidity (%)	0.997 *					0.995 *
	Wind speed (km/h)	1.003 *		1.018 *			1.025 *
	Precipitation (mm/h)						0.920 *
	Snow	–	–	–	–	–	–
	Thunder						
	Cloud cover	1.214 *	1.162 *	1.141 *	1.358	1.164 *	1.305 *
	Heavy cloud cover		1.064 *	1.106 *		1.055 *	0.928 *
	Fog	1.303 *					1.363

Note: Coefficients indicated with no asterisk are significant at $\alpha = 0.05$ and coefficients indicated with an asterisk (*) are significant at $\alpha = 0.01$. Variables corresponding to all insignificant coefficients were omitted during the model estimation process.

The AOMA also recorded trip duration automatically, which allowed us to investigate weather impacts on duration, which have been difficult to enumerate with many other pedestrian studies due to the challenges of human perception or limitations with the technology used. Generally, the magnitude of effect on duration was small. Air temperature, for instance, had a very weak effect on trip duration. Snow led to increases of trip duration when present, where both commuting and transit trips saw an associated increase in trip times in the winter (8.6% and 6.0%), and transit times in spring (14.6%).

4. Interpretation & conclusion

Our results provide insights in terms of identifying and quantifying to what extent weather characteristics impact the frequency and duration of pedestrian trips and how they vary across the population by season and by time. Several important elements in this regard can be identified. Temperature, overall, had a positive relationship with trip frequencies regardless of other weather and seasonality, with it having a greater effect during weekends versus weekdays. Relative to temperature, wind effects had generally smaller, positive effects on trip frequencies (with the exception of Boston's winters where wind chill could explain the negative effect observed). Light cloud cover was positively associated with trip frequency and duration in both cities.

Substantively speaking, weather factors had little impact on the duration of trips once a trip was initiated, although a statistically significant relationship was present. Presuming that the AOMA recorded many required trips as noted, it is likely that adverse weather would affect whether the trip started or not rather than the duration: once a trip initiated, the weather conditions showed minimal impact. We can understand this in physiological terms as well. A person can only walk so quickly or slowly due to human physiological limits, despite the impetus to avoid adverse weather conditions.

We observed different effects of weather conditions between the two cities on trip volume, which affirms findings of de Montigny et al. (2012), despite the larger spatial consideration of this study. We hypothesize that the apparent differences are likely due to the overall profile of weather in each case study location, and how inhabitants acclimatized to the particular patterns. However, additional analysis of individual data is required to understand the particular reasons for these differences. Studies of multiple discrete cities at scale, particularly

Table 3
Impact of weather factors on trip duration in Greater Boston.

			Weekday				Weekend
Season	Variable	All trips	All weekday	Commute	Transit (commute)	Non-commute	
All	Temperature (°C)	1.002 *	1.001 *	1.001 *	1.001 *	1.001 *	1.001 *
	Humidity (%)	1.000 *	1.000 *	1.000 *	1.000 *		
	Wind speed (km/h)	0.999 *	1.000 *	0.999	1.000 *	0.999 *	
	Precipitation (mm/h)	0.995			0.995	0.987 *	
	Snow	1.087 *	1.110 *	1.156	1.110 *	1.066	
	Thunder	1.123 *	1.120	1.134	1.120		
	Cloud cover		1.010 *	1.016 *	1.010 *		1.020
	Heavy cloud cover	1.014 *					
	Fog					1.082 *	
Winter	Temperature (°C)	1.002 *				1.002	
	Humidity (%)			1.001			1.001
	Wind speed (km/h)			0.999			
	Precipitation (mm/h)	0.986 *	0.991		0.991	0.908 *	0.949
	Snow	1.068 *	1.060 *	1.086 *	1.060 *		
	Thunder						
	Cloud cover						1.060
	Heavy cloud cover						0.955
	Fog					1.106 *	
Spring	Temperature (°C)	1.002 *	1.002 *	1.002 *	1.002 *		
	Humidity (%)	0.999 *	0.999 *	0.999 *	0.999 *	1.000	0.999 *
	Wind speed (km/h)	0.999 *	0.999		0.999	0.999 *	0.998
	Precipitation (mm/h)						
	Snow	1.088 *	1.146		1.146		
	Thunder	2.312					
	Cloud cover	0.984					
	Heavy cloud cover	1.026 *	1.036 *	1.042 *	1.036 *	1.029 *	
	Fog						
Summer	Temperature (°C)					0.995 *	
	Humidity (%)	0.999 *	0.998 *	0.999	0.998 *	0.998 *	
	Wind speed (km/h)	1.003 *	1.003 *	1.004 *	1.003 *		1.003
	Precipitation (mm/h)						
	Snow						
	Thunder						
	Cloud cover		1.022	1.033	1.022		
	Heavy cloud cover	1.026 *					
	Fog						
Autumn	Temperature (°C)	1.002 *	1.002 *	1.004	1.002 *		1.002 *
	Humidity (%)	0.999 *	0.999 *	0.999	0.999 *		0.999 *
	Wind speed (km/h)						
	Precipitation (mm/h)			1.016		0.989	
	Snow			2.770			
	Thunder	1.107					
	Cloud cover						
	Heavy cloud cover	1.034 *	1.022 *		1.022 *	1.025 *	
	Fog						

