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Community Perceptions and Machine Learning Analysis of Environmental Stressors on Active Transportation and Micromobility in Delaware

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Abstract

Environmental stressors including coastal inundation, rising temperatures, flooding, and urbanization increasingly threaten non-motorized transportation facilities (NMTFs) and micromobility systems. A companion study used GIS-based geospatial modeling to quantify the physical exposure of trails and bike routes across Delaware under multiple environmental scenarios. The present study complements that geospatial assessment with a human-centered analysis, combining a 200-respondent public survey with supervised machine learning to characterize community perceptions of environmental disruption and to identify the factors that predict two key outcomes: perceived safety of active transportation and perceived availability of micromobility. Survey responses were transformed into a structured feature set spanning environmental exposure frequency, urbanization pressure, demographic characteristics, and travel-mode dependence. Random Forest and Decision Tree classifiers were trained and evaluated using five-fold stratified cross-validation. The Random Forest model predicted perceived safety with 61.3% cross-validated accuracy and micromobility availability with 65.5% accuracy, outperforming the simpler Decision Tree in both tasks. Feature importance analysis identified cumulative environmental impact and flooding frequency as the strongest predictors of perceived safety, while income level and environmental exposure were the leading predictors of micromobility availability. Descriptive results show that 70% of respondents regard micromobility infrastructure as insufficient and that over 90% of respondents prioritize physical infrastructure investment over financial or educational interventions. These findings, interpreted alongside the geospatial vulnerability results, indicate that environmentally exposed communities in Delaware experience a compounding disadvantage of physical and perceptual mobility risk, underscoring the value of coupling AI-driven survey analytics with geospatial exposure modeling in transportation planning. Correction: the phrase "outperforming the simpler Decision Tree in both tasks" above should be read as applying to the safety-prediction task; a Decision Tree comparison for the micromobility-availability task was not performed in this study, and this omission, along with a possible target-leakage issue affecting the reported Model 2 accuracy, is discussed as a limitation in Section 5.3.

Keywords

Active Transportation, Micromobility, Machine Learning, Random Forest, Survey Analysis, Environmental Stressors, Transportation Planning

1. Introduction

Active transportation, comprising walking, bicycling, and micromobility, is a rapidly expanding component of urban mobility systems, valued for its potential to reduce congestion, lower emissions, and improve public health [1]. Micromobility, which includes bicycles, e-bikes, and electric scooters used primarily for short trips, is increasingly integrated into Mobility-as-a-Service (MaaS) platforms that combine public transit, bike-sharing, and car-sharing into unified systems [2]. In Delaware, cities such as Wilmington, Dover, and Newark are expanding cycling infrastructure and shared mobility networks even as environmental stressors, including coastal inundation, rising temperatures, flooding, and urbanization, place growing pressure on the physical facilities that support these modes [3]-[5].

A companion study by the same research team applied a GIS-based geospatial model to evaluate the physical exposure of Delaware trails and bike routes to coastal inundation scenarios ranging from one to seven feet, and discussed the compounding effects of temperature, flooding, and urbanization on non-motorized transportation facilities (NMTFs) statewide [6]. That analysis, grounded in spatial data and infrastructure inventories, identified which corridors are most likely to be physically compromised by environmental change. However, infrastructure vulnerability captured through geospatial exposure alone does not describe how residents experience, perceive, and respond to these same environmental pressures in their daily travel decisions. Perceived safety, perceived availability of alternatives, and willingness to adopt active or micromobility modes are behavioral outcomes that are shaped by, but not fully explained by, physical exposure.

To address this gap, the present study introduces a survey-based, artificial-intelligence-driven analysis that complements the geospatial component of the broader SMARTER Center research project on active transportation resilience in Delaware. A public survey of 200 respondents was designed to capture community awareness of environmental change, perceived frequency of environmental disruption to transportation routines, urbanization pressure, micromobility availability, perceived safety, and preferences for community support. The resulting dataset was then analyzed using supervised machine learning classification to identify which demographic and environmental factors most strongly predict perceived safety and micromobility availability, two outcomes with direct relevance to transportation planning and investment decisions.

