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Geographical Exploration of the Underrepresentation of Ethnic Minority Cyclists in England

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Abstract: Cycling is encouraged as a means of sustainable urban transport, yet its uptake rate is uneven between different ethnic groups. The ethnic minority population in England is underrepresented as cyclists, but the reasons for this are unclear. Through linear regression and Geographically Weighted Regression (GWR), this research investigates the spatial distribution of the propensity to cycling among the ethnic minority population and the white population across England with the aim to identify the contributing factors toward the discrepancy of cycling rates between both groups and how these factors vary geographically. Results from OLS regression suggest that cycle rates are generally affected most by *hilliness*, the *presence of school-age children*, and *income*, with the presence of school-age children affecting the ethnic minority group and hilliness affecting the white group the most. The use of GWR revealed that *income* generally reduces cycle rates but has a positive impact in London for both groups. *The length of cycleways* and the *length of 20 mph speed limit roads* per unit area were statistically insignificant, but their local coefficients in GWR showed strong regional variations for both groups. The study also found that, with the exception of the *level of income*, ethnic minority cyclists are less sensitive to contributing factors than the white cyclists.

Keywords: barrier to cycle; ethnic minority; cycle to work; geographically weighted regression; regression analysis; urban mobility

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Citation: Kokayi, A.; Shiode, S.; Shiode, N. Geographical Exploration of the Underrepresentation of Ethnic Minority Cyclists in England. *Sustainability* **2023**, *15*, 5677. https://doi.org/10.3390/su15075677

Academic Editors: Gianluca Scaccianoce and Socrates Basbas

Received: 1 February 2023
Revised: 28 February 2023
Accepted: 20 March 2023
Published: 24 March 2023

1. Introduction

Cycling is widely accepted as an environmentally, economically, and socially sustainable mode of transport, and this tendency is particularly prominent in Europe and other developed countries. For instance, the UN Regional Information Centre for Western Europe (2023) [1] identifies cycling as "an essential element of development strategies that aim to achieve the Sustainable Development Goals (and) meeting the needs of people who cycle continues to be a critical part of the mobility solution for helping cities de-couple population growth from increased emissions, and to improve air quality and road safety". Similarly, the European Cyclists' Federation (ECF) promotes the potential of cycling for achieving 11 of the 17 Global Goals [2]. They strive to collaborate with the UN and the OECD as well as the EU member states and other European countries to improve the conditions for cycling in Europe and beyond, with the aim to double cycling in Europe between 2016 and 2025. However, the modal share of cycling varies greatly across Europe, ranging from those with consistently high cycling rates in the region of 30–50% (e.g., the Netherlands and Denmark) to those with much lower rates at 0.1–2% in major cities [2]. As with most other European nations, the United Kingdom actively promotes sustainable and active traveling through walking or cycling [3–5]. There is also increasing awareness towards active travel as an effective means of public health intervention and improving the amount of physical activity of the wider communities [6]. Woodcock et al. (2013) [7]

estimate that increasing the average length of cycling from 0.9 min to 9.5 min and walking from 12.5 min to 16.8 min per day could reduce the total disease burden in England and Wales by 2.9%. However, at an overall cycling rate of 4% across the UK, it is some way off from achieving a high cycling rate.

Increasing the modal share of cycling is also expected to help alleviate the demand on transport networks and reduce air pollution. It is an important aspect of active travel as it can replace more trips over longer distances than walking can [8]. Cycling levels in the UK are considered low, with under 4% of commuter journeys between 1991 and 2011 using this mode [3]. In England and Wales, there was a slight increase of 0.09% in the modal share of cycling between 2001 and 2011 [3], and it has seen slow but steady growth. However, this overall pattern masks the significant local variation with some regions and Local Authority Districts (LADs) seeing large increases in commuter cycling and others seeing a decline. Aldred et al. (2016) [9] indicate that much of this slight positive change is the result of a large increase in a small number of LADs. The COVID-19 pandemic has brought significant changes in the patterns of mobility and transport use in the UK [10]. The airborne nature of the virus forced the government to discourage the use of public transport for many months, and many continued to avoid it even after lockdowns. Much discourse around transport during this time focused on how to prevent the modal shift from public transport to private vehicles. In fact, for those without access to a car, active travel, specifically walking and cycling, remained the only alternative to public transport. To meet the sudden increase in the volume of active travel, the UK Department for Transport (DfT) announced an Emergency Active Travel Fund in May 2020, allowing councils to apply for funding to adjust their local transport infrastructure to facilitate active travel and the reallocation of road space [11]. They also funded the creation of the Rapid Cycleway Prioritisation Tool, which was developed for assisting in the planning of cycleways in places with the highest 'cycling potential', i.e., places where the expected uptake of cycling is high [12]. Given these large investments towards cycle infrastructure, understanding how to make cycling more accessible and inclusive is pertinent.

While cycling offers clear health benefits and increases accessibility within cities, there are also concerns that it may not be equally accessible to all demographics in the UK [9,13]. Current UK statistics indicate that cyclists are more likely to be the white males and able-bodied adults or young adults, and there is a distinct lack of ethnic-minority cyclists [9,14]. For clarification, this study uses the term "ethnic minority" as a collective reference to all non-white ethnic groups. Until recently, the ethnic minority group in the UK was referred to as BAME (Black, Asian and Minority Ethnic) but, in 2021, the UK Commission on Race and Ethnic Disparities recommended stopping using the aggregate term BAME, as it may emphasise certain ethnic groups (namely the black and the Asian populations) over others [15]. The UK government also recommends stop capitalising ethnic groups (such as 'black' or 'white') unless that group's name includes a geographic place (for example, 'Asian', 'Indian' or 'black Caribbean'), and this study follows that style [15].

