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Outdoor lighting and active travel: A high-resolution analysis using satellite imagery and Strava data in Glasgow

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ABSTRACT

Introduction: The benefits of active travel are well-established. While previous research has explored how built environment factors (such as population density, accessibility, land use, and infrastructure) influence active travel, micro-scale features like outdoor lighting have received less attention. This study examines associations between outdoor lighting levels and active travel in Glasgow, accounting for broader contextual factors and distinguishing between daylight and dark conditions.
Methods: We used Strava data, satellite-derived outdoor lighting imagery, and other spatial datasets aggregated to small-area zones in Glasgow. Bayesian spatial models (Besag–York–Mollié) were fitted to estimate associations between contextual variables and distances travelled on foot, by bike, and by both modes combined, separately for daylight and dark hours.
Results: Outdoor lighting levels derived from night-time satellite imagery were positively associated with walking, cycling, and overall active-travel distances during both light conditions (daylight and dark). These associations were stronger during dark hours, particularly for cycling. Several contextual relationships also varied by light condition: industrial density was positively associated with cycling only during daylight, while quietness and gradient showed stronger associations during daylight. Population and income deprivation were negatively associated across all modes under both light conditions.
Conclusions: Our findings underscore the potential relevance of lighting in shaping active travel patterns after dark, particularly for cycling. They also highlight the need for future research that considers light conditions and time of day in environmental studies of mobility, as well as across broader contexts, specific locations, and diverse population groups – to better inform equitable and effective active travel policy.

1. Introduction

The benefits of active travel are well-established for both individuals and society. Active travel improves physical and mental health and, when undertaken for transport purposes, contributes to reducing air and noise pollution, carbon emissions, congestion,

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and road injuries (Fishman et al., 2015; Gössling et al., 2019; Oja et al., 2011). Hence, it is crucial to have a comprehensive understanding of the different factors that contribute to the decision to walk and cycle.

There is substantial research on how macro and meso attributes of the built environment influence active travel. Population density, proximity to essential services (accessibility), a combination of different land uses, and the availability of pedestrian and cycling infrastructure have been consistently found positively associated with walking and cycling (Cerin et al., 2017; Fraser and Lock, 2011; Heinen et al., 2010; Panter et al., 2008; Wang et al., 2016). However, the effect of micro attributes of the built environment, such as outdoor lighting, has received less attention.

Research on the subjective barriers to cycling indicates that darkness is a significant deterrent (Winters et al., 2011), and observational evidence shows that darkness reduces the number of people walking and cycling, after controlling for the time of day and other seasonal influences such as weather (Fotios et al., 2019b, 2024a; Fotios and Robbins, 2022; Uttley et al., 2020; Uttley and Fotios, 2017). Darkness has been found to be a greater deterrent for female cyclists than for males (e.g. Heinen et al., 2011; Xie and Spinney, 2018), while Fotios et al. (2024b) found no significant differences by sex for pedestrians.

Studies suggest that lighting can offset the deterrent effect of darkness on pedestrians and cyclists. Self-report and stated preference studies found that people feel safer with higher light levels (Boyce et al., 2000; Fotios et al., 2019a; Svechkina et al., 2020), and that feeling safer leads to more walking (Foster et al., 2016, 2014a; Mason et al., 2013). Fotios et al. (2015), in a qualitative approach in which people were asked where they were happy to walk (without mentioning fear or lighting), showed that people associate lighting with places where they are happy to walk at night. Furthermore, revealed preference studies based on counts of pedestrians and cyclists found that more people walk or cycle after dark in lit locations than in unlit locations (Fotios et al., 2019b; Uttley et al., 2020), and a recent review concluded that road lighting generally encourages cycling, especially among potential and less experienced cyclists (Vidal-Tortosa and Lovelace, 2024).

The effectiveness of road lighting in supporting walking and cycling depends not only on its presence, but also on how it is designed and implemented. Lighting can enhance pedestrians' perceived safety, through the choice of characteristics such as illuminance (the amount of light reaching a surface, measured in lux), lamp spectrum (the colour composition of the emitted light), and the spatial distribution of light (how uniformly light is spread across an area) playing an important role (Fotios et al., 2015).

Quantitative evidence suggests that lighting is associated with increased perceived safety while walking after dark, particularly when illuminance is higher, the light source has a higher S/P ratio (which implies lighting of a cooler or bluer appearance), and lighting is more uniform (Fotios et al., 2015). There is also some evidence that even modest but well-placed lighting, when thoughtfully designed, may help support nighttime cycling without requiring especially bright or extensive installations (Uttley et al., 2020).

Despite the growing body of research on how lighting may influence walking and cycling, several gaps in the literature remain. First, while many studies have investigated the relationship between lighting and active travel, few use high-resolution data with the spatial and temporal detail needed to capture patterns across an entire city and throughout the year. Most rely on surveys, manual counts, or short-term data, limiting their ability to detect fine-grained variation across urban settings and seasons (Vidal-Tortosa and Lovelace, 2024). Second, existing research is often not embedded within a broader understanding of travel behaviour and mode choice. As noted by Vidal-Tortosa and Lovelace (2024), lighting is only one of many interacting factors. Prior studies frequently overlook key contextual variables such as population density, income, land use, accessibility, traffic stress, and topography. Third, the limited number of studies that have considered both lighting and active travel alongside other contextual factors such as Zacharias and Meng (2021) typically rely on travel data aggregated across all hours of the day, without distinguishing between daylight and dark conditions. This limits the ability to isolate the specific role of outdoor lighting, which is primarily relevant during dark hours. Furthermore, existing research has yet to examine whether the effects of contextual variables, such as land use, traffic stress, or crime, vary between light and dark conditions. Finally, studies that use spatial data to examine this relationship often fail to account for spatial autocorrelation — the fact that active travel behaviours and lighting conditions are often similar in nearby locations. Ignoring these spatial dependencies can produce biased estimates of associations, particularly in urban environments where lighting and travel patterns are spatially clustered.

This paper addresses these gaps by examining the relationship between outdoor lighting and active travel – specifically distance travelled on foot, by bike, and by both modes combined – across the city of Glasgow. Using one year of high-resolution Strava data and night-time satellite imagery, we analyse spatial patterns in walking and cycling while accounting for key contextual factors. We model distance travelled separately for daylight and dark conditions to assess whether associations with lighting and other covariates differ depending on the light environment, and apply spatial statistical models to account for spatial autocorrelation.