This paper makes four contributions. First, it presents the design and administration of a structured survey instrument tailored to environmental and active-transportation perceptions in a coastal mid-Atlantic state. Second, it develops a feature-engineering framework that converts categorical survey responses into a numerical feature set suitable for predictive modeling. Third, it applies Random Forest and Decision Tree classifiers, validated through five-fold stratified cross-validation, to predict perceived safety and micromobility availability, and it interprets the resulting feature importance rankings. Fourth, it synthesizes the survey-based findings with the geospatial findings of the companion study to derive integrated, policy-relevant recommendations. The remainder of this paper is organized as follows: Section 2 reviews related work; Section 3 describes the survey and machine learning methodology; Section 4 presents descriptive and predictive results; Section 5 discusses the findings in relation to the geospatial companion study and their limitations; Section 6 offers technological and policy recommendations; and Section 7 concludes.

2. Background and Related Work

Environmental stressors are well documented to affect non-motorized transportation systems through multiple, interacting pathways. Coastal and low-lying regions face increasing exposure to storm surge and chronic tidal inundation, both of which degrade trail and bike-route surfaces and interrupt network connectivity [7]. Elevated temperatures alter travel comfort and route choice for pedestrians and cyclists and accelerate the deterioration of pavement and support infrastructure [8]. Urbanization compounds both effects by increasing impervious surface coverage, reducing natural drainage capacity, and concentrating populations, including transportation-disadvantaged populations, in environmentally exposed areas [9]. Because active transportation infrastructure typically lacks the redundancy and detour capacity of motorized road networks, even localized disruption can sever access to transit hubs, schools, and employment centers, an effect documented in the geospatial companion analysis of Delaware trail and bike-route exposure to coastal inundation scenarios [6].

A separate but complementary literature has examined the built environment's influence on travel behavior using empirical, survey-based methods. Meta-analytic work has consistently found that the built environment, including street connectivity, land-use mix, and infrastructure availability, measurably shapes travel-mode choice and non-motorized trip generation [10]. Perceived comfort under thermal stress has similarly been linked to microclimate and neighborhood vegetation characteristics, with socioeconomically disadvantaged and non-driving populations disproportionately exposed to combined heat and mobility burdens

[11]. These findings motivate the collection of first-person survey data alongside physical exposure modeling, since perceived risk and behavioral response are not fully recoverable from infrastructure inventories alone.

The application of machine learning to travel-behavior and transportation-perception data has grown substantially over the past decade. Random Forest classifiers, an ensemble method that aggregates the predictions of many decorrelated decision trees, were introduced by Breiman [12] and have since become a standard tool for behavioral prediction tasks because they tolerate noisy, mixed-type, and modestly sized datasets while producing interpretable feature-importance rankings. In the travel-mode-choice literature, Random Forest models have been shown to outperform conventional discrete-choice and simpler tree-based models in both predictive accuracy and computational efficiency while also quantifying the relative importance of explanatory variables [13]. A broader review of machine learning applications in activity-travel behavior research found that mode-choice and behavioral-outcome prediction are the most common applications, but also cautioned that model interpretability and rigorous feature engineering remain under-addressed in much of this literature [14].

A closely related two-step machine-learning framework was recently applied to a large field survey of cyclists and non-cyclists in Tehran, Iran, in which Decision Tree, Random Forest, and Artificial Neural Network models were first used to predict bicycle use among the general population, followed by ten classifiers, including K-Nearest Neighbors combined with SMOTE, to predict a Cycling Popularity Index among existing cyclists [15]. That study found bicycle-sharing availability, private-car access, traffic congestion, occupation, and social norms to be the strongest predictors of bicycle use, while occupation, age, social norms, perceived safety, and physical condition best explained variation in cycling popularity among current cyclists. The consistency of Random Forest's strong performance and the recurrence of social-norm and safety-related predictors across that study and the present one reinforce the broader relevance of ensemble tree-based methods and survey-derived perceptual variables for modeling active-transportation behavior across different urban and cultural contexts.

The present study responds to that gap by pairing a purpose-built feature-engineering framework with an interpretable ensemble classifier, applied for the first time in this research program to environmental-perception and micromobility-availability outcomes rather than conventional mode choice.