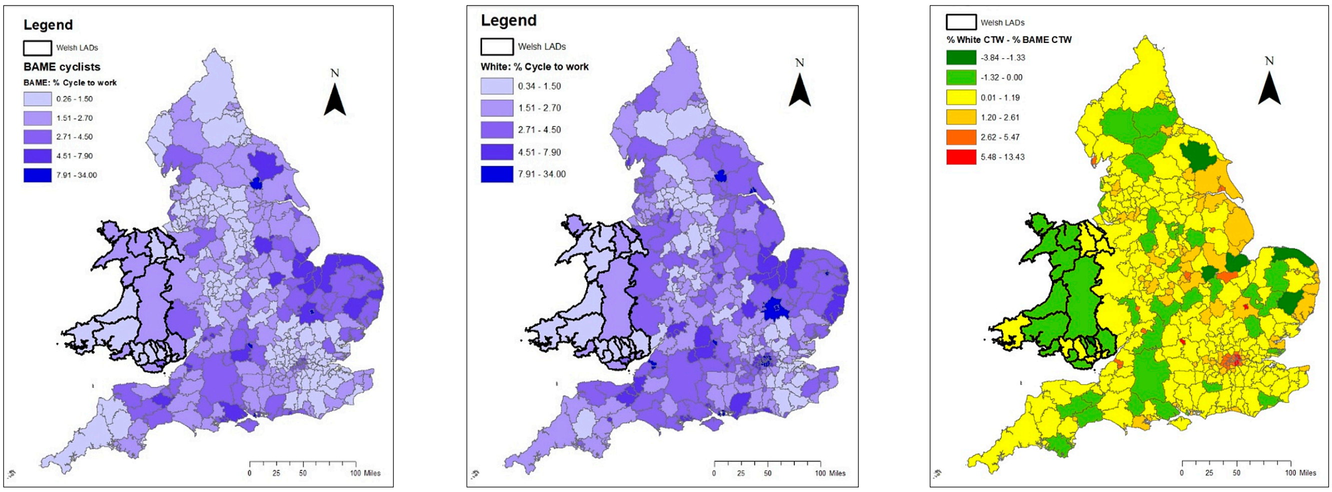
The National Travel Survey [14] shows that the ethnic breakdown of the average cycle distance travelled in miles per person per year is 61 miles among the white population, which is twice or more than that of the ethnic minority population (black 28 miles, Asian 19 miles, and mixed ethnicity 32 miles). Also, at the time of collecting census data, 4.7% of white adults were cycling, in contrast to 2.6% of ethnic minorities in the UK [16], and this imbalance persists to this date [17]. It raises the risk of investment in bike paths and other infrastructure for cycling entrenching and replicating inequality in accessibility and opportunities [18]. To resolve these challenges, we need a holistic approach to understand how the overall rates of cycling can be increased and how cycling can be made more inclusive and accessible across different ethnic groups. Martin et al. (2021) [19] emphasise that there is much to be gained from analysis of the disparity of cyclists by their ethnicity. Similarly, Fishman (2016) [20] highlights the need for more representative samples in research on cycling infrastructure, while Psarikidou et al. (2020) [18] assert that, for cycling to be truly sustainable, there is a need for an 'intersectional understanding' of its inequalities.

However, the reasons for the low cycling rate among the ethnic minority population remain understudied [17]. This research fills this gap in the literature with the aim to investigate why there are ethnic disparities in cycling with a focus on the disparity of cycle rates between the ethnic minority group and the white group and their regional variations.

2. Literature Review

2.1. Cycling and Ethnicity

Janvaria (2018) [21] undertook a systematic review of studies that looked at the barriers to cycling for ethnic minorities in any country and pointed out the scarcity of research into the low uptake rate of ethnic minority cyclists. Parkin et al. (2007) [22] conducted what was arguably the first study on the cycle-to-work trips by the non-white population in the UK and reported the low uptake rate. This tendency seems to persist, as the UK Department for Transport (2020) [14] reports that 1% of trips by black and Asian populations are cycled, compared with 2% among the white population. The UK 2011 Census also suggests that, in most Local Authority Districts, the proportion of the ethnic minority population who cycle to work is lower than that of the white population (Figure 1). At the same time, Sustrans' Bike Life survey reached out to 16,923 people in twelve UK cities and found that 55% of ethnic minority respondents who did not cycle wanted to start cycling [17]. It highlights the unmet need of this population and that, if barriers to cycling were addressed, more of the ethnic minority population may start cycling or would cycle more often. However, Song et al. (2017) [23] found that certain types of infrastructure interventions have helped increase the number of white cyclists, but they did not attract many of the ethnic minority population to switch from cars to active travel modes. These findings suggest that the barriers for the ethnic minority population are greater and/or different from those for the white population. Martin et al. (2021) [19] applied statistical analysis to examine the varying impact of investment in cycling infrastructure in 32 London boroughs depending on gender, ethnicity, age, and socio-economic status. They found that 'inequalities in the likelihood of cycling were greatest between any of the ethnic minority groups and the white British population ... and were increasing over time' [19]. Their findings highlight the need for more research into ethnic minority cyclists.



(**a**) (**b**) (**c**)

Figure 1. (**a**) Ethnic minority cycle to work rates, (**b**) white cycle to work rates, and (**c**) the difference between them.

This is notwithstanding that several qualitative studies have been carried out on the cultural background of ethnic minority cyclists. For instance, Steinbach et al. (2011) [13] explored 'the meanings of cycling' for different gender, class, and ethnic identities through in-depth interviews and focus groups, and they acknowledged that the cultural meanings of ethnicity and transport have had less attention than gender. Whilst no explicit claims were made on the link between cycling and ethnicity, they noted that some participants referred to their ethnic background when discussing cycling. Similarly, through in-depth interviews with 92 participants, Green et al. (2010) [24] noted that many of the black and Asian participants saw cycling as something not for 'people like them', which was compounded by seeing only a few black or Asian cyclists on the roads. Furthermore, some of the black and Asian women responded that they never learned how to cycle [24]. Green et al.'s work (2010) [24] also revealed that cycling was seen as 'low status' by many ethnic minority participants and it cites the same idea that came through a focus group study by Davies et al. (1997) [25]. In this vein, the differences in travel preferences by ethnicity can be understood as a reflection of different ethnic and racialised experiences.

Beyond cycling, there are noticeable differences between various ethnic groups in their travel patterns. The National Travel Survey [14] shows that, on average, those of the ethnic minority population make fewer trips and travel fewer miles each year (e.g., the average number of trips per person per year in 2015–2019 was 833 trips among the ethnic minority population and 983 trips among the white population). The value also varies between different ethnic groups (black: 773 trips, Asian: 809 trips, mixed ethnicity: 918 trips), as do the reasons for travel and the mode of travel. For instance, between 2015 and 2019, the black population used a local bus for 19% of their trips, which is more frequent than any other ethnic group, while people of mixed ethnicity had the highest frequency of walking than any other ethnic group, with 35% of their journeys being made on foot [14]. Some of these differences may have arisen from the variation in the local geography of the residential neighbourhood that is popular among specific ethnic groups, as well as any difference in the types of occupations and the travel patterns involved. However, other aspects of the disparity in travel patterns among different ethnic groups would benefit from the socio-cultural exploration of transport or cycling; i.e., ethnicity could provide insights into the nuanced interactions between people's racialised experiences and their travel patterns.