2. Materials and methods

2.1. Study area

Glasgow is Scotland's most populous city, with an estimated population of 635,130 in 2021 and a land area of 175 km^2, resulting in a population density of about 3,562 people per km^2 (National Records of Scotland, 2022). The city's terrain is relatively hilly, especially in the northern parts of the city centre and the West End (Smillie, 2023). Its climate is classified as oceanic, characterised by substantial rainfall throughout the year, mild summer temperatures, and cool winter temperatures. In 2021, Glasgow recorded 1012 mm of rainfall, and it experienced its lowest mean daily minimum temperature of −0.3 °C in January and its highest temperature of 22.8 °C in July (Met Office, 2023).

Fig. 1. Overview of the study area, Glasgow, and its SIMD data zones (Scottish Government, 2020).

According to the 2011 Scottish Census, 12.1% of Glasgow residents walk to work, while only 1.6% cycle (Scotland's Census, 2023). However, there has been a substantial increase in cycling traffic to and from the city centre, which has grown by 165% between 2009 and 2021. In contrast, pedestrian counts in the same cordon count locations have dropped by 19% overall during the same period (Whyte, 2022).

We used the data zones defined in the Scottish Index of Multiple Deprivation (SIMD) 2020 as units of analysis (Scottish Government, 2020). The SIMD identifies areas of multiple deprivation based on seven domains: income, employment, education, health, access to services, crime, and housing. Each SIMD 2020 data zone is a small geographic area with a relatively uniform population (typically between 700 and 800 people, with an average of 760), though area size can vary. Glasgow includes 746 SIMD data zones, as shown in Fig. 1.

2.2. Data

2.2.1. Response variables: Active travel

We used active travel data provided by Strava, one of the world's most widely used physical activity tracking applications, with over 100 million users across 195 countries (Strava Inc., 2023a). The app allows users to record rides, runs, and walks using a smartphone or GPS device. The data used in this study were aggregated, anonymised, and pre-filtered for the city of Glasgow (Strava Inc., 2023b).

To obtain our response variables, we first retrieved Strava trip counts for travel on foot (walking, running, and hiking) and by bike (pedal-cycle and e-bike rides), aggregated at the street-segment and hour interval levels for each month of 2021. We selected 2021 as it aligned with the availability of outdoor lighting data (Section 2.2.2) and was also the closest match to the other data sources used in the study (Section 2.2.3). Monthly datasets were then combined to create a single-year active travel dataset.

Next, we joined this dataset to street segment geometries from the OpenStreetMap using the common column "edge ID". Some observations intersected with more than one SIMD data zone. To solve this, we divided these observations by the number of zones they intersected. For example, if an observation intersected three SIMD zones, we divided it into three separate observations, each with the length of the intersection in its specific SIMD zone. This was performed using the QGIS intersection geoprocessing tool.

To assign light conditions, we used the R package 'bioRad' (Dokter et al., 2019) to obtain the daily times of sunrise, sunset and civil twilight for 2021 in Glasgow. Because the data are aggregated in hourly intervals, light conditions were assigned at the level of the whole hour rather than at the precise moments of the twilight thresholds. Hourly intervals were classified as follows:

- Daylight: hours occurring after the interval containing sunrise and before the interval containing sunset (solar altitude > 0° throughout)
- Dark: hours occurring before the interval containing the start of morning civil twilight, or after the interval containing the end of evening civil twilight (solar altitude < −6° throughout)
- Mixed: hours overlapping civil twilight at any point (i.e. containing at least one moment with solar altitude between 0° and −6°)

To estimate distance travelled by mode and light condition, we calculated the length of each segment using the R package 'sf' (Pebesma and Bivand, 2023). We then multiplied this by the number of trips on foot, by bike, and in both modes per light condition (daylight and dark) to produce the following variables, expressed in kilometres:

- *On foot distance (daylight)*: distance travelled walking, running, and hiking during daylight hour intervals
- *By bike distance (daylight)*: distance travelled bike riding and e-bike riding during daylight hour intervals
- *Total active travel (AT) distance (daylight)*: distance travelled in both modes combined during daylight hour intervals
- *On foot distance (dark)*: distance travelled walking, running, and hiking during dark hour intervals
- *By bike distance (dark)*: distance travelled bike riding and e-bike riding during dark hour intervals
- *Total active travel (AT) distance (dark)*: distance travelled in both modes combined during dark hour intervals

Finally, we aggregated the resulting variables at the SIMD data zone level (Fig. 2). These outcome variables represent total walking and cycling activity at the SIMD data zone level, based on the estimated distance travelled along street segments. They reflect cumulative movement within each zone but do not capture individual trip details such as origin and destination, trip duration, or route choice.

We used distance travelled instead of number of trips as a measure of travel for two main reasons. First, the original data format (trips counts per street segment and hour interval, without starting and ending points) did not allow us to aggregate trips by area – a single trip could have covered one or multiple segments. Only by calculating the distance travelled per segment (by multiplying the number of trips by the segment length) were we able to estimate travel at the area level. Second, distance travelled captures both frequency and duration of trips, making it a more comprehensive measure of travel than trip counts alone.

2.2.2. Explanatory variable of interest: Outdoor lighting levels

The *outdoor lighting levels* variable was based on high spatial resolution, multi-spectral night-time imagery provided by the Urban Big Data Centre (UBDC), originally captured by Chang Guang Satellite Technology Co., Ltd and ESRC (2022) in December 2021. The data were collected during nighttime hours and predominantly reflect artificial light sources such as streetlights, signage, and building lighting, although some incidental light from other sources may be present. This variable represents a spatial measure that remains constant across all time periods in the analysis.

To calculate it (Fig. 3), we merged 22 raster tiles covering Glasgow using the merge function in QGIS. We then used the QGIS zonal statistics tool to compute the mean brightness within each SIMD data zone by averaging the red, green, and blue pixel values across the three image bands.

2.2.3. Covariates

The selection of covariates was based on contextual factors previously associated with active travel, according to five previous review papers (Cerin et al., 2017; Fraser and Lock, 2011; Heinen et al., 2010; Panter et al., 2008; Wang et al., 2016). Table 1 lists the variables considered, including their names, definitions, year of collection, data sources, and the review papers in which they were reported to influence walking, cycling, and/or active travel.