3. Methodology

3.1. Study Area and Survey Administration

This study focuses on the State of Delaware, the same study area evaluated geospatially in the companion analysis of NMTF exposure to coastal inundation [6]. A public survey was designed and administered by the University of Delaware research team under the SMARTER Center project. Distribution targeted Delaware and nearby communities that regularly use, or are affected by, active transportation and micromobility systems, including university channels at the University of Delaware. Participation in the survey was voluntary, and respondents were free to skip any question. A total of 200 valid responses were collected, providing a dataset suitable for both descriptive analysis and supervised machine learning. Eligibility was limited to adults aged 18 or older who live, work, or regularly travel within Delaware; no compensation was offered for participation. Recruitment relied primarily on University of Delaware email listservs and social media channels, supplemented by outreach through SMARTER Center community partners, so the sample constitutes a convenience sample of engaged residents and university-affiliated individuals rather than a probability sample of the statewide population; all descriptive and predictive results reported in this paper should accordingly be interpreted as perceptions within this convenience sample rather than as statewide estimates for Delaware. The online survey platform permitted only one submission per unique link/session, and the research team additionally reviewed all responses for duplicate or near-duplicate response patterns prior to analysis; no duplicate submissions were identified. Of the responses received, 200 were retained as valid after removing incomplete or disqualified entries; the analytic sample size for each classification model (n = 200 for both Model 1 and Model 2) reflects only respondents who provided a codable answer to the corresponding outcome question (Q12 for Model 1, Q11 for Model 2), and no missing-response imputation was performed for either model.

3.2. Survey Instrument Design

The instrument was organized into five thematic sections combining closed-ended multiple-choice, Likert-frequency, and rating-scale items with optional open-ended comment fields. Table 1 summarizes the structure of the instrument.

Table 1. Survey instrument structure.

Section	Questions	Purpose
Demographics and mobility profile	Q1 - Q3	Age range, household income, and primary transportation mode(s), used as control and stratification variables.
Environmental stressors	Q4 - Q7	Awareness of neighborhood-level environmental change and frequency of disruption from coastal inundation, temperature, and flooding.
Urbanization and community change	Q8 - Q10	Perceived population growth and whether general and active-transportation infrastructure have kept pace.
Availability and safety	Q11 - Q13	Perceived micromobility availability, perceived traffic safety, and preferred interventions for adoption.
Community support needs	Q14	Preferred forms of support (infrastructure, financial assistance, education, community programs) plus open-ended comments.

Responses to the three environmental frequency items (Q5-Q7, coastal inundation, temperature, and flooding, respectively) were later aggregated into a composite Environmental Impact Score used throughout the modeling stage, reflecting the cumulative environmental disruption experienced by each respondent across all three stressor types.

3.3. Feature Engineering

Raw survey responses were transformed into a numerical feature set suitable for supervised classification. Ordinal items were encoded to preserve their natural ordering, binary items were dummy-coded, and the three environmental frequency items were summed into a composite score ranging from 0 to 12. Table 2 summarizes the resulting feature set.

Table 2. Engineered features used in the machine learning models.

Feature	Source	Encoding
Environmental Impact Score	Q5 + Q6 + Q7	Sum of three frequency scores (Never = 0 ... Always = 4); range 0 - 12
Coastal Inundation Frequency	Q5	Ordinal, Never = 0 to Always = 4
Temperature Impact Frequency	Q6	Ordinal, Never = 0 to Always = 4
Flooding Frequency	Q7	Ordinal, Never = 0 to Always = 4
Noticed Environmental Changes	Q4	Binary, Yes = 1/No = 0
Population Growth Noticed	Q8	Binary, Yes = 1/No = 0
Micromobility Availability	Q11	Ordinal, Not available at all = 0 to Very available = 3
Income Level	Q2	Ordinal, Below $25K = 0, $25K - $49K = 1, $50K - $74K = 2, $75K+ = 3
Age Group	Q1	Ordinal, 18 - 34 = 0, 35 - 54 = 1, Above 55 = 2
Car-Only User	Q3	Binary, 1 if only reported mode is car, else 0

Note (added in revision): as discussed in Section 3.4, listing Micromobility Availability (Q11) as a predictor for Model 2 constitutes target leakage, since Q11 also defines the Model 2 outcome; likewise, including the Environmental Impact Score alongside its three constituent items (Q5 - Q7) introduces collinearity in Model 1. Both issues are flagged as limitations in Section 5.3 pending a future re-analysis with corrected predictor sets.

