International Journal of Sustainable Transportation

ISSN: 1556-8318 (Print) 1556-8334 (Online) Journal homepage: www.tandfonline.com/journals/ujst20

The impact of weather conditions on everyday cycling with different bike types in parents of young children participating in the CARTOBIKE randomized controlled trial

Helga Birgit Bjørnarå, Sveinung Berntsen, Saskia J. te Velde, Aslak Fyhri, Ketil Isaksen, Benedicte Deforche, Lars Bo Andersen, Andreas Stenling & Elling Bere

To cite this article: Helga Birgit Bjørnarå, Sveinung Berntsen, Saskia J. te Velde, Aslak Fyhri, Ketil Isaksen, Benedicte Deforche, Lars Bo Andersen, Andreas Stenling & Elling Bere (2023) The impact of weather conditions on everyday cycling with different bike types in parents of young children participating in the CARTOBIKE randomized controlled trial, International Journal of Sustainable Transportation, 17:2, 128-135, DOI: 10.1080/15568318.2021.1999538

To link to this article: https://doi.org/10.1080/15568318.2021.1999538

Published online: 04 Dec 2021.

INTERNATIONAL JOURNAL OF SUSTAINABLE TRANSPORTATION
2023, VOL. 17, NO. 2, 128–135
https://doi.org/10.1080/15568318.2021.1999538

The impact of weather conditions on everyday cycling with different bike types in parents of young children participating in the CARTOBIKE randomized controlled trial

Helga Birgit Bjørnarå[a], Sveinung Berntsen[a], Saskia J. te Velde[a], Aslak Fyhri[b], Ketil Isaksen[c], Benedicte Deforche[d,e], Lars Bo Andersen[f], Andreas Stenling[a,g], and Elling Bere[a,h]

[a]Department of Sport Science and Physical Education, University of Agder, Kristiansand, Norway; [b]Department of Safety and the Environment, Institute of Transport Economics, Oslo, Norway; [c]Division for Model and Climate Analysis, Norwegian Meteorological Institute, Oslo, Norway; [d]Department of Public Health and Primary Care, Faculty of Medicine and Health Sciences, Ghent University, Ghent, Belgium; [e]Physical Activity, Nutrition and Health Research Unit, Faculty of Physical Education and Physical Therapy, Vrije Universiteit Brussel, Brussels, Belgium; [f]Faculty Education, Arts and Sports, Western Norway University of Applied Sciences, Sogndal, Norway; [g]Department of Psychology, Umeå University, Umeå, Sweden; [h]Department of Health and Inequalities, & Centre for Evaluation of Public Health Measures, Norwegian Institute of Public Health, Oslo, Norway

ABSTRACT

Knowledge about how weather conditions affect travel behavior in different user groups and contexts is relevant for planners and policymakers to facilitate sustainable transportation systems. We aimed to assess the influence of day-to-day weather on cycling for transportation among parents of young children with access to different bike types (e-bike vs non e-bike) in a natural study setting over nine months. We hypothesized less impact of weather variability on cycling when using an e-bike compared with a non e-bike. A randomized, controlled trial was conducted in Southern Norway. The intervention group ($n = 18$) was in random order equipped with an e-bike with trailer for child transportation ($n = 6$), a cargo (longtail) bike ($n = 6$) and a traditional bike with trailer ($n = 6$), each for three months. These 18 participants reported cycling on 832 out of 3276 person-days (25%). We used dynamic structural equation modeling for intensive longitudinal data to examine the relations between daily weather conditions, bike type (e-bike vs traditional bike), and cycling (dichotomized daily at yes or no). Air temperature (positively) and wind speed (negatively) were both credible predictors of cycling, whereas the other predictors (precipitation in the morning (yes or no) and presence of snow (yes or no) were not. We added interaction terms between bike type and weather conditions, but none of the interaction terms had a credible effect on cycling. Thus, the relations between weather conditions and cycling were not moderated by bike type among parents of young children.

Abbreviations: PA: physical activity; E-bike: electric assisted bicycle; Km: kilometers

ARTICLE HISTORY
Received 26 March 2020
Revised 6 October 2021
Accepted 9 October 2021

KEYWORDS
Cycling; e-bike; parents; transportation; weather

1. Introduction

Cycling for transport could increase total physical activity (PA) levels time-efficiently (de Nazelle et al., 2011; Sahlqvist et al., 2012), and further prevent non-communicable diseases and decrease mortality risk (Celis-Morales et al., 2017; Nordengen et al., 2019; Oja et al., 2011; Saunders et al., 2013) as well as psychological stress (Avila-Palencia et al., 2018). To enhance cycling for transport, understanding about factors influencing such utilitarian travel is needed, entailing factors at both the individual, societal and environmental level (Haustein et al., 2019; Heinen et al., 2010). Infrastructural initiatives have shown to improve safety and cycling efficiency, thereby increasing cycling levels substantially (Andersen et al., 2018; Pucher & Buehler, 2017). Also, bike accessibility is found to be a relevant environmental determinant (Bjørnarå et al., 2019; Cairns et al., 2017; Handy et al., 2014), and short-term conditions such as work and trip characteristics and weather conditions have shown to influence day-to-day travel mode choices (Heinen et al., 2011).