Note: Coefficients indicated with no asterisk are significant at $\alpha = 0.05$ and coefficients indicated with an asterisk (*) are significant at $\alpha = 0.01$. Variables corresponding to all insignificant coefficients were omitted during the model estimation process.

longitudinally over multiple trips of the same individual, within the same period have been difficult to attempt without the technologies employed in this study.

The results of our study are consistent with prior studies establishing the relationship between certain weather conditions and pedestrian trip frequencies. In comparing previous studies, we observed similar overall effects although the magnitudes differed. For instance, previous studies performed in Vermont found positive effects of increasing temperature and precipitation and negative effects of wind on trip frequencies at a single intersection in Montpellier (Flynn et al., 2012) and positive effects of temperature on trips recorded through the Vermont travel survey (Altman et al., 2010)—both consistent with the findings in our Boston analysis. However, the Montpellier study found no relationship with humidity, which is inconsistent with the negative effect found in this study. Cervero and Duncan (2003), in using the 2000 Bay Area Travel Survey, found negative effects of precipitation, consistent with this study in San Francisco.

While these pedestrian-focused studies faced limitations in their scale, our findings are also consistent with larger scale studies considering weather impacts on public transit utilization where travelers often are exposed to weather during some portion of their trip. Like pedestrian volumes, ridership on transit is higher in good weather (Guo et al., 2008), while colder temperatures and precipitation have negative effects on transit ridership (Changon, 1996; Cravo et al., 2009). We observed similarities with studies that reported differing effects based on when the trip was taken, such as the magnitude effect differing based day of the week (weekdays and weekends) and by season (Cravo et al., 2009) In Chicago, rain had stronger effects during traditional working hours, when commuting trips tended to occur, than in morning and evening periods where more discretionary trips happened (Changon, 1996).

With regard to study limitations, the flaws of the data are its virtues: it comes from the use of mobile devices. This has specific implications. First, behaviors are only able to be captured if the AOMA is downloaded and the phone carried by an individual, which may preclude or omit certain populations and activities. Second, the observed population may not necessarily be representative of the general population. Third, details that could be desirable were redacted to protect user anonymity. Generally, the population of smartphone owners and mobile application users tends to skew younger (Smith and Page, 2015), although without

Table 4
Impact of weather factors on trip duration in the San Francisco Bay Area.

