THE EFFECT OF SOCIOECONOMIC AND ENVIRONMENTAL FACTORS ON THE PREFERENCES TOWARDS PUBLIC AND ACTIVE TRANSPORT FOLLOWING THE IMPLEMENTATION OF PEDESTRIANIZATION THROUGH CONSENSUS MAKING: THE CASE OF CAFERAĞA/KADIKÖY

by

Volkan Yıldız

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ABSTRACT

THE EFFECT OF SOCIOECONOMIC AND ENVIRONMENTAL FACTORS ON THE PREFERENCES TOWARDS PUBLIC AND ACTIVE TRANSPORT FOLLOWING THE IMPLEMENTATION OF PEDESTRIANIZATION THROUGH CONSENSUS MAKING: THE CASE OF CAFERAĞA/KADIKÖY

This thesis examines how socioeconomic and environmental factors influence individuals' preferences toward public transport and active transportation following pedestrianization initiatives implemented through consensus building. Focusing on the Caferağa neighborhood in Kadıköy, Istanbul, the research integrates human-centered design principles to evaluate attitudes toward pedestrian-oriented improvements such as lane narrowing, expanded sidewalks, increased green areas, additional pedestrian crossings, and reduced parking spaces. Data were collected via face-to-face surveys with 401 participants and analyzed using multiple linear regression, stepwise regression, hierarchical regression and ordinal regression models. The findings indicate that positive perceptions of lane narrowing and additional pedestrian crossings were the most consistent predictors of increased willingness to adopt public transport and active mobility modes. Age emerged as a significant demographic factor, with older individuals demonstrating greater openness to sustainable transport options, while frequent car users expressed less favorable attitudes. Moreover, evaluations of increasing green spaces were particularly associated with intentions to use public transportation, whereas support for reducing parking was strongly linked to active transportation preferences. These results highlight the critical role of targeted, participatory urban design interventions

in shaping mobility behaviors. The study concludes that integrating safety-focused measures and inclusive community engagement can foster more sustainable and equitable transport choices. The insights are expected to inform policymakers and urban planners aiming to develop evidence-based strategies that address social inequalities, improve environmental quality, and enhance public health in densely populated urban settings.

ÖZET

KONSENSÜS YOLUYLA UYGULANAN YAYALAŞTIRMA SONRASINDA SOSYOEKONOMİK VE ÇEVRESEL FAKTÖRLERİN TOPLU TAŞIMA VE AKTİF ULAŞIM TERCİHLERİ ÜZERİNDEKİ ETKİSİ: CAFERAĞA/KADIKÖY ÖRNEĞİ

Bu tez, konsensüs yoluyla uygulanan yayalaştırma girişimlerinin ardından sosyoekonomik ve çevresel faktörlerin bireylerin toplu taşıma ve aktif ulaşım tercihlerine nasıl etki ettiğini incelemektedir. İstanbul'un Kadıköy ilçesine bağlı Caferağa Mahallesi'ne odaklanan araştırmada, kaldırım genişletme, şerit daraltma, yeşil alanların artırılması, yeni yaya geçitleri oluşturulması ve araç park alanlarının azaltılması gibi yaya odaklı iyileştirmelere yönelik tutumlar, insan merkezli tasarım yaklaşımı çerçevesinde değerlendirilmiştir. Veriler, 401 katılımcıyla yüz yüze anket yöntemiyle toplanmış ve çoklu doğrusal regresyon, adım adım regresyon ordinal regresyon ve hiyerarşik regresyon analizleriyle incelenmiştir. Bulgular, şerit daraltma ve yeni yaya geçitleri oluşturma uygulamalarına yönelik olumlu algıların, toplu taşıma ve aktif ulaşım modlarına yönelmeyi artırmada en güçlü belirleyiciler olduğunu ortaya koymuştur. Yaş değişkeni anlamlı bir demografik etken olarak öne çıkmış; daha ileri yaştaki bireylerin sürdürülebilir ulaşım seçeneklerine daha açık olduğu, buna karşılık özel araç kullanım sıklığı yüksek olan katılımcıların daha olumsuz tutum sergilediği gözlenmiştir. Ayrıca, yeşil alanların artırılmasına dair olumlu değerlendirmelerin toplu taşıma kullanım niyetini güçlendirdiği, park alanlarının azaltılmasını destekleyen görüşlerin ise aktif ulaşım tercihleriyle güçlü şekilde ilişkili olduğu belirlenmiştir. Bu sonuçlar, hedef odaklı ve katılımcı kentsel tasarım müdahalelerinin ulaşım davranışlarını şekillendirmede kritik bir rol oynadığını göstermektedir. Çalışma, güvenliğe yönelik düzenlemelerin ve kapsayıcı toplumsal katılımın bütünleşik bir biçimde ele alınmasının, daha sürdürülebilir

ve adil ulaşım tercihlerinin gelişmesine katkı sağlayacağını ortaya koymaktadır. Elde edilen bulguların, yoğun nüfuslu kentsel alanlarda sosyal eşitsizliklerin azaltılması, çevresel kalitenin artırılması ve halk sağlığının güçlendirilmesi amacıyla kanıta dayalı politika ve strateji geliştirmek isteyen karar vericilere ve şehir plancılarına yol göstermesi beklenmektedir.

TABLE OF CONTENTS

ACKNOWLEDGEMENTS . . . iii
ABSTRACT . . . iv
ÖZET . . . vi
LIST OF FIGURES . . . xiii
LIST OF TABLES . . . xvi
LIST OF SYMBOLS . . . xx
LIST OF ACRONYMS/ABBREVIATIONS . . . xxi
1. INTRODUCTION . . . 1
1.1. Problem Definition . . . 2
1.2. Contribution of the Thesis . . . 3
1.3. Outline of the Thesis . . . 3
2. LITERATURE REVIEW . . . 4
2.1. Public Transport . . . 4
2.2. Active Transport . . . 8
2.3. Consensus Making . . . 12
3. THEORY . . . 16
3.1. Streetmeter . . . 16
3.1.1. Input . . . 16
3.1.1.1. Street Widths . . . 17
3.1.1.2. Street Design . . . 19
3.1.1.3. Street Use . . . 21
3.1.2. Output . . . 23
3.1.2.1. Health . . . 24
3.1.2.2. Social . . . 27
3.1.2.3. Economy . . . 29
3.1.2.4. Mobility . . . 31
3.1.2.5. Environment . . . 35
3.2. Methods Used in Analysis . . . 37
3.2.1. Multiple Linear Regression . . . 37

3.2.2. Stepwise Regression . . . 38
3.2.3. Hierarchical Regression . . . 39
3.2.4. Ordinal Regression . . . 40
4. METHODOLOGY . . . 41
4.1. Data Collection . . . 41
4.1.1. Location . . . 41
4.1.2. Survey Implementation . . . 46
4.1.3. Sampling Method . . . 47
4.1.4. Survey Instrument . . . 52
4.2. Data Description . . . 52
4.2.1. Variables, Measurement, and Recoding . . . 52
4.2.2. Descriptive Statistics . . . 54
5. RESULTS OF ANALYSIS . . . 60
5.1. Multiple Linear Regression Analysis for Q8 . . . 60
5.1.1. Assumption Checks . . . 60
5.1.1.1. Normality . . . 60
5.1.1.2. Linearity and Homoscedasticity . . . 62
5.1.1.3. Multicollinearity . . . 62
5.1.1.4. Autocorrelation . . . 63
5.1.1.5. Outliers and Influential Observations . . . 63
5.1.2. Multiple Linear Regression Results for Q8 . . . 64
5.1.2.1. Model Summary . . . 64
5.1.2.2. ANOVA . . . 65
5.1.2.3. Regression Coefficients . . . 65
5.2. Stepwise Regression Analysis for Q8 . . . 66
5.2.1. Assumption Checks . . . 66
5.2.1.1. Normality . . . 66
5.2.1.2. Linearity and Homoscedasticity . . . 68
5.2.1.3. Multicollinearity . . . 68
5.2.1.4. Autocorrelation . . . 69
5.2.1.5. Outliers and Influential Observations . . . 69

5.2.2. Stepwise Regression Results for Q8 70
5.2.2.1. Variables Entered and Removed 70
5.2.2.2. Model Summary 71
5.2.2.3. ANOVA 71
5.2.2.4. Regression Coefficients 73
5.3. Hierarchical Regression Analysis for Q8 75
5.3.1. Assumption Checks 75
5.3.1.1. Normality 75
5.3.1.2. Linearity and Homoscedasticity 76
5.3.1.3. Multicollinearity 77
5.3.1.4. Autocorrelation 78
5.3.1.5. Outliers and Influential Observations 79
5.3.2. Hierarchical Regression Results for Q8 80
5.3.2.1. Model Summary 80
5.3.2.2. ANOVA 80
5.3.2.3. Regression Coefficients 81
5.4. Ordinal Regression Analysis for Q8 83
5.4.1. Assumption Checks 83
5.4.1.1. Model Fit 83
5.4.1.2. Goodness of Fit 83
5.4.1.3. Pseudo R-square 84
5.4.1.4. Test of Parallel Lines 84
5.4.2. Ordinal Regression Results for Q8 85
5.4.2.1. Parameter Estimates 85
5.5. Multiple Linear Regression Analysis for Q9 87
5.5.1. Assumption Checks 87
5.5.1.1. Normality 87
5.5.1.2. Linearity and Homoscedasticity 88
5.5.1.3. Multicollinearity 89
5.5.1.4. Autocorrelation 90
5.5.1.5. Outliers and Influential Observations 90