From the SIMD 2020 (Scottish Government, 2020), we obtained *population density*, *income deprivation rate*, *employment deprivation rate*, *access domain rank*, and *crime rate* for each SIMD data zone. Income deprivation rate refers to the percentage of people who are income-deprived, while employment deprivation rate represents the percentage of working-age people who are employment-deprived. Access domain rank indicates the rank of the average travel time to access essential services – including petrol stations, GP surgeries, post offices, schools, and retail centres – relative to all Scottish SIMD areas (from 1 to 6,976), with 1 indicating the area with the longest average travel time. Crime rate refers to recorded crimes of violence, sexual offences, domestic housebreaking, vandalism, drugs offences, and common assault per 10,000 population. From the OpenStreetMap (OSM) database (OpenStreetMap contributors, 2015), we calculated *recreational area density*, *commercial area density*, *industrial area density*, and *intersections density* (as a proxy for road network connectivity) per SIMD data zone. From the Openinfra project (University of Leeds, 2022), we obtained *active travel infrastructure density* (metres of infrastructure per square kilometre) also calculated per SIMD data zone. This variable is derived from the OSM database and includes features such as bridleways, cycleways, footways, living streets, paths, pedestrian areas, and steps. Finally, from the Network Planning Tool (NPT) for Scotland (University of Leeds, 2023), we gathered the *average quietness* of street segments (i.e. traffic stress levels), which is based on routing algorithms from the CycleStreets platform (CycleStreets, 2020), and the *average gradient* of street segments (i.e. hilliness), both measured per SIMD data zone.

All variables used in this study, including active-travel measures, lighting, and covariates, were harmonised to the SIMD-zone level to ensure spatial consistency across datasets.

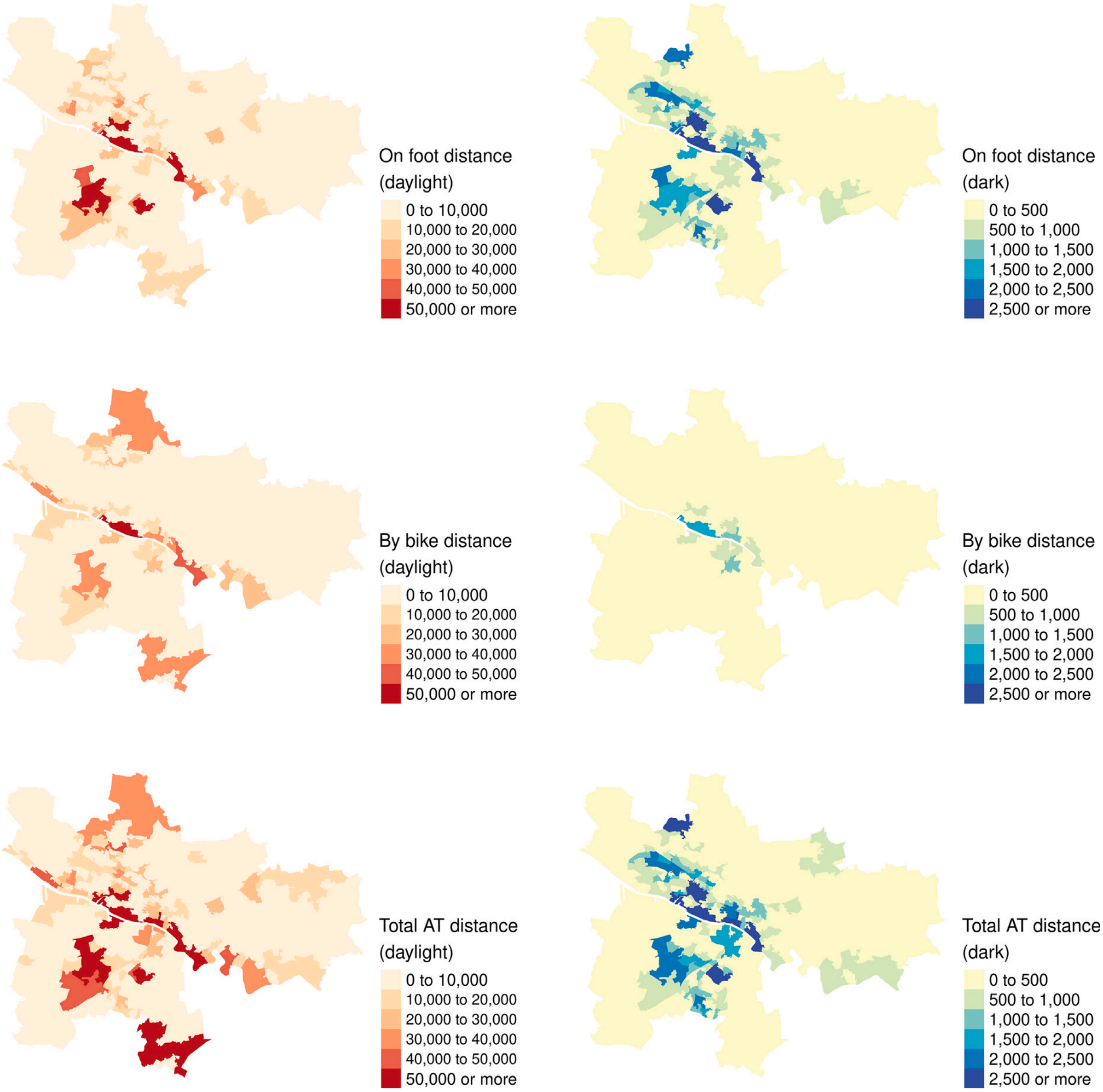

Fig. 2. On foot, by bike, and total active travel distance travelled (km) in the daylight (left) and dark (right), Glasgow 2021.

2.3. Statistical analyses

We first conducted descriptive analyses to summarise all study variables and examine patterns in Strava users, trips, and distance travelled by mode (on foot, by bike, and combined) and light condition (daylight or dark). We also explored spatial variation in travel and lighting levels across Glasgow, as well as monthly trends in distance travelled throughout the year by light condition.

Next, we used Bayesian spatial Besag–York–Mollié (BYM) models (Besag et al., 1991) with a gamma family to predict the distance travelled on foot, by bike, and by both modes combined, separately for daylight and dark conditions. All models included the same set of static covariates previously associated with active travel. While most of these variables (e.g. land use, gradient, or infrastructure) may influence travel across both light conditions, outdoor lighting – derived from night-time satellite imagery – is expected to be relevant only in the dark. Nonetheless, we included it in both sets of models to test whether its association with active travel emerges only in darkness, which would indicate a genuine lighting effect.