Internationally, western countries show similar tendencies, if to varying degrees, in the relationship between ethnicity and cycling. For instance, in the Netherlands, people of a non-western immigrant background use bicycles for 18% of their trips, compared with the modal share of 28% for cycling by people of Dutch background [26]. This also reflects the lower health benefits of cycling for non-western people [27]. Similarly, in the United States, 77% of bike trips are carried out by the non-Hispanic white population, despite that they make up 66% of the national population [28]. Stehlin (2019) [29] argues that the choices on cycling infrastructure are largely decided by white professionals and white citizen advocates and that these choices tend to facilitate or coincide with gentrification that pushes away ethnic minority populations from their respective neighbourhoods. It emphasises the racial politics behind what is often portrayed as an apolitical health and sustainability intervention [30].

2.2. Factors That Influence Barriers to Cycling as Transport

There is a large body of research that explores the general trend of cycling and the underlying factors that affect people's uptake on cycling. In general, the psychological factor of *concern over safety* is known to be a key barrier to people's decision to cycle [20]. While evidence suggests that cycling is safe [31] and that inactivity is more likely to result in premature death that reflects a higher risk to life expectancy than cycling does [32], witnessing or hearing about cycle accidents could discourage people from cycling. In this sense, the perception of risk creates as much of a barrier to cycling as the actual risk [33]. However, Aldred and Crosweller (2015) [31] argue that this perception is not unfounded. They suggest that, on average, cyclists in the UK experience a near-miss incident once a week, but these incidents do not go on record and therefore remain unnoticed in the statistics. Fishman (2016) [20] highlights the importance of installing cycling infrastructure for reducing the perception of risk, thereby supporting people's decision to cycle and improving their safety while cycling. Mölenberg et al. (2019) [34] reviewed the effect of cycle infrastructure interventions on cycling rates and observed the positive correlation between the increase in cycle infrastructure and the increased cycling rate. These findings suggest that people feel safer when there is dedicated cycling infrastructure and that this leads to an increase in cycling.

Another group of factors that could influence the decision to cycle pertains to the physical environment. Parkin et al. (2007) [22] state that *hilliness or the gradient of the slopes* is the most significant physical determinant of cycling for everyone, as it reflects the local topographical characteristics [22,35]. Other factors relate to the physical urban features and the traffic regulations applicable to each street. For instance, Grundy et al. (2009) [36] found that introducing a 20 mph zone reduced road casualties in the target zone as well as its adjacent areas. It is also expected that this increased safety would make people more comfortable with cycling. Also, a densely built environment that is associated with urbanised areas with high population density is conducive to cycling as the main urban facilities tend to be close to each other, thus making the expected distance of a journey shorter [26]. This allows the majority of people who cycle to work to commute in under 5 km [35]. The cycling infrastructure discussed earlier is also integral to the physical environment, and its safety design will likely affect people's willingness to cycle [37].

Social factors are also considered to affect the uptake of cycling. Grudgings et al. (2018) [35] found that the *percentage of school-age children* is negatively correlated to the cycle rate, especially among female commuters who may have school-run obligations that promote other modes of transport. There are also two divergent effects of income level on cycling rates, in that people with a higher income can afford a bicycle and cycle more often but may also find other modes of transport, notably cars, more convenient and may therefore cycle less [26]. Increased car ownership indeed reduces cycling by providing an alternative mode of transport to the owner, whilst also increasing road traffic and making cycling less safe and less enjoyable [22]. However, the association between car ownership and cycling rates is not consistent; countries like Germany, Denmark and the Netherlands have both a higher rate of car ownership and a higher cycling rate than the UK does [38].

While these studies explore a range of factors that affect cycle rates, they do not study the disparity in cycling between ethnic groups. Instead, most of the literature on the inequality of cycling focuses on gender difference. For instance, Shaw et al. (2020) [39] separate research on women and cycling into two perspectives: (1) the factors that impact women cyclists, such as perception of risk, cycling ability, and infrastructure preferences; and (2) a feminist perspective on the structural and social factors that affect mobility '*through gendered patterns of activity and differential access to time, money and resources*', which may then lead to '*gender-related travel perceptions, experiences and behaviour*'. This is reflected in evidence that there is variation in how, why, and when women cycle in comparison with men [39]. Grudgings et al. (2018) [35] also looked at the socioeconomic, transport, and physical factors and demonstrated that different determinants of cycling have different weights for men and women. While they are not immediately transferrable, findings from these studies on gender cycling unbalance can help design the framework and the methods with which to investigate the reasons behind the low level of cycling among the ethnic minority population.

2.3. Methodologies from Existing Research

In terms of the method of analysis, many studies use linear regression modelling to explain the choice of transport mode(s), driving factors of cycling, as well as the barriers to cycling. If the cyclists' data are disaggregated, logistic regression, logit models, and probit models are often used. For example, Wardman et al. (2007) [40] analysed the disaggregate Stated Preference Surveys (SPS) data and adopted a hierarchical logit model to understand the factors that affect the rates of cycling to work. Similarly, Martin et al. (2021) [19] used anonymised individual records of over 300,000 commuters from the UK Census microdata to obtain a granular view of the association between commuter cycling and multiple demographic markers. Modelling with disaggregate data has the benefit of interpreting the characteristics of trip makers but is often dependent on the survey data, which can make quantifying certain factors challenging and may not accurately reflect real-world behaviour [22].

Other studies use aggregate data such as census data. For instance, Aldred et al. (2016) [9] applied linear regression to census data to assess whether the rise in commuter cycling between 2001 and 2011 led to increased cycling by women or older adults. Although the census captures 94% of the resident population, they used inferential statistics because they "conceptualised 'what actually happened' as being drawn stochastically from a larger set of 'things that might have happened' based on underlying processes that shape probability distributions" [9]. They concluded that the pattern observed was likely a reflection of a real underlying process. Similarly, Grudgings et al. (2018) [35] investigated the gender gap in cycling to work in England and Wales in 2001 and used separate models for men and women to reflect on a range of socioeconomic, transport and physical factors. This approach facilitates each model to adopt a different set of explanatory variables that fit the cycling pattern by the respective group. Parkin et al. (2007) [22] and Goodman (2013) [3] also used the census *cycle-to-work* data to understand how the cycle rate by the commuters changed over time and what affected the choice of transport mode.

One notable observation is that all these studies use standard linear regression models, which are inherently non-spatial. The problem that arises from applying a non-spatial method for interpreting geographical data has been noted in the wider literature on quantitative geography. For instance, Grudgings et al. (2018) [35] ran spatial autocorrelation analysis (Moran's *I* test) on the residual term of their linear regression model and detected mild spatial autocorrelation, which is likely due to missing variables that are spatially dependent. Although both aggregated and disaggregated cycle data have a geographical component in the form of locational information, few studies have focused on the spatial aspect of cycling data, except for a small number of studies on cycle accidents [41,42].