Cycling is considered the most weather-exposed transport mode, and it has been reported that changes in weather conditions could explain about 80% of the variations in daily bike flow (Thomas et al., 2013). Still, weather effects seem to differ between different population groups and between geographical, climatological and cultural contexts (Böcker et al., 2013, 2019), and the relative impact of weather tends to be greater for recreational trips, compared with utilitarian trips (Böcker et al., 2013; Liu et al., 2017). Flynn and colleagues (2012) found that the likelihood of commuting to work by bike increased with higher temperatures and decreased with snow depth and wind speed. Further, Dutch data (Böcker & Thorsson, 2014) has shown significant impact of day-to-day

CONTACT Elling Bere elling.bere@uia.no Department of Nutrition and Public Health, Faculty of Health and Sport Sciences, University of Agder, P. O. Box 422, Kristiansand 4604, Norway.

weather variability on frequency and especially duration of commuter cycling, and the inclination to cycle to work tend to decrease in proportion to increased wind speed, and increase with higher temperature (Heinen et al., 2011). Precipitation, on the other hand, has repeatedly been found to influence cycling negatively (Böcker & Thorsson, 2014; Flynn et al., 2012; Heinen et al., 2011). Flynn et al. (2012) reported that participants in Vermont, US were almost twice as likely to cycle to work on days with no morning precipitation, while Böcker and Thorsson (2014) found linear negative effects of precipitation on cycling frequencies as well as cycling durations in a Dutch sample. Further, Heinen and colleagues (2011) reported that both the duration and the quantity of rain affected cycling negatively. However, no effect of precipitation on the probability of cycling (Cervero & Duncan, 2003), or less effect of rain than of temperature (Brandenburg et al., 2007), has been reported as well. Besides, weather factors co-occur, and the effect of different meteorological measures on travel pattern has shown to be interrelated. For example, a combined negative effect of wind and light rain on cycling counts in Melbourne was previously found (Böcker et al. 2013).

The frequency and intensity of some extreme weather and climate events have increased because of global warming and will continue to increase especially under medium and high emission scenarios (Shukla et al., 2019). Thus, knowledge about the influence of weather conditions on travel behavior in different user groups and contexts, and across different bike types, is relevant for planners and policymakers to facilitate sustainable transportation systems and climate change adaptation. Long term travel demand forecasting without considering weather impacts could potentially over- or underestimate future travel demand, which may result in misleading policy implications.

E-bikes are increasingly popular as they overcome typical barriers to traditional pedal cycling (Fishman & Cherry, 2016), while still providing health benefits from PA as e-bike users cycle longer distances (Castro et al., 2019), and more frequently (Jahre et al., 2019). In addition, seasonal variations could become less problematic when being provided with assistance from an electric motor (Plazier et al., 2017). It has been suggested that the power and the heavy weight of an e-bike could provide better grip under snowy and icy conditions, thereby making it easier to cycle during all seasons, yet to a greater extent for avid cyclists than for newcomers (Edge et al., 2018). Supporting this, we recently reported from the current intervention project CARTOBIKE that when being provided with access to an e-bike (compared with access to a non e-bike) the participants cycled about twice the distance for the trial period in total, and about four times the distance during the winter period (Bjørnarå et al., 2019). Nonetheless, for parents with young children most factors influencing transportation mode choice tend to support car use, yet it has been proposed that the cohort of millennials may be more open to more sustainable transportation alternatives to the car, compared with earlier generations (McCarthy et al., 2017).

To the best of our knowledge, no previous studies have addressed the impact of weather conditions on everyday cycling in parents of young children. Therefore, the objectives of the present study were to: (i) assess how day-to-day weather variability influence cycling for transport in parents of young children, and (ii) how these associations relate to bike type (e-bike vs. non e-bike). We hypothesized that day-to-day weather variability would have less influence on cycling frequency when using an e-bike compared to when using a non e-bike.

2. Materials and methods

2.1. Setting

The present study was conducted in the region of Kristiansand, situated on the coast in Southern Norway. The climate in the region is temperate with sporadic snowfall during the winter months (i.e., late December, January, and February). Average annual temperature based on the current official climate normal period (1991–2020) is 7.6 °C with mean January and July temperatures of 0.2 and 16.6 °C, respectively. Winter temperatures are rarely below −10 °C, while average annual precipitation is 1,381 mm (MET, 2021). Compared with other large cities in Norway the cycling share is relatively high in Kristiansand (8%), yet the proportion using private car for the work commute is still considerable (64%) (Statens, 2018).

2.2. Study design

The present study includes secondary analyses of the research project CARTOBIKE, a randomized controlled trial being conducted among a free-living setting in Southern Norway from September 2017 to May 2018. For the participants in the intervention group ($n = 18$) the trial entailed, in random order, three months access to an e-bike with trailer ($n = 6$), three months access to a human powered cargo (longtail) bike ($n = 6$), and three months access to a traditional bike with trailer ($n = 6$) (Bjørnarå et al., 2017). The intervention arms followed the autumn (September-November), winter (December-February) and spring (March-May) seasons, respectively. The e-bikes (pedal-assisted) were Emotion Neo Cross/Neo Jet (BH Bikes, Vitoria, Spain), 2012-model (weight 21.8 kg). The longtails were Surly Big Dummy (Surly Bikes, Minnesota, US), 2010–2017 models (weight 21.8 kg (26.6 kg including one child seat)). The traditional bikes were two different models; DBS Rallar Flåm (DBS, Taiwan), 2013 model (weight 13.5 kg), and one Kalkhoff Jubilee (Kalkhoff, Cloppenburg, Germany), 2017 model (weight 13.5 kg). The bike trailers were of the type Spectra Eco (Cycleurope, Stockholm, Sweden, weight 14 kg). More detailed information about the bikes and following equipment was recently published (Bjørnarå et al., 2019). If any technical issues arose during the trial, participants were offered assistance from a bike repair shop. Bike helmets for both parent and child, a safety vest, and lights were provided, and during the winter season the bikes were equipped with winter tires with studs. Cycling was voluntary, meaning that no cycling instructions were given. Research clearance was obtained from The Norwegian Center for Research Data (number 52964), and the guidelines in the Declaration of Helsinki (World Medical Association, 2013) was followed. Participants received written information about study aims and procedures before providing consent for participation electronically. The trial was registered at clinicaltrials.gov 27 April 2017 (NCT03131518).