			Weekday				Weekend
Season	Variable	All trips	All weekday	Commute	Transit (commute)	Non-commute	
All	Temperature (°C)	1.002 *	1.001 *		1.001 *	1.002 *	1.001
	Humidity (%)		1.000 *		1.000 *	1.000 *	0.999 *
	Wind speed (km/h)						
	Precipitation (mm/h)						
	Snow	–	–	–	–	–	–
	Thunder						
	Cloud cover	1.015 *					
	Heavy cloud cover	0.988 *	0.990 *	0.983 *	0.990 *		1.014
	Fog	1.100 *	1.097 *		1.097 *	1.134 *	1.070
Winter	Temperature (°C)	1.001 *	1.001				
	Humidity (%)	0.999 *	0.999 *	0.999	0.999 *	0.999 *	0.999 *
	Wind Speed (km/h)						
	Precipitation (mm/h)						
	Snow	–	–	–	–	–	–
	Thunder						
	Cloud cover	1.035 *	1.025 *			1.029 *	
	Heavy cloud cover	0.986 *	0.987	0.972			
	Fog	1.105 *	1.09 *		1.089	1.147 *	1.104 *
Spring	Temperature (°C)	1.010 *	1.004 *			1.007	
	Humidity (%)	1.001 *	1.001			1.001	
	Wind speed (km/h)						
	Precipitation (mm/h)						
	Snow	–	–	–	–	–	–
	Thunder						
	Cloud cover	1.021					
	Heavy cloud cover	0.980 *					
	Fog						
Summer	Temperature (°C)	0.991 *					
	Humidity (%)	0.997 *	0.998				
	Wind speed (km/h)	1.003 *	1.003 *		1.004 *	1.003 *	
	Precipitation (mm/h)			2.239			
	Snow	–	–	–	–	–	–
	Thunder						
	Cloud cover	1.054 *	1.035		1.064	1.041	
	Heavy cloud cover		0.984		0.955		1.048 *
	Fog						
Autumn	Temperature (°C)						
	Humidity (%)	0.999 *	1.000				
	Wind speed (km/h)	1.001 *	1.001 *				
	Precipitation (mm/h)		1.003				
	Snow	–	–	–	–	–	–
	Thunder						
	Cloud cover		0.998				
	Heavy cloud cover	0.985 *	0.986				1.027 *
	Fog		1.089				

Note: Coefficients indicated with no asterisk are significant at $\alpha = 0.05$ and coefficients indicated with an asterisk (*) are significant at $\alpha = 0.01$. Variables corresponding to all insignificant coefficients were omitted during the model estimation process.

biographical information, we cannot confirm this. Further, due to the censoring of the start and end of trips, short distance-trips were likely underrepresented.

Another limitation is the generalizability of this study to other cities. Boston and San Francisco may have a stronger culture of walking, with more pedestrian-oriented infrastructure and denser mix of diverse land-uses than many other cities in the country (Leinberger and Alfonzo, 2012). As such, the results are not necessarily generalizable to all localities.

While the study of weather and its impact on pedestrian movement is not new, the depth of empirical data presents new opportunities to develop deeper insights into pedestrian behaviors (e.g., across urban microclimates and between cities of differing climates in relation to the differing bioclimatic—*felt*—experiences of pedestrians), and future work can provide a clearer sense of how these effects may vary spatially across the city. Despite the previously highlighted limitations, our study demonstrates the utility and potential for locative data to glean new insights into how pedestrians respond to environmental conditions through their travel characteristics (e.g., the availability of measured trip duration data, which may be unique to this study). Confirmatory results support the validity and generalizability of using this new type of data that also opens up avenues of study that are otherwise beyond the limits of traditional public health surveillance approaches such as travel surveys. In addition, the heavy-tailed distribution of trip duration characteristics is comparable with previous studies (Rhee et al., 2011).

While this study finds clear associations between weather and travel behavior, we also see these new datasets as opening new opportunities to understand the more challenging aspects of the urban environment and its impact on individuals' well-being. The outcomes reveal the effects of weather on individuals over a much longer period of observation—with individual observations over an entire year, second-by-second (although the study aggregates to the hour). With the proliferation of mobile devices, these data could be scaled to a national or even international level if device and application platform-makers are willing to share the data for public health and city planning purposes. Hence this study exposes new methods to wider consideration in preventive medicine.

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Human subject participation

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Conflicts of interest

Authors have no conflicts of interest.

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