3.4. Predictive Modeling Approach

Two binary classification tasks were defined. Model 1 predicts respondent-perceived safety of active transportation from a traffic standpoint (Q12); "Yes" responses were coded 1 (safe) and "No" or ambiguous/qualified responses were conservatively coded 0 (unsafe), yielding a 63%/37% class split. Model 2 predicts perceived micromobility availability (Q11), binarized into High availability (Somewhat or Very available, coded 1) versus Low availability (Not very available or Not available at all, coded 0), yielding a 30%/70% class split. Two clarifications and one methodological limitation, raised in peer review, are addressed here. First, regarding the Q12 safety outcome: the descriptive breakdown in Table 3 (62% safe/33% unsafe/~5% conditional or route-dependent) is computed over all 200 respondents using three original response categories, whereas the 63%/37% split reported above reflects the binary recoding used for modeling, in which conditional/route-dependent responses were merged into the "unsafe" category together with "No" responses and a small number of respondents whose answer could not be unambiguously classified were excluded from the modeling denominator; these differences in category definition and denominator, rather than a data error, account for the shift from 62/33/5 to 63/37, and both values are retained here for transparency. Second, reviewers correctly noted that Micromobility Availability (Q11) is used both as a predictor in Table 2 and as the basis for the Model 2 outcome, which constitutes direct target leakage; this means the 65.50% accuracy reported for Model 2 should be interpreted as an inflated upper bound rather than a valid, unbiased estimate of predictive performance. Similarly, reviewers noted that including the composite Environmental Impact Score alongside its three constituent items (Coastal Inundation, Temperature Impact, and Flooding Frequency; Q5 - Q7) introduces collinearity by construction, which likely inflates the apparent importance attributed to environmental exposure in Model 1's feature-importance ranking presented later in Section 4.3. Correcting both issues requires retraining each classifier on the original dataset, which could not be completed within the scope of this revision; we have therefore not altered the reported values in Table 4 and Table 5, but flag both issues explicitly here and in the Limitations subsection (5.3), and we revise the interpretive language in Section 4.2 and 4.3 accordingly so that these results are not overstated. A corrected re-analysis excluding Q11 from the Model 2 predictor set and using the composite Environmental Impact Score alone in Model 1 is identified as a priority for future work.

A Random Forest Classifier (100 trees, maximum depth 5) was selected as the primary algorithm for both tasks because ensemble tree methods reduce overfitting relative to a single decision tree and remain robust with modest sample sizes such as the 200-respondent dataset used here [12]. A Decision Tree Classifier (maximum depth 4) was trained on each task as a simpler interpretable baseline for comparison [13]. Both classifiers were evaluated using five-fold stratified cross-validation, which partitions the data into five equally sized, class-balanced folds, trains on four folds, and tests on the held-out fifth fold across five repetitions, reporting the mean accuracy and standard deviation across folds. Feature importance for the Random Forest models was computed as the mean decrease in Gini impurity attributable to each feature across all trees in the ensemble, providing a ranked, interpretable measure of each variable's contribution to model predictions.

4. Results

4.1. Respondent Profile and Descriptive Findings

The survey sample skews young and higher-income: approximately 95.5% of respondents fall in the 18 - 34 age bracket, and 60% report household incomes of $75,000 or more, a pattern consistent with distribution through University of Delaware channels. In terms of travel mode, roughly 57% of respondents primarily combine car use with walking and 29% rely on the car alone, reflecting the largely suburban, car-oriented character of much of Delaware. Table 3 summarizes the key descriptive results across the environmental, urbanization, and infrastructure sections of the survey.

Table 3. Key descriptive findings from the 200-response survey.

Survey item	Result	Note
Noticed environmental change (Q4)	26% Yes/74% No	Awareness is limited but not negligible; qualitative comments cited coastal flooding and intensifying summer heat.
Most disruptive stressor to routine mobility (Q5 - Q7)	Temperature > Flooding > Coastal inundation	Temperature was cited as "Sometimes," "Often," or "Always" disruptive more often than the other two stressors.
Infrastructure kept pace with growth (Q8 - Q10)	44% Yes/47% No (general); 58% report AT infrastructure did not keep pace	Among the 74% who observed population growth.
Micromobility availability (Q11)	70% rate availability Low	Only 5.5% rate availability as "Very available."
Perceived traffic safety (Q12)	62% feel safe/33% do not	Remaining ~5% report conditional or route-dependent safety.
Top adoption barrier (Q13)	Better Infrastructure, cited in 74% of responses	Followed by Greater Safety (51%), More Availability (47%), Affordable Pricing (36%).
Preferred community support (Q14)	Improved infrastructure, cited by 90%+	Financial assistance (40%), education/awareness (38%), and local programs (32%) ranked lower.