In summary, there is an increasing awareness of and more investment in cycling to support sustainable urban mobility, yet the gap between different groups of cyclists, including the comparison between ethnic minority cyclists and white cyclists, remains largely unexplored. This study aims to fill this gap and investigates why there is a smaller number of ethnic minority cyclists than white cyclists in England, and whether the tendency of these factors varies geographically across England. Methodologically, the study will use non-spatial as well as spatial regression models to obtain a better understanding of the regional difference in the impact of the contributing factors on cycle rates.

3. Data

This study investigates the association between cycling and ethnicity across the 319 Local Authority Districts (LAD) in England. The decision to focus solely on England rather than Great Britain (including Wales and Scotland) was based on the disparity of their environmental and demographic characteristics (e.g., Wales has a much steeper topography and Scotland has a much higher proportion of the white population at 96% as opposed to 81% in England), as well as the availability of suitable data that were comparable in their granularity. The key data on ethnicity was taken from the 2011 UK Census as it was the only data source that provided information on ethnicity at a finer granularity than the regional level with the breakdown of cyclists by ethnicity. It is also the most recent census data available, as data from the 2021 UK Census were yet to be released at the time of this study. Table 1 shows potential data sources mapped against the essential components for analysing ethnicity in the context of cycling. It shows that most data sets do not contain information about ethnicity. The only data available on ethnicity-related cycling information is captured by the UK Census, and it focuses on *cycling to work* (also referred to as 'commuter cycling'), which only captures adults (people over 16) with a job in England. Those who answered, "*Work mainly at or from home*" were removed to align with the study by Martin et al. (2021) [19] and others where these responses are removed from the analysis. Commuter cycling covers roughly a third of adult cycling [9] but can be considered to represent the most common cycling pattern.

Table 1. Key data sources for cycling data in England.

Data Source	Units Smaller than Region?	Is Gender Captured?	Is Age Captured?	Is Ethnicity Captured?
Census	YES	YES	YES	YES
National Travel Survey	NO	YES	YES	YES
Cycle Hire data (TfL)	YES	X	X	X
Cycle Flows data (TfL)	YES	N/A	N/A	N/A
Strava Metro	YES	YES	YES	X
STATS19	YES	YES	YES	X

Figure 1 shows (a) ethnic minority cycle-to-work rate, (b) white cycle-to-work rate, and (c) the difference between them. These figures illustrate the substantial variations between LADs in the percentage of people who cycle to work. The highest commuter cycling rate is reported in Cambridge at 32.49%, with the lowest in Merthyr Tydfil at 0.34%. The cycle-to-work rates for the ethnic minority population and the white population resemble some of their geographical distribution patterns, and the correlation between them is indeed statistically significant (correlation coefficient = 0.828). However, the overall ethnic minority cycling to work rates are lower than those among the white population, which is reflected in Figure 1c where the majority of the LADs show positive values (i.e., ethnic minority cycle rate < white cycle rate), illustrated by yellow, orange, and red hues, and, with the exception of Wales, a relatively small number of LADs highlighted in two shades of green have a negative value (i.e., ethnic minority cycle rate > white cycle rate). The LADs of Cambridge, Oxford, and Blaenau Gwent were removed from the analysis, as their cycle-to-work rates were outliers, which can affect the distribution and can have a substantial influence on the results of the analysis.

4. Methodology

This study uses a non-spatial linear model (OLS regression) as well as a spatial regression model (Geographically Weighted Regression (GWR) [43] to understand the relationship between rates of cycling and various contributing factors. Given the geographic nature of the data, the residual term of the regression analysis was assessed for spatial autocorrelation using Moran's I statistic, as regression modelling assumes independent residuals. If the residuals show a non-random pattern and are deemed not independent, it would be difficult to judge the significance of regression coefficients. In contrast, GWR can explicitly address spatial heterogeneity, as observations of the variables are weighted by their distance from each location where a local regression model is produced using a kernel function. Since the LAD units vary in size, an adaptive kernel bandwidth was used.

For both the OLS regression and GWR, two models each were produced: Model A, which estimates cycle-to-work rates by the ethnic minority population, and Model B, which estimates cycle-to-work rates by the white population. This enabled a direct comparison between the regression coefficients for each independent variable. To aid this comparison, all independent variables were standardised. Table 2 outlines the independent variables used.

Table 2. Independent variables and their data sources.

Independent Variable	Description	Data Source
School-age children	Percentage of households with children between 5–15 years of age	UK 2011 census
Ethnic minority population *	Percentage of total population that are ethnic minority	UK 2011 census
Population density *	Number of persons per hectare	UK 2011 census
Commute under 5 km *	Percentage of people who commute under 5 km	UK 2011 census
Car ownership	Percentage of people with one car	UK 2011 census
Hilliness *	Average gradient of commutes under 10 km for LAD residents. Based on the 2011 census	Cycling Infrastructure Prioritisation
Income *	Index of Multiple Deprivation (IMD) average income score	Index of Multiple Deprivation 2015
Casualties *	Cyclist casualties recorded by police in 2011	STATS19.
Cycleways m/m^2 *	Length in metres of roads tagged as cycleways/m^2 of focus area	Open Street Map
Speed limit of 20 mph *	Length in metres of roads with speed limit of 20 mph or less/m^2 of focus area	Open Street Map

* Indicates that values for that variable were transformed (mostly log transformation) to produce a normal distribution.

The choice of the independent variables was guided by (1) the literature on factors that affect cycling rates (Section 2.2) as well as (2) a preliminary exploration of the data. For instance, our literature review identified *hilliness* as an environmental factor that hampers cycling. It is also used in this study to investigate whether the ethnic minority and the white groups react to this topographic feature differently. The literature review also revealed the impact of other environmental factors, namely *cycling infrastructure*, and this study has adopted cycleways per square meter as a proxy for cycling infrastructure. Other variables adopted from the literature are *population density* (which indicates the extent of urbanisation and, therefore, the likely distance of cycle travel), *speed limit*, *cyclist casualties* (per km^2) (as a proxy for concerns over safety, which has a large impact on people's willingness to cycle), *level of income, car ownership*, and the presence of *school-age children (5–15 population).* The study also uses the percentage of ethnic minority people, which was extracted through data observation and in relation to our research hypothesis, as we wish to explore the association between the proportion of ethnic minorities population and their cycling rate (i.e., whether cycling behaviour is affected by the ethnicity of people around). Correlation coefficients were derived to check the relationship between the independent and the dependent variables. As a result, *population density, casualties per km*^{2}, and *the percentage of households with one car* were removed from the regression modelling, due to their extremely low correlation with the dependent variables.