We used *BYM models* because our data were areal (aggregated into zones that form a partition of the study area) and, as we verified with a Moran's I test, the residuals were spatially correlated. BYM models allow assessing the effect of explanatory variables, accounting for spatial correlation, and quantifying the uncertainty in the estimates obtained (Moraga, 2023). We chose BYM models

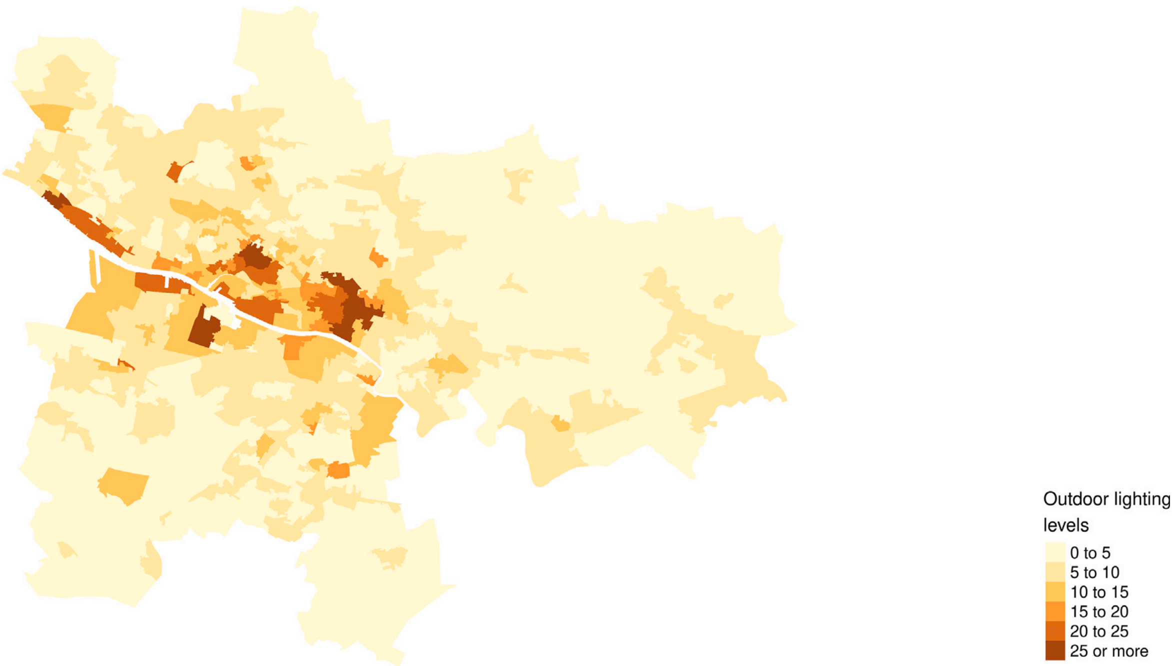

Fig. 3. Outdoor lighting levels (mean brightness of pixels), Glasgow 2021-12.

Table 1
Covariates considered.

Variable	Definition	Source	Year	Reference[a]
Population density	Population per square kilometre	SIMD 2020	2020	2, 3, 4
Income deprivation rate	Percentage of people who are income deprived	SIMD 2020	2020	3
Employment deprivation rate	Percentage of working age people who are employment deprived	SIMD 2020	2020	3
Access domain rank	Rank of the average travel time to access essential services (petrol stations, GP surgeries, post offices, schools, and retail centres), relative to all the Scottish SIMD areas (from 1 to 6,976), with 1 being the area with the highest average travel time to these services.	SIMD 2020	2020	1, 2, 3, 4, 5
Crime rate	Recorded number of crimes of violence, sexual offences, domestic housebreaking, vandalism, drugs offences, and common assault for the period 2017/2018 per 10,000 population	SIMD 2020	2020	
Recreational area density	Square metres of recreational land use including recreational ground, parks, and grass per square kilometre	OSM	2023	1, 2, 4, 5
Commercial area density	Square metres of commercial land use including commercial and retail per square kilometre	OSM	2023	1, 4
Industrial area density	Square metres of industrial land use per square kilometre	OSM	2023	1
Intersections density	Number of intersections including road junctions, roundabouts, crossings, traffic signals, and railway crossings per square kilometre	OSM	2023	1, 2, 3, 4, 5
Active travel infrastructure density	Metres of AT infrastructure including bridleways, cycleways, footways, living streets, paths, pedestrian areas, and steps per square kilometre	Openinfra project (based on OSM)	2022	1, 4, 5
Average quietness	Distance weighted average level of traffic stress of the network	NPT Scotland (based on Cyclestreets.com)	2023	1, 2, 4, 5
Average gradient	Distance weighted average gradient of the network	NPT Scotland	2023	2, 3, 4, 5

[a] (1) Cerin et al. (2017), (2) Fraser and Lock (2011), (3) Heinen et al. (2010), (4) Panter et al. (2008), and (5) Wang et al. (2016).

Table 2
Descriptive statistics of the variables considered for all the SIMD data zones of Glasgow. N=746 for all variables.

Variable	Mean	Std. Dev	Min	Pctl 25	Pctl 75	Max
On foot distance (daylight)	3148.0	9799.0	0.0	74.0	2344.0	138 510.0
By bike distance (daylight)	2284.0	6514.0	0.0	53.0	1629.0	90 487.0
Total active travel distance (daylight)	5432.0	15 192.0	0.0	161.0	4516.0	188 861.0
On foot distance (dark)	265.0	691.0	0.0	7.8	184.0	8046.0
By bike distance (dark)	47.0	142.0	0.0	0.4	33.0	1829.0
Total active travel distance (dark)	312.0	794.0	0.0	11.0	230.0	8974.0
Outdoor lighting levels	6.2	4.3	3.0	3.7	6.9	35.0
Population density	7.3	5.8	0.0	3.7	9.0	52.0
Income deprivation rate	20.0	12.0	0.0	9.0	29.0	59.0
Employment deprivation rate	14.0	9.1	0.0	6.0	21.0	47.0
Access domain rank	4776.0	1599.0	796.0	3658.0	6136.0	6975.0
Crime rate	440.0	649.0	0.0	200.0	520.0	12 441.0
Recreational area density	90.0	145.0	0.0	0.7	110.0	992.0
Commercial area density	21.0	80.0	0.0	0.0	0.0	1000.0
Industrial area density	28.0	95.0	0.0	0.0	0.0	829.0
Intersections density	0.0	0.0	0.0	0.0	0.0	0.3
AT infrastructure density	48.0	22.0	5.1	34.0	56.0	171.0
Average quietness	4.0	1.3	1.4	3.1	4.6	11.0
Average gradient	0.2	0.1	0.0	0.1	0.2	0.5

Table 3
Strava users, trips, and distance travelled (km) per mode and light condition, Glasgow 2021.