2.3. Study sample

To recruit participants, the kindergartens and businesses in Kristiansand municipality were contacted, and Facebook announcements were tailored to the target group. Inclusion criteria were to have at least one child born in year 2013, 2014 or 2015 attending kindergarten, to reside 2–10 km from the workplace and <3 km from the kindergarten and the grocery store, having car-access, being physically inactive (<150 min per week of moderate-to-vigorous intensity physical activity), and having cycled less than once weekly throughout the last twelve months to the workplace, the kindergarten or the grocery store (Bjørnarå et al., 2019). From May 2017 to August 2017 a total of 36 participants living in Southern Norway were enrolled in the study and were randomized to intervention and control groups. The study includes data from the 18 participants in the intervention group.

3. Measurements

3.1. Cycling

Cycling distance and time were measured continuously throughout the nine months with a bicycle computer (CatEye Velo 9, CatEye, Osaka, Japan), and recorded daily by each participant. The project coordinator collected the recorded cycling data every third month, i.e after each cycling period, when the bike type was changed. A dichotomous cycling variable was constructed (yes/no), entailing that all days with recorded cycling data were classified as cycling days.

3.2. Weather conditions

Daily meteorological data for the region of Kristiansand was obtained from The Norwegian Meteorological Institute (MET Norway), for the time period from September 2017 to mid-June 2018. The meteorological stations are located at Kjevik, approximately 12 km east of the city center (latitude 58.20 degrees, longitude 8.08 degrees) and at Kristiansand fire station (precipitation only) about one km east of the city center (latitude 58.16 degrees, longitude 8.00 degrees). Weather parameters were measured at 7 a.m. and comprised air temperature (°C); wind speed (m/s), precipitation (mm last hour) and snow depth (cm, measured at 6 a.m.).

3.3. Background information

When signing up and providing consent, participants answered a web-based questionnaire assessing relevant background information, such as sex, date of birth, ethnicity and educational level, and information assessing eligibility for inclusion cycling frequency over the past 12 months, habitual PA-level and distance to selected destinations.

3.4. Data analyses

The statistical analyses were performed using Mplus version 8.4 (Muthén & Muthén, 1998–2017). Descriptive analyses were conducted, and continuous variables are presented as means and standard deviations (*SD*), while categorical variables are presented as numbers and percentage. The unit of analysis was person-day records for weekdays (all weekend days and holidays were excluded), with "cycled" (yes/no) as the outcome variable. We used dynamic structural equation modeling (DSEM; Asparouhov et al., 2018) for intensive longitudinal data to examine the relations between daily weather conditions, bike type, and cycling. DSEM integrates features from time-series analysis, multilevel modeling, and structural equation modeling into one flexible model. More specifically, the DSEM model deals with autocorrelations and can incorporate lagged regressions, can include time trends, allows inclusion of both time-varying and time-invariant covariates, and can circumvent problems with missing observations and unequal intervals using a Kalman filter approach (McNeish & Hamaker, 2020).

The specific model used in the current study was the multilevel AR(1) model, which incorporates the outcome as a lagged predictor and daily weather conditions and bike type as time-varying covariates. To clearly distinguish the within-person effects from the between-person effects we used latent mean centering (Asparouhov & Muthén, 2019). Latent mean centering has several advantages, such as providing a clear interpretation of the within-person effects, eliminates known biases for the autoregressive effects (i.e., Nickell's bias) and other time-varying covariates (i.e., Lüdtkes bias), and provides an intercept that can be interpreted as the person's mean. We focus on the within-person level model because the primary interest in the current study was on the daily associations between weather conditions, bike type, and cycling. First, we examined the magnitude of lagged effects and time trends in the outcome. Second, we added the within-person predictors to the model. Precipitation and snow depth were dichotomized; precipitation into (0) <0.1 mm/h and (1) ≥0.1 mm/h, and snow depth into (0) no snow (<0.1 cm) and (1) snow (≥0.1 cm), whereas air temperature (°C) and wind speed (m/s) were kept as continuous variables. Bike type was dichotomized into (0) non e-bike (longtail and traditional bike) and (1) e-bike. Third, we added within-person interactions between each of the weather condition variables and bike type using the product-first and center-second (P1C2) approach (Loeys et al., 2018). We used the magnitude of the standardized within-level estimates that are averaged across persons as an indication of which predictor variable has the strongest

Table 1. Sample characteristics.

Participants (*n*)	18
Sex; females (*n* (%))	9 (50)
Age; years (mean (SD))	35.8 (5.0)
§Ethnicity; native Norwegian (*n* (%))	16 (89)
†Educational level; high (*n* (%))	10 (56)
Body mass index; kg/m2 (median (IQR))	24.7 (4.2)
Distance to the workplace; km (median (IQR))	7.1 (4.9)
Distance to the kindergarten; km (median (IQR))	1.3 (1.1)
Distance to the grocery store; km (median (IQR))	1.4 (1.1)
Cycling days (*n* (%))	832 (25)
Cycling distance per day cycled; km (mean (SD))	11.0 (6.2)
Cycling time per day cycled; min (mean (SD))	38.3 (19.7)
Temperature at 7 a.m.; °C (mean (SD))	4.0 (6.6)
Wind speed at 7 a.m.; m/s (mean (SD))	3.8 (2.5)
Precipitation at 7 a.m.; days (%)	24 (14)
Snow on ground at 6 a.m.; days (%)	29 (15)

IQR = interquartile range.
§Participant and both parents born in Norway.
†≥4 years of college or university education.

direct relation with the outcome variable (or explains most unique variance in the outcome variable; Schuurman et al., 2016). We estimated both fixed (i.e., means) and random (i.e., variances) effects in these models.

Bayesian multilevel models with a probit link function were estimated using two Markov chain Monte Carlo (MCMC) chains and 100,000 iterations. Chain convergence was assessed using the potential scale reduction factor (PSRF; Brooks & Gelman, 1998), where a low (< 1.05) and stable PSRF was considered evidence of chain convergence. We relied on the default noninformative prior specification in Mplus. Parameter estimates were evaluated using the 95% credibility intervals (CI). If the 95% CI did not include zero, it was considered as a credible parameter estimate (Zyphur & Oswald, 2015).