5. Analysis

5.1. OLS Regression Modelling

Both Model A (the ethnic minority model) and Model B (the white model) showed a relatively high goodness-of-fit with Model A: R^2 = 0.621, AIC = 606.099; Model B: R^2 = 0.678, AIC = 555.164. The two models share the same set of independent variables; i.e., contributing factors influence both groups of cyclists broadly in a similar way but the extent of contribution of each factor is different (Table 3). The outcomes also suggest that the relative importance of each independent variable is different between the two models. For instance, the variable with the highest influence in Model A is *5–15 population* with a regression coefficient of −0.519. This confirms the results of the study by Grudging et al. (2018), in that as the percentage of households with school-age children increases, the rates of cycling to work among the ethnic minority population declines. The next significant variable in Model A is *hilliness*, which shows a coefficient of −0.491; i.e., it has a negative impact on cycle rate in that a hilly area dissuades people from cycling, but not as much as having school-age children. In Model B, on the other hand, the variable with the most influence is *hilliness*, which has a regression coefficient of −0.551, followed by *5–15 population*, which has a value of −0.526. This means that the ranking of *5–15 population and hilliness* is different between the ethnic minority and white populations, and, more importantly, both variables have relatively high coefficient values for white cyclists, thus implying that both variables have a stronger impact on white cyclists than they affect ethnic minority cyclists.

Table 3. Outputs from ethnic minority and white OLS regression analyses.

Variables	Model A (Ethnic Minority Cyclists)			Model B (White Cyclists)		
	Coefficient	**t-Statistic**	**Probability**	**Coefficient**	**t-Statistic**	**Probability**
Intercept	0.022	0.634	0.526	0.003	0.109	0.913
Commute under 5 km	0.286	5.917	>0.001 *	0.269	6.043	>0.001 *
Income	−0.470	−10.024	>0.001 *	−0.368	−8.488	>0.001 *
Hilliness	−0.491	−12.929	>0.001 *	−0.551	−15.730	>0.001 *
Ethnic minority population	−0.175	−3.319	0.001 *	0.126	2.593	0.010 *
5–15 population	−0.519	−11.494	>0.001 *	−0.526	−12.619	>0.001 *
Cycleways	0.064	1.015	0.311	0.111	1.908	0.057
20 mph limits	0.014	0.228	0.820	0.039	0.692	0.489

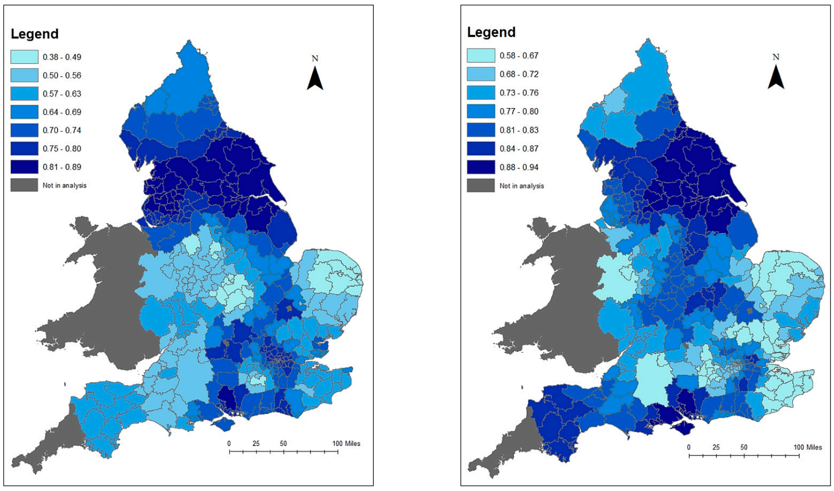
* indicates a statistically significant *p*-value.

Income was the third most important variable in both models, where the negative regression coefficients suggest that a higher income decreases cyclists, but it seems to affect ethnic minority cyclists more (regression coefficients: −0.470 with Model A and −0.368 with Model B). *Commutes under 5 km* (rank 4) and the proportion of the *ethnic minority population* (in the respective neighbourhood) (rank 5) are also statistically significant in both models. Interestingly, though, the proportion of the *ethnic minority population* seems to have a contrasting effect for the two models with the regression coefficient being negative for Model A (−0.175) and positive for Model B (0.126). In other words, an increase in the ethnic minority population percentage decreases the number of ethnic minority cyclists, but it increases the number of white cyclists.

Cycleways and *20 mph limits* have very low coefficients that are not statistically significant, thus suggesting that both variables contribute only marginally to the two models. However, the *cycleways* variable in Model B has a larger coefficient value, and its statistical significance is around the border line (at $\alpha = 0.05$), meaning that the white cyclists value is more responsive to the installation of cycleways. It also turned out that both models had statistically significant spatial autocorrelation in their residual term (Moran's $I = 0.1384$ *** for Model A and Moran's $I = 0.188$ *** for Model B), which confirms the benefit of applying a spatial regression model.

5.2. Geographically Weighted Regression (GWR)

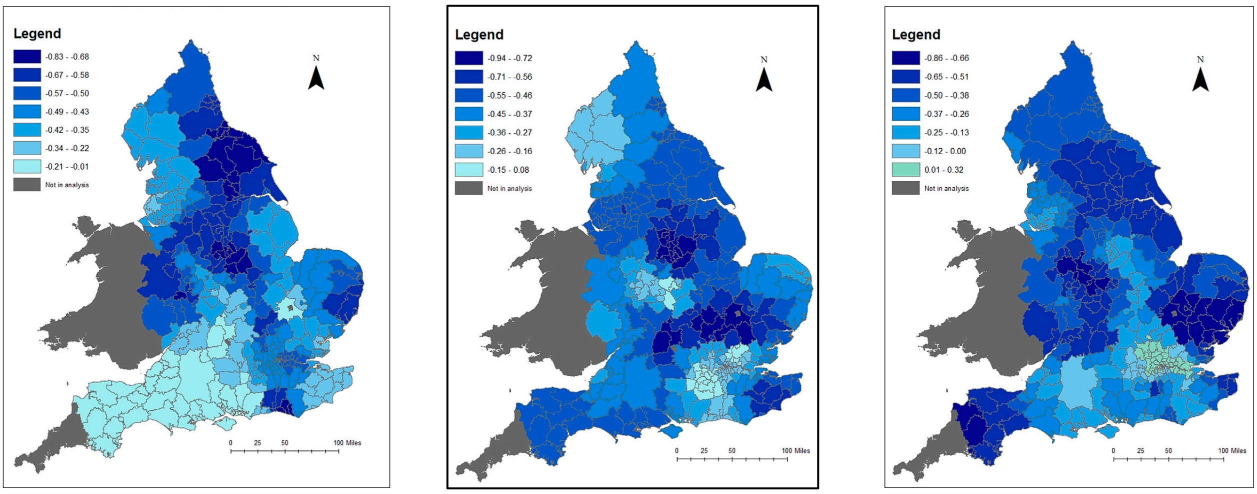
Application of GWR not only controlled the spatial dependency in the residual term but also improved the goodness-of-fit compared with OLS regression for both ethnic minority and white models (Model A: global adjusted $R^2 = 0.739$, AIC = 588.141; Model B: global adjusted $R^2 = 0.813$, AIC = 481.226). The Moran's I and associated p-value for the GWR residuals indicate that the residuals are no longer spatially autocorrelated (Model A: Moran's $I = -0.028$, p-value = 0.204; Model B: Moran's $I = 0.007$, p-value = 0.596), which also confirms the benefit of applying GWR. Figure 2a shows the geographical distribution of local goodness-of-fit (in the form of local R^2), where Model A is best fitted in Northern England (dark blue) as well as in small pockets in and around Hampshire, Sussex and London. It is worst in the Midlands as well as the East Coast (Norwich and Suffolk), as illustrated in pale blue. The local goodness-of-fit for Model B is slightly better overall (with a higher global R^2, as stated above); the best fits can be found in and around Yorkshire and the Humber, Devon, and Sussex, whilst the worst fits are found in the east of England region (Figure 2b). Areas where the goodness-of-fit was relatively low (including London) need closer investigation of the contributing factors that affect all cyclists across different ethnicities. On the other hand, a wider range of local R^2 was identified (ranging from 0.38 to 0.89) for Model A as opposed to the lower range of local R^2 values in Model B (ranging from 0.58 to 0.94), which implies the presence of other factors that may affect ethnic minority cyclists more strongly than they affect white cyclists, and that this tendency stands both across the country and more locally in areas with poor fit of the model.