Mode	Users[a]	Trips	Distance (km)							
			Daylight	%	Dark	%	Mixed	%	Total	%
On foot	58 724	1 132 742	2 348 297	80.0	197 790	6.7	390 507	13.3	2 936 594	100
By bike	21 946	344 470	1 703 780	90.8	34 696	1.8	137 370	7.3	1 875 847	100
Total AT[b]	–	1 477 212	4 052 078	84.2	232 486	4.8	527 877	11.0	4 812 441	100

[a] The total number of active travel users is not available and unsummable – some may have made trips on foot and by bike.
[b] Total AT = total active travel (walking and cycling combined).

with a gamma family because our response variables were continuous and strongly skewed to the right. Existing research using distance travelled as a response variable has also used regression models with a gamma family (e.g. Brännäs and Laitila, 1991; Namkung et al., 2023; Plötz et al., 2017).

Since gamma models require strictly positive response values, we replaced zeros in the outcome variables with a small constant (0.00001) to allow model fitting. This approach assumes that it is unlikely any SIMD data zone recorded truly zero distance travelled on foot or by bike across the full year. The proportion of observations with zero values that were adjusted was as follows: 1.1% for on foot distance (daylight), 1.6% for by bike distance (daylight), 0.5% for total active travel distance (daylight), 4.0% for on foot distance (dark), 15.7% for by bike distance (dark), and 3.2% for total active travel distance (dark).

To check for multicollinearity among explanatory variables, we calculated the Variance Inflation Factor (VIF). We found a high correlation between income deprivation rate and employment deprivation rate. To address this, we excluded the latter because its correlation coefficients with the response variables were slightly lower than those for the income deprivation rate. After excluding this variable, all the explanatory variables had VIF values below 3, indicating no problematic multicollinearity. Variables were standardised (mean subtracted and divided by standard deviation) to allow for comparison of effect sizes. The BYM models were fitted using the R package 'R-INLA' (Lindgren and Rue, 2015).

3. Results

3.1. Descriptive analyses

Table 2 presents descriptive statistics for all variables considered in the study across the 746 SIMD data zones in Glasgow. Table 3 summarises the number of Strava users, trips, and total distance travelled by mode and light condition in 2021. In total, Strava users logged 1,477,212 trips and travelled 4,812,441 kilometres, of which 2,936,594 were made on foot (walking, running, and hiking) and 1,875,847 by bike (bike riding and e-bike riding). The majority of this distance (84.2%) was travelled during daylight hours, with a larger proportion of cycling (90.8%) than on-foot activity (80.0%) occurring in daylight conditions.

The distance travelled in both active modes during daylight was concentrated in SIMD data zones along the riversides and in areas with recreational grounds and parks (Fig. 2). During dark hours, the areas with the greatest distance travelled on foot were largely the same as during daylight. However, cycling distance during dark hours appeared more concentrated in central areas. The most illuminated areas after dark were located in the city centre and along both banks of the river (Fig. 3).

The distance travelled on foot was higher between January and April, despite generally adverse weather conditions and reduced daylight hours during these months (Fig. 4). In contrast, the distance travelled by bike was greater between March and September.

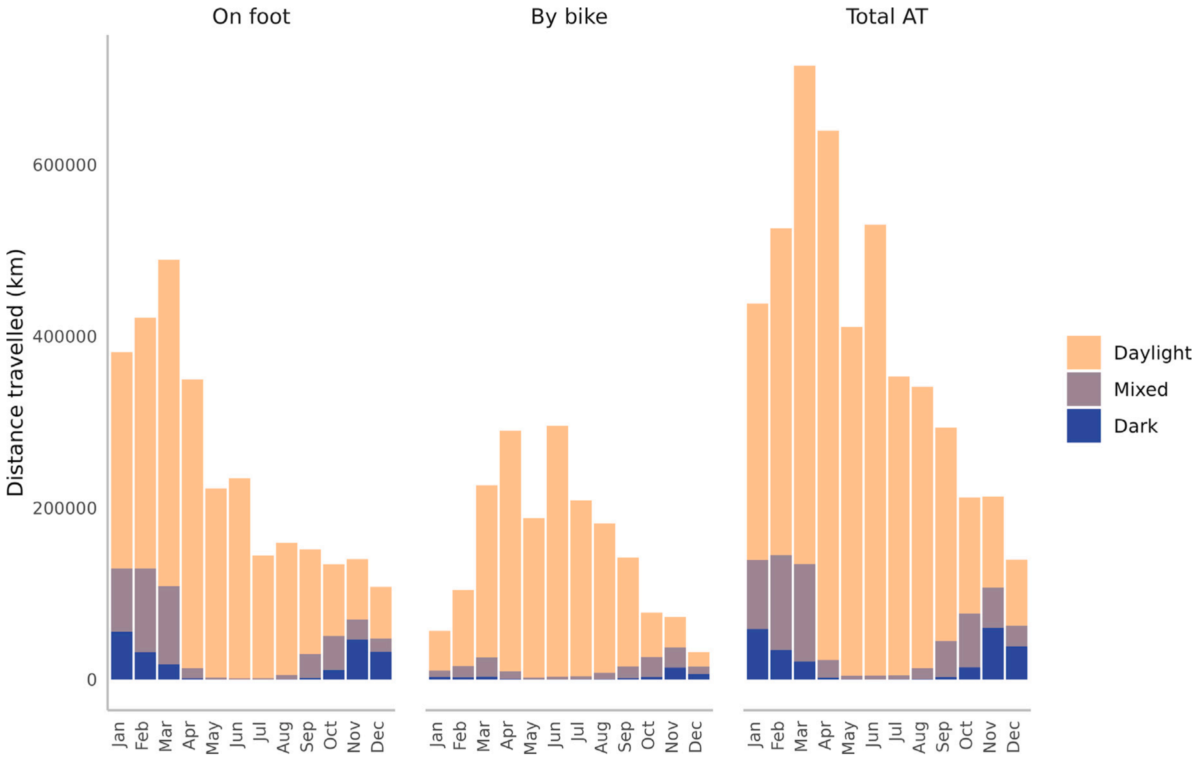

Fig. 4. Distance travelled (km) each month per mode and light condition, Glasgow 2021.