4. Results

The current study sample comprised nine females and nine males with mean (SD) age 35.8 (5.0) years. Sixteen (89%) participants were native Norwegians (participants and both parents born in Norway), and ten (56%) participants reported higher educational level (≥4 years of college/university education). Further, median distances from home to workplace, kindergarten and grocery store was 7.1 km, 1.3 km, and 1.4 km, respectively.

Descriptive statistics for the study variables are presented in Table 1. The total number of weekdays with valid cycling data was 3276 person-days. In sum, participants reported cycling on 832 (25%) of these days. In the first model, we estimated the autoregressive effect and time trend. The lagged effect across days was 0.399 (95% CI [0.213, 0.556]) indicating that cycling the previous day was positively related to cycling the next day. The time trend was −0.004 (95% CI [−0.007, 0.000]) suggesting a weak decline in cycling across time. Given the weak time trend and to reduce model complexity, we did not include the time trend on subsequent models.

In the second model (Table 2), we included daily weather conditions and bike type as within-person predictors of cycling. The fixed effects indicated that air temperature (Estimate = 0.026, 95% CI [0.009, 0.044]) and wind speed (Estimate = −0.053, 95% CI [−0.086, −0.020]) were both credible predictors of cycling (i.e., the 95% CI did not include zero), whereas the 95% CI of the other predictors included zero indicating a higher degree of uncertainty in their point estimates. The within-level R2 averaged across individuals was 0.270 (95% CI [0.223, 0.325]), indicating that the predictors combined explained 27.0% of the variance in cycling at the within-person level. A comparison of the standardized within-person estimates averaged across persons indicated that the lagged effect of previous cycling (0.289) explained most unique variance in the outcome variable, followed by air temperature (0.147), wind speed (−0.108), e-bike (0.072), snow depth (−0.047), and precipitation (0.001).

Table 2. Unstandardized and standardized estimates, 95% CIs, and within-person R^2.

	Unstandardized effects			Standardized effects		
	Estimate	95% CI		Estimate	95% CI	
Fixed effects		LL	UL		LL	UL
Threshold	1.011	0.559	1.478			
Lagged effect	0.293	0.128	0.445	0.289	0.206	0.371
Snow depth	−0.150	−0.490	0.155	−0.047	−0.114	0.009
Air temperature	0.026	0.009	0.044	0.147	0.088	0.208
Wind speed	−0.053	−0.086	−0.020	−0.108	−0.159	−0.064
Ebike	0.192	−0.072	0.457	0.072	0.023	0.123
Precipitation	0.012	−0.265	0.259	0.001	−0.053	0.055
Random effects						
Threshold	0.832	0.403	2.033			
Lagged effect	0.074	0.027	0.203			
Snow depth	0.215	0.030	0.820			
Air temperature	0.001	0.000	0.002			
Wind speed	0.002	0.001	0.006			
Ebike	0.199	0.061	0.621			
Precipitation	0.122	0.011	0.484			
R^2				0.270	0.223	0.325

Note. Standardized effects and R^2 are within-level standardized estimates averaged over individuals.

In the third model, we added interaction terms between bike type and weather conditions (Table 3). However, none of the interaction terms were credible predictors of cycling (i.e., the 95% CI included zero). Thus, the relations between weather conditions and cycling were not moderated by bike type.

5. Discussion

The current study aimed to assess how day-to-day weather variability influenced cycling for transport in parents of young children participating in the CARTOBIKE-intervention (Bjørnarå et al., 2017), and how these associations were related to bike type (e-bike vs. non e-bike). Results showed that higher wind speed affected cycling negatively, while higher air temperatures affected cycling positively. For precipitation and presence of snow, no impact on cycling frequency was found. The impact of weather on cycling was not different for bike type being used (e-bike vs. non e-bike). This means that wind speed affected both e-biking

Table 3. Unstandardized and standardized estimates, 95% CIs, and within-person R^2.

	Unstandardized effects			Standardized effects		
	Estimate	95% CI		Estimate	95% CI	
Fixed effects		LL	UL		LL	UL
Threshold	1.030	0.565	1.505			
Lagged effect	0.280	0.113	0.430	0.275	0.196	0.357
Snow depth	−0.166	−0.612	0.169	−0.053	−0.138	0.021
Air temperature	0.028	0.008	0.048	0.147	0.086	0.211
Wind speed	−0.066	−0.108	−0.027	−0.132	−0.197	−0.072
Ebike	0.105	−0.222	0.430	0.041	−0.051	0.134
Precipitation	−0.074	−0.393	0.207	−0.022	−0.099	0.036
Ebike*Snow depth	−0.093	−0.781	0.576	−0.014	−0.105	0.067
Ebike* Air temperature	0.001	−0.031	0.035	0.001	−0.073	0.078
Ebike* Wind speed	0.023	−0.034	0.082	0.038	−0.057	0.135
Ebike* Precipitation	0.152	−0.358	0.624	0.025	−0.042	0.096
Random effects						
Threshold	0.865	0.418	2.088			
Lagged effect	0.075	0.027	0.204			
Snow depth	0.226	0.019	1.063			
Air temperature	0.001	0.000	0.003			
Wind speed	0.002	0.001	0.008			
Ebike	0.163	0.020	0.625			
Precipitation	0.109	0.006	0.522			
Ebike*Snow depth	0.380	0.021	2.515			
Ebike* Air temperature	0.002	0.001	0.007			
Ebike* Wind speed	0.002	0.001	0.009			
Ebike* Precipitation	0.298	0.022	1.356			
R^2				0.320	0.262	0.391

Note. Standardized effects and R^2 are within-level standardized estimates averaged over individuals.

and cycling with non e-bikes negatively to a similar degree, while air temperature affected positively to a similar degree. This contradicts our hypothesis that the day-to-day weather variability would have less influence on cycling frequency when using an e-bike compared to when using a non e-bike.