5.5.2. Multiple Linear Regression Results for Q9 91
5.5.2.1. Model Summary 91
5.5.2.2. ANOVA 92
5.5.2.3. Regression Coefficients 92
5.6. Stepwise Regression Analysis for Q9 93
5.6.1. Assumption Checks 93
5.6.1.1. Normality 93
5.6.1.2. Linearity and Homoscedasticity 95
5.6.1.3. Multicollinearity 95
5.6.1.4. Autocorrelation 96
5.6.1.5. Outliers and Influential Observations 96
5.6.2. Stepwise Regression Results for Q9 97
5.6.2.1. Variables Entered and Removed 97
5.6.2.2. Model Summary 98
5.6.2.3. ANOVA 98
5.6.2.4. Regression Coefficients 99
5.7. Hierarchical Regression Analysis for Q9 100
5.7.1. Assumption Checks 100
5.7.1.1. Normality 100
5.7.1.2. Linearity and Homoscedasticity 102
5.7.1.3. Multicollinearity 102
5.7.1.4. Autocorrelation 103
5.7.1.5. Outliers and Influential Observations 104
5.7.2. Hierarchical Regression Results for Q9 105
5.7.2.1. Model Summary 105
5.7.2.2. ANOVA 105
5.7.2.3. Regression Coefficients 106
5.8. Ordinal Regression Analysis for Q9 108
5.8.1. Assumption Checks 108
5.8.1.1. Model Fit 108
5.8.1.2. Goodness of Fit 108

5.8.1.3. Pseudo R-square 108
5.8.1.4. Test of Parallel Lines 109
5.8.2. Ordinal Regression Results for Q9 109
5.8.2.1. Parameter Estimates 109
5.9. Discussion of Theoretical and Practical Implications of the Results . . . 112
6. CONCLUSION 117
REFERENCES 119

LIST OF FIGURES

Figure 3.1. Street widths parameters. 17

Figure 3.2. Street design parameters. 19

Figure 3.3. Street use parameters. 22

Figure 3.4. Streetmeter performance dimensions. 24

Figure 3.5. Health dimension metrics. 25

Figure 3.6. Social dimension metrics. 28

Figure 3.7. Economy dimension metrics. 30

Figure 3.8. Mobility dimension metrics. 32

Figure 3.9. Environment dimension metrics. 35

Figure 4.1. Districts of Istanbul [1]. 42

Figure 4.2. Colored political map of Kadıköy district showing population distribution [2]. 43

Figure 4.3. Detailed boundary map of Caferağa neighborhood [3]. 44

Figure 4.4. Location 1 – A wide multi-lane road lacking pedestrian crossing infrastructure. 45

Figure 4.5. Location 2 – A narrow urban street with circulation problems and limited pedestrian accessibility. 46

Figure 5.1. Histogram of regression standardized residuals for the multiple linear regression model for Q8. 61

Figure 5.2. Normal P–P of regression standardized residuals for the multiple linear regression model for Q8. 61

Figure 5.3. Scatterplot of standardized residuals versus predicted values for the multiple linear regression modelfor Q8. 62

Figure 5.4. Histogram of regression standardized residuals for the stepwise regression model for Q8. 67

Figure 5.5. Normal P–P Plot of regression standardized residuals for the stepwise regression model for Q8. 67

Figure 5.6. Scatterplot of standardized residuals versus predicted values for the stepwise regression model for Q8. 68

Figure 5.7. Histogram of regression standardized residuals for the hierarchical regression model for Q8. 75

Figure 5.8. Normal P–P plot of regression standardized residuals for the hierarchical regression model for Q8. 76

Figure 5.9. Scatterplot of standardized residuals versus predicted values for the hierarchical regression model for Q8. 77

Figure 5.10. Histogram of regression standardized residuals for the multiple linear regression model for Q9. 87

Figure 5.11. Normal P–P plot of regression standardized residuals for the multiple linear regression model for Q9. 88

Figure 5.12. Scatterplot of standardized residuals versus predicted values for the multiple linear regression model for Q9. 89

Figure 5.13. Histogram of regression standardized residuals for the stepwise regression model for Q9. 94

Figure 5.14. Normal P–P plot of regression standardized residuals for the stepwise regression model for Q9. 94

Figure 5.15. Scatterplot of standardized residuals versus predicted values for the stepwise regression model for Q9. 95

Figure 5.16. Histogram of regression standardized residuals for the hierarchical regression model for Q9.. 101

Figure 5.17. Normal P–P Plot of regression standardized residuals for the hierarchical regression model for Q9. 101

Figure 5.18. Scatterplot of standardized residuals versus predicted values for the hierarchical regression model for Q9. 102

LIST OF TABLES

Table 4.1. Estimated sample sizes for Kadıköy districts calculated using the Yamane equation (error margin = 0.01) 49

Table 4.2. Estimated sample sizes for Kadıköy districts calculated using the Yamane equation (error margin = 0.05) 50

Table 4.3. Estimated sample sizes for Kadıköy districts calculated using the Yamane equation (error margin = 0.1) 51

Table 4.4. Descriptive statistics for continuous and ordinal variables 55

Table 4.5. Frequency and percentage distributions for demographic variables . 57

Table 5.1. Regression coefficients for the multiple linear regression model for Q8. 63

Table 5.2. Model summary of the multiple linear regression model for Q8. . . 63

Table 5.3. Residual statistics for the multiple linear regression model for Q8. . 64

Table 5.4. Model summary of the multiple linear regression model for Q8. . . 64

Table 5.5. ANOVA results of the multiple linear regression model for Q8. . . 65

Table 5.6. Regression coefficients for the multiple linear regression model for Q8. 66

Table 5.7. Regression coefficients for the stepwise regression model for Q8. . . 69

Table 5.8. Model summary of stepwise regression model for Q8. 69

Table 5.9. Residual statistics for the stepwise regression model for Q8. 70

Table 5.10. Model summary of stepwise regression model for Q8. 71

Table 5.11. ANOVA results of the stepwise regression model for Q8. 73

Table 5.12. Regression coefficients for the stepwise regression model for Q8. . . 74

Table 5.13. Regression coefficients for the hierarchical regression model for Q8. 78

Table 5.14. Model summary of the hierarchical regression model for Q8. 79

Table 5.15. Residual statistics for the hierarchical regression model for Q8. . . 79

Table 5.16. Model summary of the hierarchical regression model for Q8. 80

Table 5.17. ANOVA results of the hierarchical regression model for Q8. 81

Table 5.18. Regression coefficients for the hierarchical regression model for Q8. 82

Table 5.19. Model fitting information for ordinal regression model for Q8. . . . 83

Table 5.20. Goodness-of-fit statistics for ordinal regression model for Q8. . . . 83

Table 5.21. Pseudo R-square values for ordinal regression model for Q8. 84

Table 5.22. Test of parallel lines for the ordinal regression model for Q8. 84

Table 5.23. Parameter estimates for the ordinal regression model for Q8. . . . 86

Table 5.24. Regression coefficients for the multiple linear regression model for Q9. 90

Table 5.25. Model summary of the multiple linear regression model for Q9. . . 90

Table 5.26. Residual statistics for the multiple linear regression model for Q9. . 91

Table 5.27. Model summary of the multiple linear regression model for Q9. . . 91

Table 5.28. ANOVA results of the multiple linear regression model for Q9. . . 92

Table 5.29. Regression coefficients for the multiple linear regression model for Q9. 93

Table 5.30. Regression coefficients for the stepwise regression model for Q9. . . 96

Table 5.31. Model summary of the stepwise regression model for Q9. 96

Table 5.32. Residual statistics for the stepwise regression model for Q9. 97

Table 5.33. List of Variables Entered and Removed of Stepwise Regression Model of Q9. 98

Table 5.34. Model summary of the stepwise regression model for Q9. 98

Table 5.35. ANOVA results of the stepwise regression model for Q9. 99

Table 5.36. Regression coefficients for the stepwise regression model for Q9. . . 100

Table 5.37. Regression coefficients for the hierarchical regression model for Q9. 103

Table 5.38. Model summary of the hierarchical regression mdel for Q9 104

Table 5.39. Residual statistics for the hierarchical regression model for Q9. . . 104

Table 5.40. Model summary of the hierarchical regression model for Q9. 105

Table 5.41. ANOVA results of the hierarchical regression model for Q9. 106

Table 5.42. Regression coefficients for the hierarchical regression model for Q9. 107

Table 5.43. Model fitting information for ordinal regression model for Q9. . . . 108

Table 5.44. Goodness-of-fit statistics for ordinal regression model for Q9. . . . 108

Table 5.45. Pseudo R-square values for ordinal regression model for Q9. 109

Table 5.46. Test of parallel lines for the ordinal regression model for Q9. 109

Table 5.47. Parameter estimates for the ordinal regression model for Q9. . . . 111

Table 5.48. Regression model estimates and model fit statistics for predictors of public transportation intentions 112

Table 5.49. Ordinal regression model estimates and model fit statistics for predictors of public transportation intentions 112

Table 5.50. Regression model estimates and model fit statistics for predictors of active transportation intentions 114

Table 5.51. Ordinal regression model estimates and model fit statistics for predictors of active transportation intentions 114

LIST OF SYMBOLS

ln	Natural logarithm
$logit(\theta_i)$	Log-odds transformation of θ_i
$x_{i1}, x_{i2}, \ldots, x_{iU}$	Values of the predictor variables for the ith unit
$X_1, X_2, \ldots, X_m$	Independent variables (predictors) in linear regression
Y	Dependent variable (response) in linear regression
β_0	Intercept term
$\beta_1, \beta_2, \ldots, \beta_m$	Regression coefficients for predictors $X_1, X_2, \ldots, X_m$ in linear regression
$\beta_1, \beta_2, \ldots, \beta_U$	Regression coefficients measuring the effect of each predictor on the log-odds in ordinal regression
ε	Error term (residual) in linear regression
θ_i	Probability of the event of interest for the ith observation