(**a**) (**b**)

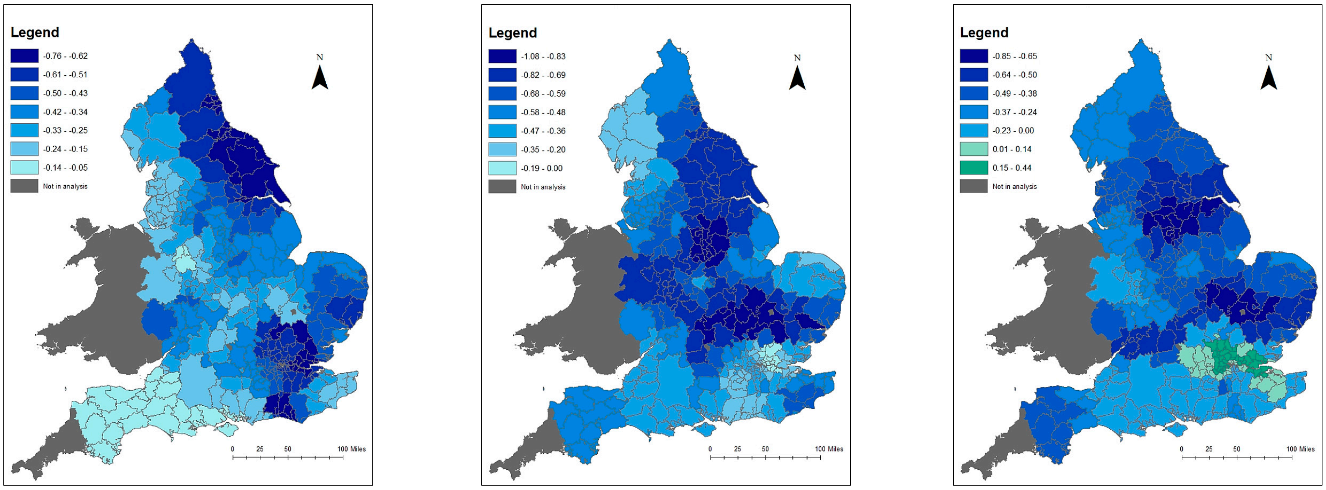
Figure 2. Map of local R^2 for (**a**) Model A (ethnic minority cyclists) and (**b**) Model B (white cyclists).

Figures 3 and 4 illustrate the geographical distributions of local regression coefficients of Model A (Figure 3) and Model B (Figure 4) for 5–15 population, *hilliness*, and *income*, respectively. Interpreting the spatial variation of a regression coefficient across the study area, as well as the differences between different variables, helps understand how the different variables affect the cycle-to-work rate differently in different parts of the study area, and, by comparing these outcomes between Models A and B, the two figures compare the difference and similarity in their variation across the study area. For instance, the local regression coefficient maps for the 5–15 population variable (Figures 3a and 4b) show negative impacts on both the ethnic minority and the white cyclists across the entire study area. The patterns of their local distribution are somewhat similar, as the most affected region is in the northeast (large negative values in dark blue), with the least influence felt in the southwest (small negative values illustrated in pale blue). At the same time, there is a contrasting pattern in the Central England region, where ethnic minority cyclists react more strongly (i.e., an increase in school-age children will decrease ethnic minority cyclists more significantly in that area), while the opposite pattern is found in London and the surrounding areas where an increase in school-age children will decrease white cyclists. The local coefficient map for *hilliness* shows a similar pattern for both ethnic minority and white cyclists (Figures 3b and 4b) and a negative impact in almost all the areas, thus suggesting that *hilliness* tends to hamper cycling across both ethnic groups, which confirms the literature; i.e., the steeper the hills, the fewer cyclists. At the same time, the range of local coefficient differs across England, with the most influence felt in Central England and the least influence in and around London. Finally, the *income* variable highlights that in and around London, the relationship between income and commuter cycling is positive, and this tendency holds for both ethnic minority and white cyclists (Figures 3c and 4c), but this pattern is much more prominent for white cyclists. These findings are consistent with the outcome of the TfL's survey [16], which found cyclists in London to be typically white, under 40, with a medium to high household income. Martin et al. (2021) [19] also noted that, in contrast with England as a whole, cycling in London has shifted from being dominated by commuters with lower socioeconomic status to commuters with higher socioeconomic status. This means that the overall relationship between income and cycle rate where an increase in income means a decrease in cyclists may not hold true in London and its surrounding areas.