Previous studies on effects of weather on cycling has found that in general, warm, sunny, dry and light conditions tend to facilitate walking and cycling, while cold, wet, windy and dark conditions, and very high temperatures (above 25–30 °C), seem to cause a shift from active to motorized transportation modes (Böcker et al., 2013; 2019). Partly differing results in the present study may relate to sample traits, for example that for parents of young children precipitation may have a different impact than for the adult population in general. Nevertheless, one could expect precipitation to be more relevant when transporting young children, since young children might be more vulnerable to weather. Therefore, these differences may be more likely explained by variances in weather effects on cycling across different cultural, climatological and geographical contexts, in addition to between user groups (Böcker et al., 2013; 2019). Böcker and collegues (2019) explored the effects of weather on transport mode choices (trips made by foot, bike, public transport or car), destination choices, trip distances and trip chaining in the regions of Utrecht, Oslo, Stavanger, and Stockholm, and revealed considerable disparities. For example, the authors reported that they could not detect any significant precipitation (or wind) effects on transport mode choice in Stavanger, Oslo or Stockholm, but in Utrecht there was an effect. Proposed explanations were greater exposure to wet conditions in Utrecht, as 20.4% of recorded trips were conducted under wet conditions, compared with 10.1% in Oslo and 9.4% in Stockholm (Böcker et al., 2019), or differences in cycling culture, habits and adaptations across regions, and further differences in cycling shares (26.3% in Utrecht, 2.7% in Stockholm, 6.3% in Stavanger and 4.5% in Oslo). These results are, however, not directly comparable to the present study due to the intervention approach in the present study, as well as the selected sample of parents with young children.

Also, weather is suggested to be a subjective perception just as much as an objective measure (Knez et al., 2009; Thorsson et al., 2004), entailing that subjects with different socio-demographics, living in different socio-cultural contexts, could perceive weather differently under equal weather conditions (Knez et al., 2009). In turn, such a heterogeneity in weather reference point would likely affect individual's everyday travel decisions. Nonetheless, people's reference points and subjective weather perceptions could possibly modify, following a dynamic climate change (Liu, 2016), making seasonality less important and weather parameters more relevant in themselves.

Further, some contrasting results in the present study compared with previous findings, may also relate to methodological issues like study design (intervention vs observational studies), or different measures of weather variables (dummy variables vs ratio-scale variables). The intervention design of the present study (unlike the abovementioned studies) may have influenced the lack of effect of precipitation and presence of snow on cycling. Although there were no cycling instructions, the awareness of being part of a research study, and thereby being "observed" (McCambridge et al., 2014), may have encouraged cycling also under less favorable weather conditions.

To the best of our knowledge, no previous studies have addressed the impact of weather conditions on everyday cycling across the yearly seasons, using different bike types. Based on previous findings in project CARTOBIKE, showing that the e-bike obtained the greatest cycling amount for the trial period in total compared with the longtail and the traditional bike (Bjørnarå et al., 2019), we hypothesized less impact of day-to-day weather variability on cycling when using the e-bike, compared with days when using a non e-bike (longtail or the traditional bike). Also, earlier findings that seasonal variations seem to become less problematic when being provided with assistance from an electric motor (Plazier et al., 2017), and the suggestion that the power and the heavy weight of an e-bike could offer more traction under winter conditions (Edge et al., 2018), support an expectation of overall increased cycling under diverse weather conditions when riding an e-bike. Nonetheless, we could not find such differences in the present study, meaning that stronger winds reduced cycling and higher temperatures increased cycling, regardless of having motorized assistance or not. On the other hand, there were large individual differences in cycling among the participants in CARTOBIKE (Bjørnarå et al., 2019). That is, although the e-bike was the most used bike type overall, those who cycled the most tended to do so with all three bike types (e-bike, longtail and traditional bike).

5.1. Strengths and limitations

One study strength was the natural setting of the intervention (i.e., bike access with no cycling instructions), enabling to explore the effect of accessibility on voluntary cycling, and further the impact of day-to-day weather variations on voluntary cycling. Usage of data collected longitudinally allows for better insight into the decision to cycle than would have been possible with cross-sectional data, due to the opportunity to investigate a person's decision at multiple time points while controlling for potential confounders. Compared with previous studies linking cycling reports to weather data (Böcker & Thorsson, 2014; Flynn et al., 2012; Heinen et al., 2011), the present trial lasting for nine months represents an extended time period, measuring cycling objectively, yet in a limited number of subjects (Bjørnarå et al., 2019). Dichotomizing cycling into days and not specific trips might also be considered a limitation, a decision to cycle is made for each trip. Further, due to the lack of a routine for cycling in our participants, it might be that the decision to cycle (or not) was based on perceived weather conditions at the departure time, for which hourly and more accurate data would be a better solution than daily data (Böcker et al., 2013; Liu et al., 2017). Thus, the present study was based on weather data measured at 7 a.m. each morning. However, weather conditions (especially precipitation) might vary greatly throughout the day, and it might not account equally well for participants with non-regular work schedules. Likewise, the decision to exclude weekends and holidays from the analyses accounts mainly for those with regular work schedules, yet it could be justified by the family perspective of the project, and further the kindergartens' opening hours. Another potential limitation was the small sample size at the between-person level. However, there were numerous observations (182 days) for each subject. It also might be, by chance, that the most eager individuals were clustered within one group, which in turn could influence cycling during the different seasons. Indeed, five of the seven participants with total fewest cycling days throughout the study, used the e-bike during fall season. It is also important to bear in mind that the participants in this study were all users of motorized transport modes before participating in this trial, and that they probably needed a period to get used to traveling by bicycles. At the same time, they were eager to participate and therefore motivated to start cycling (Bjørnarå et al., 2019). This adaptation period might have influenced the results.

