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# Impacts of weather on cycling and walking on twin trails in Seattle

Jinbao Zhao[a], Cong Guo[b,*], Ruhua Zhang[c], Dong Guo[a], Mathew Palmer[d]

[a] *School of Transporttaion and Vehicle Engineering, Shandong University of Technology, Shandong 255000, China*
[b] *College of Urban Planning and Architecture, Beijing University of Technology, Beijing 100124, China*
[c] *School of Qilu Transportation, Shandong University, Shandong 250061, China*
[d] *School Planning & Transportation, North Carolina State University, Raleigh, NC 27695, United States*

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ABSTRACT

Active travel is associated with various health, environmental, social, and economic benefits. However, barriers exist in active travel activities and promotion. In particular, cycling and walking tend to be more severely affected by inclement weather than encapsulated modes, such as passenger and transit vehicles. This study analyzes the impacts of weather and climate conditional changes on the usage of twin multi-use trails in Seattle, United States. Both comparative analysis and residual regression analysis methods are used to examine the impacts. The buffered effects of rainfall on cycling and walking are particularly investigated. The findings indicate that at the daily level, weather conditions are more influential on active travel on the two trails on weekdays than on weekends. Nevertheless, cyclists and pedestrians on weekdays tend to be more resilient to weather influence than weekend riders and walkers at the hourly level. Cycling could be more severely influenced by weather condition changes than walking, especially on weekdays. The concurrent rainfall not only affects the concurrent active travel, but it also affects the usage of trails 1 h earlier. Comparatively, the delay effects of rainfall on active travel can last a longer period of time for cycling on weekdays. Note that self-selection in a time-series data analysis, particularly at a finer temporal scale, must be controlled. This study discusses the implications of these findings and highlights the potentials of accurate real-time or near real-time weather prediction, weather information push service for active travelers, and facilities' clearing in improving the cycling and walking experience.

## 1. Introduction

Active travel, which is also termed as non-motorized transport, received increasing attention from both academicians and practitioners because of its societal benefits that are associated with various health, environmental, social, and economic factors (e.g., Gössling and Choi, 2015; Knight et al., 2018; Leinberger and Alfonzo, 2012; Park et al., 2013; Sallis et al., 2004; Sehatzadeh et al., 2011). Research findings indicate that an active travel lifestyle could help achieve recommended levels of physical activity and decrease the chance of chronic diseases such as obesity (Frank et al., 2008; Laverty et al., 2013), cardiovascular diseases (Hamer and Chida, 2008; Jia et al., 2018), diabetes (Healy et al., 2008; Riiser et al., 2018), and depression (Biddle and Asare, 2011; Mammen and Faulkner, 2013). Research also highlights the potential of active travel to resolve the automobile-related challenges posed by air pollution and traffic congestion (Litman, 2002). Practitioners advocate and implement a number of infrastructure and health behavior programs to promote active travel, such as the initiative of active and safe routes to school (Buttazzoni et al., 2018; Miller

* Corresponding author.
*E-mail address:* congguo@bjut.edu.cn (C. Guo).

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et al., 2018), construction of active travel networks (Jensen, 2013; SDOT, 2017a), implementation of bike sharing systems (Noland et al., 2016; Zhao et al., 2015), and effective organization of urban land use and transport planning departments (Koglin, 2015). By implementing a number of cycle policies, such as construction of green cycle tracks, maintenance of greenspaces, and snow clearing, in some cities (e.g., Copenhagen) cycling as an everyday form of urban mobility, appealed to a wide range of citizens, and it is as significant for urban life as automobility (Jensen, 2013).

Although active travel is increasing in popularity, barriers exist. In particular, compared to encapsulated modes, active travel as a mode choice is more likely to be influenced by adverse weather conditions. Cyclists and pedestrians are entirely exposed to the outdoor environment and concurrent climate events. Over the past decades, a growing concern over weather impacts on active travel has been observed (e.g., Aultman-Hall and Lambert, 2009; Burchfield et al., 2012; Böcker et al., 2013; Creemers et al., 2015; Liu et al., 2015a; Khattak, 1991; Richardson, 2000; Sabir, 2007; Shirgaokar and Habib, 2018; Simpson, 2018; Thomas et al., 2013; Winters et al., 2007; Zhao et al., 2018). Both survey data analysis and big data mining were conducted to investigate the impacts. While considerable differences exist over the study context, data sources, and analytical methods, weather is consistently considered as a major defining factor that affects active travel.

Existing research into climate impacts on active travel explored the association of weather with active travel at a specific site, but only a few studies compared differential impacts at multiple sites during a weather event. Much of the big data analysis is focused on the influence of weather on cycling or walking separately; some focused on cycling. To the best of our knowledge, no study explored big data to compare the weather impacts on active travel between walking and cycling. Although big data analysis examined weather impacts on active travel at the hourly scale, the time of day analysis remains undiscovered, hindering a deeper understanding of the heterogeneous impacts of weather on active travel caused by trip direction (departure or back home). In particular, the buffered (anticipatory and delay) temporal and spatial effects of some adverse weather conditions, such as rainfall, on active travel have arguably yet to be fully understood. The scarcity of the evidence on the weather impacts' variations caused by active travel modes, sites, time, and buffered effects limits the application of previous studies in fully understanding the mechanisms of weather variations affecting who, where, when, and how active travel occurs.

This study aims to fill some of these research gaps and enrich the existing literature by exploring and comparing the impacts of weather on walking and cycling on a seaside trail and a forest trail at both daily and hourly scales across four seasons. More specifically, we collected big data for walking and cycling on the Elliott Bay and Burke–Gilman trails in Seattle, Unites States together with detailed meteorological records to form an integrated database. Both comparative and regression analyses are conducted to examine the association of weather with active travel. The finer temporal data also allow us to examine the buffered effects of rainfall on active travel.

The remainder of this paper is organized as follows: Section 2 reviews and elaborates on a previous research; Section 3 presents the study context and data sources; Section 4 introduces the analytical methodology; Section 5 explains the results and findings; and finally, Section 6 discusses the findings and concludes.

## 2. Literature review

An established body of research on the effects of weather on active travel exists (e.g., Aultman-Hall and Lambert, 2009; Burchfield et al., 2012; Creemers et al., 2015; Liu et al., 2015a; Richardson, 2000; Shirgaokar and Babib, 2018; Simpson, 2018; Thomas et al., 2013; Zhao et al., 2018) and several reviews summarized the relationship (Böcker et al., 2013; Liu et al., 2017). Below, we review some of the key issues in this literature with a focus on research and practice implications of big data mining.

Compared to research using survey data, big data analysis is less but more efficient and cost-effective. Only in recent years with the availability of smart-counter data and smart card data has there been a growing number of studies exploring big data. Aultman-Hall and Lambert (2009) examined the weather–walking relationship by exploring 12 months of automated hourly pedestrian counter data in a single location in downtown Montpelier, United States. The findings indicate that weather and season variables accounted for approximately 30% of pedestrian variation. Precipitation reduced the average hourly pedestrian volumes by approximately 13% and pedestrians by 16% in the winter months. Precipitation and season affected the pedestrian levels, even when the time of day and the day of week were controlled. Although weather related factors account for a moderate variation in active travel (Burchfield et al., 2012), the remaining variation is still large, which could be attributed to the unaccounted factors such as holidays, personal features, and household characteristics (Sabir, 2011; Shirgaokar and Habib, 2018; Thomas et al., 2013).

Miranda-Moreno and Nosal (2011) investigated cycling data at five automatic counting stations on primarily utilitarian bike facilities in the city of Montreal, Canada. The daily bicycle volumes on these utilitarian bike facilities were 65–89% lower on weekends than on the weekday with the lowest cycling volume (Monday). Cycling increased with a temperature up to 28 °C and declined beyond this temperature. This optimum temperature could be compared to 24.4 °C for active travel on an urban greenway in Knoxville, United States (Burchfield et al., 2012). The findings from the previous studies generally support a 'crest' relationship between temperature and active travel, but the optimum temperatures are often contextual. In addition, Miranda-Moreno and Nosal (2011) noted that hourly bicycle use in Montreal varied not only with the concurrent rainfall but also with the rainfall 3 h earlier, suggesting a delay effect of rainfall on cycling.

A detailed hourly analysis of the weather–bike sharing relationship conducted by Gebhart and Noland (2014) correlated weather patterns with both the usage of bicycles and the duration of trips performed. Precipitation, colder weather, and humidity reduced both bike sharing usage and their duration. Snow resulted in no impact on trip generation, but it reduced the duration of bike sharing trips. Seasonality was clearly a factor affecting the bike sharing usage. Bike sharing stations that were more proximate to transit stations were used less in adverse weather, suggesting some substitution effects. Another study examining the bike sharing trip generation suggested that the variation in weather is likely one of the main culprits affecting the applicability of bike sharing trip forecasting models for new stations (Noland et al., 2016).

In a recent study, Zhao et al. (2018) found that the impacts of weather on cycling significantly depended on the cycling facilities (off-road trails and on-road bike lane) and time (day of week and time of day). In particular, weekend cyclists on off-road trails tended to be more severely affected by bad weather conditions than those on on-road bike lanes, especially during weekend peak hours. Nevertheless, weekday cycling on on-road bike lanes was more likely to be affected by adverse weather than on off-road trails, especially during weekday peak hours. Importantly, Zhao et al. (2018) noted that rainfall not only resulted in a delay effect on cycling, but it also significantly affected the bicycle volumes an hour before the rainfall.

