safety

Article

Identifying and Assessing Perceived Cycling Safety Components

Michelle Duren [1,*], Bryce Corrigan [2], Ryan David Kennedy [1], Keshia M. Pollack Porter [1] and Johnathon Ehsani [1]

[1] Johns Hopkins Bloomberg School of Public Health, 615 N Wolfe Street, Baltimore, MD 21205, USA
[2] Johns Hopkins Krieger School of Arts and Sciences, 3400 N Charles Street, Baltimore, MD 21218, USA
* Correspondence: mduren3@jhmi.edu

Abstract: Perceived safety is recognized throughout the mode choice literature as a key barrier to cycling, yet its constructs are poorly understood. Although commonly understood to relate to crash and injury risk and sometimes vulnerability to crime, health impact assessments identify numerous other pathways through which cycling can negatively impact health. This study leverages a nationally representative survey of U.S. adults in 2022 to assess a set of eleven factors as potential components of perceived cycling safety. We use principal component analysis to identify components of perceived cycling safety and then employ principal component regression to assess these components in relation to predicting unsafe cycling perception. We identify five key dimensions of perceived safety. Specifically, we found that perceived bicycling safety can be encompassed in the following components: (1) contaminant exposure, (2) injurious collision risk, (3) street conditions, (4) weather conditions, and (5) crime risk. In evaluating each identified component, we found that injurious collision risk and street conditions were the most predictive of considering cycling as unsafe. We further develop an understanding of how differences in cycling behavior, such as using cycling for commuting purposes, may contribute to differences in how cycling safety components coalesce into perceived safety.

Keywords: perceived safety; principal component analysis; cycling; public health; policy

Citation: Duren, M.; Corrigan, B.; Kennedy, R.D.; Pollack Porter, K.M.; Ehsani, J. Identifying and Assessing Perceived Cycling Safety Components. *Safety* **2023**, *9*, 75. https://doi.org/10.3390/safety9040075

Academic Editor: Raphael Grzebieta

Received: 18 September 2023
Revised: 17 October 2023
Accepted: 19 October 2023
Published: 1 November 2023

1. Introduction

Cycling is a mode of active transportation with significant public health implications, both positive and negative [1]. During periods of heightened infectious disease risk, such as during the COVID-19 pandemic, cycling offers a way to travel without requiring people to be in close physical spaces for extended periods of time, such as on public transport [2,3]. A shift to active transportation can improve individual health through increased physical activity; it can also on aggregate improve air quality and reduce emissions contributing to climate change [4]. Cycling, however, also presents safety and other health concerns. For example, people who use bicycles for transportation are known to increase their exposure to harmful pollutants such as ozone and particulate matter [5]. Deaths and injuries from cycling also occur and have increased in the U.S. in recent years. U.S. cyclist fatalities increased by 16 percent from 846 deaths in 2019 to an estimated 985 deaths in 2021 [6,7].

Perceived safety is consistently recognized as a key determinant for cycling. Specifically, the literature identifies perceived safety as a key barrier regardless of the travel purpose, [8] perceived benefits of cycling [9], or individual characteristics such as sex [10]. Despite its general importance, there are notable differences in how groups perceive bicycle safety, which can impact who chooses to cycle. For example, one study reported that safety due to traffic was the most significant barrier to cycling for 77 percent of non-riding women, compared to only 54 percent of non-riding men [11]. Such findings point to the importance of developing a better understanding of perceived cycling safety to inform policies and programs designed to promote cycling.

Measuring perceived safety with respect to cycling is challenging given its multiple dimensions. Although there are many risks from cycling, how (and whether) such risks factor into individuals' perceived cycling safety is poorly understood. In some studies, perceived safety has been defined as the risk of being involved or injured in a crash [12–14], while other studies measure the risk of being a victim of crime while cycling [15–17]. Moreover, many studies do not define perceived safety, leaving its definition open to interpretation [18,19]. For example, one study comparing objective injury risk with cyclists' self-assessments of safety acknowledged that some of the divergence between the two measures could be due to other safety-related factors influencing individuals' responses [20]. Health impact assessments and related research have characterized the pathways through which transportation impacts health—ranging from air pollution to ultraviolet radiation exposure [21–24]. No study to date has considered whether—if at all—the full range of potential health effects factor into the public's perception of cycling safety.

The research that follows aims to develop an improved understanding of the factors underlying individuals' perceived safety of cycling using data from a national online survey. It identifies key components of perceived safety from a comprehensive set of health impacts of cycling using principle component analysis. It then evaluates the explanatory power of each identified component for whether an individual considers cycling an unsafe activity using logistic regression models. This research fills an important gap in the knowledge by assessing an expanded set of health effects for their potential to influence bicycle safety perceptions using a nationally representative sample of U.S. adults.

2. Data and Methods

2.1. Sample

The Johns Hopkins Bloomberg School of Public Health Institutional Review Board approved the protocol and deemed this study to be exempt from a human subject review on 20 December 2021, as the research team was receiving de-identified data (IRB 15673). Study participants were U.S. adults (aged 18 years and older) recruited from the AmeriSpeak Panel, a probability-based sample managed by NORC at the University of Chicago. Informed consent was obtained from all participants. The survey was fielded between 4 May and 10 June 2022, in English and Spanish. Survey invitations were emailed to an initial sample of 21,315 adults from across the U.S. This was followed up with four reminder emails. The final sample was 6735 individuals aged 18 and older.

2.2. Measures

Several aspects of perceived safety were assessed. First, an overall assessment of cycling safety was obtained by asking respondents to rate their perceived safety for cycling using a five-point scale ranging from very safe to very unsafe. Cycling safety was purposefully left undefined for survey respondents in order to assess the contribution of a set of factors on how respondents conceptualized perceived safety. Later in the survey, respondents were asked to rate the importance of this set of factors to their overall sense of cycling safety using a five-point scale ranging from very important to very unimportant. These factors were obtained from a review of health impact assessments and related research, which characterized the potential health effects of cycling [21–24]; these factors are listed and defined in Table 1.

Additional measures were included as covariates and to measure bicycling behavior. Covariates were sex (measured as male or female), age, and a binary variable to indicate whether the respondent resided in a metropolitan area (as defined by the U.S. Office of Management and Budget). Bicycling behavior was included as an explanatory variable for perceived safety. Bicycling behavior was ascertained through two survey questions. The first question asked respondents to describe their bicycling behavior; respondents who indicated bicycling at least a few times each year were classified as cyclists with all others classified as non-cyclists. For respondents classified as cyclists, they were further asked what they use a bicycle for and were given four response options (recreational purposes, to get from place to place, to access public transport, and to commute).

Table 1. Definition of factors related to perceived safety.