LIST OF ACRONYMS/ABBREVIATIONS

AST	Active School Transport
ATS	Active Transport to School
BTWD	Bike to Work Day
dBA	A-weighted decibels
kvm	kvadratmeter (square meter)
NACTO	National Association of City Transportation Officials
pcs	pieces
SD	Standard Deviation
SEK	Swedish krona
SEM	Structural Equation Modeling
TL	Turkish lira

1. INTRODUCTION

People are seen every day, terrified, hopeless, and wandering around in search of a glimpse of help. They are encountered everywhere in different personas: a mother is heard desperately crying out, a handicapped person is observed trying to sell napkins for an uncertain fee, or an old man is noticed thinking about what will be eaten today. Worse still, this situation has been grown accustomed to by society, and instead of help being offered to these people, anger is directed toward those by whom help is tried to be given. This quiet tragedy is unfolded in plain sight, yet by most passersby it is chosen to be looked away from, and such scenes are regarded as an inevitable part of urban life. On the other hand, the lives of other people are caught by the eye. In those completely different universes, people have no idea about situations they have never witnessed or about other people they have never seen. Altogether, social inequality is a known fact worldwide. In fact, debates about social inequality have spanned from the eras of Aristotle and Plato through the works of Rousseau, Karl Marx, Max Weber, and countless modern scholars [4]. Additionally, among the Sustainable Development Goals prepared by the UN, SDG 10 has been designated as "Reduced Inequalities" [5]. Unfortunately, this inequality is deeply felt in Istanbul. At the same time, there is another issue that silently shapes our daily lives: environmental degradation. From polluted air that clouds the sky to water sources contaminated by waste, the consequences of neglecting nature have become impossible to ignore. Children grow up breathing in toxins they cannot see, while adults silently accept that the green areas around them shrink each year. This constant erosion of the environment does not only harm ecosystems but also deepens the suffering of vulnerable communities. When nature is damaged, it is always the people with the least resources who face the harshest impacts first. In this sense, environmental concern has become inseparable from social responsibility. Humankind has the power to alter the world they live in. This power may vary from one to another. One could have massive power to change a nation's fate like Mustafa Kemal Atatürk whereas a little girl changing its imaginary world while she is playing house. The common point of these examples is that the main character of these events is human. This spectrum of influence highlights how every individual,

regardless of their scale of impact, contributes to shaping the shared reality. In the same sense, as for civil engineers, people have to be prioritized when a new concept is designed. Building upon this perspective, pedestrianization emerges as a concept that places people at the center of urban spaces. Pedestrianization is defined in the dictionary as "making an area into one where vehicles are not allowed to go." [6]. In a broader concept, this term's meaning could be expanded to create a safer and more livable environment since the human presence will grow voluntarily. This transformation not only restricts vehicles but also encourages social interaction, healthier lifestyles, and a stronger sense of belonging. As more people feel safe and welcome, public spaces can regain their role as vibrant centers of daily life. In this context, the notion of "human-centered design" naturally arises as an essential framework for shaping pedestrian-focused environments. Human-centered design means trusting that even the toughest problems are solvable and that those experiencing them hold the key to solutions. It invites problem solvers to work with communities, understand their needs, generate ideas, and create innovative solutions rooted in real life [7]. When it comes to working together, consensus building can be a key factor in accelerating the implementation of pedestrianization.

1.1. Problem Definition

The rapid growth of urban populations has intensified challenges related to mobility, environmental degradation, and social inequality. In densely populated districts like Caferağa in Kadıköy, these issues manifest through traffic congestion, limited pedestrian safety, and unequal access to public spaces. Although pedestrianization has emerged as a promising strategy to create more livable and inclusive environments, its success depends not only on spatial transformation but also on the active participation and consensus of diverse stakeholders. Socioeconomic status and environmental perceptions play a decisive role in shaping how individuals respond to such interventions and whether they shift toward public transport or continue to rely on private vehicles. Understanding these dynamics is essential for designing human-centered, equitable urban policies that align with the needs and expectations of the community, as improvements in pedestrian infrastructure can act as a catalyst that encourages

people to reconsider their daily travel choices and embrace more sustainable modes of mobility.

1.2. Contribution of the Thesis

This thesis aims to contribute to the understanding of how socioeconomic and environmental factors influence individuals' preferences toward public transport following the implementation of pedestrianization achieved through consensus building. By focusing on the case of Caferağa in Kadıköy, the research offers empirical insights into the interplay between urban design interventions, community perceptions, and sustainable mobility choices. The findings are expected to inform policymakers, urban planners, and civil engineers about the conditions under which pedestrianization can effectively promote equitable and environmentally responsible transport behaviors. Ultimately, this study aspires to support the development of inclusive, human-centered urban policies that address both social inequality and environmental challenges.

1.3. Outline of the Thesis

This thesis is structured into six chapters. The first chapter introduces the background of the research, defines the problem and its justification, explains the contribution of the study, and describes the structure of the thesis. The second chapter reviews relevant literature, including theoretical perspectives, previous studies on consensus building, and approaches related to urban planning and public transport. The third chapter discusses the conceptual foundations and analytical methods used to explore the research questions. The fourth chapter describes the methodology, detailing the data collection process, the selection of observation periods, and the procedures applied in the analyses. The fifth chapter presents the results, highlighting the relationships between socioeconomic and environmental factors, pedestrianization practices, and preferences toward sustainable mobility. Finally, the sixth chapter concludes with a summary of key findings, reflections on their implications, and recommendations for future work.

2. LITERATURE REVIEW

2.1. Public Transport

There are various studies that examine the factors influencing public transportation usage, ranging from psychological determinants such as attitudes and habits to demographic variables and service-related characteristics. In a study of 377 respondents in Kanazawa, Japan, structural equation modeling showed that intentions to use public transport were significantly shaped by attitudes, subjective norms, perceived behavioral control, personal norms, and environmental concern. Access by public transport was positively associated with actual behavior, while travel cost consciousness had no significant effect [8]. Similarly, in a study conducted in Norway with 546 participants and analyzed using Structural Equation Modeling (SEM), intentions to use public transport were positively influenced by transport priorities such as comfort and safety and by favorable attitudes, while strong car use habits negatively affected both intention and actual usage, indicating that habitual behavior may outweigh attitudinal factors in shaping travel choices [9]. This connection between habit and attitude is further explored in a study conducted in China with 6,602 participants using structural equation modeling, where psychological factors such as attitude, habit, satisfaction, and subjective norm were found to significantly influence public transportation usage. Behavioral intention emerged as the strongest predictor. Gender-based analysis showed that perceived car control affected men more, while satisfaction played a key role for women. The study highlights the need for gender-sensitive strategies and system improvements to promote transit use [10]. Affective aspects also emerged as stronger predictors than instrumental motives in a study of 180 respondents, where structural equation modeling showed that public transport use was positively predicted by habits, behavioral intentions, and anticipated emotions. Instrumental motives (e.g., convenience, time) were less influential compared to affective and habitual factors [11]. In a related vein, a study based on a sample of 868 participants found that attitudes significantly influence public transit use. Social perceptions, such as how transit is viewed by friends and family, strongly shape individual choices. Additionally, prefer-

ences for a reliable, low-stress, and productive commute were important determinants, indicating that public transit can be more appealing than cars in congested metropolitan areas. Ignoring these attitudinal factors may lead to underestimating the impact of service changes on ridership [12]. Expanding on both positive and negative evaluative components, a study of 279 low-income residents in South Los Angeles identified key attitudes influencing transit use, including perceptions of affordability, reliability, environmental benefits, avoidance of traffic stress, and opportunities for social interaction. Individuals who viewed transit as cheap, timely, and eco-friendly were more likely to use it, particularly when safety concerns were minimal. However, concerns about theft, violence, discomfort at stops, physical safety, and crowding on board significantly reduced willingness to use public transportation [13]. The role of social norms was directly examined in a study of 465 participants in Shanghai, where a structural equation model was used to examine how social norms affect public transport use. It was found that injunctive norms (perceived social approval) influenced behavior both directly and indirectly via attitudes and perceived behavioral control, while descriptive norms (perceptions of others' behavior) affected usage indirectly through similar pathways [14]. As a different branch, a market segmentation analysis of 2,778 respondents found that women showed greater concern for safety, comfort, and environmental impact, whereas men emphasized practicality and performance. The segmentation revealed five attitudinal clusters with distinct transport mode preferences, varying notably by gender [15]. This gender-based segmentation aligns with broader findings on how socio-demographic characteristics influence transport decisions. In two field studies with 437 people in Bochum/Dortmund and 796 in Frankfurt, structural equation modeling showed that social context significantly shaped public transport behavior. Frankfurt residents, reflecting a postindustrial milieu, reported stronger social and personal norms, greater guilt over car use, and higher intention and control toward using public transport. Social norms played a key mediating role, influencing attitudes and behavior more strongly in Frankfurt than in Bochum/Dortmund, where normative pressures were weaker [16]. Further emphasizing the role of demographics, a study conducted in Vietnam with 288 participants and analyzed using Structural Equation Modeling (SEM) found that perceptions of public transport service quality were signif-

icantly influenced by gender, age, income, and education. Among these users, service reliability, comfort, and safety emerged as the most critical factors affecting satisfaction and usage intentions [17]. Adding another layer to this perspective, a study conducted at Ohio State University's Columbus campus with 2,632 participants revealed that while gender was not a direct predictor of public transport use, men and women differed markedly in how their attitudes translated into behavior. Women prioritized comfort, whereas men emphasized flexibility, sensitivity to travel time, and aversion to transfers. Both groups, however, shared the perception that public transport was safer in bad weather and responded similarly to changes in service levels [18]. In a similar context of demographic differentiation, a study in Abu Dhabi reported that most public transport users were young, low-income, full-time South Asian males. Here, age, income, nationality, employment status, and access to bus stops were found to significantly influence transit use. The main barriers included long walking distances and limited network coverage, suggesting that addressing last-mile connectivity is essential for supporting transit-dependent populations [19]. While demographic characteristics shape who uses public transport, the quality of the service itself—along with physical infrastructure and surrounding environments—plays a decisive role in shaping satisfaction and continued use. In a study of 412 respondents in Kuala Lumpur using SEM, it was found that both service quality and perceived value directly influenced behavioral intentions to use public transportation. Key service attributes such as vehicle safety, cleanliness, service reliability, and grievance handling significantly shaped user perceptions. Improvements in these areas enhanced satisfaction and loyalty, indirectly reinforcing continued public transport use [20]. Complementing this, a study conducted in Madrid with 740 participants focused on user satisfaction at the Moncloa transport hub. A path model revealed that perceived information provision and safety were the strongest predictors of satisfaction. While design and environmental quality had indirect effects, waiting time and user age influenced access to information. Notably, younger women reported feeling less safe, indicating a need for improvements in both informational systems and perceived security [21]. Among international visitors in Greater Manchester, service experience was also shaped by practical elements. It was found that public transport satisfaction was primarily influenced by two key factors:

Ease of Use and Efficiency-Safety. The former included clear information, simple ticketing, and supportive staff, while the latter encompassed punctuality, travel time, and safety which highlights that even short-term users place strong emphasis on both clarity and reliability [22]. The importance of user experience also becomes evident when comparing perceptions between public transport users and private vehicle users. In a study conducted in Madrid with 876 participants using Mann–Whitney U tests, significant differences were found in service quality perceptions, satisfaction, and attitudes. Current public transport users expressed higher satisfaction and more positive views regarding accessibility, environmental impact, and service frequency, while private vehicle users viewed public transport as less comfortable, slower, and less compatible with their lifestyle [23]. Beyond perceptions, the influence of car ownership itself cannot be ignored. In a comparative study conducted in Guangzhou and Brisbane with 1,182 participants, car ownership was found to negatively influence attitudes toward public transport. Perceived usefulness, comfort, and reliability acted as key mediators in this relationship, suggesting that reducing car dependency requires enhancing these very service dimensions [24]. Interestingly, mobility behaviors may also shift due to life changes and relocation. In a British case study of 219 respondents, it was found that moving to an area with better public transport access was associated with increased bus use, particularly among those with pro-transit attitudes. Favorable views on walking, proximity to bus stops, and positive perceptions of transit played a significant role in this increase [25]. To add, a study of 264 participants in Johor Bahru, Malaysia, drew attention to the challenges faced by low-income and non-car-owning individuals. Attributes such as bus stop location, fare costs, service frequency, and seat availability were seen as highly important. However, satisfaction with passenger information remained low. Although features like cleanliness and entertainment were rated as less critical—likely due to lower expectations—users still struggled with long access distances and last-mile issues, indicating persistent spatial inequalities in service delivery [26].

2.2. Active Transport

There are various studies that examine the factors influencing active transportation usage, ranging from psychological determinants such as attitudes and habits to demographic variables and service-related characteristics. In a study consisting of 460 residents from Oklahoma, it was found that positive attitudes toward walking were significantly associated with support for most active transport policies. Participation in active commuting and favorable attitudes toward bicycling were also linked to stronger support for bike infrastructure. Attitudes and personal experience with active travel modes emerged as key predictors of policy support [27]. Building upon the influence of personal values and motivation, a study involving 404 participants in Valencia, Spain, used Structural Equation Modeling to examine how personal values, attitudes, and social context influence travel behavior. Values such as stimulation, which reflects a desire for novelty and excitement, and achievement, associated with personal success and self-improvement, were positively related to active transport. In contrast, security, reflecting a need for safety and stability, and conformity-tradition, which emphasize adherence to social norms and established routines, were negatively associated with walking and cycling. These values also shaped attitudes toward transport modes, which in turn affected travel choices. Companion characteristics, such as the number of non-family members, communication frequency, and distance to companions, were also influential. Active travel was more likely among those with diverse and nearby social networks, whereas car use was associated with longer distances, face-to-face contact, and a higher share of male companions [28]. Attitudes are also shaped through experience and specific travel events. In a study of 2,030 "Bike to Work Day" (BTWD) participants in Denver, many respondents were classified as "interested but concerned" and chose to commute by bike only for the event day, reverting to driving afterward. Their decision to cycle was primarily influenced by the perceived convenience, security, and comfort of bicycling compared to other modes. Safety concerns were not prominent among those who participated, though they may still be relevant for individuals who have never tried cycling to work [29]. Similarly, in a study of 375 employed adults in the United States, the relationship between eco-friendly attitudes and active commuting behavior was examined. Participants with higher ecological awareness reported

more frequent walking or cycling to work, greater self-efficacy, more motivators, and fewer barriers related to active commuting. Age was negatively and education positively associated with eco-friendly attitudes [30]. The impact of lifestyle preferences and attitudes is also evident in a study of 7,931 post-secondary students in Toronto, which found that transportation lifestyles were strongly shaped by socio-demographic factors, as well as travel attitudes and residential preferences. Those valuing walkability or limiting driving for environmental reasons were more active, whereas safety concerns and limited housing choice aligned with greater transit dependence [31]. The difference in findings across methodological approaches is highlighted in a study which indicates that the factors influencing active transport vary depending on the analytical strategy used. Cross-sectional analysis emphasizes psychological and socio-demographic parameters, such as individual attitudes and residential preferences, highlighting the role of self-selection in shaping active transport behavior. In contrast, quasi-longitudinal analysis underscores the sustained impact of physical environmental factors, particularly neighborhood design and walkability, as key determinants of active transport over time. Overall, the study identifies attitudes, preferences, environmental characteristics, neighborhood structure, and the residential selection process as critical parameters shaping active transport behavior [32]. To add, based on a sample of 769 participants across six small U.S. cities, another study found that bicycle commuting is influenced by a combination of individual attitudes, socio-demographic characteristics, and both physical and social workplace environments. Key factors positively associated with bicycling to work included a personal preference for bike-friendly living environments, short commuting distances, safe streets, high parking costs, and supportive social environments at the workplace [33]. While psychological factors such as attitudes and values play a key role in shaping active transport behavior, socio-demographic variables including age, gender, income, and family dynamics, also exert significant influence. In a cross-sectional study from four New Zealand cities involving 217 children, binomial generalized estimation equation modeling was used to examine factors influencing active transport to school (ATS). It was found that shorter distance to school, older age, city of residence, and neighborhood self-selection were significant predictors of ATS. Children living more than 2000 m from school were much less likely to use ATS, and

those aged 11–14 were more likely to walk or cycle than younger children [34]. Age-based differences were similarly evident in a study of 1,897 elementary school children in Michigan, where logistic regression showed that walking to school was more likely among older children and those who perceived it as time-saving or safe. In contrast, walking decreased with greater distance to school, parental car ownership, and access to a school bus. These factors remained significant after controlling for demographic, environmental, and attitudinal variables [35]. Parental influence is another critical dimension of children's active travel. In a study involving 1,007 parents and 1,219 children in the USA, generalized linear mixed models were used to examine factors influencing the frequency of active school travel, accounting for distance and variation across schools. The results showed that perceived barriers by parents, particularly child resistance and concerns about safety and weather, were associated with lower levels of active travel, while a higher percentage of Hispanic students at the school was linked to increased walking or cycling to school [36]. Family routines and parenting styles also shape mobility patterns. In a study of children aged 6 to 11 from King County, Washington, and San Diego County, California, non-distance factors influencing active transport to school were examined among those living within a 20-minute walk of school. It was found that children were more likely to walk or cycle if they were older and had parents who also used active transport. In contrast, having strict family rules requiring the child to stay within sight of the parent or home, as well as longer parental working hours, were associated with lower odds of active transport [37]. Concerns about safety further vary across income and gender lines. In a study of 1,273 residents in Accra, Ghana, socio-demographic and neighborhood factors influencing perceptions of active mobility safety were examined through an online survey. The findings showed that low vehicular traffic improved perceived safety, while longer walking distances to bus stops, unplanned neighborhoods, and dense housing were linked to greater safety concerns. Women and low-income earners reported lower perceived safety compared to men and higher-income individuals [38]. Age and gender-related trends are also evident in mode choice among children. In a GPS-based study of 79 Dutch children aged 6 to 11, 79.2% of recorded school trips were made using active transport. Walking was more common at shorter distances, while cycling and motorized transport increased

with longer distances. Nearly all trips under 300 meters were active, whereas trips over 900 meters were more often passive [39]. In older populations, different dynamics emerge. Using data from the 2009 Victorian Integrated Survey of Travel Activity in Melbourne, a study examined active transport among adults aged 65 and over. While 22 percent of trips were made by walking, private motorized transport remained dominant at 70 percent, with walking distance and speed declining notably after age 75. Older males were more likely to drive, whereas females relied more on walking and public transit. Reduced trip frequency after retirement was linked to decreased mobility and well-being [40]. Children's mobility patterns are further shaped by intersecting socio-demographic and logistical factors. In a study of 1,070 participants in Leipzig, Germany, about 59% of children and 51% of adolescents used active school transport (AST). AST rates declined with age and were not significantly different by gender. Higher socioeconomic status was associated with greater morning AST but less afternoon AST in summer. Distance and heavy schoolbags were common barriers across age groups. For younger children, additional obstacles included lack of walking companions, parental errands, and traffic. Adolescents and their parents also cited traffic, time constraints, and bad weather as barriers [41]. What's more, a Denmark-based study examined active school transport (AST) among 1,250 students aged 11–13. AST rates were high overall, but significantly influenced by the school's walkability level. In medium/high walkable areas, AST remained high up to 2 km, whereas in low walkable areas it declined sharply beyond 0.5 km. No significant gender differences were observed, and factors such as safe cycling infrastructure and strong social norms supported AST. Distance to school, traffic speed, and the presence of cycling paths were key determinants [42]. While attitudes and socio-demographic characteristics are important in shaping active transportation behavior, the physical and spatial context in which individuals live can exert an equally strong—if not stronger—influence. The design of the built environment, proximity to key destinations, and neighborhood structure often define the possibilities and limitations for walking and cycling, regardless of individual intention. In a study of 1,048 individuals in Chengdu, China, it was found that urban form variables influenced active transport, though patterns were complex. Work-unit neighborhoods had higher rates of walking and cycling to work, likely due