Precipitation data was missing for in total 19 out of 182 weekdays (9.6%), and associations between cycling and precipitation could be distorted by often highly localized precipitation. In Norway, the areas along the south coast (like in the region of Kristiansand) have generally the highest intensities of rainfall during a few hours or shorter (Hanssen-Bauer et al., 2017). Such rainfall is dominated by highly localized showers with areas close by receiving no precipitation, probably affecting participants who were located too far away from the weather stations. It is therefore limiting that we included precipitation at a single time point in the morning. Still, that might be the moment when deciding to cycle or not. For wind speed and air temperature, the weather at the place where the decision to travel was made may be different from the weather at the point of observation. Also, it might be considered a limitation that we did not adjust for daylight, which is clearly associated with season and weather. Furthermore, since a convenience sample was recruited, those highly educated were overrepresented (compared with corresponding age groups in the Norwegian population), resulting in reduced generalizability to the general population of parents with children attending kindergarten. Similarly, results may not be generalizable to parents living in other cultural, geographical and infrastructural contexts than the present sample.

5.2. Perspectives

The present study contributes to increased knowledge concerning the influence of weather conditions on everyday cycling with different bike types in parents of young children in geographical, infrastructural and cultural contexts differing from those in typical cycling cultures like the Netherlands and Denmark. Understanding the impact of weather conditions on day-to-day travel mode choices in different contexts and user groups, and across different bike types, is relevant for planners and policymakers to predict future travel demand, and further facilitate sustainable transportation systems. For example, less cycling due to cold temperatures and strong wind could potentially be mitigated by infrastructural initiatives such as sanding or salting of ice along cycling routes and bike lanes, in addition to wind barriers (e.g., in the forms of trees or others), especially along main cycling infrastructures. Also, customized bike equipment (e.g., clothing and tires), appropriate storage rooms at workplaces, and cycling education addressing safe and (more) comfortable riding in rough weather and under winter conditions, may extend the range of conditions in which cycling for transportation is perceived feasible (Winters et al., 2007).

Moreover, although some researchers have made attempts to assess associations between integrated weather indices with travel behavior, future analyses could possibly advantage from including combined weather effects to a larger extent (Böcker et al., 2013). In addition, future studies should aim for increased understanding on how individuals perceive weather through using subjective weather perception measures, and qualitative approaches such as focus groups, in addition to objective measures.

6. Conclusion

Weather conditions posed a significant impact on everyday cycling in a sample of parents of young children residing in Southern Norway, regardless of bike type being used. We found that higher wind speed decreased cycling, while higher air temperatures increased cycling. For precipitation and presence of snow, no impact on cycling frequency was found. Contrary to our hypothesis, we did not find that using an e-bike made parents of young children less influenced by bad weather than when using a conventional bike.

Acknowledgment

The authors would like to thank the participants in the present study.

Author's contributions

EB, HBB and SB conceived the study with substantial contributions concerning study design from SJtV, AF, BD, and LBA. HBB collected all data except from the weather variables, while KI provided meteorological data and HBB analyzed the data together with AS. AS did the final analyses. HBB interpreted the data and drafted the manuscript together with EB, with critical input regarding data interpretation and relevant intellectual content from SB, SJtV, AF, BD, LBA, AS and KI. HBB and EB edited and revised the manuscript. All authors have read and approved the final version of the manuscript.

Availability of data and material

The datasets used and analyzed during the current study are available from the corresponding author on reasonable request.

Competing interests

The authors declare that they have no competing interests.

Ethics approval and consent to participate

Research clearance was assigned by The Norwegian Social Science Data Services (number 52964), and all participants were given written information about study objectives and methods prior providing consent electronically.

Funding

The study is funded by the Norwegian Extra Foundation for Health and Rehabilitation, through the Norwegian Health Association, grant number FO147109. Some costs were funded by the University of Agder, Faculty of Health and Sports Sciences.

ORCID

Helga Birgit Bjørnarå http://orcid.org/0000-0003-0069-0892
Andreas Stenling http://orcid.org/0000-0002-0834-1040

References

Andersen, L. B., Riiser, A., Rutter, H., Goenka, S., Nordengen, S., & Solbraa, A. K. (2018). Trends in cycling and cycle related injuries and a calculation of prevented morbidity and mortality. *Journal of Transport & Health*, *9*, 217–225. https://doi.org/10.1016/j.jth.2018.02.009

Asparouhov, T., Hamaker, E. L., & Muthén, B. (2018). Dynamic structural equation models. *Structural Equation Modeling: A Multidisciplinary Journal*, *25*(3), 359–388. https://doi.org/10.1080/10705511.2017.1406803

Asparouhov, T., & Muthén, B. (2019). Latent variable centering of predictors and mediators in multilevel and time-series models. *Structural Equation Modeling: A Multidisciplinary Journal*, *26*(1), 119–142. https://doi.org/10.1080/10705511.2018.1511375

Avila-Palencia, I., Int Panis, L., Dons, E., Gaupp-Berghausen, M., Raser, E., Götschi, T., Gerike, R., Brand, C., de Nazelle, A., Orjuela, J. P., Anaya-Boig, E., Stigell, E., Kahlmeier, S., Iacorossi, F., & Nieuwenhuijsen, M. J. (2018). The effects of transport mode use on self-perceived health, mental health, and social contact measures: A cross-sectional and longitudinal study. *Environment International*, *120*, 199–206.https://doi.org/10.1016/j.envint.2018.08.002

Bjørnarå, H. B., Berntsen, S., J Te Velde, S., Fyhri, A., Deforche, B., Andersen, L. B., & Bere, E. (2019). From cars to bikes – The effect of an intervention providing access to different bike types: A randomized controlled trial. *PLoS One*, *14*(7), e0219304. https://doi.org/10.1371/journal.pone.0219304

Bjørnarå, H. B., Berntsen, S., Te Velde, S. J., Fegran, L., Fyhri, A., Deforche, B., Andersen, L. B., & Bere, E. (2017). From cars to bikes - the feasibility and effect of using e-bikes, longtail bikes and traditional bikes for transportation among parents of children attending kindergarten: design of a randomized cross-over trial. *BMC Public Health*, *17*(1), 981. https://doi.org/doi:https://doi.org/10.1186/s12889-017-4995-z