Factor	Definition
1. Crash risk	Risk of being involved in a crash
2. Injury risk	Risk of being seriously injured in a crash
3. Crime	Vulnerability to being mugged or assaulted
4. Air pollution	Exposure to air pollution (such as from vehicle exhausts)
5. Noise pollution	Exposure to noise pollution (such as traffic noise)
6. Temperature	Exposure to extreme temperature (including hot or cold conditions)
7. Infection	Exposure to infectious illness
8. UV	Exposure to ultraviolet radiation (UV) from the sun (e.g., resulting in sunburns)
9. Precipitation	Exposure to precipitation (including rainy or snowy conditions)
10. Poor surfaces	Unsafe road surfaces (such as glass or debris or potholes on route)
11. Poor lighting	Lack of lighting along route after dark

From these survey responses on cycling purpose, respondents were grouped into the following four categories: (1) non-cyclists (those who do not currently cycle at least a few times each year), (2) recreational (those who identified cycling for recreation), (3) commuters (those who identified cycling to get to work or school), and (4) functional (those who identified cycling to access public transport or other places of interest, such as a grocery store). Although those who cycle to commute may be considered a type of functional cyclist, since they are using cycling as a means of transportation, we isolated these respondents into a separate category given prior research on the uniqueness of bike commuters [25,26]. Previous studies have identified similar groupings of cyclists, such as Fraboni et al. (2021) who identified three categories including those who cycle exclusively for leisure/training (termed "Leisure-time Cyclists"), those who prefer cycling to driving and cycle for many purposes (termed "Resolute Cyclists"), and those who cycle for personal business or leisure but not for commuting (termed "Convenience Cyclists") [27]. The groupings we selected closely align with these cycling categories but with slight definitional differences, given the survey items from which our categories were derived. Table 2 includes detail on the relevant survey items used to categorize cyclists and their corresponding percentage of the total sample. All cyclists in the survey identified as cycling for at least one of the four purposes (recreational; functional—two types; or commuter). Since the analysis considers only one comparison within a given model (e.g., those who cycle for recreation as compared to those who cycle for other purposes), the categories were not made to be mutually exclusive.

Table 2. Cyclist categories and corresponding weighted percentages of respondents.

Survey Response Option	Category	Percent of Respondents
For recreational purposes (for example, exercising)	Recreational	32.7 percent
To get from place to place (for example, the grocery store)	Functional	7.6 percent
To access public transport (for example, to reach a bus stop)		
To commute to work or school	Commuter	3.0 percent

Note: Respondents may fall into multiple categories; the table does not include respondents who do not use a bicycle on at least an occasional basis (i.e., a few times each year)—64.3% of respondents classified as non-cyclists and are not included in the table.

3. Analysis

The data analysis was conducted in three stages. In the first stage, descriptive statistics were estimated from the survey to provide an introductory understanding of perceived safety in relation to bicycling behavior and perceived safety factors. Chi-square tests were used to determine the significance of perceived safety differences between cyclists and non-cyclists. The weighted mean and standard error were estimated for each perceived safety factor.

Principal components analysis (PCA) was used as a dimension reduction technique to identify a smaller subset of representative variables accounting for a large share of the variation in the original set. More specifically, this technique identifies a sequence of linear combinations in the data that have maximal variance and are mutually uncorrelated [28]. The PCA provided information on how the eleven factors outlined in Table 1 could be effectively summarized using a reduced set of dimensions. The number of components was selected based on a review of a scree plot, where a point is identified in the plot at which the proportion of variance explained by a subsequent component becomes marginal [28]. Factor loadings greater or equal to $|0.6|$ were used as cut-off values to define components [29]. The Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy justified the use of PCA for the current sample, with a value of 0.87 [30]. Bartlett's sphericity test further confirmed the data's suitability for PCA ($X^2 = 35074.38$, $p < 0.001$) [31].

In the last analysis stage, principal component regression (PCR) examined the association between each dimension and the outcome of interest (in this case, whether respondents rate cycling as unsafe). Specifically, odds ratios from the PCR were used to examine the directionality and relative magnitude of each component on the outcome. These analyses incorporated interactions for cycling purposes to assess differences in bicycle safety perceptions by cycling purposes (recreation, to commute to work/school, etc.). In addition, the average predicted probability of perceiving cycling as unsafe was calculated for a quantile shift in each component. For all analyses, R version 4.0.3 [32] as well as the "radiant" [33], "sjPlot" [34], and "ggplot2" [35] packages were used.

3.1. Results: Descriptive Statistics

Sample

The sample included 6735 adults and was weighted to reflect the U.S. adult population, according to the March 2022 U.S. Census Bureau's Current Population Survey. Survey weighting accounted for survey nonresponse through a weighting class method, where the weighting classes are defined by age, race/ethnicity, sex, and education; a raking ratio adjustment is further applied to the nonresponse adjusted base weights to align the sample with known population benchmarks. Table 3 presents the study sample statistics weighted to reflect the U.S. adult population.

Overall, over half of the sample responded that they consider cycling to be moderately safe or neither safe nor unsafe (i.e., neutral). Among both cyclists and non-cyclists, the moderately safe category captured the largest portion of respondents (39.9 and 34.2 percent, respectively). This is a surprising finding, with past research finding high rates of an unsafe cycling perception and identifying cycling as being considered less safe than driving, which was a significant barrier to greater cycling uptake [36–38]. Among those in our sample, cyclists are more likely to consider cycling as safe than those who do not cycle (p-value < 0.01), while non-cyclists are more likely to consider cycling as very unsafe (p-value = 0.002) or be neutral (p-value = 0.04) on this question. Chi-square tests indicate significant safety rating differences between cyclists and non-cyclists for all comparisons except the moderately unsafe rating (p-value < 0.05).

Table 4 presents the weighted mean corresponding to each perceived safety factor measured in the survey. Each factor was measured using a five-point scale with 1 indicating the factor was very unimportant to the respondent's overall sense of safety while bicycling, 5.0 indicating the factor was very important, and 3.0 indicating neutrality. The mean value for all respondents ranged from 1.5 for infection risk to 3.0 for injury risk. Each factor ranged from 1 to 5.

Table 3. Weighted sample statistics.

Sample Characteristic	Total Sample (N = 6735)
Sex	
Male	3265 (48.5%)
Female	3470 (51.5%)
Race	
White, non-Hispanic	4186 (62.2%)
Black, non-Hispanic	809 (12.0%)
Asian, non-Hispanic	313 (4.6%)
Hispanic	1152 (17.1%)
Other	274 (4.0%)
Urbanicity	
Urban	1779 (26.4%)
Suburban	3195 (47.4%)
Rural	1729 (25.7%)
Household Income	
Less than $30,000	1799 (26.7%)
$30,000 to $59,999	1728 (25.7%)
$60,000 to $99,999	1559 (23.1%)
$100,000 or more	1649 (24.5%)
Age Group	
18–29	1315 (19.5%)
30–44	1765 (26.2%)
45–59	1606 (23.9)
$\geq$60	2048 (30.4%)
Cycling Status	
Cyclist	2403 (35.7%)
Non-cyclist	4332 (64.3%)

Table 4. Factors related to perceived safety, weighted mean, and standard error.