A review of the existing literature on the big data analysis revealed that no study compared the weather and active travel relationship between walking and cycling. Only a few studies examined the buffered effects of weather events on active travel but only on cycling (Miranda-Moreno and Nosal, 2011; Zhao et al., 2018). Nevertheless, findings from the big data analysis are in agreement with the broader literature on the survey data analysis, which revealed that adverse weather severely affects active travel activities (e.g., Bergström and Magnusson, 2003; Liu et al., 2015a; Müller et al., 2008; Sabir, 2011; Shirgaokar and Habib, 2018; Simpson, 2018; Winters et al., 2007). The survey data analysis demonstrates clear advantages in investigating the impact of weather on active travel mode choice by controlling household characteristics (household income, car ownership, etc.), personal features (age, gender, etc.), and trip characteristics (travel purpose, time, etc.), which generally rely on a large-scale survey. Comparatively, big data mining can explore the weather and active travel relationship at finer temporal and spatial scales over a long time and a large spatial scale at relatively low costs. Herein, we examined the association of weather with walking and cycling by using big data for active travel on two popularly mixed-use trails in Seattle, United States. An emphasis of this analysis is on the buffered effects of rainfall on active travel.

## 3. Study context and data source

### 3.1. Study context

Located on the west coast of the United States with a land area of 217.3 $km^2$ and residents of over 650,000, Seattle is the largest city in both the state of Washington and the Pacific Northwest region of North America. Although private cars are the primary trip-making mode in this city, the mode share of walking and cycling continues to climb in recent years (SDOT, 2014; 2017a). As Fig. 1 shows, the commute mode share of walking and cycling increased from 14% in 2013 to 16% in 2016, while that of single-driver and carpool decreased from 63% to 59% during the same period (SDOT, 2014; 2017a). Among large US cities, Seattle ranks 5th regarding the number of people who walk to work (SDOT, 2017a). This can be partly attributed to a series of active travel promotion programs such as the implementation of the Seattle Pedestrian Master Plan, Bicycle Master Plan, and the continuing investment in the construction of a citywide active travel network (SDOT, 2017a). This network consists of walking and cycling facilities such as multi-use off-road trails, neighborhood greenways, and protected bike lanes, which collectively aim to provide people of all ages and abilities with comfortable and safe environments for active travel.

Of these active travel facilities, the multi-use trail allows for two-way off-street pedestrian and bicycle use. Wheelchairs, joggers, skaters, and other non-motorized users are also permitted. These trails are frequently found in parks, along rivers, beaches, and in greenbelts or utility corridors where there are a few conflicts with motorized vehicles. These trails play an important role in encouraging and attracting more people to walk or ride bicycles (SDOT, 2017b). Herein, two popularly used trails, namely the Elliott Bay Trail and the Burke–Gilman Trail, were selected for the case study analysis. This selection was based on two main reasons: First, since October 2012, the SDOT installed automated counters at 10 locations (Fig. 2). Four of the 10 counters can record both pedestrian and bicycle volumes. Of the four trails, the Elliott Bay Trail and the Burke–Gilman Trail are more popularly used, and their active travel patterns are more stable and regular than the other two trails (Fig. 3). Thus, the weather conditions rather than the random effects may play a role in affecting the fluctuation of daily and hourly active travel. Second, the cycling and walking patterns

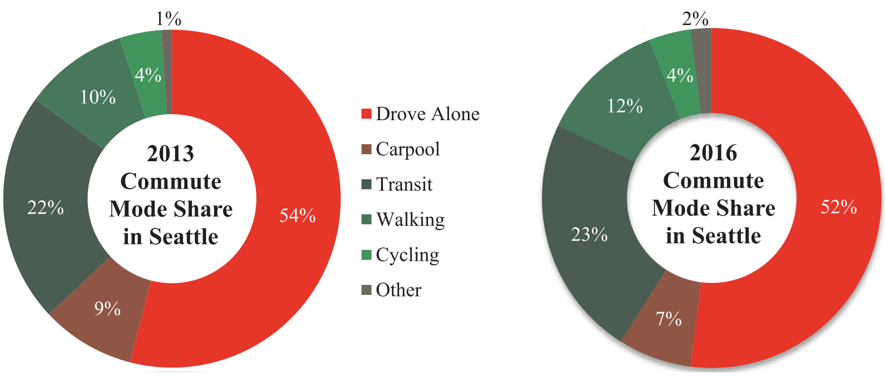


**Fig. 1.** Commute mode share in Seattle.
*Source:* SDOT (2014 and 2017a), redrawn by the authors.

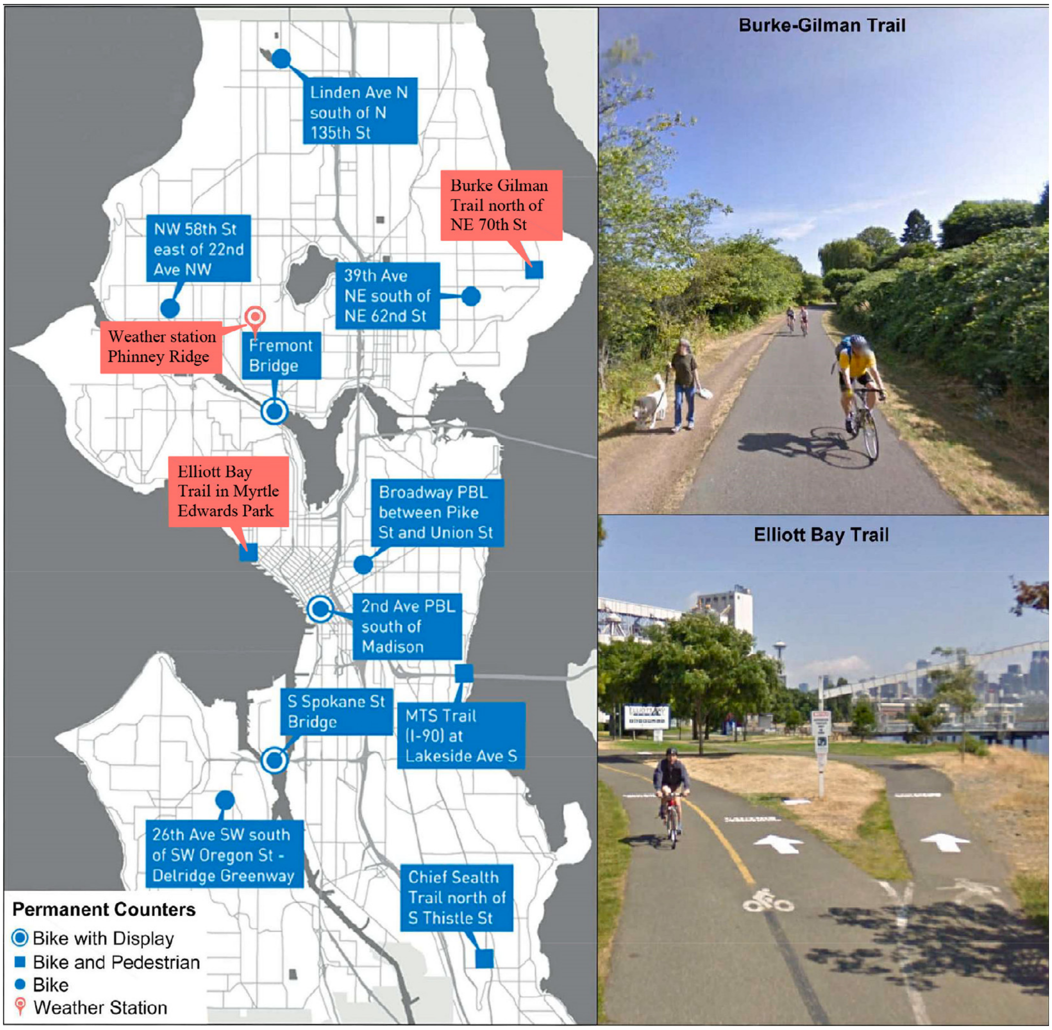


**Fig. 2.** Study context.
*Source:* SDOT (2017a) and Google Street View (www.maps.google.com), redrawn by the authors.

on the two trails are very typical. As Fig. 3 shows, the hourly cycling on weekdays on the two trails demonstrates a double peak nature (7–9 AM and 4–6 PM) and a single-peak property on weekends (11 AM to 4 PM). Walking on the Elliott Bay Trail on weekdays presents a ternary-peak pattern (7–9 AM, 12–2 PM, and 4–6 PM). Comparatively, walking on the Burke–Gilman Trail tends to be more stable over day of week and time of day.

### *3.2. Data sources*

The automated counter data and the meteorological records were the two main data sources used in this study. An automated counter dataset covering a 12-month period from January 1 to December 31, 2014 was provided by SDOT (2017c). This freely accessing dataset separately records the hourly walking and cycling volumes on the two trails. The wires in a diamond formation in the concrete detected the bikes, while an infrared sensor mounted on a wooden post detected the pedestrians. The automated counters were accurate in counting the cyclists and the pedestrians for all of 2014 (SDOT, 2017c). Nevertheless, the automated counters temporarily did not count in some months of 2015 and 2016; thus, herein, the 2014 data were used for the analysis.

While active travel activities on the two trails tended to be stable and regular over day of week and time of day as Fig. 3 shows, some days exhibited quite high active travel levels because of some special events, such as music festivals or sports events. Five such days together with 10 federal holidays (OPM, 2014) with abnormal active travel patterns in 2014 were cleaned out for analysis because active travel was significantly affected by the events or holidays unrelated to the weather condition changes. For the hourly active travel analysis, the hours selected for examination were between 6 AM and 8 PM because many zero values were observed in the other hours (Fig. 3). Thus, the sample sizes for the daily and hourly analyses were 350 days and 5250 h, respectively.