to residual proximity between homes and workplaces. In contrast, affordable housing areas showed lower active travel for non-work trips, possibly due to peripheral location and limited nearby amenities [43]. Further emphasizing the interaction between environmental structure and individual preferences, a study of 642 adults aged 20–65 in Aarhus, Denmark, identified three distinct self-selection patterns related to neighborhood choice. Preferences emphasizing safety and ease of walking or cycling varied across life stages. In multivariable models, higher neighborhood walkability was associated with less motorized transport and more walking and cycling. However, this relationship was partially attenuated by self-selection effects and by life stage influences on transport behavior [44]. A broader perspective on built environment factors was offered in a study of 3,708 individuals in Brisbane, Australia, where the association between urban form and walking for transport was analyzed using both cross-sectional and panel data. Findings showed that living in areas with well-connected street networks and accessible train stations increased the likelihood of walking. Longitudinal results confirmed these associations and also highlighted the influence of travel attitudes and perceptions. While the built environment remains a key factor, the study suggests that changing social norms is also important to promote walking [45]. Finally, built environment features may be especially critical for older populations. In a study conducted with 702 older and 3,772 younger adults in Nanjing, China, it was found that for the elderly, proximity to markets, parks, and social spaces such as chess or card rooms significantly affected how often and how long they engaged in active travel. Compared to younger adults, the built environment had a greater impact on older people's mobility. In contrast, personal attitudes toward active travel did not significantly affect behavior among seniors, suggesting that self-selection played a minimal role [46].

2.3. Consensus Making

There are various studies that explore how consensus is formed within groups, focusing on the cognitive, psychological, and behavioral foundations that shape collective decisions. These studies emphasize how individuals interact, respond to group dynamics, and process conflicting information as they navigate toward shared out-

comes. In a study on neural dynamics, it was suggested that consensus-making involves a competitive interplay between neural systems dedicated to abstract reasoning and those guiding sensorimotor decisions. This perspective emphasizes that real-time decision-making in groups may be influenced by underlying neurological structures that weigh options simultaneously before arriving at a group-coherent response [47]. Group coordination can also emerge in informal and nonverbal ways. A study examining movement decisions in animals found that leadership often arises spontaneously from individual initiative rather than fixed hierarchies. Spatial positioning and directional cues were shown to contribute significantly to group consensus, highlighting the role of emergent, bottom-up processes in collective behavior [48]. While consensus is often assumed to improve group decisions, it does not always guarantee optimal outcomes. Research comparing consensus-based strategies to devil's advocacy found that encouraging dissenting viewpoints can lead to better decision quality. The findings suggest that consensus may suppress alternative thinking when not managed carefully and that structured disagreement may serve as a useful counterbalance [49]. Further insight into cognitive consensus was provided by a study that compared different decision rules, such as majority voting and unanimity. The results indicated that shared cognition or so-called "cognitive consensus" was more likely when decision rules fostered broad participation and open communication. Groups that relied too heavily on quick majority decisions often sacrificed mutual understanding and reasoning depth [50]. A substantial strand of consensus research adopts formal and computational approaches to model group decision-making, with a focus on preference aggregation, iterative convergence, and optimization under uncertainty. These studies often rely on fuzzy logic, multi-criteria evaluation, and simulation techniques to analyze how consensus can be reached efficiently and equitably among heterogeneous agents. One influential framework proposed the integration of diverse preference formats—including fuzzy preference relations, utility-based preferences, and multiplicative preference values—into a unified consensus model. By developing methods to transform and reconcile these formats, the study enabled more robust aggregation in group decision settings with varied input structures [51]. Complementing this approach, a dynamic model introduced iterative preference adjustment among agents. Through repeated feedback and

refinement cycles, participants gradually modified their preferences in light of others' positions. The model emphasized convergence behavior over time and demonstrated that consensus could be achieved even in initially polarized groups through structured iteration [52]. The speed and effectiveness of such convergence processes may depend on the choice of distance functions used to measure disagreement. In a comparative analysis, different distance functions were found to yield different consensus speeds and final agreement levels. This finding suggests that seemingly technical modeling choices can significantly affect the outcome of consensus-based systems [53]. Another study introduced a fuzzy decision-making model that accounts for heterogeneous importance among experts. Instead of equal weighting, participants were assigned differentiated influence, and personalized feedback mechanisms were applied to guide them toward consensus. This approach reflects a more realistic view of power asymmetries in group settings and allows for more adaptive negotiation dynamics [54]. Similarly, a multicriteria decision-making framework utilizing intuitionistic fuzzy numbers was developed to support interactive decision-making environments. Through iterative evaluation and re-evaluation of criteria weights, the model facilitated the exploration of consensus in settings where both objective evaluations and subjective hesitation coexist [55]. Beyond internal cognition and formal mechanisms, consensus formation is also deeply embedded in the social structures through which decisions are made. Power asymmetries, network centrality, institutional opacity, and culturally grounded norms all influence how consensus is built, challenged, or maintained in group and organizational settings. A study examining consensus within social networks found that group agreement is not necessarily the result of equal interaction or influence. Instead, factors such as centrality, density, and relational asymmetries shape who contributes most to collective outcomes. Members with higher network centrality were more likely to influence the final decision, raising concerns about equity and representation in otherwise collaborative processes [56]. These concerns are echoed in institutional contexts, such as the Council of the European Union. A study revealed that while formal voting rules exist, most decisions are reached through informal consensus practices. However, this informal process often masks unequal power dynamics and reduces transparency. The result is what the author describes as "democratic opacity," where the appearance of

unanimity conceals strategic negotiation and political dominance by more influential actors [57]. Finally, a contrasting perspective comes from the Danish model of governance, where societal consensus is largely built on high levels of institutional trust and cooperative norms. Rather than relying on strict formal procedures or hidden bargaining, consensus in Denmark emerges through repeated interaction, public accountability, and a cultural emphasis on social cohesion. This case suggests that consensus can be cultivated more openly and inclusively when embedded in a trust-based democratic tradition [58].

Despite extensive research on either pedestrianization or public transport behavior, there remains a limited understanding of how consensus-based urban interventions influence individual transport preferences, particularly in socially and spatially diverse contexts. Few studies have empirically examined the combined role of socioeconomic and environmental factors in shaping public transport usage following participatory street transformations. Moreover, the intersection between community perceptions, urban design, and sustainable mobility outcomes is often overlooked, especially at the neighborhood scale. This thesis addresses these gaps by focusing on Caferağa in Kadıköy, offering context-sensitive evidence on how pedestrianization achieved through consensus making can foster more equitable and environmentally sustainable transport behaviors.

3. THEORY

In this thesis, a multidimensional and human-centered evaluation of urban street environments was conducted through both conceptual and empirical approaches. To achieve this, the Streetmeter framework was employed as the primary theoretical tool for assessing physical, functional, and perceptual qualities of streets. In addition, a series of quantitative analysis methods, including multiple linear regression, stepwise regression, hierarchical regression, and ordinal regression, were utilized to explore the relationships between street design features, demographic characteristics, environmental perceptions, and behavioral outcomes. These combined approaches allowed for a comprehensive understanding of how urban design interventions influence mobility choices.

3.1. Streetmeter

Streetmeter is a software developed to evaluate the multidimensional impacts of urban street spaces. This approach emphasizes that streets are not merely corridors for transportation but also shape many factors simultaneously, ranging from health and economy to social life and environmental sustainability. The software consists of two layers: input parameters that define the physical and functional characteristics of the street, and output metrics that measure performance across multiple dimensions.

3.1.1. Input

The input parameters used in the Streetmeter framework are primarily derived from internationally recognized design guidelines, most notably those published by the National Association of City Transportation Officials (NACTO). These parameters reflect evidence-based practices in street design and urban mobility planning. While it is evident that the structure of the inputs is informed by such scientific sources, the developer of the software has not made the full documentation or formulation of these parameters publicly available. As a result, although the approach is grounded in

credible literature, the precise implementation details remain proprietary.

3.1.1.1. Street Widths. This section captures the physical dimensions of the street, including the total public right-of-way, pedestrian clear zones, flex zones, and dedicated lanes for bikes, transit, and vehicles. These measurements are essential for assessing the allocation of space among different modes of transport and for understanding the spatial structure of the street environment. Street widths parameters are shown in Figure 3.1.

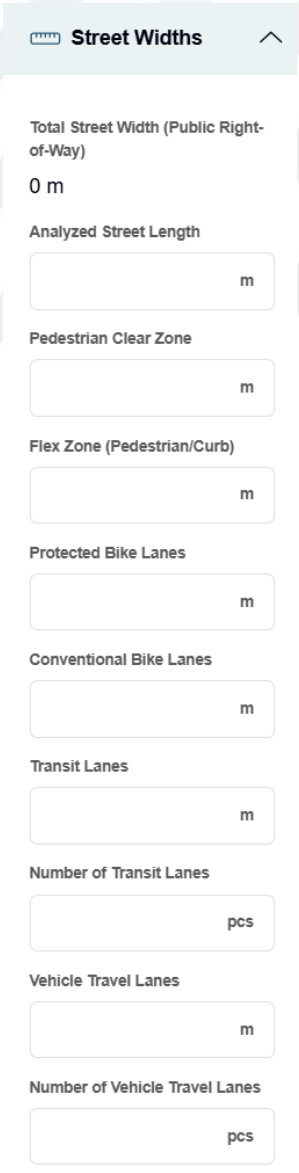

Figure 3.1. Street widths parameters.