Factor	Mean [Standard Error]
1. Crash risk	2.9 [0.20]
2. Injury risk	3.0 [0.22]
3. Crime	2.2 [0.20]
4. Air pollution	1.9 [0.20]
5. Noise pollution	1.8 [0.20]
6. Temperature	2.7 [0.16]
7. Infection	1.5 [0.19]
8. UV	2.3 [0.19]
9. Precipitation	2.5 [0.19]
10. Poor surfaces	2.7 [0.20]
11. Poor lighting	2.6 [0.21]

3.2. Results: Principal Component Analysis

The PCA identified five components from the eleven perceived cycling safety factors considered. After five components, the decreases in the mean square error of prediction and increases in the explained variance were negligible (see Figure 1).

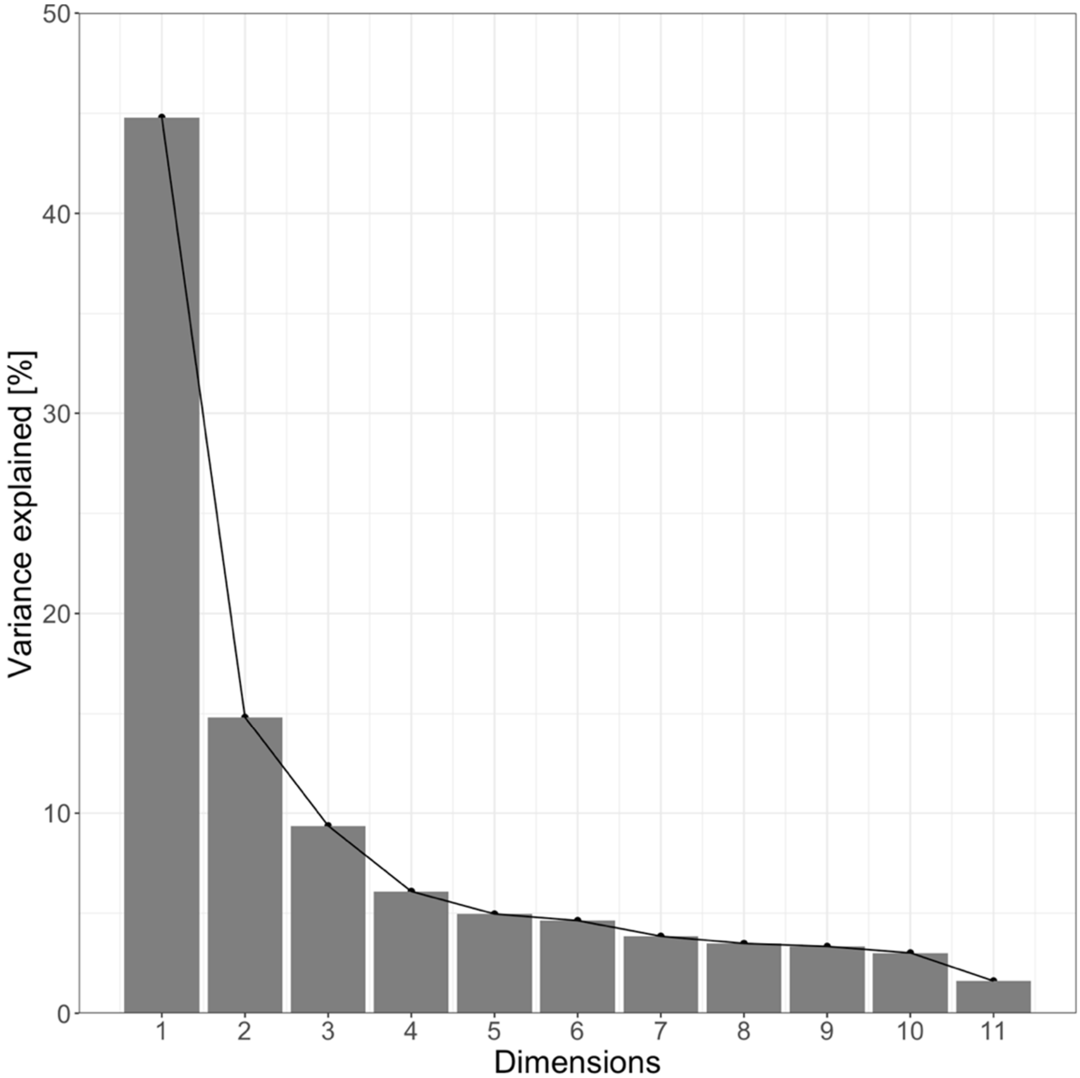

Figure 1. Scree plot showing the variance explained by each component.

The loadings for each of the five components are presented in Table 4. Collectively, these components account for 80 percent of the variation among responses for the eleven safety factors. Each component had a standard deviation of 1. The five components can accurately predict unsafe cycling ratings 74 percent of the time based on a cross-validated mean test classification error rate. From the principal component loadings presented in Table 5, we can characterize the five components of safety-related factors in the following manner:

- Component 1—contaminant exposure—exposure to air pollution, noise pollution, infection risk, and UV radiation are significant factors.
- Component 2—injurious collision risk—crash and injury risk are significant factors.
- Component 3—street conditions—poor road surfaces and poor lighting factor most highly.
- Component 4—weather conditions—temperature and precipitation are the predominant factors.
- Component 5—crime risk—crime risk is the predominant factor for the last component.

Table 5. Principal component loadings.

Factors	Components				
	1	2	3	4	5
Noise pollution	**0.86**	0.06	0.14	0.18	0.05
Air pollution	**0.80**	0.23	0.16	0.03	0.15
Infection	**0.70**	−0.04	0.11	0.18	0.44
UV	**0.63**	0.15	0.06	0.52	0.10
Crash risk	0.12	**0.90**	0.22	0.12	0.13
Injury risk	0.11	**0.89**	0.25	0.13	0.12
Poor surfaces	0.22	0.30	**0.80**	0.09	0.02
Poor lighting	0.11	0.23	**0.79**	0.17	0.20
Temperature	0.26	0.18	0.18	**0.83**	0.11
Precipitation	0.07	0.06	0.59	**0.60**	0.07
Crime	0.33	0.27	0.18	0.13	**0.84**
% of variance	44.8	14.8	9.4	6.1	5.0

Note: Factor loadings $\geq |0.6|$ are indicated with a bold typeface.