(**a**) (**b**) (**c**)

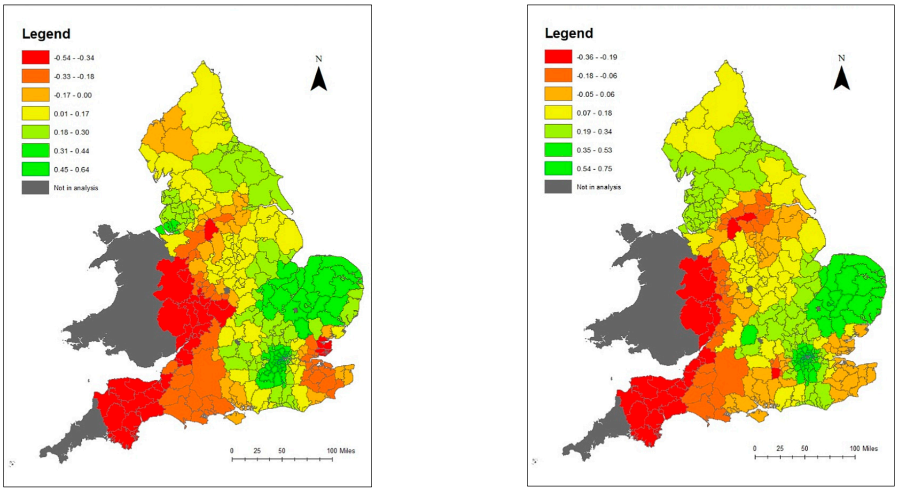
Figure 3. Local coefficients for ethnic minority population on (**a**) 5–15 population, (**b**) hilliness, and (**c**) income.



(**a**) (**b**) (**c**)

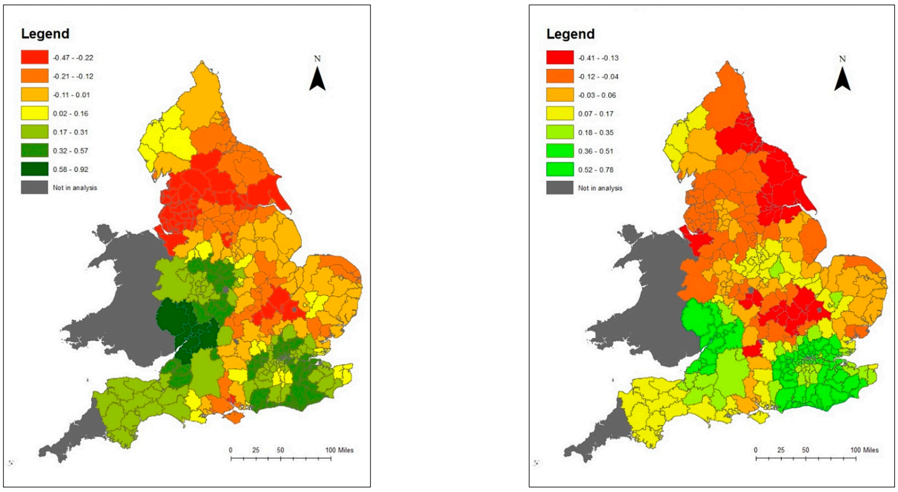
Figure 4. Local coefficients for white population on (**a**) 5–15 population, (**b**) hilliness, and (**c**) income.

The *cycleways* and *20 mph limit* variables were not statistically significant in the global OLS models, but the local coefficients vary in direction and show a bipolar tendency, with some LADs having a highly positive (green areas) relationship with the cycle rates, while other LADs show a highly negative (red areas) relationship (Figures 5 and 6).



(**a**) (**b**)

Figure 5. Cycleway local regression coefficient from (**a**) Model A (ethnic minority cyclists) and (**b**) Model B (white cyclists).



(**a**) (**b**)

Figure 6. The 20-mph limit local regression coefficient from (**a**) Model A (ethnic minority cyclists) and (**b**) Model B (white cyclists).

It could be that these two variables did not come up as statistically significant in the global models because their values cancelled out between the highly positive and the highly negative areas, and this illustrates the importance of exploring the local variation of these models. The general pattern of influence for *cycleways* across the study area is similar for the ethnic minority and white populations. (Figure 5a,b). Although the overall impact of cycleway was confirmed to be positive in the global model (i.e., installing a cycleway results in more cycling), the local model reveals contrasting results between the eastern and the western regions of England: the impact of cycleway installation is low in the western regions (red/orange areas), which is the opposite of what is seen in the eastern regions. The local coefficients for the *20 mph limits* variable also show similar patterns (Figure 6a,b), but there is a north–south divide instead, whereby, in the northern region (red/orange areas) impact of the 20 mph limits is low and is opposite to those felt in the southern regions. For both *cycleways* and *20 mph limits*, Southeast England (including London) shows a positive coefficient; i.e., these transport infrastructures and transport controls are effective in increasing cycling. At the same time, it shows that ethnic minority cyclists are less affected by the cycle infrastructure.

6. Discussion

Outcomes from the OLS regression and GWR regression yield several interesting facts, especially in terms of how the cycle-related factors influence the cycle rates differently for the ethnic minority and the white populations. For instance, *hilliness* was found to be a key contributing factor for cycle rates, which aligns with findings in many other studies. Both models (Model A for ethnic minority cyclists and Model B for white cyclists) returned similar patterns of distribution across the LADs, probably because both groups have responded to the physical challenges of the topographical characteristics in a similar fashion. Maps of the local regression coefficients revealed that the negative impact of a hilly landscape seems to be felt more prominently by the white population, and this is reflected in the stronger overall negative reaction from the white cyclists against hilliness. However, there is a distinctly smaller impact of hilliness in London and the neighbouring LADs, and this is despite the wide range of public transport available in this area. Commuting into and around London by car can be time-consuming and costly (e.g., congestion charges and parking fees), whilst the current situation with the public transport around London requires some physical exertion and forces inconvenience, thus resulting in cycling being perceived as a preferred option for some commuters (both of the ethnic minority and the white populations) even when the commute is hilly. To increase cycling rates among the ethnic minority and the white populations regardless of the gradient, increased access to e-bikes may prove beneficial as hilliness is clearly an influential obstacle outside the greater London region.

The negative impact *of 5–15 population* showed that those of the ethnic minority population with dependents in the school-age group were particularly affected. This is consistent with the outcomes of the National Travel survey, in that education and educational escort (i.e., school runs) are much less significant reasons for travelling for the white population than they are for the ethnic minority population (Educational Escort: white 11%, black 23%, and Asian 21%). Whilst it is possible to travel by bike with children onboard, it may not be a cultural norm for some of the ethnic minority groups, and this could make cycling a less appealing mode of transport for those who have the educational escort responsibility.

In terms of *income* level, its overall impact is negative with a greater negative influence on ethnic minority cyclists than on white cyclists. The reason behind increased income leading to less cycling may be the ability to afford cars [26], and this tendency seems to be more prominent among the ethnic minority population. There is some qualitative research suggesting that car ownership is seen as a status symbol in some ethnic minority groups, while cycling is associated with lower status [13,24]. It could be also linked to the lower average income of the ethnic minority population, whereby the increase in income encourages some groups within the ethnic minority population to move away from cycling and shift to other modes of transport. Interestingly, in the local model, some LADs in Southeast England showed a positive relationship between income and cycle rates, but this was more prominent with white cyclists.