The increased walking activity early in the year may be attributed to the reintroduction of mobility restrictions in Scotland during the winter of 2021 due to the COVID-19 pandemic, which likely led to a greater need for outdoor exercise. A similar rise in outdoor activities among Strava users was observed during the UK-wide lockdown in March and April 2020 (McGregor, 2021). Seasonal motivations, such as New Year's resolutions, may have also contributed. The lower distance travelled by bike during these months may be because adverse weather conditions such as cold, rain, and wind are stronger determinants for cyclists compared to pedestrians and runners.

3.2. Regression analyses

We found a significant positive association between outdoor lighting levels and active travel distance during dark hours (Table 4 and Fig. 5). Brighter areas were associated with greater distances travelled on foot, by bike, and in total active travel. These associations were strongest for cycling (mean = 0.59; 95% CI: 0.28–0.89), followed by walking (mean = 0.36; 95% CI: 0.15–0.56), and total active travel (mean = 0.38; 95% CI: 0.19–0.58). During daylight, associations remained statistically significant across all modes, although effect sizes were smaller. The estimates were as follows: cycling (mean = 0.36; 95% CI: 0.17–0.56), walking (mean = 0.26; 95% CI: 0.10–0.43), and total active travel (mean = 0.30; 95% CI: 0.13–0.46).

We observed some differences in associations between contextual variables and active travel across light conditions. Recreational area density was positively associated with on-foot distance in both light conditions, with a stronger association in daylight (mean = 0.33 vs. 0.22). Industrial area density was positively associated with cycling only in daylight (mean = 0.20; 95% CI: 0.05–0.34), but not significantly in the dark. Average quietness was consistently and strongly associated with active travel in daylight, and with cycling in the dark, but not with walking in the dark.

Population density showed a consistent negative association across all models, with slightly stronger effects for walking and total distance during daylight. Income deprivation also had negative associations, particularly for walking in the dark (mean = −0.64; 95% CI: −0.80 to −0.47). Gradient was negatively associated with both walking and cycling distance in daylight, and with cycling in the dark, but not significantly with walking in the dark.

4. Discussion

4.1. Main findings

This study examined the relationship between outdoor lighting and active travel – measured as distance travelled on foot, by bike, and by both modes combined – across the city of Glasgow, accounting for contextual factors and distinguishing between daylight and

Table 4
Estimates (posterior means) and 95% credible intervals for the associations between outdoor lighting levels, other contextual factors, and distance travelled (km) on foot, by bike, and by both modes combined per light condition.

	Distance (daylight)									Distance (dark)								
	On foot			By bike			Total AT			On foot			By bike			Total AT		
	mean	0.025	0.975	mean	0.025	0.975	mean	0.025	0.975	mean	0.025	0.975	mean	0.025	0.975	mean	0.025	0.975
Outdoor lighting levels	**0.26**	0.10	0.43	**0.36**	0.17	0.56	**0.30**	0.13	0.46	**0.36**	0.15	0.56	**0.59**	0.28	0.89	**0.38**	0.19	0.58
Population density	**−0.56**	−0.73	−0.40	**−0.51**	−0.69	−0.33	**−0.56**	−0.73	−0.40	**−0.51**	−0.69	−0.34	**−0.34**	−0.56	−0.13	**−0.49**	−0.66	−0.32
Income deprivation rate	**−0.55**	−0.69	−0.40	**−0.35**	−0.52	−0.19	**−0.45**	−0.59	−0.31	**−0.64**	−0.80	−0.47	**−0.49**	−0.74	−0.25	**−0.59**	−0.75	−0.43
Access domain rank	−0.02	−0.18	0.14	−0.08	−0.25	0.10	−0.03	−0.18	0.12	0.01	−0.15	0.18	−0.05	−0.29	0.18	0.01	−0.16	0.17
Crime rate	0.14	−0.05	0.33	0.18	−0.08	0.44	0.13	−0.05	0.32	0.19	−0.07	0.46	0.47	−0.06	1.22	0.20	−0.06	0.45
Recreational area density	**0.33**	0.22	0.45	0.10	−0.03	0.23	**0.25**	0.14	0.36	**0.22**	0.08	0.35	0.12	−0.06	0.30	**0.19**	0.06	0.31
Commercial area density	0.03	−0.14	0.20	0.06	−0.13	0.26	0.03	−0.13	0.20	0.06	−0.14	0.25	0.10	−0.17	0.36	0.04	−0.14	0.23
Industrial area density	0.12	−0.01	0.25	**0.20**	0.05	0.34	**0.16**	0.04	0.28	0.09	−0.06	0.23	0.15	−0.05	0.34	0.09	−0.05	0.23
Intersections density	0.12	−0.03	0.27	0.16	−0.02	0.34	0.13	−0.02	0.28	0.13	−0.04	0.30	0.17	−0.07	0.42	0.14	−0.03	0.30
AT infrastructure density	0.02	−0.15	0.18	0.03	−0.14	0.21	0.03	−0.13	0.19	0.12	−0.06	0.31	0.09	−0.14	0.31	0.09	−0.08	0.27
Average quietness	**0.52**	0.38	0.67	**0.60**	0.44	0.75	**0.54**	0.41	0.68	0.16	−0.01	0.33	**0.50**	0.28	0.72	**0.25**	0.10	0.41
Average gradient	**−0.30**	−0.47	−0.12	**−0.36**	−0.55	−0.17	**−0.29**	−0.46	−0.12	−0.18	−0.38	0.02	**−0.43**	−0.68	−0.18	**−0.25**	−0.44	−0.06

Note:
Lighting is included in both models to assess whether associations are stronger during hours of darkness, when artificial lighting is functionally active.
Bold estimates denote statistically significant results.