3.3. Results: Principal Component Regression

Table 6 presents logistic regression models for the five principal components identified through the PCA described in the previous section. The model coefficients adjust for individual-level factors recognized as being associated with perceived safety; these factors include whether an individual cycles, their age, sex, and location (whether a respondent lives in a metropolitan area). Four models were used to identify the association between the aforementioned predictors and a respondents' perception that cycling is unsafe. The first model uses the predictors as regular regression coefficients, while the remaining models incorporate interaction terms for each of the principal components—one interacting non-cycling status with each component and two interacting cycling purposes with each component (one focused on recreational cycling and another on bike commuting).

The first model identifies two components as significant predictors of unsafe cycling perception. This suggests that individuals who are concerned with cycling risk (namely, crash and injury risk) have increased odds of considering cycling as unsafe compared with those attributing less importance to cycling risk. Second, those concerned with street conditions (e.g., pavement quality) have increased odds of considering cycling as unsafe, but the association is not as strong as for the injurious collision component. In addition to the safety components, we find that an individual's sex, whether they reside in a metropolitan area, and whether they cycle are significant factors for predicting perceived cycling safety.

The second model incorporates an interaction term, which enables us to compare non-cyclists in relation to cyclists across the five safety components. In this model reflecting the effects among non-cyclists, the same components as the prior model are significant, as well as the component representing weather exposure; the weather component is also the only interaction term significant for predicting unsafe cycling perception. The weather interaction term suggests that compared to cyclists, non-cyclists perceive safety in a way that aligns more closely with their concerns about weather conditions. Figure 2 presents the average prediction of unsafe cycling perceptions. As the importance of weather conditions increases, the predicted probability of perceiving cycling as unsafe increases for non-cyclists. In contrast, as the importance of weather conditions increases, cyclists have a lower predicted probability of perceiving cycling as unsafe. More generally, the weather interaction term suggests that non-cyclists are more intimidated by adverse weather conditions than cyclists.

Table 6. Logistic regression models—unsafe cycling perception.

Variable	Model 1 (Base)	Model 2 (Non-Cyclist Interactions)	Model 3 (Cycling Purpose Interactions—Recreational)	Model 4 (Cycling Purpose Interactions—Commuting)
Contaminant component	1.03	1.01	1.03	1.00
Injurious collision component	2.38 ***	2.47 ***	1.92 ***	2.54 ***
Street conditions component	1.31 ***	1.37 ***	1.13	1.39 ***
Weather component	0.98	0.91 *	0.85	0.92
Crime component	0.94	0.96	0.92	0.98
Sex	1.22 ***	1.22 **	1.24 *	1.23
Age	1.00	1.00	1.01 *	1.01 *
Metro area	1.36 ***	1.36 ***	1.77 ***	1.76 ***
Non-cyclist	1.31 ***	1.35 ***	--	--
Cyclist purpose [recreation/commute]	--	--	0.80	1.20
Contaminant interaction	--	1.03	0.96	0.98
Injurious collision interaction	--	0.95	1.42 *	0.73
Street conditions interaction	--	0.93	1.30 *	0.79
Weather interaction	--	1.14 *	1.11	0.92
Crime interaction	--	0.97	1.08	0.91

Significance indicators: '***' 0.001 '**' 0.01 '*' 0.05. Note: odds ratios are presented in the table. Models 1 and 2 used the full sample (6735 participants). Models 3 and 4 were limited to cyclists (2403 participants). In Model 3, 2204 participants identified as cycling for recreational purposes. In Model 4, 203 participants identified as cycling to commute to work or school. The interaction terms in Models 3 and 4 compared recreational and bike commuters to all other cyclists, respectively.

The third model incorporates a comparison between those who cycle for recreational purposes (e.g., exercising) and those who cycle for functional purposes (e.g., to access public transport). For the purposes of this comparison, the model is limited to cyclists (i.e., those who reported bicycling at least on an occasional basis). The Model 3 interaction terms presented in Table 5 display differences for recreational cyclists in relation to functional cyclists. In this model, the only statistically significant safety component is the injurious collision risk component, suggesting that respondents ascribing greater importance to cycling risk have increased odds of considering cycling unsafe. In terms of the interactions, both the injurious collision risk and the street conditions interaction terms were statistically significant. These findings indicate that those who cycle recreationally have an increased odds compared to functional cyclists to consider cycling unsafe as they place a greater importance on cycling risks and street conditions. As shown in Figure 3, for those considering collision risk as unimportant, few consider cycling as unsafe, and recreational cyclists are less likely than other cyclists to consider cycling as unsafe. In contrast to Figure 2, in Figure 3, the two comparison groups exhibit the same general trend with all cyclists having a greater probability of considering cycling as unsafe as the collision component increases in importance. However, as the collision component becomes more important, recreational cyclists have a greater probability of considering cycling as unsafe compared to other cyclists.