Street Widths Parameters

- *Total Street Width (Public Right-of-Way) (m)*

  Total street width is defined as the total width of the street from facade to facade excluding front yard space.
- *Analyzed Street Length (m)*

  The analyzed street length is defined as the length of the analyzed stretch.
- *Pedestrian Clear Zone (m)*

  The pedestrian clear zone is defined as the total width of sidewalks and pedestrian areas, where on combined pedestrian and bicycle paths, half of the width is counted as pedestrian area, and on pedestrian streets and shared spaces, the width is equal to the street's width.
- *Flex Zone (Pedestrian/Curb) (m)*

  The flex zone is defined as the total width of space allocated for furniture, parking, loading, stops, and plantings, including setbacks that constitute part of the street, while refuges are not counted.
- *Protected Bike Lanes (m)*

  Protected bike lanes are defined as the total width of bike lanes, where on combined pedestrian and bicycle paths, half of the width is counted as protected bike lane, while bicycle streets are not counted.
- *Conventional Bike Lanes (m)*

  Conventional bike lanes are defined as the total width of conventional bike lanes, with the entire roadway on bicycle streets counted as a conventional bike lane.
- *Transit Lanes (m)*

  Transit lanes are defined as the total width of bus lanes and tram tracks, where the roadway in bus stop lanes and combined tram and car lanes are counted, whereas other bus stop areas are not counted.
- *Number of Transit Lanes (pcs)*

  Number of transit lanes is defined as the total count of dedicated bus lanes and tram tracks within the analyzed street segment.
- *Vehicle Travel Lanes (m)*

Vehicle travel lanes are defined as the total width of mixed traffic lanes.

- *Number of Vehicle Travel Lanes (pcs)*
  Number of vehicle travel lanes is defined as the total count of mixed traffic lanes within the analyzed street segment.

3.1.1.2. Street Design. Street Design focuses on the physical features and amenities present along the street. It records the quantity and area of green spaces, outdoor dining, parking facilities, street furniture such as benches and lighting, as well as pedestrian crossings and entrances. This information helps evaluate the quality, comfort, and visual character of the public realm. Street Design parameters are shown in Figure 3.2.

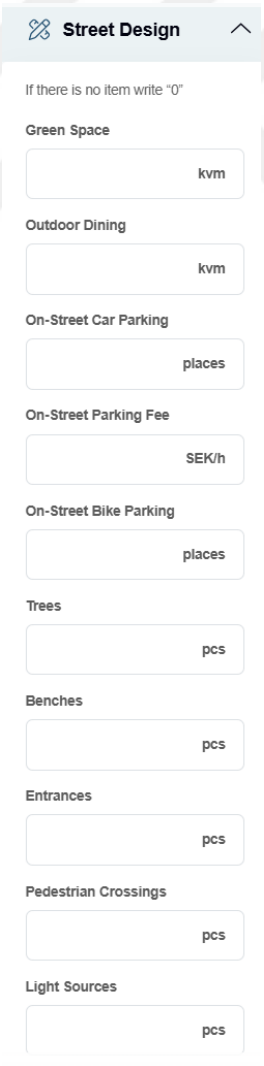

Figure 3.2. Street design parameters.

Street Design Parameters

- *Green Space (kvm)*

  Green space is defined as the total area with vegetation, where pots and plantings above ground are counted, while tree pits are not counted.
- *Outdoor Dining (kvm)*

  Outdoor dining is defined as the total area with outdoor seating during the season, including seating located both on private property and in public space.
- *On-Street Car Parking (places)*

  On-street car parking is defined as the total number of spaces for loading and parking, where in the absence of marked boxes, each space is assumed to be 20 feet long. Loading zones without no-stopping restrictions are counted as the number of passenger cars that fit, while loading zones with no-stopping restrictions are counted as one space. Loading and parking on private property are not counted.
- *On-Street Parking Fee (SEK/h)*

  On-street parking fee is defined as the average hourly rate for visitor parking on weekdays during paid hours of the day, which affects the on-street car parking revenue.
- *On-Street Bike Parking (places)*

  On-street bike parking is defined as the total number of bike parking spaces, where bollards with space for two bikes are counted as two spaces, and bike parking on private property is not counted.
- *Trees (pcs)*

  Trees are defined as the total number of trees, regardless of size.
- *Benches (pcs)*

  Benches are defined as the total number of benches and other public seating furniture.
- *Entrances (pcs)*

  Entrances are defined as the total number of entrances facing the street for residential buildings, courtyards, and businesses, while garage entrances and service entrances are not counted.

- *Pedestrian Crossings (pcs)*

  Pedestrian crossings are defined as the total number of marked crosswalks across the street, including both guarded and unguarded crossings, while crosswalks along the length of the street and pedestrian passages are not counted.

- *Light Sources (pcs)*

  Light sources are defined as the total number of lighting points, such as fixtures and lamps, where lighting belonging to properties and purely decorative lighting are not counted.

3.1.1.3. Street Use. This section gains information regarding how the street is utilized on a daily basis, including counts of pedestrian, bike, transit, and motor traffic, the proportion of heavy vehicles, average vehicle speeds, and the presence of retail along the street. These usage patterns provide insight into the intensity and diversity of street activity. Street Use parameters are shown in Figure 3.3.

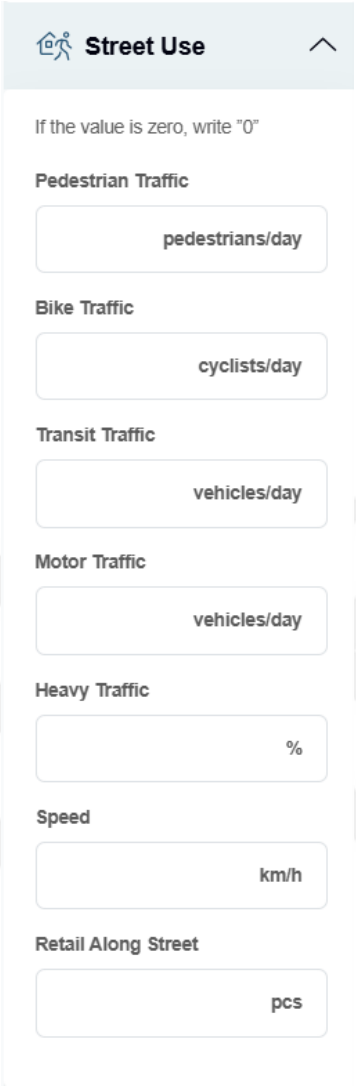

Figure 3.3. Street use parameters.

Street Use Parameters

- *Pedestrian Traffic (pedestrians/day)*
  Pedestrian traffic is defined as the total number of passing pedestrians per day in both directions.
- *Bike Traffic (cyclists/day)*
  Bike traffic is defined as the total number of passing cyclists per day in both directions.
- *Transit Traffic (vehicles/day)*

Transit traffic is defined as the total number of passing buses per day in both directions.

- *Motor Traffic (vehicles/day)*

  Motor traffic is defined as the total number of passing motor vehicles per day in both directions, including heavy traffic.

- *Heavy Traffic (%)*

  Heavy traffic is defined as the percentage of passing motor vehicles that are classified as heavy traffic.

- *Speed (km/h)*

  Speed is defined as the measured or simulated speed, or alternatively the posted speed limit, where pedestrian streets correspond to a speed of 5 km/h and bicycle streets correspond to a speed of 20 km/h.

- *Retail Along Street (pcs)*

  Retail along the street is defined as the total number of ground floor businesses with service functions, including commerce, restaurants, cafes, cultural activities, newsstands, and hairdressers, while specialized office activities, such as real estate agencies, are not counted.

3.1.2. Output

Streetmeter systematically analyzes how street design contributes to user experience, the quality of public space, and ecological effects through a set of indicators defined across different dimensions. The five core dimensions considered within the Streetmeter framework are health, social, economy, mobility, and environment, and the metrics used in each dimension serve as output measures of the assessment. Streetmeter performance dimensions are shown in Figure 3.4.

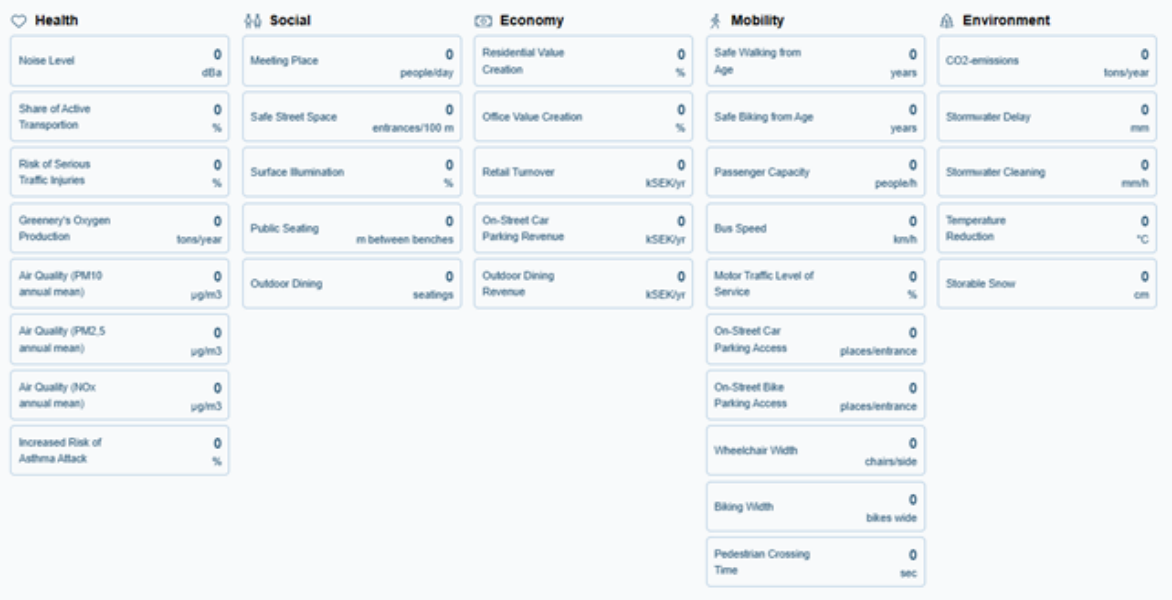

Figure 3.4. Streetmeter performance dimensions.