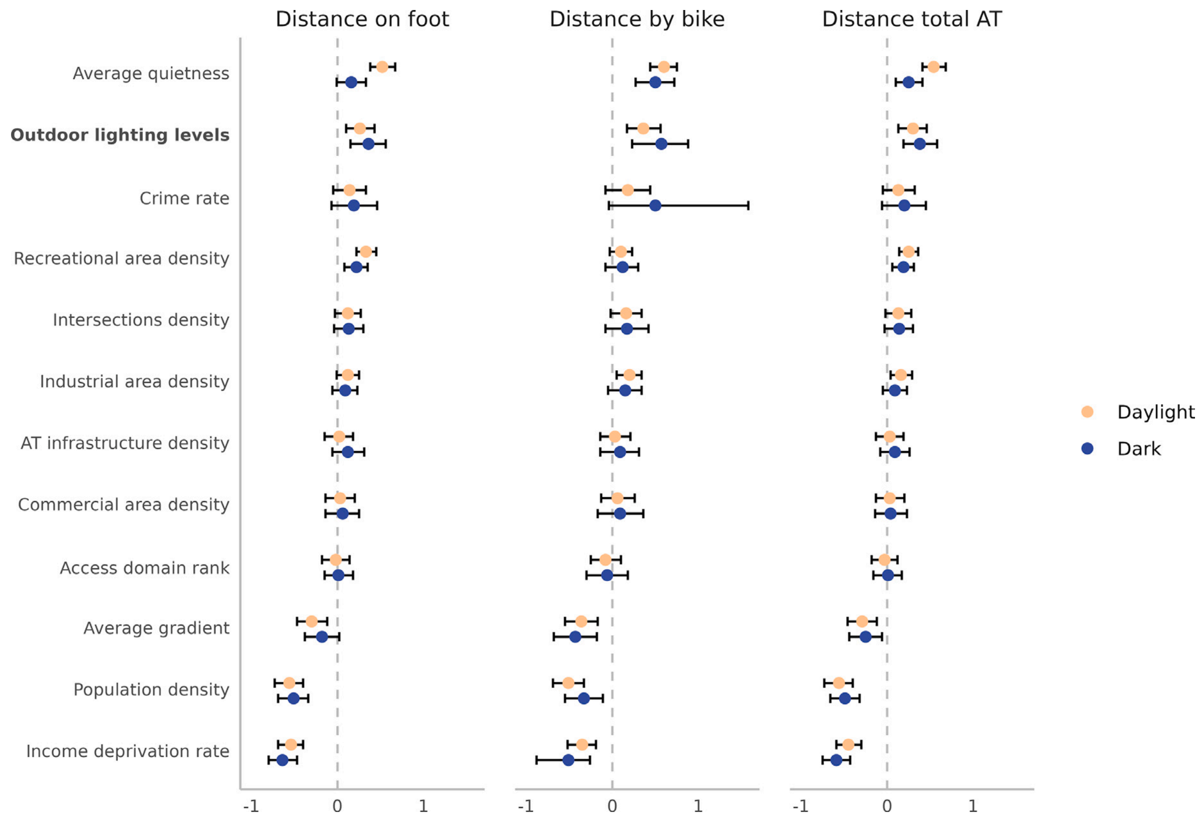

Fig. 5. Estimates (posterior means) and 95% credible intervals for the associations between outdoor lighting levels, other contextual factors, and distance travelled (km) on foot, by bike, and by both modes combined per light condition, in descending order.

dark conditions. We found a significant positive association between outdoor lighting levels and distances travelled on foot, by bike, and total active travel during the dark hours, while considering population density, income deprivation, access to services, crime rate, recreational and commercial area densities, industrial area density, intersection density, active travel infrastructure density, average quietness, and terrain gradient.

These findings are consistent with previous research. For example, Fotios et al. (2019b) examined pedestrian and cyclist counts from multiple counters on ‘cycle trails, on-street cycle lanes and footpaths’ in Arlington County, US and found that more people walked and cycled after dark if the infrastructure was lit than if it was unlit. Similarly, Uttley et al. (2020) explored cyclist counts in Birmingham, UK and found that the drop in cycling levels after dark was substantially greater in unlit locations than in lit locations.

The association was stronger for distances travelled by bike than on foot. This may reflect cyclists' greater need to detect surface hazards at higher speeds, and their more frequent interaction with motor traffic, where lighting improves visibility to drivers. Although cyclists may use personal bicycle lights, usage is far from universal — in UK observations, only 42% of cyclists in Oxford rode with both front and rear lamps lit at dusk while 50% rode with no lighting at all (Fotios and Castleton, 2017). Road lighting may therefore still contribute to perceived safety and route attractiveness, particularly on busier roads or shared corridors. In a different setting, using automated count data from Arlington County (USA), Fotios et al. (2019b) reported that the difference between lit and unlit routes after dark was larger for pedestrians than for cyclists, suggesting that the role of lighting may differ by context.

While outdoor lighting is primarily relevant during hours of darkness, we also found a significant (although weaker) association between outdoor lighting levels and active travel distances during daylight hours. This may reflect that areas with higher active-travel activity tend to be more illuminated, or that individuals continue to use well-lit and familiar routes across times of day. Both explanations are compatible with the data but cannot be disentangled within the cross-sectional study design.

Beyond lighting, several contextual variables were also associated with active travel, with some showing variation between daylight and darkness. While most differences were modest, patterns for variables such as land use, quietness, and gradient suggest potential interactions between environmental context and lighting conditions — an area that remains underexplored and deserves further investigation.

Independent of light conditions, some of our findings regarding contextual factors diverge from previous research. For instance, higher population density has often been linked with increased active travel (e.g. Fraser and Lock, 2011; Heinen et al., 2010; Panter et al., 2008); however, our findings suggest the opposite. This discrepancy could be explained by a combination of behavioural, spatial, and data-related factors. Because we measured total distance travelled rather than number of trips, dense, mixed-use areas may show lower totals, as walking trips are typically shorter and zones themselves are smaller, limiting the distance that can accumulate within them. In addition, Strava data primarily capture longer, leisure-oriented trips, which are more common in less-dense areas with larger open spaces. Together, these factors plausibly explain the negative association between density and total active-travel distance.

Similarly, we found no significant association between active travel distance and factors such as access to services, commercial areas density, intersection density, or active travel infrastructure — despite previous studies reporting positive associations (e.g. Cerin et al., 2017; Fraser and Lock, 2011; Heinen et al., 2010; Panter et al., 2008; Wang et al., 2016). These differences may reflect the nature of Strava data, which skews towards leisure travel, or differences in the control variables used across studies.

As for crime levels, the literature remains mixed. While many studies report a negative relationship between crime and walking and cycling (e.g. Appleyard and Ferrell, 2017; Deka et al., 2018; Ferrell and Mathur, 2012; Janke et al., 2016; Kremers et al., 2012; Sun et al., 2017); others have found no significant (including our study), or even positive associations (Foster et al., 2014b; Hood et al., 2011; Lachapelle and Noland, 2015).