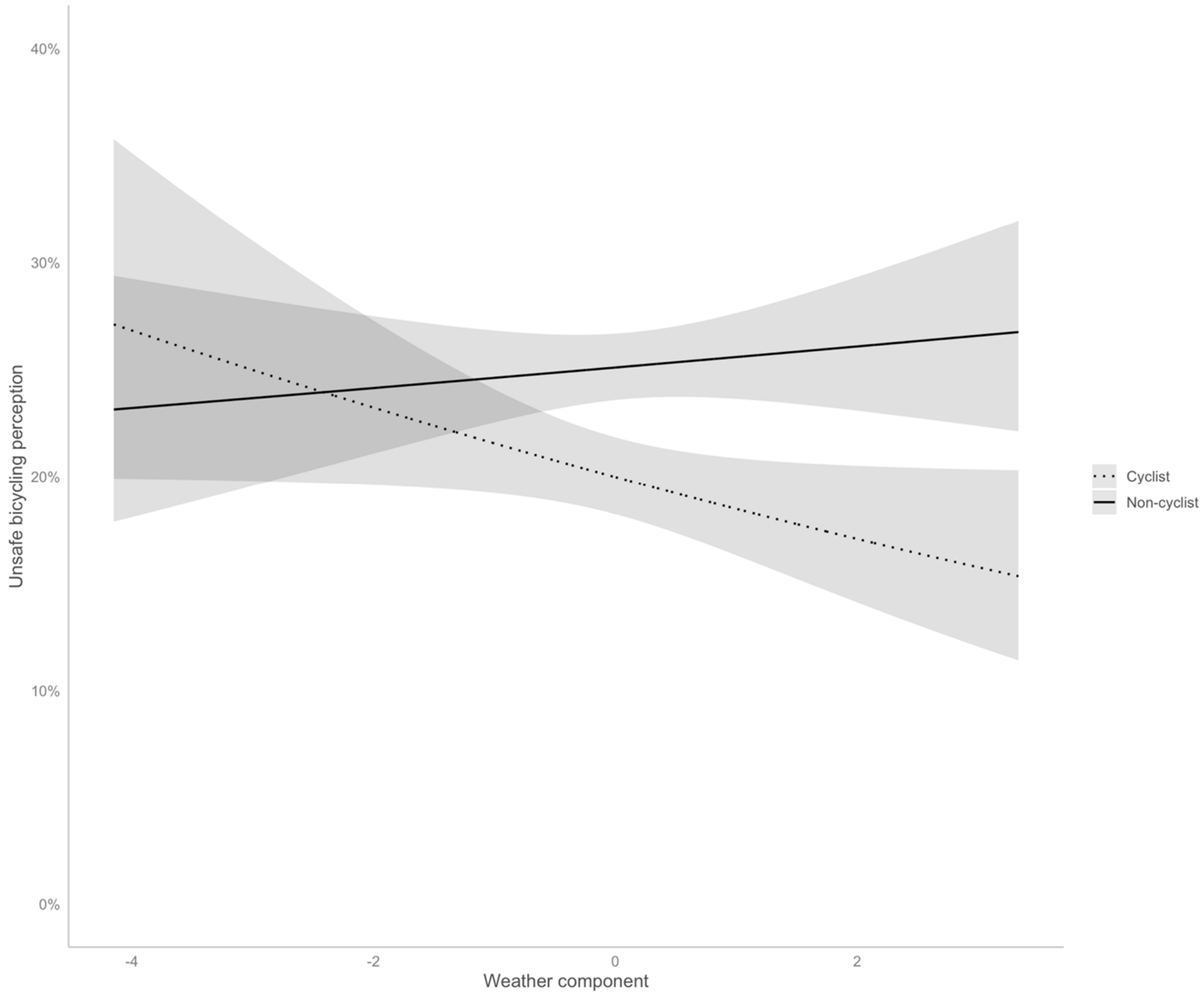

Figure 2. Average predictions of unsafe cycling perception for cyclists and non−cyclists according to weather component value.

The final model incorporates a comparison between those who cycle for commuting purposes and those who cycle but not to commute to work or school. As with the previous models, this analysis includes a subset of the survey respondents who identified cycling at least on an occasional basis. Since model two provided a comparison between cyclists and non-cyclists, models three and four are included to isolate differences between cyclists. For this model comparing bike commuters to other cyclists, the base variable findings are largely the same, with injurious collision risk and street conditions being the key safety components determining unsafe perceptions of cycling. In contrast to the previous two models, there were no statistically significant interaction terms; this could be due, in part, to a smaller sample size of bike commuters in contrast to other cyclist categories. Despite this limitation, the directionality of the estimated odds ratios for each interaction term provides unique insight into this small faction of cyclists. All five interaction terms were negative, suggesting that bike commuters place less importance on each safety component compared to other cyclists, with the possible exception of the contaminant component, which showed a nearly null effect.

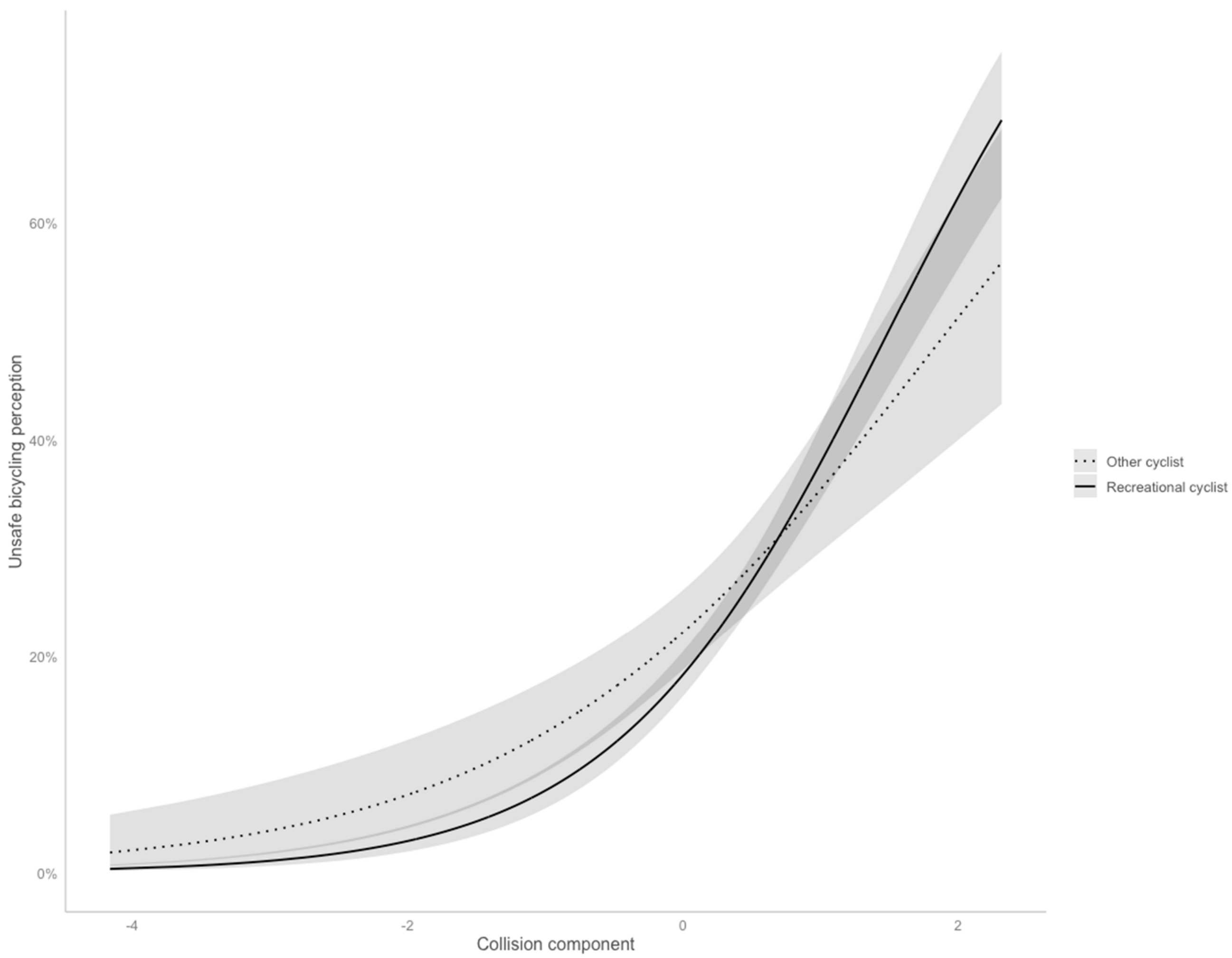

Figure 3. Average predictions of unsafe cycling perception for recreational and other cyclists according to collision component value.