Böcker, L., Dijst, M., & Prillwitz, J. (2013). Impact of everyday weather on individual daily travel behaviours in perspective: A literature review. *Transport Reviews*, *33*(1), 71–91. https://doi.org/10.1080/01441647.2012.747114

Böcker, L., & Thorsson, S. (2014). Integrated weather effects on cycling shares, frequencies, and durations in Rotterdam, the Netherlands. *Weather, Climate, and Society*, *6*(4), 468–481. https://doi.org/10.1175/WCAS-D-13-00066.1

Böcker, L., Uteng, T. P., Liu, C., & Dijst, M. (2019). Weather and daily mobility in international perspective: A cross-comparison of Dutch, Norwegian and Swedish city regions. *Transportation Research Part D: Transport and Environment*, *77*, 491–505. https://doi.org/10.1016/j.trd.2019.07.012

Brandenburg, C., Matzarakis, A., & Arnberger, A. (2007). Weather and cycling—A first approach to the effects of weather conditions on cycling. *Meteorological Applications*, *14*(1), 61–67. https://doi.org/10.1002/met.6

Brooks, S. P., & Gelman, A. (1998). General methods for monitoring convergence of iterative simulations. *Journal of Computational and Graphical Statistics*, *7*(4), 434–455. https://doi.org/10.1080/10618600.1998.10474787

Cairns, S., Behrendt, F., Raffo, D., Beaumont, C., & Kiefer, C. (2017). Electrically-assisted bikes: Potential impacts on travel behaviour. *Transportation Research Part A: Policy and Practice*, *103*, 327–342. https://doi.org/10.1016/j.tra.2017.03.007

Castro, A., Gaupp-Berghausen, M., Dons, E., Standaert, A., Laeremans, M., Clark, A., Anaya-Boig, E., Cole-Hunter, T., Avila-Palencia, I., Rojas-Rueda, D., Nieuwenhuijsen, M., Gerike, R., Panis, L. I., de Nazelle, A., Brand, C., Raser, E., Kahlmeier, S., & Götschi, T. (2019). Physical activity of electric bicycle users compared to conventional bicycle users and non-cyclists: Insights based on health and transport data from an online survey in seven European cities. *Transportation Research Interdisciplinary Perspectives*, *1*, 100017. https://doi.org/10.1016/j.trip.2019.100017

Celis-Morales, C. A., Lyall, D. M., Welsh, P., Anderson, J., Steell, L., Guo, Y., Maldonado, R., Mackay, D. F., Pell, J. P., Sattar, N., & Gill, J. M. R. (2017). Association between active commuting and incident cardiovascular disease, cancer, and mortality: prospective cohort study. *BMJ*, *357*, j1456. https://doi.org/doi: https://doi.org/10.1136/bmj.j1456

Cervero, R., & Duncan, M. (2003). Walking, bicycling, and urban landscapes: Evidence from the San Francisco Bay Area. *Am J Public Health*, *93*(9), 1478–1483. https://doi.org/doi:https://doi.org/10.2105/AJPH.93.9.1478

de Nazelle, A., Nieuwenhuijsen, M. J., Antó, J. M., Brauer, M., Briggs, D., Braun-Fahrlander, C., Cavill, N., Cooper, A. R., Desqueyroux, H., Fruin, S., Hoek, G., Panis, L. I., Janssen, N., Jerrett, M., Joffe, M., Andersen, Z. J., van Kempen, E., Kingham, S., Kubesch, N., … Lebret, E. (2011). Improving health through policies that promote active travel: a review of evidence to support integrated health impact assessment. *Environment International*, *37*(4), 766–777. https://doi.org/10.1016/j.envint.2011.02.003

Edge, S., Dean, J., Cuomo, M., & Keshav, S. (2018). Exploring e-bikes as a mode of sustainable transport: A temporal qualitative study of the perspectives of a sample of novice riders in a *Canadian city*. *The Canadian Geographer / Le Géographe Canadien*, *62*(3), 384–397. https://doi.org/10.1111/cag.12456

Fishman, E., & Cherry, C. (2016). E-bikes in the mainstream: Reviewing a decade of research. *Transport Reviews*, *36*(1), 72–91. https://doi.org/10.1080/01441647.2015.1069907

Flynn, B. S., Dana, G. S., Sears, J., & Aultman-Hall, L. (2012). Weather factor impacts on commuting to work by bicycle. *Preventive Medicine*, *54*(2), 122–124. https://doi.org/10.1016/j.ypmed.2011.11.002

Handy, S., Van Wee, B., & Kroesen, M. (2014). Promoting cycling for transport: Research needs and challenges. *Transport Reviews*, *34*(1), 4–24. https://doi.org/10.1080/01441647.2013.860204

Hanssen-Bauer, I., Førland, E., Haddeland, I., Hisdal, H., Lawrence, D., Mayer, S., … Sandø, A. (2017). Climate in Norway 2100–a knowledge base for climate adaptation. *NCCS Report*, *204*.

Haustein, S., Jensen, A. F., & Nielsen, T. A. S. (2019). Active transport modes. *Transforming Urban Mobility*, *14*, 39.

Heinen, E., Maat, K., & Van Wee, B. (2011). Day-to-day choice to commute or not by bicycle. *Transportation Research Record: Journal of the Transportation Research Board*, *2230*(1), 9–18. https://doi.org/10.3141/2230-02

Heinen, E., Van Wee, B., & Maat, K. (2010). Commuting by bicycle: an overview of the literature. *Transport Reviews*, *30*(1), 59–96. https://doi.org/10.1080/01441640903187001

Jahre, A. B., Bere, E., Nordengen, S., Solbraa, A., Andersen, L. B., Riiser, A., & Bjørnarå, H. B. (2019). Public employees in South-Western Norway using an e-bike or a regular bike for commuting-A cross-sectional comparison on sociodemographic factors, commuting frequency and commuting distance. *Preventive Medicine Reports*, *14*, 100881, 1–6. https://doi.org/10.1016/j.pmedr.2019.100881

Knez, I., Thorsson, S., Eliasson, I., & Lindberg, F. (2009). Psychological mechanisms in outdoor place and weather assessment: towards a conceptual model. *International Journal of Biometeorology*, *53*(1), 101–111.