4.2. Strengths and limitations

This paper has several strengths. First, it uses high-resolution data for both the response variables (active travel, measured using Strava data) and the main predictor (outdoor lighting levels, measured using nighttime satellite imagery). The high spatial and temporal resolution of Strava data enables a detailed analysis of active travel patterns across the city of Glasgow at an hourly scale and over a full year. Meanwhile, night-time satellite imagery provides consistent, city-wide measurements of outdoor lighting, offering insights that are difficult to achieve with traditional data sources. Second, it examines the association between outdoor lighting levels and active travel while taking into account contextual factors previously linked to travel behaviour, including population density, income deprivation, access to services, crime rate, recreational and commercial area densities, industrial area density, intersection density, active travel infrastructure density, average quietness, and terrain gradient. Third, it disaggregates active travel data into daylight and dark conditions, enabling us to assess whether outdoor lighting is more strongly associated with travel behaviour during hours when it is functionally relevant, and to examine whether other contextual associations differ by light condition. Fourth, it applies spatial statistical models (Besag–York–Mollié models) to control for spatial autocorrelation, improving the reliability of the findings and reducing the risk of biased results.

Nevertheless, the results should be interpreted in light of several limitations. First, while our study identifies a positive association between outdoor lighting and active travel, this does not imply causation or indicate the direction of the relationship. As an observational cross-sectional study, we are limited in our ability to determine whether lighting influences active travel or whether areas with higher active-travel activity are more likely to be illuminated. Moreover, although we control for many relevant contextual variables, unmeasured confounders may still influence the observed relationship. For example, lighting improvements may co-occur with broader environmental enhancements – such as upgraded street design or streetscape investments – or with underlying urban characteristics such as proximity to the urban centre or proximity to main roads, which could also contribute to increased walking and cycling, especially at night. Second, our analysis is based on aggregated active travel data, which means we cannot capture individual trip details, such as origins, destinations, or complete trip routes. Instead, walking and cycling activity is measured as the total distance travelled within each area. While this approach is appropriate for assessing area-level associations, it does not permit analysis of individual travel behaviours.

Third, although GPS-based data from platforms like Strava are increasingly used to study active travel due to their scalability and spatial resolution (Lee and Sener, 2021; Sun, 2017), they are not representative of the general walking and cycling population. Strava users tend to be more active, fitter, and are disproportionately men and working-age adults, with underrepresentation of women, children, and older adults — groups for whom darkness may pose greater barriers to mobility (e.g. Heinen et al., 2011;

Fotios et al., 2024b; Meyer and Denise, 2014; Xie and Spinney, 2018). This likely results in an underestimation of the negative effects of poor lighting, as the most affected individuals are less present in the data. Nonetheless, the fact that we still observe significant associations suggests the true effects may be even stronger in the broader population. Strava data are also skewed towards leisure travel, particularly for walking. While users can label trips as commutes, this is done inconsistently (mainly by cyclists) and the feature is not widely used. We therefore treated the data as reflective of general active travel behaviour, with a probable emphasis on leisure. Fourth, although our outdoor lighting levels data were up to date, high resolution, and taken on a supposedly clear night, they may not provide a complete picture of the total amount of light due to the presence of imperceptible clouds, trees, or other objects that could be obstructing the view. Even so, there is evidence to suggest that estimates of light levels based on aerial imagery highly correlate with on-the-ground measurements of illuminance (Hale et al., 2013). Another potential limitation of using satellite imagery is that it only provides a snapshot of the lighting conditions in one evening, whereas we were using active travel data from an entire year. It is possible that the light conditions changed over the year. Finally, since all variables were harmonised to the SIMD-zone level, variations within zones – for example, differences in lighting between main and side streets – could not be captured. This spatial aggregation may therefore mask finer-scale heterogeneity in both lighting exposure and active-travel activity.

4.3. Further research

Our findings suggest directions for future research. First, the observed differences in associations by light condition and mode highlight the importance of considering time of day in environmental studies of mobility. Disaggregating active travel data by daylight and darkness may reveal context-specific patterns that are obscured in aggregate analyses, providing more targeted insights for planning and policy.

Second, more work is needed to explore the direct relationship between lighting levels and active travel rates in specific locations. While this study focused on general outdoor lighting levels and area-level travel patterns (at the SIMD data zone level), understanding whether changes to lighting infrastructure at the street or path level led to increased walking and cycling remains an open question.

Third, studies covering a wider geographic scope are needed to investigate if the findings of this paper generalise beyond Glasgow. With the increasing availability of active travel datasets, remote sensing imagery, and standardised indicators of transport behaviour and urban context, multi-city or cross-country analyses are becoming more feasible for many of the variables explored here.

Fourth, further research is needed to examine how outdoor lighting affects different socio-demographic groups. Due to the format of the Strava data, we were unable to look at variations of associations by sex and age. There has been a growing concern in the media about how darkness may have a disproportionate effect on men and women while exercising outdoors (e.g. Minsberg, 2018; Salter, 2020; Snaith, 2022; Vinter, 2022). However, studies on this topic are scarce. Research considering these and other sociodemographic factors such as income or ethnicity is necessary to inform policies aimed at promoting inclusive active travel.

5. Conclusions

This study provides new evidence on the relationship between outdoor lighting and active travel, using high-resolution spatial and temporal data across the city of Glasgow. Our findings reveal a significant positive association between outdoor lighting levels and distances travelled on foot, by bike, and by both modes combined during dark hours, even after adjusting for multiple contextual factors. These associations were strongest for cycling and remained significant (though weaker) during daylight hours, possibly due to residual spatial or behavioural patterns.

While most contextual associations were consistent across light conditions, a few such as average quietness, gradient, and industrial land use varied between daylight and darkness. Additionally, some overall associations including those related to population density and infrastructure differed from previous research, likely reflecting the nature of Strava data and its focus on leisure travel.

Overall, the results underscore the potential role of outdoor lighting in supporting active travel after dark, especially for cycling. They also highlight the need for future research that considers light conditions in environmental studies of mobility, as well as across broader contexts, specific locations, and diverse population groups to better inform equitable and effective active travel policy.

CRediT authorship contribution statement

Eugeni Vidal-Tortosa: Writing – original draft, Visualization, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Eva Heinen:** Writing – review & editing, Methodology, Conceptualization. **Jim Uttley:** Writing – review & editing, Methodology, Funding acquisition, Conceptualization. **Demet Yesiltepe:** Writing – review & editing, Methodology, Conceptualization. **Steve Fotios:** Writing – review & editing, Methodology, Funding acquisition. **Robin Lovelace:** Writing – review & editing, Methodology, Funding acquisition, Conceptualization.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work, specifically in the revision phase after peer review, the author(s) used ChatGPT 4o in order to improve the readability and language of the revised manuscript in response to reviewer feedback. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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