Table 7 presents the change in average predicted probability of unsafe bicycling perception as respondents' shift from a moderate concern to a moderate unconcern for each safety component. The component with the greatest change in average predicted probability of perceiving cycling as unsafe was injurious collision with the contaminant component having the smallest average predicted effect. Specifically, respondents changing from moderate concern for injurious collision to moderate unconcern had a 21.6 percent reduced average predicted probability of perceiving cycling to be an unsafe activity. The components representing injurious collision, street conditions, and contaminants were found to lower the probability of perceiving cycling as unsafe moving from a moderate concern to a moderate unconcern. The components representing weather and crime worked in the opposite direction; as these components shifted to becoming less of a concern, the probability of perceiving cycling as unsafe increased, although the percent difference was small.

Table 7. Average predicted probability difference for moderate concern and moderate unconcern, by safety component.

Component	Average Probability—Moderate Concern [95% Confidence Interval]	Average Probability—Moderate Unconcern [95% Confidence Interval]	Percent Difference
Contaminant component	0.2701 [0.2666–0.2737]	0.2661 [0.2626–0.2697]	0.4
Injurious collision component	0.3702 [0.3682–0.3721]	0.1538 [0.1528–0.1549]	21.6
Street conditions component	0.2995 [0.2958–0.3032]	0.2352 [0.232–0.2383]	6.4
Weather component	0.2657 [0.2622–0.2692]	0.2706 [0.267–0.2741]	0.5
Crime component	0.2614 [0.2579–0.2648]	0.2757 [0.2722–0.2793]	1.4

Note: Average differences in predicted probabilities of unsafe bicycling perceptions between moderate concern and moderate unconcern, defined as the third and first quartile of the concern component.

4. Discussion

This research aimed to identify underlying components of perceived safety and assess them in relation to whether an individual considers cycling as unsafe. This research identified five key dimensions of perceived safety: contaminant exposure, injurious collision risk, street conditions, weather conditions, and crime risk. Of these classifications, factors falling within the injurious collision risk and street conditions factors contain the items most predictive of whether someone considers cycling as unsafe. Additionally, whether someone cycles and for what purpose are key attributes contributing to differences in how cycling safety components coalesce into perceived safety.

There are policy implications from this work. One insight is that there are a significant portion of Americans who are neutral on the question of cycling safety. To the extent that perceived safety influences one's decision to cycle, there is a significant portion who may be persuaded to consider cycling as safe. Only a minor portion of respondents had strong negative views on cycling safety [7% considered cycling as very unsafe]. Furthermore, one key factor important to cycling safety for non-cyclists and all types of cyclists was the street conditions. Implementing local policies such as Complete Street Ordinances, which improve the quality of street and bike lane surfaces could impact perceived safety and thereby increase the likelihood of a shift towards cycling, even for those who feel less strongly or neutral regarding perceived safety. For example, establishing a Department of Public Works policy to maintain bike lanes and routinely clean away debris in bike lanes could be one strategy to improve street conditions for cyclists.

Several factors for which evidence of adverse health effects is accumulating did not appear to significantly influence perceived cycling safety in our sample. Most notably, contaminant exposure—including air pollution—was not a significant predictor of perceiving cycling as unsafe despite the negative health effects of air pollution becoming increasingly understood [39] and with climate change expected to worsen air quality over time [40]. At the same time, contaminant exposure factors were identified as a distinct component of perceived safety and accounted for the largest share of variation in perceived safety responses. Our findings suggest that education may be needed to both inform cyclists of the pollution risks associated with cycling, and to develop strategies to reduce their pollution exposure such as by cycling on less congested streets.

Lastly, our findings specific to bike commuters suggest that those choosing to use cycling as a means to travel to work and school are a unique subset of cyclists. These cyclists appear generally less concerned with the various components of safety in comparison to other cyclists and non-cyclists. This finding suggests that greater experience with cycling leads to reduced safety concerns given the increased frequency with which bike commuters cycle through mechanisms such as increased self-efficacy (i.e., confidence in one's cycling ability) or decreased perceived susceptibility to adverse outcomes. Alternatively, it could suggest that those opting to bike commute are less risk adverse compared to others, which impacts their safety perceptions surrounding cycling. Further, perceived safety may be less influential as a behavioral determinant when there is no viable alternative, for instance, if cyclists do not have access to a vehicle or live in a community with reliable public transportation. Past work has found that lower perceived neighborhood safety was not a barrier for children walking to school when no accessible alternative existed [41]. More research is needed to develop a better understanding of bike commuters, which may require purposeful sampling techniques to over-sample this small subset of the broader cyclist population. Further research could also employ qualitative techniques such as the use of focus groups to explain our findings.

Our PCR approach segmented survey respondents based on one variable—the purposes for which respondents identified cycling. Alternative cyclist typologies exist in the literature such as the typology developed by Roger Geller (2006), which incorporates variables such as comfort level for bicycling on different types of facilities [42,43]. It is possible that our findings may have differed if we had used alternative typologies; however, the segmentation we selected employs a straightforward approach that closely aligns with more recent typologies from the literature on this topic [25,27].

Lastly, the focus of this paper is on understanding components of perceived safety—one factor influencing an individual's decision of whether to bicycle [44]. Policymakers seeking to encourage cycling should consider mode choice decisions comprehensively. Such factors have the potential to have an antagonistic or synergistic effect; for example, policy changes that improve perceived safety may worsen the convenience of cycling or could improve its convenience relative to other transportation modes. Strategies to influence cycling should consider the potential impact on other mode choice factors in addition to their effect on perceived safety.

5. Conclusions

As transportation and health officials are considering ways to encourage cycling, our research offers insight from the perspective of perceived safety and contributes to the literature in several ways. First, it identified five key dimensions of perceived safety. Second, it found that two dimensions of perceived safety were significantly associated with whether the respondents considered cycling to be unsafe. By identifying factors that significantly contribute to perceiving cycling as an unsafe activity, our research has identified potential avenues through which the policymakers can reduce safety concerns. Concerns related to crashes and injuries while cycling are an important component of perceived safety. Strategies consistent with a Safe System approach, including investing in cycling infrastructure (particularly those separating cyclists from motorized traffic), speed reductions, or filtering traffic such as with the creation of bicycle boulevards, could also benefit perceived safety [45–47]. In addition, street conditions were identified as a key component of perceived safety and one that was strongly associated with unsafe cycling perceptions. Routine cleaning of the cycling infrastructure to reduce debris on roadways or filling potholes could represent key strategies for improving street conditions for cyclists. Concerns such as crime and air pollution were relatively less predictive of rating cycling as unsafe, suggesting that they play a lesser role in an individual's decision to cycle.