The meteorological records for Seattle were obtained from the three following sources: (1) the National Oceanic and Atmospheric

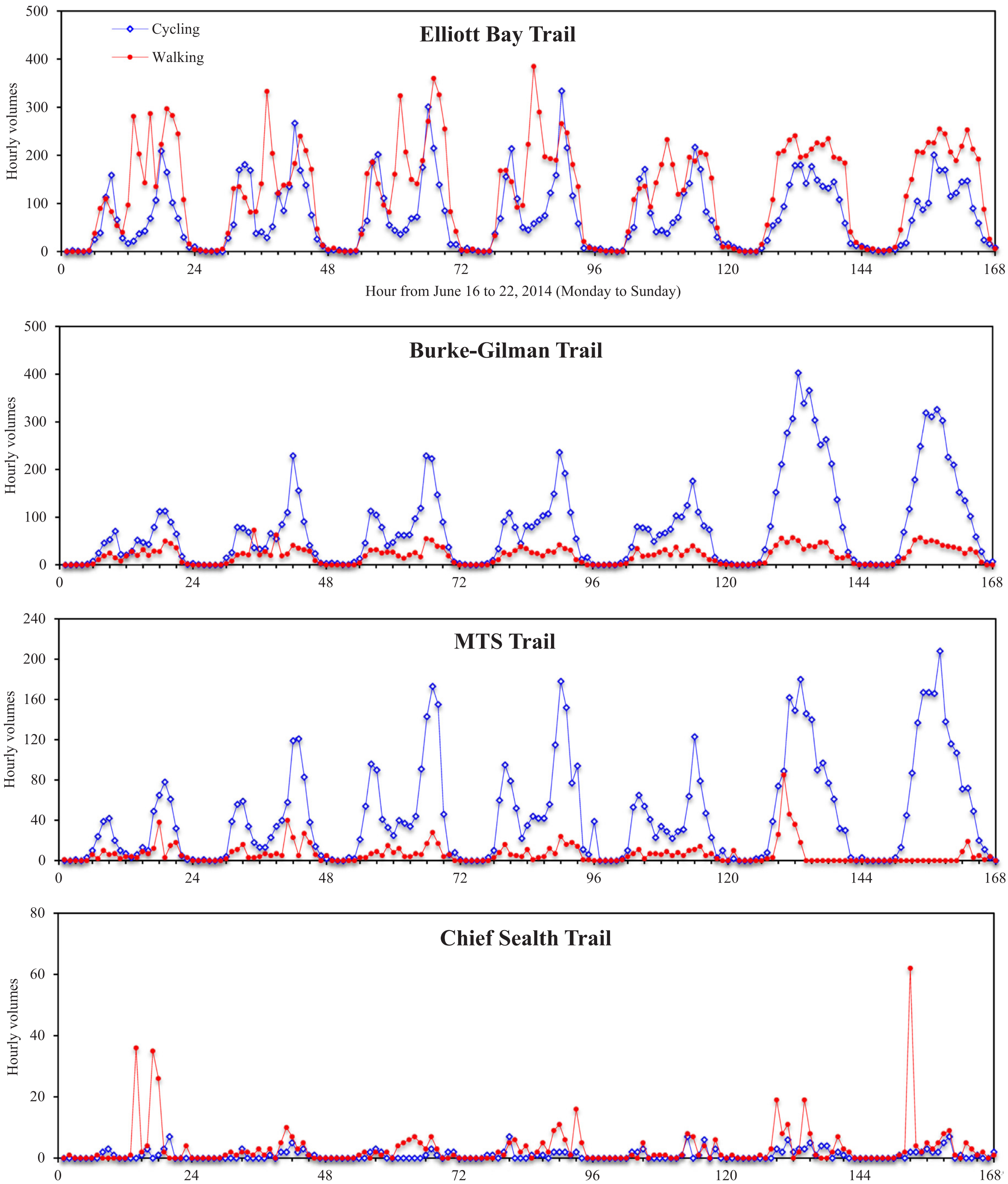


**Fig. 3.** Hourly active travel patterns of walking and cycling on the four trails from June 16 to 22, 2014 (from Monday to Sunday).

Administration (NOAA), (2) the World Weather Online (WWO), and (3) the Weather Underground. The three data sources, especially NOAA and Weather Underground, are popularly used by researchers to examine the weather impacts on travel behavior (e.g., Burchfield et al., 2012; Singhal et al., 2014; Gebhart and Noland, 2014). Although NOAA tends be more reliable in providing weather information, the daily weather dataset downloaded from its official website only contains main weather events such as daily maximum temperature, minimum temperature, and precipitation. WWO provides other daily weather conditions such as humidity and wind speed. The daily weather information provided by NOAA and WWO are highly consistent. For instance, the Pearson correlation coefficient of the maximum temperatures between the two data sources is 0.95. Thus, the two datasets were applied to reflect the daily weather conditions in Seattle. The hourly weather events of temperature, humidity, wind speed, and precipitation were

**Table 1**
Variable statistics.

| Daily statistics ($N$ = 350) | Minimum | Maximum | Mean | S.D. | Skewness | Kurtosis |
|---|---|---|---|---|---|---|
| *Elliott Bay Trail* | | | | | | |
| Cycling | 44 | 2577 | 1154.35 | 603.04 | 0.35 | −0.88 |
| Walking | 276 | 4555 | 2145.41 | 951.05 | 0.27 | −0.96 |
| *Burke–Gilman Trail* | | | | | | |
| Cycling | 15 | 3688 | 1091.57 | 706.92 | 0.93 | 0.55 |
| Walking | 96 | 729 | 374.97 | 125.42 | 0.27 | −0.54 |
| *Weather variables* | | | | | | |
| Temperature (°C) | −4.6 | 25.4 | 11.87 | 5.88 | −0.13 | −0.57 |
| Humidity (%) | 35 | 98 | 77.62 | 13.11 | −0.77 | 0.09 |
| Wind speed (km/h) | 0 | 19 | 4.20 | 3.77 | 1.40 | 1.73 |
| Precipitation (mm) | 0 | 46 | 3.34 | 6.82 | 2.90 | 9.81 |
| Hourly statistics ($N$ = 5250) | Minimum | Maximum | Mean | S.D. | Skewness | Kurtosis |
| *Elliott Bay Trail* | | | | | | |
| Cycling | 0 | 460 | 73.24 | 66.17 | 1.61 | 3.17 |
| Walking | 0 | 689 | 138.05 | 94.94 | 0.89 | 1.02 |
| *Burke–Gilman Trail* | | | | | | |
| Cycling | 0 | 735 | 70.24 | 65.50 | 1.96 | 6.65 |
| Walking | 0 | 173 | 24.38 | 16.46 | 1.35 | 4.94 |
| *Weather variables* | | | | | | |
| Temperature (°C) | −7 | 33.8 | 12.87 | 6.93 | 0.23 | −0.36 |
| Humidity (%) | 19 | 99 | 74.71 | 18.26 | −0.70 | −0.48 |
| Wind speed (km/h) | 0 | 72.4 | 12.79 | 10.19 | 1.42 | 2.50 |
| Precipitation (mm) | 0 | 7.6 | 0.14 | 0.55 | 5.89 | 43.05 |

acquired from the Weather Underground. NOAA records Seattle's weather at Seattle–Tacoma International Airport and is assumed to be a representative of the weather conditions across this city. We could not obtain the weather station information from WWO. The hourly weather information from the Weather Underground was recorded by the weather station of Phinney Ridge (Fig. 2). The straight-line distances from this weather station to the two smart counters for the Elliott Bay and Burke–Gilman trails are approximately 4.2 km and 7.1 km, respectively.

Table 1 presents the descriptive statistics for the dependent and independent variables. The Elliott Bay Trail is more preferred by pedestrians than by cyclists, while the Burke–Gilman Trail is more popularly used for cycling than walking. Seattle is typically featured by temperate marine climate with cool wet winters and mild relatively dry summers. Although Seattle receives relatively less precipitation than many other US cities, this city has a reputation for frequent rain. Precipitation fell on 166 days and 1066 h in 2014. Thus, this city provides a suit study context to understand the impacts of rainfall on active travel. Seattle typically receives some snowfall on an annual basis, but heavy snow is rare. The relatively small sample of snowfall may hinder a finer exploration on the effect of snowfall on active travel. Both the skewness and kurtosis of precipitation for daily and hourly statistics exceed 1.96, indicating that the precipitation distribution is seriously skewed. Thus, four discrete categories, namely, no rainfall (0 mm), light rainfall (0–10 mm), moderate rainfall (10–25 mm), and heavy rainfall (> 25 mm) are defined for daily precipitation. The counterparts for the hourly precipitation in this study are 0 mm, 0–2.5 mm, 2.5–5.0 mm, and > 5.0 mm, respectively.

## 4. Analytical methodology

### 4.1. Dependent and independent variables

We chose a 9-term moving average to compare a day's or an hour's active travel to the same day of the week for the daily analysis, the same hour in the same day of the week for the hourly analysis in the prior four, and the following four weeks to control for the fluctuations in active travel associated with the non-weather-related factors over time. The 9-term moving was introduced by Kalstein et al. (2009) and furthered developed by Zhao et al. (2018) by considering the autocorrelation effect. According to Kalstein et al. (2009), the 9-term moving average is defined as follows:

$$\overline{WoC}_t^{\mathrm{MA}\pm4} = \frac{\sum_{\tau=-4}^{4} WoC_{t+7\tau}}{9} \tag{1}$$

where $\overline{WoC}_t^{\mathrm{MA}\pm4}$ is the 9-term moving average of walking or cycling for a specific day $t$ or hour $t$; index $\tau$ represents weeks; and $(t + 7\tau)$ goes from 28 days before to 28 days after by sevens. The percentage difference between the raw daily or hourly cycling or walking during a particular day and hour and the 9-term moving average for that day and hour is defined as the dependent variable. The dependent variable is specifically defined by the following equation:

$$\Delta WoC_t = \frac{WoC_t - \overline{WoC}_t^{\mathrm{MA}\pm4}}{\overline{WoC}_t^{\mathrm{MA}\pm4}} \tag{2}$$

where $\Delta WoC_t$ is the walking or cycling residual standardized in percentage terms to compare residual across days of week or hours of day. Similar to the dependent variable, some weather variables demonstrate intrinsic temporal variations, especially temperature, humidity, and wind speed. The residual weather equation for the three weather variables is defined as follows:

$$\Delta W_t = \frac{W_t - \overline{W}_t^{\mathrm{MA}\pm4}}{\overline{W}_t^{\mathrm{MA}\pm4}} = \frac{W_t - \frac{\sum_{\tau=-4}^{4} W_{t+7\tau}}{9}}{\frac{\sum_{\tau=-4}^{4} W_{t+7\tau}}{9}} \tag{3}$$

where $\Delta W_t$ represents the residuals of temperature, humidity, and wind speed; $W_t$ is the observed weather conditions in a particular day $t$ or hour $t$; and $\overline{W}_t^{\mathrm{MA}\pm4}$ is the 9-term moving average of the weather conditions in that day $t$ or hour $t$.