3.1.2.1. Health. The health dimension of Streetmeter focuses on how street environments affect the well-being of individuals who use them daily. It highlights the idea that streets are not just routes for movement but spaces that can either support or undermine public health. Considering this perspective helps planners and decision-makers create urban areas that promote healthier lifestyles and reduce exposure to harmful conditions. Health dimension metrics are shown in Figure 3.5.

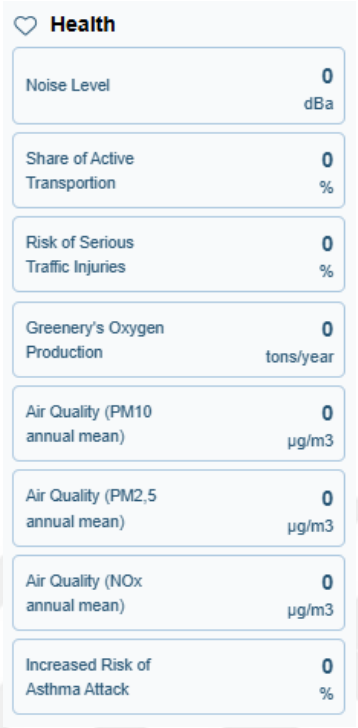

Figure 3.5. Health dimension metrics.

Health Dimension Metrics

- *Noise Level (dBa)*

  Noise level is defined as the noise measured 33 feet from the road center. Exposure to elevated noise can disturb daily activities and diminish the quality of life for people who live, work, or walk along the street. Numerous factors, including hearing loss, sleep disturbance, cardiovascular impacts, psychophysiologic effects, psychiatric symptoms, and prenatal development, make noise harmful to health [59]. This metric indicates the degree of acoustic disturbance experienced by people in the street environment.

- *Share of Active Transportation (%)*

  Share of active transportation is defined as the proportion of all trips made by walking, cycling, and transit. Active transportation could be defined as using your own power to get from one place to another [**?**]. Health benefits may result from active transportation initiatives [60]. To support this, various studies bring

out the importance of active transportation modes for improving public health outcomes [61–67]. This metric indicates the extent to which active travel modes are chosen over motorized transport.

- *Risk of Serious Traffic Injuries (%)*

  Risk of serious injury is defined as the estimated risk based on crash force curves for older adults, the most vulnerable group of road users. The societal costs of road safety are considerable, and the sorrow experienced by victims and their relatives is immense [68]. Lowering this risk is essential for creating safer streets that protect the vulnerable populations.

- *Greenery's Oxygen Production (tons/year)*

  Annual oxygen production is defined as the annual amount of oxygen produced by trees. There is growing evidence linking home greenspace to improved health [69]. This measure underscores the role of urban vegetation in enhancing environmental quality and supporting public health. This metric indicates the contribution of street greenery to cleaner air and healthier urban living.

- *Air Quality – PM10 Annual Mean ($\mu g/m^3$)*

  Air quality – PM10 annual mean is defined as the concentration of coarse particles in the street air. PM10 refers to particles that are 10 micrometers or smaller in diameter. These very fine particles are small enough to move through the nose and throat and penetrate deep into the lungs. When breathed in, they can affect both the lungs and the heart, potentially causing serious health issues [70]. This metric indicates the concentration of coarse particulate matter present in the street air.

- *Air Quality – PM2.5 Annual Mean ($\mu g/m^3$)*

  Air quality – PM2.5 annual mean is defined as the concentration of fine particles in the street air. PM2.5 consists of particles that are 2.5 micrometers or smaller in diameter. Because of their extremely small size, they can travel deep into the lungs and even enter the bloodstream. There is strong evidence that long-term exposure to PM2.5 over several years can lead to harmful health effects [70]. This metric indicates the presence of fine particulate pollutants that penetrate deep into the lungs.

- *Air Quality – NO_x Annual Mean ($\mu g/m^3$)*

  Air quality – NO_x annual mean is defined as the concentration of nitrogen oxides in the street air. NO_x emissions contribute to smog formation and are associated with asthma and other respiratory problems. Although diesel engines produce less CO than comparable petrol engines, they emit much higher levels of nitrogen oxides (NO_x), a fact that is often overlooked. In the EU28 countries, together with Norway and Switzerland, road transport is responsible for about 40% of all land-based NO_x emissions [71]. This metric indicates the level of nitrogen oxide emissions affecting air quality and health.
- *Increased Risk of Asthma Attack (%)*

  Increased risk of asthma attack is defined as the daily increase in the number of acute, asthma-related medical visits caused by particle emissions from motor traffic on the street. Pollutants such as particles, sulfur dioxide, nitrogen oxides, ozone, carbon monoxide, and lead are often increased by smoking, fuel combustion, and exhaust. These substances worsen asthma and can lead to hospitalization [72]. This metric indicates the additional probability of asthma-related medical incidents due to air pollution.

3.1.2.2. Social. The social dimension examines the capacity of streets to foster interaction, inclusion, and a sense of belonging among community members. Streets play a central role in everyday social life, offering opportunities for people to connect, share experiences, and participate in public activities. This dimension emphasizes the importance of designing spaces that are welcoming and supportive of diverse social needs. Social Dimension Metrics are shown in Figure 3.6.

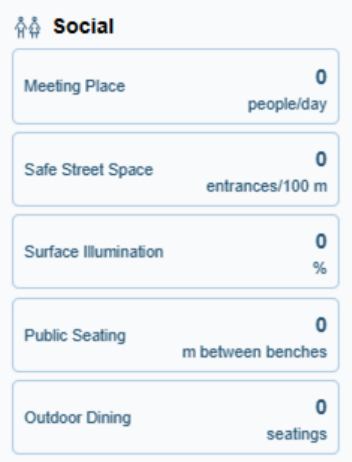

Figure 3.6. Social dimension metrics.

Social Dimension Metrics

- *Meeting Place (people/day)*

  Meeting Place are defined as the total number of visitors to the street, including pedestrians, cyclists, and arriving motorists. Rural areas have long symbolized the ideal of a local community, where establishing meeting places was especially central to bringing people together [73]. Such spaces enable social bonds and shared experiences to flourish. This metric captures the number of people who visit the street daily, reflecting its role as a social hub that supports interaction among pedestrians, cyclists, and motorists.

- *Safe Street Space (entrances/100 m)*

  Safe Street Space is defined as the number of entrances per 330 feet, assuming they are evenly distributed on both sides of the street. It is important to design streets that not only serve their functional purpose but also create a public realm where everyone, especially women, feels comfortable and safe [74]. This metric indicates how many building entrances open onto the street, contributing to perceived safety and natural surveillance by creating an active, socially engaging frontage.

- *Surface Illumination (%)*

  Surface Illumination is defined as the percentage of the total street area that

is illuminated, assuming lighting fixtures are mounted on poles with an average height of 26 feet. Street lighting has become an omnipresent part of modern society, based on the idea that improved lighting both reduces crime and enhances people's subjective sense of safety [75]. This metric measures how much of the street area is lit, influencing perceived security and the street's usability during evening and nighttime hours.

- *Public Seating (m between benches)*

  Public seating is defined as the average distance between benches and other public seating, assuming they are evenly distributed on one side of the street segment. Public seating plays an important role in expressing social relationships and reinforcing shared norms within a community. If we were to offer historical evidence, in England the rise of traditions around public seating reflected and strengthened the hierarchical structure of urban society in the early modern period [76]. This metric describes the average spacing of benches and seating, which affects comfort, opportunities for rest, and the likelihood of spontaneous social interaction.

- *Outdoor Dining (seatings)*

  Outdoor dining is defined as the total number of seats in outdoor seating areas, where one seat is assumed to occupy one square meter. The design of urban public spaces plays a crucial role in building social connections, promoting community health, and supporting overall well-being [77]. This metric quantifies the availability of outdoor seating for dining, highlighting the street's capacity to support vibrant, socially oriented activities.

3.1.2.3. Economy. The economic dimension reflects how street environments contribute to the prosperity and sustainability of local communities. By shaping the attractiveness and functionality of public spaces, streets can stimulate economic activity and encourage investment. Understanding this dimension is essential for creating vibrant areas where economic and social life reinforce each other. Economy Dimension Metrics are shown in Figure 3.7.

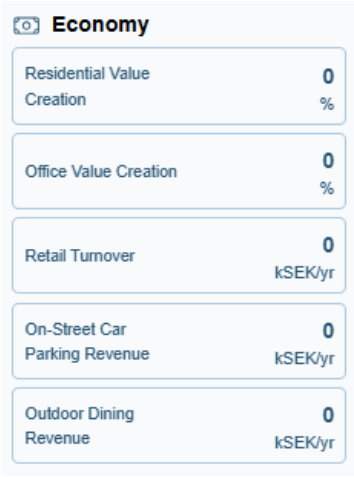

Figure 3.7. Economy dimension metrics.