Author Contributions: M.D.: Conceptualization, Methodology, Formal analysis, Software, Visualization, and Writing—Original draft preparation. B.C.: Conceptualization, Methodology, and Writing—Review and Editing. R.D.K.: Conceptualization and Writing—Reviewing and Editing. K.M.P.P.: Conceptualization and Writing—Reviewing and Editing. J.E.: Conceptualization and Writing—Reviewing and Editing. All authors have read and agreed to the published version of the manuscript.

Funding: This work was funded in part by the Center for Advancing Research on Transportation Emissions, Energy and Health, a US Department of Transportation University Transportation Center (grant #69A3551747128), and by a grant from the U.S. Centers for Disease Control and Prevention, National Institute for Occupational Safety and Health to the Johns Hopkins Education and Research Center for Occupational Safety and Health (award number T42 OH0008428).

Institutional Review Board Statement: The study was conducted in accordance with the Declaration of Helsinki. Its protocol was approved by the Institutional Review Board of Johns Hopkins Bloomberg School of Public Health (protocol code FWA #00000287 and date of approval 20 December 2021) and deemed to be exempt from a human subject review as the research team was receiving de-identified data.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data that support the findings of this study are available from the corresponding author, MD, upon reasonable request.

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

References

1. de Hartog, J.J.; Boogaard, H.; Nijland, H.; Hoek, G. Do the Health Benefits of Cycling Outweigh the Risks? *Environ. Health Perspect.* **2010**, *118*, 1109–1116. [CrossRef]
2. Habib, M.A.; Anik, A.H. Impacts of COVID-19 on Transport Modes and Mobility Behavior: Analysis of Public Discourse in Twitter. *Transp. Res. Rec.* **2021**, *2677*, 65–78. [CrossRef]
3. Troko, J.; Myles, P.; Gibson, J.; Hashim, A.; Enstone, J.; Kingdon, S.; Packham, C.; Amin, S.; Hayward, A.; Van-Tam, J.N. Is public Transport a Risk Factor for Acute Respiratory Infection? *BMC Infect. Dis.* **2011**, *11*, 16. [CrossRef]
4. Macmillan, A.; Connor, J.; Witten, K.; Kearns, R.; Rees, D.; Woodward, A. The Societal Costs and Benefits of Commuter Bicycling: Simulating the Effects of Specific Policies Using System Dynamics Modeling. *Environ. Health Perspect.* **2014**, *122*, 335–344. [CrossRef]
5. Panis, L.I.; de Geus, B.; Vandenbulcke, G.; Willems, H.; Degraeuwe, B.; Bleux, N.; Mishra, V.; Thomas, I.; Meeusen, R. Exposure to Particulate Matter in traffic: A Comparison of Cyclists and Car Passengers. *Atmos. Environ.* **2010**, *44*, 2263–2270. [CrossRef]
6. National Center for Statistics and Analysis. *Early Estimates of Motor Vehicle Traffic Fatalities and Fatality Rate by Sub-Categories in 2021*; Crash•Stats Brief Statistical Summary, Report No. DOT HS 813 298; National Highway Traffic Safety Administration: Washington, DC, USA, 2022.
7. National Center for Statistics and Analysis. *Bicyclists and Other Cyclists: 2019 Data*; Traffic Safety Facts, Report No. DOT HS 813 197; National Highway Traffic Safety Administration: Washington, DC, USA, 2021.
8. Greig, R. Qualitative Research into Motivations and Barriers to Cycling. In Proceedings of the Australasian Transport Research Forum (ATRF), 35th, 2012, Perth, Western Australia, Australia. Publication Date: 2012-9. Available online: https://api.semanticscholar.org/CorpusID:106688576 (accessed on 5 November 2022).
9. Gatersleben, B.; Appleton, K.M. Contemplating Cycling to Work: Attitudes and Perceptions in Different Stages of Change. *Transp. Res. Part A Policy Pract.* **2007**, *41*, 302–312. [CrossRef]
10. Heesch, K.C.; Sahlqvist, S.; Garrard, J. Gender Differences in Recreational and Transport Cycling: A Cross-Sectional Mixed-Methods Comparison of Cycling Patterns, Motivators, and Constraints. *Int. J. Behav. Nutr. Phys. Act.* **2012**, *9*, 106. [CrossRef]
11. Fowler, S.L.; Berrigan, D.; Pollack, K.M. Perceived Barriers to Bicycling in an Urban U.S. Environment. *J. Transp. Health* **2017**, *6*, 474–480. [CrossRef]
12. Noland, R.B. Perceived Risk and Modal Choice: Risk Compensation in Transportation Systems. *Accid. Anal. Prev.* **1995**, *27*, 503–521. [CrossRef]
13. Dozza, M.; Schwab, A.L.; Pietrantoni, L.; Cherry, C.R. Editorial: Cycling Safety. *J. Transp. Saf. Secur.* **2020**, *12*, 1–2. [CrossRef]
14. Schepers, P.; Hagenzieker, M.; Methorst, R.; van Wee, B.; Wegman, F. A Conceptual Framework for Road Safety and Mobility Applied to Cycling Safety. *Accid. Anal. Prev.* **2014**, *62*, 331–340. [CrossRef] [PubMed]
15. Rees-Punia, E.; Hathaway, E.D.; Gay, J.L. Crime, Perceived Safety, and Physical Activity: A Meta-Analysis. *Prev. Med.* **2018**, *111*, 307–313. [CrossRef] [PubMed]
16. Ceccato, V. Safety on the Move: Crime and Perceived Safety in Transit Environments. *Secur. J.* **2014**, *27*, 127–131. [CrossRef]
17. Márquez, L.; Soto, J.J. Integrating Perceptions of Safety and Bicycle Theft Risk in the Analysis of Cycling Infrastructure Preferences. *Transp. Res. Part A Policy Pract.* **2021**, *150*, 285–301. [CrossRef]
18. Elvik, R.; Bjørnskau, T. How Accurately Does the Public Perceive differences in Transport Risks? An Exploratory Analysis of Scales Representing Perceived Risk. *Accid. Anal. Prev.* **2005**, *37*, 1005–1011. [CrossRef]
19. Götschi, T.; de Nazelle, A.; Brand, C.; Gerike, R. Towards a Comprehensive Conceptual Framework of Active Travel Behavior: A Review and Synthesis of Published Frameworks. *Curr. Environ. Health Rep.* **2017**, *4*, 286–295. [CrossRef]
20. Winters, M.; Babul, S.; Becker, H.J.E.H.; Brubacher, J.R.; Chipman, M.; Cripton, P.; Cusimano, M.D.; Friedman, S.M.; Harris, M.A.; Hunte, G.; et al. Safe Cycling: How Do Risk Perceptions Compare with Observed Risk? *Can. J. Public Health = Rev. Can. Santé Publique* **2012**, *103* (Suppl. S3), S42–S47. [CrossRef]