As for the weather events of precipitation, four discrete categories are defined as mentioned earlier. For the dummy snow variable, two snowy days were recorded in the sample. Thus, the two days and the hours in those two days are defined as snowfall. Note that the small sample size of snowfall may hinder an accurate estimation of the impact of snowfall on active travel. In addition, for the daily models, the wind speed is represented by the average value and by the highest value during a given hour observed by the Weather Underground for the hourly analysis.

### 4.2. Analytical model

Although the 9-term moving average residual performs well in controlling the inherent temporal variations of active travel associated with non-weather effects (Kalstein et al, 2009), the residual itself still demonstrates a time-series nature. That is, the concurrent active travel patterns tend to be associated with the active travel levels during previous days or hours. Failing to consider the temporal autocorrelation or such self-dependency is likely to generate biased estimations. In addition, active travel may vary not only with the concurrent weather conditions but also with the buffered effects (Miranda-Moreno and Nosal, 2011; Zhao et al, 2018). The analytical model used herein takes the following general form to examine these hypotheses:

$$\begin{aligned}\Delta WoC_t = \beta_0 + \beta_1 \Delta WoC_{t-1} + \beta_2 \Delta T_t + \beta_3 \Delta H_t + \beta_4 \Delta W_t + \beta_5 LRain_t + \beta_6 LRain_{t-n} \\ + \beta_7 MRain_t + \beta_8 MRain_{t-n} + \beta_9 HRain_t + \beta_{10} HRain_{t-n} \\ + \beta_{11} Snow_t + \beta_{12} Snow_{t-n}\end{aligned} \tag{4}$$

where $\Delta WoC_t$ denotes the cycling residuals in day $t$ or hour$t$; $\Delta WoC_{t-1}$ is the cycling residuals in day $t-1$ or hour$t-1$; and $\Delta T_t$, $\Delta H_t$, and $\Delta W_t$ are the daily and hourly residuals of temperature, relative humidity, and wind speed, respectively. $LRain_t$, $MRain_t$, $HRain_t$, and $Snow_t$ denote the weather conditions of light rainfall, moderate rainfall, heavy rainfall, and snowfall or not, respectively.

### 4.3. Analytical strategy

In the following, we first conducted a comparative analysis to provide an overall view on the impacts of the day of week, rainfall, wind speed, and temperature on active travel and analyzed the impacts' differences between cycling and walking. We then examined the autocorrelation effects on the modeling results and highlighted the importance of controlling the self-dependency in the time-series data analysis. The buffered effects of rainfall on cycling and walking were then investigated. In addition, a number of regression models were performed to examine how the weather condition changes affect daily and hourly active travel on the two trails. For the daily regression, we estimated the models for weekdays and weekends separately, while for the hourly regression, we used the models for 3750 weekday hours, 1500 weekend hours, weekday peak hours (7–9 AM and 4–6 PM), weekend peak hours (11 AM to 4 PM), and other hours to address as to what extent the real-time weather condition changes affect active travel.

## 5. Results

### 5.1. Comparative analysis

Fig. 4 shows a comparison of the average daily cycling and walking volumes between 250 weekdays and 100 weekends. In 2014, the cycling volumes on the Elliott Bay Trail on weekdays were 57.5% more than that on weekends, while weekday walking on this trail was slightly less than weekend walking. Comparatively, the Burke–Gilman Trail was more popularly used by both cyclists and pedestrians on weekends than on weekdays. The averagely daily cycling and walking on the Burke–Gilman Trail on weekdays were 35.3% and 37.3% more than on weekends, respectively. The differences in the geographical locations of the two trails and the trip purposes of the users may play a role in leading to the variation in the use patterns over days of week. Considering that the active travel patterns obviously vary between weekdays and weekends, and the sample size for weekdays was larger than that for weekends, weekdays' data were used to conduct the comparative analysis of the impacts of rainfall, temperature, and wind on active travel and reduce the random effects of the weekends' sample on the results.

Fig. 5 shows the daily and hourly cycling and walking volumes in different rainfall conditions on average. Both the daily and hourly walking on the Elliott Bay Trail were more severely affected by rainfall than cycling but less severely affected than cycling on

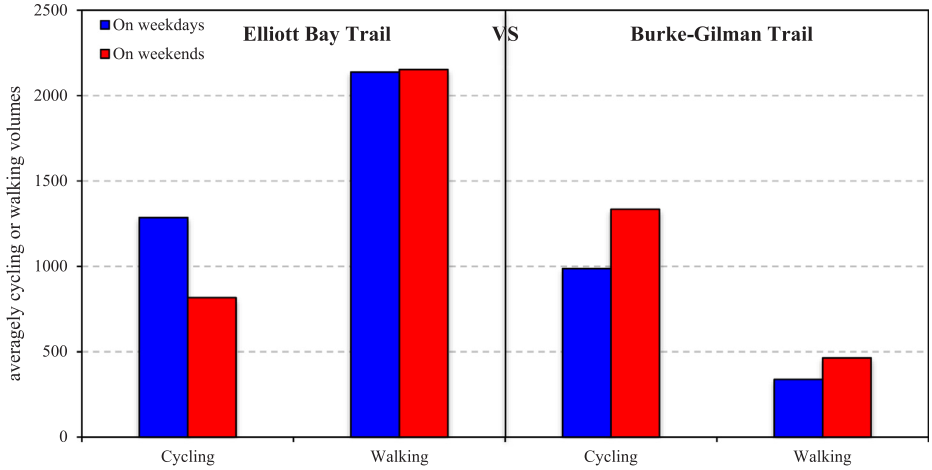


**Fig. 4.** Averagely daily cycling and walking volumes on weekdays and weekends.

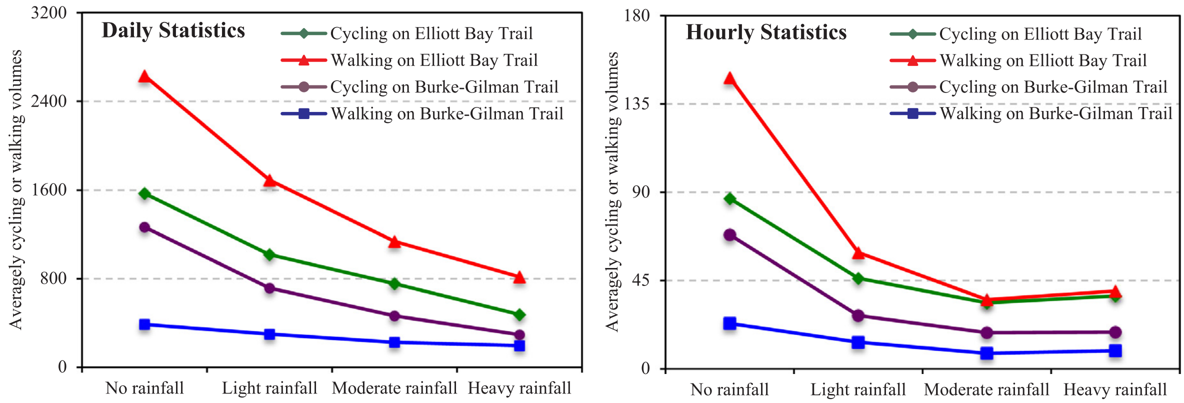


**Fig. 5.** Averagely daily and hourly cycling and walking volumes in different rainfall conditions.

the Burke–Gilman Trail. The daily walking on the Elliott Bay and Burke–Gilman trails could reduce by 40.9% and 28.9% on average in all rainy days than in sunny days, respectively. These figures could be compared to their cycling counterparts of 42.7% and 50.1%, respectively. Daily cycling and walking on the Elliott Bay and Burke–Gilman trails reduced by 40.9%, 42.7%, 50.1%, and 28.9% on average in all the rainy days based on the sunny days compared with the hourly counterparts of 49.1%, 61.9%, 61.8%, and 44.6%, respectively. These results indicated that rainfall more severely affected active travel at the hourly level than at the aggregate daily level. Although rainfall led to inconvenience and difficulty for active travel, it did not act as an insurmountable barrier because more