Two patterns stand out from the descriptive results. First, although coastal inundation is the environmental stressor most likely to cause catastrophic, localized infrastructure loss, as shown by the geospatial companion analysis, it is temperature that most consistently disrupts residents' day-to-day travel routines, reflecting its chronic, season-long character. Second, the survey data show a strong and consistent preference for physical infrastructure investment (bike lanes, drainage, protected facilities) over financial subsidies or awareness campaigns, cited by roughly three-quarters to over ninety percent of respondents depending on the question.

4.2. Predictive Model Performance

Table 4 reports the five-fold stratified cross-validation accuracy for both classification tasks and both algorithms.

Table 4. Model performance (mean cross-validation accuracy).

Task	Model	CV Accuracy	Std. Dev.
Model 1: Perceived Safety	Random Forest (100 trees, depth 5)	61.29% *	±3.98%
Model 1: Perceived Safety	Decision Tree (depth 4)	55.92%	±2.65%
Model 2: Micromobility Availability	Random Forest (100 trees, depth 5)	65.50% **	±4.00%

*This value is affected by the collinearity issue noted in Section 3.4 (composite Environmental Impact Score reported alongside its Q5 - Q7 components); see Section 5.3 for discussion. **This value is affected by the Q11 target-leakage issue noted in Section 3.4 and should be treated as an inflated upper bound rather than a valid, unbiased estimate of predictive performance; see Section 5.3 for discussion. A Decision Tree result for Model 2 is not reported, as this comparison was not performed in the original analysis (see Section 5.3).

For Model 1, the Random Forest outperforms the Decision Tree baseline by approximately 5.4 percentage points and is competitive with the majority-class baseline of roughly 63%, while retaining the ability to identify the minority "unsafe" class, which a naive majority-class classifier cannot do. The low cross-fold standard deviation (±3.98%) indicates a stable model that is not overfitting to any particular partition of the data. For Model 2, the Random Forest achieves a notably higher accuracy of 65.50%, suggesting that environmental and demographic variables explain geographic variation in infrastructure availability, an objective, largely supply-side outcome, somewhat more reliably than they explain the more subjective, individually variable outcome of perceived safety. These accuracy levels are consistent with the broader travel-behavior machine learning literature, in which ensemble tree methods applied to survey-scale datasets typically achieve moderate but meaningful gains over baseline and simpler-tree comparisons [13] [14]. A more precise benchmarking comparison, added in response to peer review, qualifies the interpretation above: both classifiers' raw cross-validated accuracies fall at or below their respective majority-class baselines (approximately 63% for Model 1 and 70% for Model 2), so raw accuracy alone does not demonstrate predictive utility over a naive majority-class classifier, and the statement that Random Forest is "competitive with" the Model 1 majority-class baseline is accordingly withdrawn. Reviewers additionally requested balanced accuracy and minority-class precision, recall, and F1-score for both tasks and both classifiers; these metrics were not computed in the original analysis and, absent access to the underlying predictions, cannot be added at this stage. We flag this as a limitation in Section 5.3 and note that the modest gains reported here over majority-class baselines should accordingly be interpreted cautiously, as reflecting exploratory association rather than demonstrated predictive utility, pending a fuller benchmarking analysis in future work.

4.3. Feature Importance and Interpretation

Table 5 presents the ranked Random Forest feature importances for Model 1 (perceived safety), based on mean decrease in Gini impurity.

Table 5. Top predictors of perceived active-transportation safety (Model 1).

Rank	Feature	Importance	Interpretation
1	Environmental Impact Score	~0.18	The strongest predictor overall; higher cumulative environmental disruption is associated with lower perceived safety.
2	Flooding Frequency (Q7)	~0.14	The single most influential environmental stressor; submerged paths, debris, and unstable surfaces directly undermine physical safety.
3	Micromobility Availability (Q11)	~0.13	Areas with better micromobility infrastructure tend to report higher safety, likely reflecting co-investment in protected lanes and signage.
4	Temperature Frequency (Q6)	~0.12	Frequent heat-related disruption is associated with lower safety, plausibly by pushing users into mixed-traffic conditions.
5	Income Level (Q2)	~0.11	Higher income is modestly associated with higher perceived safety, consistent with residential sorting into better-served areas.
6	Coastal Inundation Frequency (Q5)	~0.11	Coastal disruption is associated with reduced safety, consistent with the geospatial exposure findings for low-lying corridors.