Another interesting variable was the *ethnic minority (residential) population*, which showed a contrasting effect on the ethnic minority and the white cyclists. A possible hypothesis for the two models yielding the opposite coefficients is that, in Model A, the size of the ethnic minority population acts as a proxy for population density and, by extension, the size of the overall population in the area, since cities and urban areas tend to have a larger an ethnic minority population and a higher proportion thereof. This, in turn, means that there will be more of the white population also, even if their proportion may be lower in the area; additionally, as the white population tends to cycle more, an increase in the ethnic minority population leads to more white cyclists. This links back to the earlier discussion about region-specific characteristics, specifically for London and its surrounding areas, where the global tendency found in the OLS regression may not apply.

Neither *cycleways* nor the *20-mph limit* had a statistically significant regression coefficient in any of the models, which shows that these factors are unimportant for both ethnic minority and white cyclists (with even lower importance for ethnic minorities). However, in Model B, *cycleways* missed the significance threshold by a narrow margin, and the difference between the global and the local regression models was useful in recognising the regional variation of this factor. On the global scale, the lack of influence of *cycleways* in the global model is consistent with findings reported by Grudging et al. (2018) [35] through regression modelling of the census data. However, findings at the local scale identified through the application of GWR suggest that the impact of infrastructure-based intervention is felt strongly in particular locations [44], reflecting local preference, especially in East England, towards bike paths, which can separate the cyclists safely from traffic. This aligns with reports on certain types of cycleways increasing people's propensity to cycle [37]. It would be worth investigating what types of cycleway design appeal to cyclists and whether it is region specific or affected by an underlying local condition. In fact, areas showing a positive relationship between cycleways and cycling rates are largely rural areas that attract tourists, and the cycleways may be catering to recreational demand rather than commuting purposes. Elsewhere, many LADs returned a negative relationship between cycleways and the ethnic minority and the white cycling rates. Parkin et al. (2007) [22] noted that the trend in *car ownership* has a significant effect on cycle use and offsets the positive effect of the provision of off-road routes for cycle traffic but only in districts that are flat or moderately hilly. Interpretation of the outcomes with respect to multiple factors including the *level of income* (which is linked to *car ownership*) and *cycle infrastructure (cycleway)* is challenging and requires further investigation to confirm whether the provision of infrastructure alone is effective in engendering higher levels of cycling.

7. Conclusions

This study investigated the propensity of cycle-to-work rates across England and their regional variance for the ethnic minority and the white populations. It showed that cycle rates are affected by physical and social factors and that the local context adds different weights to these factors in different areas. In general, the study found that ethnic minority cyclists are slightly less sensitive to many factors than white cyclists are, and this tendency was reflected in the regression coefficients of the two global models. Some variables had little impact on both the ethnic minority and the white populations; for instance, *cyclist casualties* were expected to directly affect *concerns over safety* and serve as a barrier to cycling, yet no significant reduction of cyclists was found. Similarly, *car ownership* was assumed to have a direct impact on the mode of transport but had little impact on cycling rates. Instead, it was the level of income that affected the cycling rate, and this is despite the implied association between income and car ownership. This study also found a reasonable amount of overlap between the ethnic minority and the white models to explain low cycle rates. In fact, there was no specific variable that significantly affected the ethnic minority cyclists only, and the main difference between the two models was in the order of the explanatory variables. These are subtle differences and require close and careful attention to correctly understand the ways in which they affect either model at specific locations.

As discussed in the literature review, some studies have argued the relevance of the sociocultural context in the underrepresentation of ethnic minority cyclists. A qualitative interpretation of the cultural factors in local areas would help understand the process of decision-making and why people choose whether or not to cycle in their respective local areas. The literature suggests that attitudes and culture affect people's transport decisions and that a culture where cycling and cyclists are viewed positively can encourage cycling [45]. These qualitative inquiries were not pursued in this study, but their impact on ethnic minority cycling rates could prove useful in understanding the background behind some of the tendencies found in this study.

Finally, this study was constrained by the lack of data on the ethnicity of people cycling at a fine spatial granularity. As shown in Table 1, many datasets contain no data on ethnicity, and finding a relevant dataset would be a key to the next stage of investigation on whether there is unequal access to this form of transport. A more granular analysis would almost certainly reveal variation within the ethnic minority category and might also account for some of the spatial variation found in the local models. Indeed, it is well-documented that different groups of ethnic minorities have different travel patterns and travel for different reasons; thus, it is likely that the barriers to cycling are also different for different groups of the ethnic minority population or between ethnic minority males and females. The publication of much more granulated data is awaited. Further analysis with new data (the 2021 UK Census when it is published) is another future aspiration. Still, this study marks the first step towards understanding the contributing factors for the uptake of cycling and the difference and similarity between the ethnic minority and the white populations and offers insights into the regional variation of the factors that affect these populations.

Author Contributions: Conceptualization, A.K.; methodology, A.K. and S.S.; validation, A.K., S.S. and N.S.; formal analysis, A.K.; writing—original draft preparation, A.K., S.S. and N.S.; writing—review and editing, N.S. and S.S.; visualization, A.K.; supervision, S.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Datasets used in this study were obtained from the following websites. All data are publicly accessible. **The ethnic minority cycle-to-work rate, the white cycle-to-work rate, school-age children, ethnic minority population, population density, commute under 5 km** and **car ownership 2011**. Source: Office for National Statistics- 2011 census. Available at: https://www.nomisweb.co.uk/sources/census_2011 (accessed on 1 October 2021). **Hilliness 2011.** Source: Lovelace et al. (2017) [46]. Available under the Creative Commons License 4.0. **Casualties 2011.** Source: Department for Transport. Available at: https://data.gov.uk/dataset/cb7ae6f0-4be6-4935-9277-47e5ce24a11f/road-safety-data (accessed on 1 October 2021). Accessed using stats19 r package created by Lovelace et al. (2019) [47]. **Average Income Score 2015.** Source: Contains public sector information licensed under the Open Government Licence v3.0. Available at: https://www.gov.uk/government/statistics/english-indices-of-deprivation-2015 (accessed on 1 October 2021). **20mph limits Source** and **Cycleways Source:** © OpenStreetMap contributors Licence v.3.0. License under the Open Data Commons License. **LAD Geometries 2011,** Source: Office for National Statistics licensed under the Open Government Licence v.3.0 Available at: https://statistics.ukdataservice.ac.uk/dataset/2011-census-geography-boundaries-local-authorities (accessed on 1 October 2021).

Conflicts of Interest: The authors declare no conflict of interest.

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