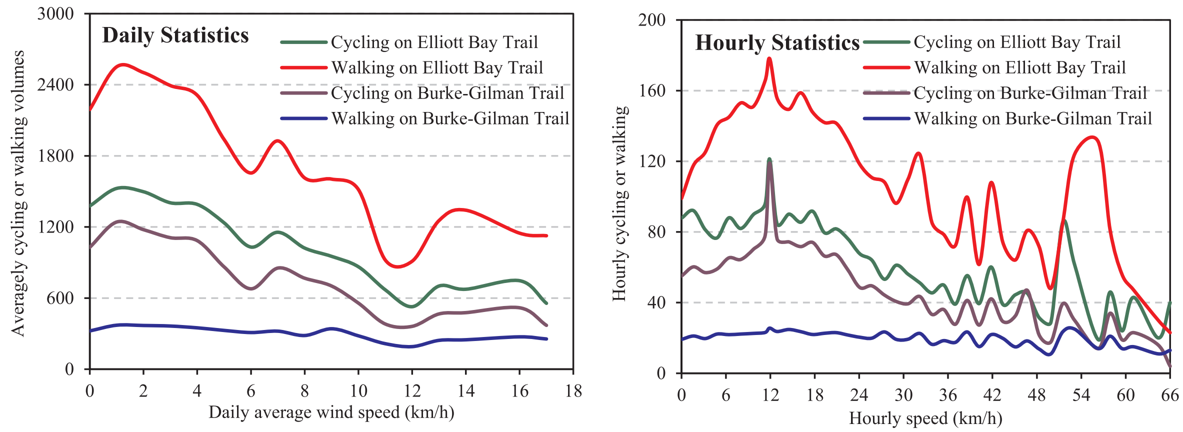


**Fig. 6.** Association of wind speed with cycling and walking at the daily (left) and hourly (right) scales.

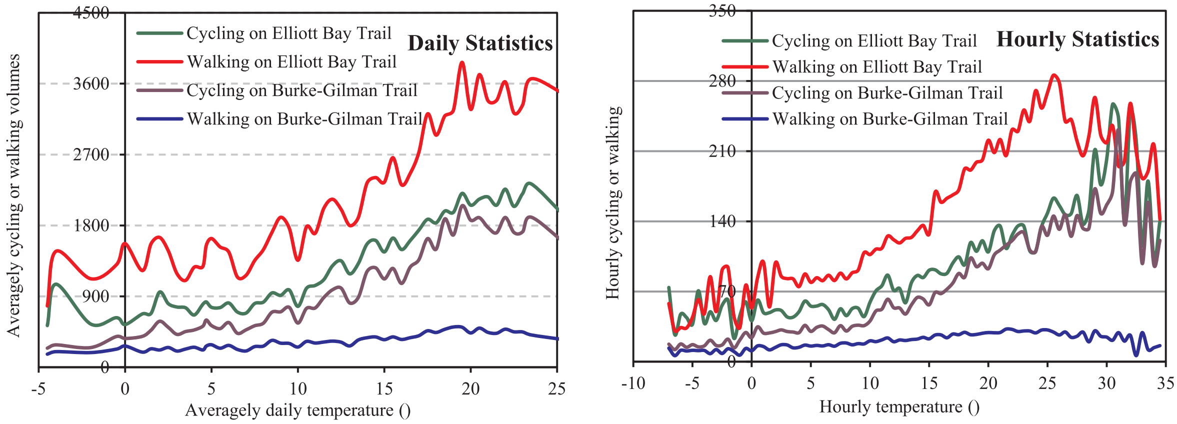


**Fig. 7.** Relationship of temperature with cycling and walking at the daily (left) and hourly (right) scales.

than 28% of active travelers still kept cycling or walking during rainfall.

Fig. 6 depicts the association of wind speed with active travel at the daily (left) and hourly (right) scales. Active travel increased with the wind flow up to a certain speed at both daily and hourly scales and generally declined beyond this speed. This result reveals a "crest" relationship between wind speed and active travel and indicates that a gentle breeze may reduce the feeling of unpleasantness in muggy setting, thereby increasing the active travel level; however, a strong wind could obviously reduce active travel. Nevertheless, the hourly walking on the Elliott Bay Trail was observed with a sudden increase around the wind speed of 55 km/h. This saltation may be caused by the shifting from other travel modes to walking in stormy wind due to the suspended operation of urban transit systems or abandonment of other travel modes such as passenger cars.

Fig. 7 shows the relationship between temperature and active travel. The daily active travel increased with the daily medium temperature up to 20 °C in Seattle and then fluctuated beyond this temperature. Nevertheless, the hourly cycling and walking significantly varied with temperature. At the hourly level, the optimum temperature for cycling in Seattle was approximately 30 °C, which was 5 °C higher than that for walking. Walking in high temperature is unpleasant. Meanwhile, cyclists with a faster travel speed and a relatively faster wind flow tend to be more resistant to high temperature than pedestrians (a relatively faster wind speed may play a role in relieving the discomfort caused by high temperature).

## *5.2. Regression analysis*

### *5.2.1. Autocorrelation effect*

Table 2 summarizes the autocorrelation effects on the modeling results. At the hourly scale, considering the autocorrelation could significantly improve the models' goodness of fit. For instance, the models' R-square for cycling on the Elliott Bay and Burke–Gilman trails increased from 0.125 and 0.123 to 0.442 and 0.440, respectively. Nevertheless, the impacts of autocorrelation on the modeling results for daily walking tended to be absent, but it still played a significant role in affecting the daily cycling, especially in the Elliott Bay Trail. These findings suggest that controlling the autoregressive effect is important for the time-series data estimation, particularly at a finer temporal scale. As Tobler (1970) noted, four decades ago, "everything is related to everything else, but near things are more related to each other." However, the strong autocorrelation could eclipse the explanation power of the weather elements in affecting active travel because the *t*-statistics for weather elements became less significant or even absent by considering the self-dependency.

### *5.2.2. Buffered effects of rainfall*

In this section, we mainly examined the buffered effects of rainfall on active travel at the hourly scale because the sample size of rainy hours (n = 643 of a total of 5250 h) tended to be adequate for the estimation. The strong autocorrelation could significantly eclipse the impacts of rainfall on active travel as mentioned earlier; hence, we excluded the self-dependency for the buffered effects' estimation. Tables 3 and 4 present the anticipatory and delay effects of rainfall on active travel, respectively.

Significant and negative anticipatory effects of rainfall were found on weekday cycling and walking of the previous 1 h. Nevertheless, the anticipatory effects on the weekend active travel were less significant or even absent. The concurrent rainfall did not result in a significantly negative impact on cycling of the previous 2 h. A plausible reason may be that 95% of cyclists could finish their cycling activities within half an hour (Zhao et al., 2018); thus, most cyclists would not care much about whether it would rain or not 2 h later. However, the anticipatory effect of the rainfall on the weekday walking on the Burke–Gilman Trail was estimated with a significant coefficient of −0.078, contrary to the significantly positive coefficient of 0.156 estimated for the weekend walking on this trail. A possible reason for this is that daily walking on the Burke–Gilman Trail was more stable on weekends than on weekdays, and pedestrians on this trail tended to be more flexible to adjust walking activities at the hourly scale on weekends than on weekdays.

Compared to the anticipatory effects, the delay effects of rainfall on active travel could last longer, especially for active travel on weekends. Its negative effects on active travel could last for at least 2 h or even 3 h for cycling on the Burke–Gilman Trail on

**Table 2**
Examination of the autocorrelation effect.

| | Daily models | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Excluding autoregressive effect | | | | Including autoregressive effect | | | |
| | Cycling | | Walking | | Cycling | | Walking | |
| | Coeffi. | $t$ | Coeffi. | $t$ | Coeffi. | $t$ | Coeffi. | $t$ |
| (Constant) | 0.051 | 3.402 | 0.066 | 4.485 | 0.057 | 3.809 | 0.067 | 4.527 |
| | **0.071** | **4.319** | **0.050** | **4.145** | **0.075** | **4.545** | **0.050** | **4.126** |
| $\Delta WoC_{t-1}$ | –[a] | – | – | – | 0.142 | 3.523 | /[b] | / |
| | **–** | **–** | **–** | **–** | **0.080** | **2.032** | / | / |
| $\Delta T_t$ | 0.429 | 10.907 | 0.337 | 8.706 | 0.374 | 8.968 | 0.328 | 7.964 |
| | **0.559** | **12.978** | **0.253** | **7.931** | **0.519** | **11.034** | **0.260** | **7.736** |
| $\Delta H_t$ | −0.645 | −8.552 | −0.626 | −8.426 | −0.523 | −6.403 | −0.598 | −7.032 |
| | **−0.665** | **−8.047** | **−0.161** | **−2.635** | **−0.590** | **−6.533** | **−0.172** | **−2.721** |
| $\Delta W_t$ | −0.294 | −8.978 | −0.242 | −7.508 | −0.273 | −8.325 | −0.238 | −7.219 |
| | **−0.323** | **−9.006** | **−0.136** | **−5.135** | **−0.309** | **−8.507** | **−0.139** | **−5.173** |
| $LRain_t$ | −0.084 | −3.362 | −0.122 | −4.969 | −0.091 | −3.681 | −0.123 | −4.994 |
| | **−0.148** | **−5.391** | **−0.088** | **−4.333** | **−0.152** | **−5.549** | **−0.088** | **−4.354** |
| $MRain_t$ | −0.234 | −6.260 | −0.307 | −8.312 | −0.240 | −6.521 | −0.307 | −8.323 |
| | **−0.324** | **−7.892** | **−0.252** | **−8.318** | **−0.327** | **−8.000** | **−0.252** | **−8.315** |
| $HRain_t$ | −0.417 | −6.110 | −0.404 | −6.001 | −0.439 | −6.514 | −0.403 | −5.986 |
| | **−0.451** | **−6.029** | **−0.189** | **−3.417** | **−0.459** | **−6.160** | **−0.189** | **−3.421** |
| $Snow_t$ | −0.436 | −3.095 | / | / | −0.420 | −3.025 | / | / |
| | **−0.401** | **−2.594** | / | / | **−0.385** | **−2.502** | / | / |
| *Model Statistics* | | | | | | | | |
| $R^2$ | 0.590 | | 0.579 | | 0.604 | | 0.580 | |
| | **0.623** | | **0.399** | | **0.628** | | **0.400** | |
| $F$ | 70.22 | | 67.32 | | 65.04 | | 58.87 | |
| | **80.83** | | **32.40** | | **71.89** | | **28.39** | |