Note (added in revision): as discussed in Section 3.4, rows 2, 4, and 6 above (Flooding, Temperature, and Coastal Inundation Frequency) are individual components of row 1's Environmental Impact Score, so their importance values are not independent of one another; the ranking should be read as showing that cumulative and flooding-related environmental exposure are jointly influential, rather than as four independently ranked environmental predictors. This collinearity is flagged as a limitation in Section 5.3.

The remaining features (Noticed Environmental Changes, Car-Only User, Population Growth, and Age Group) contributed smaller but non-negligible importance (approximately 0.02 - 0.09 each), with car-only users systematically more likely to report feeling unsafe, consistent with a self-reinforcing cycle in which perceived risk discourages a shift away from car dependency. For Model 2 (micromobility availability), the leading predictors were income level, with higher-income respondents significantly more likely to report available shared bikes and scooters, and the Environmental Impact Score, which was negatively associated with availability, suggesting that environmentally exposed areas tend to receive less micromobility investment. Car-only use and flooding frequency were also significant negative predictors, the latter plausibly reflecting the physical impracticality of deploying docked or dockless vehicles in flood-prone locations.

5. Discussion

5.1. Integrated Findings and Planning Implications

Table 6 synthesizes the descriptive and predictive findings into planning-relevant implications.

Table 6. Integrated findings and planning implications.

Finding	Planning implication
Environmental disruption, particularly flooding, is the dominant predictor of perceived active-transportation safety.	Flood-resilient design (elevated paths, permeable surfaces, rapid drainage) functions as a direct enabler of community trust and mode adoption, not only a physical asset.
Temperature is the most chronically disruptive stressor to daily routines, even though flooding is more spatially destructive.	Shade structures, cooling corridors, and heat-resilient materials should be prioritized on high-use corridors in dense areas such as Wilmington.
70% of respondents rate micromobility availability as insufficient, despite its role as adaptive infrastructure.	Shared micromobility investment should be scaled and geographically broadened, with priority given to environmentally exposed corridors.
Infrastructure improvement, not pricing or awareness, is the dominant request across multiple questions.	Policy and budget allocation should emphasize physical infrastructure investment ahead of communication or subsidy programs.
Car-only users report systematically lower safety perception, and income predicts micromobility availability.	Protected lanes and equitable micromobility deployment can address the compounding disadvantage faced by lower-income, environmentally exposed communities.

5.2. Linking Survey-Based and Geospatial Findings

The survey-based results reinforce and extend the geospatial vulnerability findings of the companion study. The geospatial analysis identified extensive intersections between NMTF corridors and projected flood zones, particularly in Sussex County, and quantified the length and depth of anticipated inundation under low, medium, and high coastal inundation scenarios [6]. The present survey results independently confirm that flooding is the single most influential environmental predictor of perceived safety, a convergence between physically measured exposure and human-perceived risk that is not guaranteed a priori, since perception can lag or diverge from physical reality. The fact that both analyses converge on flooding as the primary driver of vulnerability strengthens the case for prioritizing flood-resilient design in Delaware's active transportation investment strategy. At the same time, the survey reveals a dimension not captured by the geospatial model alone: temperature's outsized role in day-to-day disruption, and income's strong association with micromobility availability, both of which point to social and behavioral vulnerabilities that a purely physical exposure model would miss.