21. de Nazelle, A.; Nieuwenhuijsen, M.J.; Antó, J.M.; Brauer, M.; Briggs, D.; Braun-Fahrlander, C.; Cavill, N.; Cooper, A.R.; Desqueyroux, H.; Fruin, S.; et al. Improving Health through Policies that Promote Active Travel: A Review of Evidence to Support Integrated Health Impact Assessment. *Environ. Int.* **2011**, *37*, 766–777. [CrossRef]
22. Nieuwenhuijsen, M.J. Urban and Transport Planning, Environmental Exposures and Health-New Concepts, Methods and Tools to Improve Health in Cities. *Environ. Health A Glob. Access Sci. Source* **2016**, *15* (Suppl. S1), 161–171. [CrossRef]
23. Mueller, N.; Rojas-Rueda, D.; Cole-Hunter, T.; de Nazelle, A.; Dons, E.; Gerike, R.; Götschi, T.; Panis, L.I.; Kahlmeier, S.; Nieuwenhuijsen, M. Health Impact Assessment of Active Transportation: A Systematic Review. *Prev. Med.* **2015**, *76*, 103–114. [CrossRef]
24. Winters, M.; Davidson, G.; Kao, D.; Teschke, K. Motivators and Deterrents of Bicycling: Comparing Influences on Decisions to Ride. *Transportation* **2010**, *38*, 153–168. [CrossRef]
25. Kroesen, M.; Handy, S. The Relation between Bicycle Commuting and Non-Work Cycling: Results from a Mobility Panel. *Transportation* **2014**, *41*, 507–527. [CrossRef]
26. Heinen, E.; van Wee, B.; Maat, K. Commuting by Bicycle: An Overview of the Literature. *Transp. Rev.* **2010**, *30*, 59–96. [CrossRef]
27. Fraboni, F.; Prati, G.; Casu, G.; De Angelis, M.; Pietrantoni, L. A Cluster Analysis of Cyclists in Europe: Common Patterns, Behaviours, and Attitudes. *Transportation* **2022**, *49*, 591–620. [CrossRef]
28. James, G.; Witten, D.; Hastie, T.; Tibshirani, R. *An Introduction to Statistical Learning: With Applications in R*; Springer: New York, NY, USA, 2013.
29. Chin, W.W.; Gopal, A.; Salisbury, W.D. Advancing the Theory of Adaptive Structuration: The Development of a Scale to Measure Faithfulness of Appropriation. *Inf. Syst. Res.* **1997**, *8*, 342–367. [CrossRef]
30. Kaiser, H.F.; Rice, J. Little Jiffy, Mark Iv. *Educ. Psychol. Meas.* **1974**, *34*, 111–117. [CrossRef]
31. Bartlett, M.S. Tests of Significance in Factor Analysis. *Br. J. Stat. Psychol.* **1950**, *3*, 77–85. [CrossRef]
32. R Core Team. *R: A Language and Environment for Statistical Computing*; R Foundation for Statistical Computing: Vienna, Austria, 2021. Available online: https://www.R-project.org/ (accessed on 5 November 2022).
33. Nijs, V. Radiant: Business Analytics Using R and Shiny. 2021. Available online: https://CRAN.R-project.org/package=radiant (accessed on 5 November 2022).
34. Lüdecke, D. sjPlot: Data Visualization for Statistics in Social Science. R Package Version 2.8.12. 2022. Available online: https://CRAN.R-project.org/package=sjPlot (accessed on 5 November 2022).
35. Wickham, H. *ggplot2: Elegant Graphics for Data Analysis*; Springer: New York, NY, USA, 2016.
36. UK Department for Transport (UK DfT). *British Social Attitudes Survey 2013: Public Attitudes Towards Transport*; UK DfT: London, UK, 2014. Available online: https://assets.publishing.service.gov.uk/media/5a74d98ced915d502d6cb7cd/british-social-attitudes-survey-2013.pdf (accessed on 11 October 2023).
37. Lawson, A.R.; Ghosh, B.; Pakrashi, V. Quantifying the Perceived Safety of Cyclists in Dublin. In *Proceedings of the Institution of Civil Engineers—Transport*; 2015; Volume 168, pp. 290–299. [CrossRef]
38. Manton, R.; Rau, H.; Fahy, F.; Sheahan, J.; Clifford, E. Using Mental Mapping to Unpack Perceived Cycling Risk. *Accid. Anal. Prev.* **2016**, *88*, 138–149. [CrossRef]
39. Gelb, J.; Apparicio, P. Cyclists' Exposure to Atmospheric and Noise Pollution: A Systematic Literature Review. *Transp. Rev.* **2021**, *41*, 742–765. [CrossRef]
40. Kinney, P.L. Climate Change, Air Quality, and Human Health. *Am. J. Prev. Med.* **2008**, *35*, 459–467. [CrossRef]
41. Rossen, L.M.; Pollack, K.M.; Curriero, F.C.; Shields, T.M.; Smart, M.J.; Furr-Holden, C.D.M.; Cooley-Strickland, M. Neighborhood Incivilities, Perceived Neighborhood Safety, and Walking to School Among Urban-Dwelling Children. *J. Phys. Act. Health* **2011**, *8*, 262–271. [CrossRef] [PubMed]
42. Geller, R. *Four Types of Cyclists*; Portland Bureau of Transportation: Portland, OR, USA, 2006.
43. Dill, J.; McNeil, N. Revisiting the Four Types of Cyclists: Findings from a National Survey. *Transp. Res. Rec. J. Transp. Res. Board* **2016**, *2587*, 90–99. [CrossRef]
44. Schneider, R.J. Theory of Routine Mode Choice Decisions: An Operational Framework to Increase Sustainable Transportation. *Transp. Policy* **2013**, *25*, 128–137. [CrossRef]
45. Schultheiss, B.; Sanders, R.; Judelman, B.; Boudart, J.; Blackburn, L.; Brookshire, K.; Nordback, K.; Thomas, R.; Van Veen, D.; Embry, M. Literature Review: Resource Guide for Separating Bicyclists from Traffic. FHWA-SA-18-030; 2018. Available online: https://rosap.ntl.bts.gov/view/dot/43672 (accessed on 11 October 2023).
46. Arason, N. Canada and the Safe Systems Approach to Road Safety. *Inst. Transp. Eng. ITE J.* **2019**, *89*, 26–30.
47. Larsson, P.; Tingvall, C. The Safe System Approach—A Road Safety Strategy Based on Human Factors Principles. In *Engineering Psychology and Cognitive Ergonomics. Applications and Services*; Don Harris, D., Ed.; Lecture Notes in Computer Science; Springer: Berlin/Heidelberg, Germany, 2013; pp. 19–28. [CrossRef]