| | Hourly models | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Excluding autoregressive effect | | | | Including autoregressive effect | | | |
| | Cycling | | Walking | | Cycling | | Walking | |
| | Coeffi. | $t$ | Coeffi. | $t$ | Coeffi. | $t$ | Coeffi. | $t$ |
| (Constant) | 0.059 | 6.840 | 0.037 | 5.703 | 0.029 | 4.224 | 0.023 | 4.293 |
| | **0.051** | **5.647** | **0.035** | **4.554** | **0.025** | **3.555** | **0.024** | **3.375** |
| $\Delta WoC_{t-1}$ | – | – | – | – | 0.595 | 54.622 | 0.531 | 46.767 |
| | **–** | **–** | **–** | **–** | **0.593** | **54.409** | **0.366** | **28.728** |
| $\Delta T_t$ | / | / | 0.012 | 2.776 | / | / | / | / |
| | **0.021** | **3.421** | **0.014** | **2.600** | **0.010** | **2.155** | **0.012** | **2.572** |
| $\Delta H_t$ | −1.034 | −20.976 | −0.819 | −22.074 | −0.439 | −10.766 | −0.384 | −11.820 |
| | **−0.941** | **−18.373** | **−0.334** | **−7.540** | **−0.418** | **−9.933** | **−0.232** | **−5.615** |
| $\Delta W_t$ | / | / | −0.044 | −5.056 | / | / | −0.023 | −3.095 |
| | **−0.056** | **−4.610** | **−0.024** | **−2.304** | **−0.018** | **−1.827** | / | / |
| $LRain_t$ | −0.201 | −7.429 | −0.317 | −15.548 | −0.121 | −5.610 | −0.199 | −11.489 |
| | **−0.272** | **−9.682** | **−0.257** | **−10.571** | **−0.146** | **−6.449** | **−0.175** | **−7.674** |
| $MRain_t$ | −0.296 | −4.137 | −0.563 | −10.439 | −0.189 | −3.298 | −0.305 | −6.675 |
| | **−0.437** | **−5.874** | **−0.482** | **−7.488** | **−0.263** | **−4.411** | **−0.341** | **−5.686** |
| $HRain_t$ | −0.549 | −3.673 | −0.567 | −5.040 | −0.195 | −1.635 | −0.290 | −3.063 |
| | **−0.579** | **−3.729** | **−0.518** | **−3.862** | **−0.238** | **−1.917** | **−0.339** | **−2.709** |
| $Snow_t$ | −0.506 | −4.767 | / | / | −0.250 | −2.944 | / | / |
| | / | / | **0.236** | **2.481** | / | / | / | / |
| *Model Statistics* | | | | | | | | |
| $R^2$ | 0.125 | | 0.198 | | 0.442 | | 0.434 | |
| | **0.123** | | **0.061** | | **0.440** | | **0.189** | |
| $F$ | 106.59 | | 184.86 | | 519.28 | | 502.61 | |
| | **105.11** | | **48.91** | | **513.93** | | **152.69** | |

*Note:* Non-bolded numbers are estimated for the Elliott Bay Trail, while bolded numbers are estimated for the Burke–Gilman Trail.

[a] '–' indicates that the variable is not included.

[b] '/' indicates that a significance level of less than 90% is not presented.

**Table 3**
Anticipatory effects of rainfall on active travel.

| | Advanced for 1 h (n = − 1) | | | | | | | | Advanced for 2 h (n = − 2) | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Weekdays | | | | Weekdays | | | | Weekdays | | | | Weekdays | | | |
| | Cycling | | Walking | | Cycling | | Walking | | Cycling | | Walking | | Cycling | | Walking | |
| | Coeffi. | $t$ | Coeffi. | $t$ | Coeffi. | $t$ | Coeffi. | $t$ | Coeffi. | $t$ | Coeffi. | $t$ | Coeffi. | $t$ | Coeffi. | $t$ |
| (Constant) | 0.129 | 14.181 | 0.023 | 3.203 | −0.097 | −4.724 | 0.088 | 5.848 | 0.125 | 13.818 | 0.019 | 2.625 | −0.103 | −5.048 | 0.080 | 5.341 |
| | **−0.022** | **−2.644** | **−0.033** | **−3.900** | **0.264** | **10.929** | **0.230** | **13.362** | **−0.027** | **−3.250** | **−0.037** | **−4.394** | **0.252** | **10.469** | **0.220** | **12.899** |
| $\Delta T_t$ | /[a] | / | 0.011 | 2.797 | 0.097 | 2.593 | / | / | / | / | 0.011 | 2.770 | 0.098 | 2.621 | / | / |
| | **0.016** | **3.566** | **0.015** | **3.029** | **0.124** | **2.795** | / | / | **0.016** | **3.541** | **0.015** | **3.015** | **0.126** | **2.832** | / | / |
| $\Delta H_t$ | −0.906 | −18.189 | −0.808 | −20.503 | −1.057 | −8.481 | −0.806 | −8.794 | −0.918 | −18.498 | −0.818 | −20.832 | −1.083 | −8.749 | −0.842 | −9.233 |
| | **−0.851** | **−18.922** | **−0.386** | **−8.265** | **−1.231** | **−8.354** | **−0.314** | **−2.996** | **−0.862** | **−19.245** | **−0.399** | **−8.560** | **−1.285** | **−8.766** | **−0.351** | **−3.373** |
| $\Delta W_t$ | / | / | −0.030 | −3.321 | −0.074 | −2.514 | −0.072 | −3.321 | / | / | −0.031 | −3.399 | −0.075 | −2.561 | −0.074 | −3.388 |
| | **−0.036** | **−3.467** | / | / | **−0.071** | **−2.052** | / | / | **−0.037** | **−3.542** | / | / | **−0.074** | **−2.127** | / | / |
| $LRain_t$ | −0.191 | −7.274 | −0.302 | −14.538 | −0.327 | −5.410 | −0.483 | −10.863 | −0.185 | −7.057 | −0.296 | −14.297 | −0.315 | −5.236 | −0.468 | −10.537 |
| | **−0.192** | **−8.080** | **−0.241** | **−9.790** | **−0.546** | **−7.631** | **−0.409** | **−8.051** | **−0.185** | **−7.833** | **−0.236** | **−9.584** | **−0.523** | **−7.328** | **−0.392** | **−7.748** |
| $LRain_{t-n}$[b] | −0.102 | −2.656 | −0.071 | −2.332 | / | / | −0.177 | −2.445 | / | / | / | / | / | / | / | / |
| | **−0.086** | **−2.468** | **−0.121** | **−3.346** | **−0.219** | **−1.881** | / | / | / | / | **−0.078** | **−1.857** | / | / | **0.156** | **1.720** |
| $Snow_t$ | NA | NA | NA | NA | −0.381 | −2.896 | / | / | NA | NA | NA | NA | −0.386 | −2.926 | / | / |
| | **NA** | **NA** | **NA** | **NA** | **−0.291** | **−1.868** | / | / | **NA** | **NA** | **NA** | **NA** | **−0.299** | **−1.915** | / | / |
| *Model statistics* | | | | | | | | | | | | | | | | |
| $R^2$ | 0.123 | | 0.203 | | 0.126 | | 0.200 | | 0.122 | | 0.202 | | 0.126 | | 0.197 | |
| | **0.144** | | **0.065** | | **0.150** | | **0.073** | | **0.142** | | **0.063** | | **0.149** | | **0.074** | |
| $F$ | 105.37 | | 190.45 | | 35.93 | | 62.19 | | 103.92 | | 189.1 | | 35.81 | | 60.96 | |
| | **126.12** | | **51.66** | | **44.02** | | **19.56** | | **124.71** | | **50.01** | | **43.39** | | **19.88** | |

NA: not available.
*Note:* Non-bolded numbers are estimated for the Elliott Bay Trail, while the bolded numbers are estimated for the Burke–Gilman Trail.
[a] '/' indicates that a significance level of less than 90% is not presented.
[b] Results for the advanced effects are shown in bold numbers.