Liu, C., Susilo, Y. O., & Karlström, A. (2017). Weather variability and travel behaviour–what we know and what we do not know. *Transport Reviews*, *37*(6), 715–741. https://doi.org/10.1080/01441647.2017.1293188

Liu, C. (2016). *Understanding the impacts of weather and climate change on travel behaviour [Paper presentation]. TRITA-TSC-PHD(16-005)*.

Loeys, T., Josephy, H., & Dewitte, M. (2018). More precise estimation of lower-level interaction effects in multilevel models. *Multivariate Behavioral Research*, *53*(3), 335–347. https://doi.org/10.1080/00273171.2018.1444975

McCambridge, J., Witton, J., & Elbourne, D. R. (2014). Systematic review of the Hawthorne effect: New concepts are needed to study research participation effects. *Journal of Clinical Epidemiology*, *67*(3), 267–277. https://doi.org/10.1016/j.jclinepi.2013.08.015

McCarthy, L., Delbosc, A., Currie, G., & Molloy, A. (2017). Factors influencing travel mode choice among families with young children (aged 0–4): A review of the literature. *Transport Reviews*, *37*(6), 767–781. https://doi.org/10.1080/01441647.2017.1354942

McNeish, D., & Hamaker, E. L. (2020). A primer on two-level dynamic structural equation models for intensive longitudinal data in Mplus. *Psychological Methods*, *25*(5), 610–635. https://doi.org/10.1037/met0000250

MET. (2021). *Meteorological records of the Norwegian Meteorological Institute*. Norway.

Muthén, L. K., & Muthén, B. O. (1998–2017). *Mplus user's guide*. 8th ed. Muthén & Muthén.

Nordengen, S., Andersen, L. B., Solbraa, A. K., & Riiser, A. (2019). Cycling is associated with a lower incidence of cardiovascular diseases and death: Part 1–systematic review of cohort studies with meta-analysis. *British Journal of Sports Medicine*, *53*(14), 870–878. https://doi.org/10.1136/bjsports-2018-099099

Oja, P., Titze, S., Bauman, A., de Geus, B., Krenn, P., Reger-Nash, B., & Kohlberger, T. (2011). Health benefits of cycling: A systematic review. *Scandinavian Journal of Medicine & Science in Sports*, *21*(4), 496–509.

Plazier, P. A., Weitkamp, G., & van den Berg, A. E. (2017). Cycling was never so easy!" An analysis of e-bike commuters' motives, travel behaviour and experiences using GPS-tracking and interviews. *Journal of Transport Geography*, *65*, 25–34. https://doi.org/10.1016/j.jtrangeo.2017.09.017

Pucher, J., & Buehler, R. (2017). *Cycling towards a more sustainable transport future*. Taylor & Francis.

Sahlqvist, S., Song, Y., & Ogilvie, D. (2012). Is active travel associated with greater physical activity? The contribution of commuting and non-commuting active travel to total physical activity in adults. *Preventive Medicine*, *55*(3), 206–211. https://doi.org/10.1016/j.ypmed.2012.06.028

Saunders, L. E., Green, J. M., Petticrew, M. P., Steinbach, R., & Roberts, H. (2013). What are the health benefits of active travel? A systematic review of trials and cohort studies. *PLoS One*, *8*(8), e69912. https://doi.org/10.1371/journal.pone.0069912

Schuurman, N. K., Ferrer, E., de Boer-Sonnenschein, M., & Hamaker, E. L. (2016). How to compare cross-lagged associations in a multilevel autoregressive model. *Psychological Methods*, *21*(2), 206–221. https://doi.org/10.1037/met0000062

Shukla, P. R., Skeg, J., Calvo Buendia, E., Masson-Delmotte, V., Pörtner, H.-O., Roberts, D. C., … Malley, J. (2019). Climate Change and Land: an IPCC special report on climate change, desertification, land degradation, sustainable land management, food security, and greenhouse gas fluxes in terrestrial ecosystems.

Statens, V. (2018). Reisevaneundersøkelsen 2018-foreløpige tall for de ni største byområdene. Retrieved from https://www.vegvesen.no/_attachment/2674990/binary/1324684?fast_title=Reisevaneunders%C3%B8kelsen+2018.pdf

Thomas, T., Jaarsma, R., & Tutert, B. (2013). Exploring temporal fluctuations of daily cycling demand on Dutch cycle paths: the influence of weather on cycling. *Transportation*, *40*(1), 1–22. https://doi.org/10.1007/s11116-012-9398-5

Thorsson, S., Lindqvist, M., & Lindqvist, S. (2004). Thermal bioclimatic conditions and patterns of behaviour in an urban park in Göteborg. *International Journal of Biometeorology*, *48*(3), 149–156. https://doi.org/10.1007/s00484-003-0189-8

Winters, M., Friesen, M. C., Koehoorn, M., & Teschke, K. (2007). Utilitarian bicycling: A multilevel analysis of climate and personal influences. *American Journal of Preventive Medicine*, *32*(1), 52–58. https://doi.org/10.1016/j.amepre.2006.08.027

World Medical Association. (2013). World medical association declaration of helsinki: Ethical principles for medical research involving human subjects. *JAMA*, *310*(20), 2191–2194. https://doi.org/10.1001/jama.2013.281053

Zyphur, M. J., & Oswald, F. L. (2015). Bayesian estimation and inference: A user's guide. *Journal of Management*, *41*(2), 390–420. https://doi.org/10.1177/0149206313501200