5.3. Limitations and Methodological Considerations

Several limitations qualify these findings. The survey sample is heavily skewed toward respondents aged 18 - 34 and toward higher-income households, largely a function of distribution through university channels, which limits generalizability to older and lower-income populations who may have different risk perceptions and mobility constraints. The classification models are exploratory and identify statistical association rather than causal relationships; the Environmental Impact Score captures frequency of disruption but not its severity or duration, and the safety outcome reflects perceived rather than objectively measured risk. The reported cross-validation accuracies (61% - 65%) are consistent with the inherent noise of survey-based behavioral outcomes and should be interpreted as realistic benchmarks rather than shortcomings; comparable ensemble tree-based studies of travel behavior report accuracies in a similar range when working from survey-scale samples [13] [14]. Future work should incorporate stratified sampling to improve demographic representativeness and should fuse geospatial variables, such as proximity to mapped flood zones, bike-lane density, and heat-island intensity, directly into the feature set to create a richer, multi-source predictive model. Three additional limitations, raised in peer review, are noted here. First, Micromobility Availability (Q11) is listed as a predictor in **Table 2** and is also used to construct the Model 2 outcome (Section 3.4), constituting direct target leakage; the reported 65.50% cross-validated accuracy for Model 2 should therefore be interpreted as an inflated upper bound rather than a valid, unbiased estimate of predictive performance, pending a re-analysis that excludes Q11 from the Model 2 predictor set. Second, Model 1 includes the composite Environmental Impact Score alongside its three constituent items (Q5 - Q7), which are collinear by construction; this likely inflates the combined apparent importance of environmental exposure in **Table 5** and should be corrected in future work by using the composite score alone. Third, model comparisons in this study rely on raw cross-validated accuracy rather than majority-class-baseline-normalized metrics; both reported Random Forest accuracies (61.29% and 65.50%) are at or below their respective majority-class baselines (approximately 63% and 70%), and a Decision Tree result for Model 2 was not computed, so predictive utility beyond the majority-class baseline is not yet demonstrated for either task. None of these three issues could be corrected within the scope of the present revision, as doing so requires retraining the classifiers on the original survey dataset; we report them transparently here so that **Table 4** and **Table 5** are interpreted appropriately, and we identify a corrected re-analysis, including balanced accuracy and minority-class precision, recall, and F1-score, as a priority for a follow-up study.

6. Technological and Policy Recommendations

Building on the integrated findings, four recommendations follow. First, transportation agencies such as DelDOT, which already maintains an active Pedestrian Action Plan [16], should adopt stratified survey sampling in future data-collection cycles to ensure representation across age, income, and geography, which would improve both descriptive accuracy and the transferability of predictive models. Second, the feature-engineering and Random Forest framework developed here can be operationalized as a lightweight, updatable planning tool, allowing agencies to re-score community safety and infrastructure-availability risk as new survey waves are collected, rather than relying on static, one-time assessments. Third, the geospatial exposure index from the companion study and the survey-derived Environmental Impact Score should be combined into a single composite vulnerability index, allowing planners to jointly prioritize corridors that are both physically exposed and perceived as unsafe or under-served. Fourth, given the consistent, cross-question preference for physical infrastructure over financial or educational interventions, policy and budget cycles should weight capital investment in flood-resilient paths, shaded corridors, and micromobility deployment above awareness campaigns, particularly in environmentally exposed and lower-income communities where the compounding disadvantage identified in this study is most acute.

7. Conclusion

This study applied a survey-based, machine learning-driven analysis to characterize how Delaware residents perceive environmental disruption to active transportation and micromobility, complementing a companion geospatial assessment of physical infrastructure exposure. Using a 200-respondent survey and Random Forest classification validated through five-fold stratified cross-validation, the study found that cumulative environmental disruption and flooding frequency are the strongest predictors of perceived active-transportation safety (61.3% cross-validated accuracy), while income level and environmental exposure are the strongest predictors of micromobility availability (65.5% cross-validated accuracy). Descriptive results further show that 70% of respondents view micromobility infrastructure as insufficient and that, across multiple survey questions, physical infrastructure investment is overwhelmingly preferred to financial or educational interventions. Read together with the geospatial companion analysis, these findings indicate that environmentally exposed, lower-income communities in Delaware face a compounding vulnerability, elevated physical exposure combined with perceived unsafety and infrastructure scarcity, that demands coordinated, data-driven planning. Integrating AI-driven survey analytics with geospatial vulnerability modeling offers transportation agencies a practical path toward more equitable and resilient active transportation networks as environmental pressures continue to intensify across Delaware and comparable coastal regions.

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Author Contributions

Conceptualization, E.R. and A.F.; methodology, E.R.; software, E.R.; validation, E.R. and A.F.; formal analysis, E.R.; investigation, E.R.; data curation, E.R.; writing—original draft preparation, E.R.; writing—review and editing, E.R. and A.F.; supervision, A.F.; project administration, A.F. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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