**Table 4**
Delay effects of rainfall on active travel.

| | **Delay for 1 h ($n$ = 1)** | | | | **Delay for 2 h ($n$ = 2)** | | | | **Delay for 3 h ($n$ = 3)** | | | | **Delay 4 h ($n$ = 4)** | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Weekdays | | Weekends | | Weekdays | | Weekends | | Weekdays | | Weekends | | Weekdays | | Weekends | |
| | Cycling | Walking | Cycling | Walking | Cycling | Walking | Cycling | Walking | Cycling | Walking | Cycling | Walking | Cycling | Walking | Cycling | Walking |
| | Coeffi. | Coeffi. | Coeffi. | Coeffi. | Coeffi. | Coeffi. | Coeffi. | Coeffi. | Coeffi. | Coeffi. | Coeffi. | Coeffi. | Coeffi. | Coeffi. | Coeffi. | Coeffi. |
| (Constant) | 0.133 | 0.023 | −0.087 | 0.099 | 0.131 | 0.017 | −0.088 | 0.092 | 0.124 | 0.018 | −0.095 | 0.079 | 0.124 | 0.018 | −0.102 | 0.070 |
| | **−0.017** | **−0.036** | **0.280** | **0.237** | **−0.021** | **−0.037** | **0.273** | **0.239** | **−0.029** | **−0.043** | **0.264** | **0.223** | **−0.029** | **−0.040** | **0.253** | **0.216** |
| $\Delta T_t$ | / | 0.011 | 0.099 | / | / | 0.011 | 0.098 | / | / | 0.011 | 0.098 | / | / | 0.011 | 0.098 | / |
| | **0.016** | **0.014** | **0.127** | / | **0.016** | **0.014** | **0.126** | / | **0.016** | **0.014** | **0.125** | / | **0.016** | **0.014** | **0.125** | / |
| $\Delta H_t$ | −0.888 | −0.804 | −1.027 | −0.776 | −0.899 | −0.822 | −1.043 | −0.812 | −0.918 | −0.820 | −1.064 | −0.845 | −0.918 | −0.819 | −1.076 | −0.846 |
| | **−0.830** | **−0.387** | **−1.185** | **−0.290** | **−0.859** | **−0.392** | **−1.229** | **−0.298** | **−0.866** | **−0.407** | **−1.258** | **−0.336** | **−0.865** | **−0.402** | **−1.276** | **−0.336** |
| $\Delta W_t$ | / | −0.029 | −0.070 | −0.067 | / | −0.032 | −0.066 | −0.066 | / | −0.031 | −0.070 | −0.074 | / | −0.031 | −0.075 | −0.077 |
| | **−0.033** | / | **−0.064** | / | **−0.0365** | / | **−0.061** | / | **−0.038** | / | **−0.067** | / | **−0.038** | / | **−0.074** | / |
| $LRain_t$ | −0.197 | −0.303 | −0.341 | −0.499 | −0.194 | −0.295 | −0.338 | −0.486 | −0.184 | −0.295 | −0.327 | −0.466 | −0.184 | −0.296 | −0.318 | −0.458 |
| | **−0.199** | **−0.239** | **−0.569** | **−0.420** | **−0.189** | **−0.237** | **−0.554** | **−0.419** | **−0.183** | **−0.229** | **−0.539** | **−0.398** | **−0.183** | **−0.232** | **−0.526** | **−0.391** |
| $LRain_{t-n}$ | −0.169 | −0.074 | −0.242 | −0.332 | −0.104 | / | −0.231 | −0.261 | / | / | / | / | / | / | / | 0.285 |
| | **−0.175** | **−0.083** | **−0.454** | **−0.207** | **−0.079** | / | **−0.407** | **−0.175** | / | / | **−0.217** | / | / | / | / | **0.271** |
| $Snow_t$ | NA | NA | −0.395 | / | NA | NA | −0.391 | / | NA | NA | −0.387 | / | NA | NA | −0.383 | / |
| | **NA** | **NA** | **−0.318** | / | **NA** | **NA** | **−0.307** | / | **NA** | **NA** | **−0.301** | / | **NA** | **NA** | **−0.295** | / |
| *Model statistics* | | | | | | | | | | | | | | | | |
| $R^2$ | 0.126 | 0.203 | 0.130 | 0.210 | 0.124 | 0.202 | 0.130 | 0.204 | 0.122 | 0.202 | 0.127 | 0.197 | 0.122 | 0.202 | 0.126 | 0.204 |
| | **0.148** | **0.062** | **0.159** | **0.077** | **0.144** | **0.062** | **0.155** | **0.076** | **0.143** | **0.062** | **0.150** | **0.072** | **0.143** | **0.062** | **0.148** | **0.078** |
| $F$ | 107.82 | 190.44 | 37.13 | 66.21 | 105.69 | 189.88 | 37.27 | 63.59 | 103.83 | 189.27 | 36.13 | 60.99 | 103.82 | 189.21 | 35.77 | 63.64 |
| | **130.18** | **50.3** | **49.91** | **20.71** | **126.07** | **49.77** | **45.67** | **20.51** | **124.97** | **49.66** | **43.92** | **19.44** | **125.12** | **42.29** | **43.35** | **20.96** |

[a] '/' indicates that a significance level of less than 90% is not presented.
[b] Results for the advanced effects are shown in bold numbers.
NA: not available.
*Note:* Non-bolded numbers are estimated for the Elliott Bay Trail, while the bolded numbers are estimated for the Burke–Gilman Trail.

**Table 5**
Daily, hourly, and peak-hour regression results.

| | Daily models | | | | | Hourly models | | | | Peak hour models | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Weekday models | | | Weekend models | | Weekend models | | Weekend models | | Weekend models | | | | Weekend models | | | |
| | Cycling | Walking | | Cycling | Walking | Cycling | Walking | Cycling | Walking | AM peak (7–9 AM) | | PM peak (4–6 PM) | | Midday peak (11 AM–4 PM) | | Other hours | |
| | Coeffi. | Coeffi. | | Coeffi. | Coeffi. | Coeffi. | Coeffi. | Coeffi. | Coeffi. | Cycling | Walking | Cycling | Walking | Cycling | Walking | Cycling | Walking |
| (Constant) | 0.051 | 0.064 | | 0.091 | 0.088 | 0.054 | 0.01 | /[a] | 0.052 | 0.075 | −0.093 | 0.151 | 0.079 | 0.27 | 0.092 | −0.327 | 0.03 |
| | **0.061** | **0.048** | | **0.123** | **0.054** | **−0.015** | **−0.031** | **0.14** | **0.151** | **−0.055** | **−0.115** | **0.144** | **0.09** | **0.557** | **0.407** | **−0.068** | **0.041** |
| $\Delta WoC_{t-1}$ | /[a] | −0.094 | | 0.271 | 0.326 | 0.551 | 0.486 | 0.62 | 0.596 | 0.635 | 0.421 | 0.766 | 0.813 | 0.47 | 0.566 | 0.239 | 0.599 |
| | / | **−0.114** | | **0.252** | / | **0.512** | **0.273** | **0.622** | **0.438** | **0.664** | **0.285** | **0.864** | **0.48** | **0.441** | **0.243** | **0.399** | **0.451** |
| $\Delta T_t$ | 0.352 | 0.354 | | 0.484 | 0.295 | / | / | / | / | / | / | / | 0.048 | 0.305 | 0.104 | / | / |
| | **0.534** | **0.285** | | **0.518** | **0.183** | **0.009** | **0.014** | **0.069** | / | / | / | **0.047** | **0.039** | **0.364** | / | **0.058** | / |
| $\Delta H_t$ | −0.541 | −0.7 | | −0.523 | −0.347 | −0.435 | −0.435 | −0.41 | −0.284 | / | −0.154 | −0.365 | −0.275 | −0.53 | −0.333 | −0.483 | −0.212 |
| | **−0.63** | **−0.174** | | **−0.496** | **−0.178** | **−0.447** | **−0.313** | **−0.473** | **−0.152** | **−0.172** | **−0.282** | **−0.308** | **−0.193** | **−0.595** | / | **−0.539** | / |
| $\Delta W_t$ | −0.232 | −0.276 | | −0.28 | / | / | −0.022 | / | / | / | −0.028 | 0.062 | / | −0.123 | / | / | / |
| | **−0.325** | **−0.183** | | **−0.218** | / | / | / | / | / | / | / | **0.068** | / | **−0.09** | / | / | / |
| $LRain_t$ | −0.092 | −0.124 | | −0.124 | −0.145 | −0.108 | −0.173 | −0.187 | −0.266 | −0.119 | −0.171 | / | / | −0.414 | −0.333 | −0.148 | −0.221 |
| | **−0.132** | **−0.087** | | **−0.224** | **−0.094** | **−0.101** | **−0.153** | **−0.285** | **−0.266** | **−0.07** | **−0.088** | **0.061** | **−0.126** | **−0.568** | **−0.406** | **−0.255** | **−0.221** |
| $LRain_{t-n}$ | –[b] | – | – | – | – | / | / | / | −0.125 | −0.156 | −0.122 | / | / | / | / | −0.2 | −0.146 |
| | – | – | – | – | – | **−0.083** | / | **−0.146** | / | **−0.095** | / | / | / | / | / | **−0.305** | **−0.231** |
| $MRain_t$ | −0.19 | −0.285 | | −0.495 | −0.448 | −0.183 | −0.316 | −0.23 | −0.282 | / | −0.242 | / | / | −0.585 | −0.378 | −0.213 | −0.251 |
| | **−0.277** | **−0.25** | | **−0.559** | **−0.289** | **−0.204** | **−0.304** | **−0.419** | **−0.449** | / | / | **0.205** | **−0.297** | **−0.891** | **−0.773** | **−0.357** | **−0.3** |
| $MRain_{t-n}$ | – | – | – | – | – | / | 0.404 | / | / | / | / | / | / | / | / | / | / |
| | – | – | – | – | – | / | / | / | / | / | / | / | / | **1.388** | **0.905** | / | / |
| $HRain_t$ | −0.444 | −0.467 | | −0.499 | −0.462 | / | / | −0.373 | −0.362 | / | −0.32 | 0.657 | / | −0.712 | −0.502 | / | / |
| | **−0.501** | **−0.307** | | **−0.523** | **−0.145** | / | **−0.384** | / | **−0.382** | / | **−0.351** | **−0.421** | **−0.646** | **−0.776** | **−0.761** | / | / |
| $HRain_{t-n}$ | – | – | – | – | – | NA | NA | / | / | NA | NA | NA | NA | NA | NA | / | / |
| | – | – | – | – | – | **NA** | **NA** | / | / | **NA** | **NA** | **NA** | **NA** | **NA** | **NA** | / | / |
| $Snow_t$ | NA | NA | | −0.342 | / | NA | NA | −0.293 | / | NA | NA | NA | NA | / | / | −0.358 | / |
| | **NA** | **NA** | | / | / | **NA** | **NA** | / | / | **NA** | **NA** | **NA** | **NA** | / | / | **−0.371** | / |
| $Snow_{t-n}$ | – | – | – | – | – | / | / | NA | NA | NA | NA | NA | NA | NA | NA | NA | NA |
| | – | – | – | – | – | / | / | **NA** | **NA** | **NA** | **NA** | **NA** | **NA** | **NA** | **NA** | **NA** | **NA** |
| Model statistics | | | | | | | | | | | | | | | | | |
| $R^2$ | 0.661 | 0.613 | | 0.621 | 0.6 | 0.414 | 0.402 | 0.437 | 0.499 | 0.641 | 0.561 | 0.656 | 0.69 | 0.461 | 0.614 | 0.139 | 0.423 |
| | **0.677** | **0.456** | | **0.609** | **0.449** | **0.406** | **0.136** | **0.474** | **0.266** | **0.561** | **0.176** | **0.713** | **0.278** | **0.501** | **0.269** | **0.27** | **0.232** |
| $F$ | 67.55 | 54.83 | | 18.67 | 17.07 | 263.67 | 251.33 | 96.28 | 123.49 | 146.96 | 104.95 | 157.08 | 157.08 | 45.8 | 84.96 | 11.93 | 54.15 |
| | **72.42** | **30.15** | | **17.73** | **9.27** | **255.05** | **58.69** | **111.5** | **44.84** | **105.01** | **17.52** | **204.23** | **31.66** | **53.62** | **19.66** | **2732** | **22.35** |

*Note:* Non-bolded numbers are estimated for the Elliott Bay Trail, while the bolded numbers are estimated for the Burke–Gilman Trail.
[a] '/' indicates that a significance level of less than 90% is not presented.
[b] '–' indicates that this variable is not included for estimation.

weekends. Nevertheless, it was estimated with significantly positive coefficients for weekend walking on both the Elliott Bay and Burke–Gilman trails 3 h later, indicating that the walking volume experienced an hour-on-hour growth because the weather improves or the trail surface becomes better. The delay effects of rainfall on active travel could be compared to the findings of Tao et al. (2018), indicating that rainfall did not result in a significant delay effect on bus ridership on weekdays, but it significantly affected bus ridership on weekends after the rainfall.

#### 5.2.3. Daily, hourly, and time of day regression results

We then estimated a number of regression models to examine the association of weather with active travel at the daily, hourly, and time of day scales. Table 5 presents the regression results.

From the goodness-of-fit and *F*-test statistics, all models were statistically valid. At the daily scale, both cycling and walking significantly increased with temperature and decreased with humidity, wind speed, and rainfall. The explanatory power varied, and the weekday models had a higher *R*-square than the weekend models, indicating that the weather impact accounted for a larger percentage of the variation in active travel on weekdays than on weekends. Comparatively, a number of studies on the weather impacts on urban transit ridership found that weekend models explained a higher variation compared to their weekday counterparts (e.g., Guo et al., 2007; Kalstein et al., 2009; Singhal et al., 2014). For the same location and same day of week, cycling was more related to the weather conditions than walking.

At the hourly scale, adverse weather conditions, especially rainfall and humidity, still resulted in significantly negative impacts on both cycling and walking. Nevertheless, in contrary to the daily modeling results, the weekday models for the hourly active travel were estimated with a lower *R*-square than the weekend models. One of the possible explanations for this is that active travelers on weekends are more flexible to adjust their activities according to the real-time weather conditions than on weekdays; thus, the overall active travel level tends to be more stable on weekends than on weekdays. At both daily and hourly scales, walking on the woodsy Burke–Gilman Trail was the least affected by the weather condition changes, indicating that walking on this trail was very stable. One possible reason for this result is that the Burke–Gilman Trail is a recreational trail; hence, its comfortable environment and approximation to a number of communities make it a favorite place for people to conduct regular walking activities such as relaxing, walking, and dog walking, among others. Although this explanation makes sense, a detailed examination of this explanation and other possible reasons is beyond this observational study because no one was surveyed or interviewed.

The peak-hour models for active travel on weekdays indicated that the AM-peak (7–9 AM) models explained a higher variation in both the cycling and walking activities compared to their PM-peak (4–6 PM) counterparts. This result suggests that active travel during weekday-PM was more severely affected by the weather conditions than that during weekday-AM. A plausible reason for this variation may highlight the role of the direction of travel or trip purposes in affecting the association of weather with active travel. Under conditions of adverse weather, cyclists and pedestrians during the weekday-AM period exhibit little flexibility to change their departure times (mainly from home to other destinations). In contrast, later in the PM period, they have more flexibility and could decide to delay or prepone their departure time (mainly from other destinations to home). This finding is highly consistent with that obtained by Singhal et al. (2014). The time of day models for the weekends indicated that both cycling and walking during the midday peak hours (11 AM to 4 PM) were more severely affected by inclement weather than those during other hours.

## 6. Discussion and conclusions

This study made use of big smart-counter data on active travel and voluminously meteorological records in a finer temporal resolution to explore the influence of weather condition changes on both cycling and walking on two popularly multi-use trails in Seattle, United States. The findings endorse previous studies in recognizing the negative impact of adverse weather conditions like cold temperature, strong wind, and rainfall on active travel. Nevertheless, this study enriches the existing literature by conducting a comparative analysis between the weather–cycling and weather–walking relationship and examining the buffered effects of rainfall on both cycling and walking.

The buffered effects of rainfall on active travel suggest that when it rains, its negative impact not only continues, but it could also be "anticipated" by active travelers. The concurrent rainfall significantly affects not only the concurrent active travel but also the usage of trails 1 h earlier. Compared to the anticipatory effects of rainfall, its delay effects on active travel can last for a longer time for 2 h or even 3 h for cycling on weekdays. The results from the daily models indicate that the daily active travel on weekdays is more severely affected by adverse weather than on weekends. Nevertheless, the hourly active travel activities on weekdays are more resilient to weather influences than on weekends. Self-dependency or temporal autocorrelation must be considered for the time-series data analysis, particularly at a finer temporal scale. Additionally, cyclists tend to be more likely affected by weather condition changes than pedestrians, especially on weekdays. The findings from this study reveal useful information on how active travelers respond to weather differently in terms of different modes (walking and cycling), sites (seaside trail and forest trail), day of week (weekdays and weekends), and time of day (peak and off-peak hours). In addition, a series of meaningful implications for active travel activity analysis and promotion could be derived from the analyses and are discussed as follows.

First, considering the anticipatory effects of rainfall on active travel, accurate weather forecasts and warnings could play a role in improving the travel experience of cyclists and pedestrians. Weather officials should provide active travelers with a real-time or near real-time weather prediction, thereby allowing cyclists and pedestrians time to adjust their outdoor activities. At a time when fiscal resources are shrinking and capital expenditures are soaring, weather prediction using traditional techniques and without the provision of extra funding is becoming ineffective because of drastic climatic changes and financial difficulties (Fowdur et al., 2018; Mahony, 2016). Considering the social benefits of walking and cycling in alleviating the urban sequelae, such as air pollution and traffic congestion, increasing budgets for providing accurate weather forecasts and warnings for active travelers is both necessary and cost effective. In addition, specific weather mobile and phone apps pushing a real-time or near real-time weather prediction for cyclists or pedestrians may help improve the effectiveness of weather warnings and allow active travelers to rely upon the improved weather information to comprehensively avoid cycling or walking in rains rather than purchasing fenders and rain gear and clothing.

Second, pavement maintenance could lessen the delay effects of rainfall. Although rainfall sometimes quickly stops, its negative effects on active travel could last for a long time. Cycling and walking on water or snow-agglomerated roads are very undesirable. Planners in Copenhagen clearly stated the importance of comfort and the quality of cycling infrastructure and stressed snow clearing as one of the key factors for maintaining the comfort level of cycling (Zhao et al., 2018). Rainfall or snowfall could be a temporary barrier for active travelers but would not be a strong barrier in places that engage in proactive behavior to clear facilities. In addition, related to the negative effects of rainfall and larger cultural contexts, many employers require dress codes but without providing lockers for changing clothing or preparing umbrellas for employees' departure. Most active travelers usually have cycling or walking back to their homes as the mode used when they leave their homes. However, the findings from this study indicate that active travelers during weekday-PM are more severely affected by adverse weather compared to those during weekday-AM. Aside from the possible reason that they may have more flexibility to delay or prepone their departure time after work, the lack of appropriate dress or rain gear when leaving may also play a role. Thus, advocating relatively casual clothing and providing necessary rain gear may promote active travel activities.

The third policy recommendation is related to the weather impacts on multimodal transportation systems. A number of survey studies analyzed the heterogeneous impacts of weather on different segments of travelers (e.g., Bergström and Magnusson, 2003; Liu et al., 2015a, 2015b; Müller et al., 2008; Sabir, 2011; Shirgaokar and Habib, 2018; Simpson, 2018). This paper endorses findings from survey studies in recognizing that cyclists are generally more sensitive to adverse weather than pedestrians. Nevertheless, the results from big data analysis indicate that the influence of weather at finer temporal and spatial resolutions is more heterogeneous than is previously thought. For instance, at the hourly scale, cycling on the seaside Elliott Bay Trail on weekends was less severely affected by the weather condition changes than walking. Although the negative impacts of adverse weather on the travelers' activities are fairly obvious, the mechanisms of the weather variations affecting where, when, how, and how much travel occurs have, arguably, yet to be fully understood. In addition, weather can directly affect the active travel demand as well as others, such as transit systems and passenger cars (Guo et al., 2007; Singhal et al., 2014; Böcker et al., 2013; Liu et al., 2015a); hence, its impacts on all potential travelers and transportation infrastructure in a region can simultaneously result in a large net impact (Hyland et al, 2018). Thus, the weather influence on multimodal transportation systems needs subsequent studies, and effective measures on how to lessen the impacts should be given sustained attention from both academicians and practitioners.

Several limitations are noted in this study. First, not examined or discussed are the potential impacts of the nuances of physical context, such as the very hilly and oceanic location of Seattle, on active travel. The demographics of the adjacent neighborhoods around the two sites may bias the results. For instance, the impacts of wind on active travel may vary depending on its direction and whether or not there are hills, trees, or open stretches of water that might redirect or magnify the breezes. Second, although the weather station is not unreasonably distant from the trails, the levels of orographic rainfall and foliage density differences between the two chosen sites that may confound the results are not accounted for. Third, Seattle typically receives some snowfall on an annual basis, but heavy snow is rare. The relatively small sample of snowfall observations hinders the finer exploration on the effects of snowfall on active travel at different levels. Copenhagen or Minnesota may be worth looking into when pursuing further research with respect to the snowy effects. Finally, this study relies on quantitative big data and several assumed proxies to draw its conclusions and discussion. The explanatory power of this study may be augmented in the future through subsequent studies where people are actually asked to explain their relationships with weather vis-à-vis their mobility. For instance, future research could do more work on the role of real-time weather forecasts, weather information push service, and maintenance of trails (mud or snow clearing) in promoting travelers to walk or ride. Although weather impacts on transportation systems received increasing attention, mysteries still exist. This study provides a useful step toward a better understanding of the relationship between weather and active travel, particularly on the evidence of a "buffer" of reduced walking and cycling trips targeted around rainfall.

## Declaration of Competing Interest

None.

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