Economy Dimension Metrics

- *Residential Value Creation (%)*

  Residential Value Creation is defined as the percentage increase in the value of residential properties attributable to the street's design. The most appreciated areas in cities are those that exemplify successful urban design, consistently generating strong investment returns and a lasting sense of quality over many decades or even centuries [78]. Such value is often reflected in measurable economic outcomes. This metric measures the percentage increase in residential property values associated with street improvements.

- *Office Value Creation (%)*

  Office value creation is defined as the percentage increase in office rents attributable to the street's design. Urban design and the creation of added value are becoming ever more significant factors influencing real estate performance [79]. This relationship between design quality and economic return is particularly evident in commercial properties. This metric indicates the percentage growth in office property values resulting from enhancements to the surrounding public space.

- *Retail Turnover (kSEK/yr)*

Retail turnover is defined as the total annual turnover for all ground floor retail. Urban neighborhoods are shaped not only by residents but also by the commercial activity and investment that support local economies and bring streets to life [80]. Measuring this economic vitality helps illustrate the broader impact of street design. This metric captures the annual retail sales generated on the street, reflecting the street's role in supporting commercial activity.

- *On-Street Car Parking Revenue (kSEK/yr)*

  On-street car parking revenue is defined as the total annual revenue from on-street parking, based on assumptions about fee periods, occupancy rates, and the influence of ground floor retail. On-street parking, which includes both paid and unpaid spaces along the roadside, is a common parking type where parked vehicles share the road width with moving traffic [81]. Tracking its financial impact provides insight into its role in urban revenue streams. This metric measures the yearly revenue collected from on-street parking, indicating how parking contributes to municipal income.

- *Outdoor Dining Revenue (kSEK/yr)*

  Outdoor dining revenue is defined as the total annual revenue from all outdoor seating areas. By increasing seating capacity and creating inviting spaces for informal socializing, outdoor bars and dining areas boost revenue, with 2022 research showing that nearly 40% of consumers were more likely to choose restaurants offering outdoor seating [82, 83]. Understanding this preference helps illustrate the economic value of well-designed outdoor spaces. This metric shows the annual income generated by outdoor dining areas, emphasizing their economic contribution to street life.

3.1.2.4. Mobility. The mobility dimension considers the role of streets in facilitating safe and efficient movement for all users. It highlights the importance of balancing different modes of transport and ensuring that streets are accessible, connected, and comfortable to navigate. This perspective supports the development of urban spaces that prioritize human-centered mobility over car-dominated approaches. Mobility Dimension Metrics are shown in Figure 3.8.

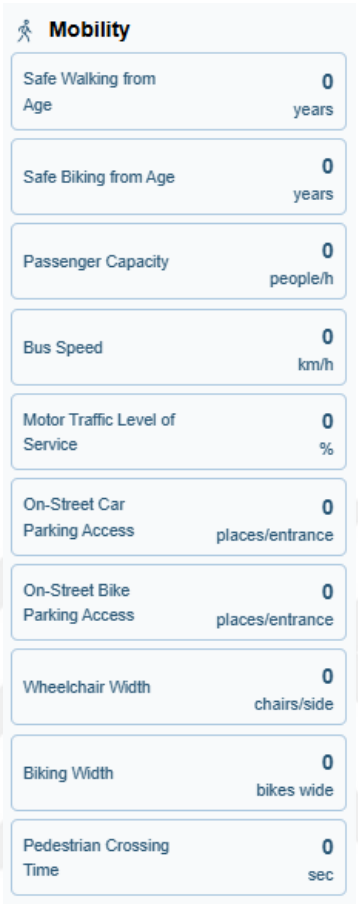

Figure 3.8. Mobility dimension metrics.

Mobility Dimension Metrics

- *Safe Walking from Age (years)*

  Safe walking from age is defined as the minimum age at which children can walk safely on the street. Built environment elements that reduce vehicle speeds (traffic calming measures) or create separate spaces for children away from traffic (such as playgrounds) are linked to children being able to walk safely at younger ages and experiencing fewer pedestrian injuries [84]. This metric indicates the minimum age at which children can safely walk along the street without adult supervision.

- *Safe Biking from Age (years)*

  Safe biking from age is defined as the minimum age at which children can bike safely on the street. It is widely suggested that safe, well-designed cycling infras-

tructure makes bicycling more attractive, supports active transportation habits, and plays a central role in enabling people to feel safe enough to cycle independently [85]. This metric measures the minimum age at which children can safely cycle on the street independently.

- *Passenger Capacity (people/h)*

  Passenger capacity is defined as the maximum number of road users that can theoretically pass through the street per hour. An effective regional passenger transport system should be primarily demand-driven and aim to efficiently use available resources to provide services that meet the needs of both users and operators [86]. This metric shows the number of passengers the street infrastructure can accommodate per hour across all modes.

- *Bus Speed (km/h)*

  Bus speed is defined as the average speed of bus traffic along the street segment, including the time spent at bus stops, and is assumed to be 40 percent of the speed in mixed traffic. Buses, which are the backbone of public transport in many cities, often experience significant delays due to traffic congestion, and providing dedicated bus lanes is a straightforward way to improve their speed and reliability [87]. Since buses typically share lanes with private vehicles, their travel times are highly sensitive to congestion levels. This metric reflects the average speed of buses along the street, indicating public transport efficiency.

- *Motor Traffic Level of Service (%)*

  Motor traffic level of service is defined as traffic lane congestion expressed as a percentage of maximum capacity, where lower congestion indicates better traffic flow. Level of Service (LOS) employs specific measures to capture how travelers perceive the performance of the transportation system and is widely used to assess road service quality from the user's perspective, typically expressed through a grading scale ranging from A (best conditions) to F (worst conditions) [88]. This metric measures how well motor vehicle traffic flows relative to ideal conditions, expressed as a percentage.

- *On-Street Car Parking Access (places/entrance)*

  On-street car parking access is defined as the number of parking spaces per en-

trance, where a dash indicates that the street has parking but no entrances. Residential on-street parking constitutes a significant share of the total parking supply and primarily serves local residents, with the number of spaces per property largely determined by the lot sizes along the street [89]. This metric indicates the average number of car parking spaces available per entrance along the street.

- *On-Street Bike Parking Access (places/entrance)*

  On-street bike parking access is defined as the number of bicycle parking spaces per entrance. Lack of sufficient bike racks leads people to park their bicycles improperly, often securing them to trees, fences, utility poles, traffic signs, or streetlights [90]. Providing enough designated bike parking can help prevent these issues and make cycling a more practical option. This metric shows the average number of bicycle parking spaces per entrance, supporting bike accessibility.

- *Wheelchair Width (chairs/side)*

  Wheelchair width is defined as the number of pedestrians and wheelchairs that can travel side by side or pass each other, assuming the pedestrian area is divided into two equally wide sidewalks on each side of the street, except on shared space streets and pedestrian streets. The length, topography, and surface texture of sidewalks can have a significant impact on the mobility and accessibility experienced by wheelchair users [91]. This metric measures how many wheelchairs can be accommodated side by side along the sidewalk.

- *Biking Width (bikes wide)*

  Biking width is defined as the total number of cyclists that can fit side by side across the street, regardless of direction. A cycle highway should be wide enough to let cyclists of varying speeds and abilities overtake safely and to allow people to ride side by side, supporting both efficient travel and social interaction [92]. This metric describes the number of cyclists who can ride side by side safely.

- *Pedestrian Crossing Time (sec)*

  Pedestrian crossing time is defined as the average time it takes for pedestrians to cross the street's roadway, assuming crossings are evenly distributed along the segment and a walking speed of 5 km/h. Pedestrian crosswalks that are painted or marked are among the most widely implemented traffic control measures for

pedestrians [93]. Their presence can directly influence how quickly and safely people are able to cross. This metric captures the time required for a pedestrian to cross the street safely.

3.1.2.5. Environment. The environmental dimension addresses how street design influences ecological sustainability and resilience. Streets are key interfaces between the built environment and natural systems, shaping how cities manage challenges such as pollution, climate impacts, and resource use. Integrating this dimension into planning practices helps promote healthier urban ecosystems and supports broader sustainability goals. Environment Dimension Metrics are shown in Figure 3.9.

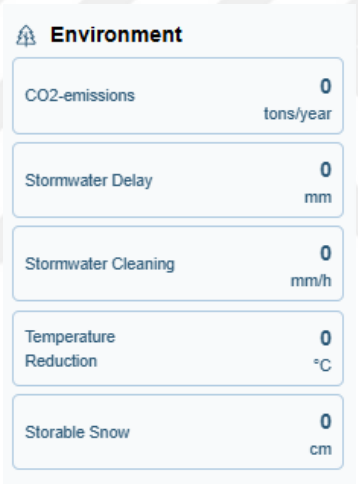

Figure 3.9. Environment dimension metrics.

Environment Dimension Metrics

- *CO_2-emissions (tons/year)*

  CO_2 emissions are defined as the annual amount of net carbon dioxide emissions from motor traffic along the analyzed street segment, after absorption by trees and green areas. Street canyons containing trees perform better than treeless ones in reducing the accumulation of CO_2 generated by traffic [94]. This highlights the need to more thoroughly assess the role of urban trees in mitigating carbon emissions. This metric measures the annual carbon dioxide emissions resulting

from traffic and assesses how the presence of vegetation influences these emissions.

- *Stormwater Delay (mm)*

  Stormwater delay is defined as the amount of rainfall that can be delayed per hour, assuming green areas function as grass areas. Green infrastructure represents a range of measures that use plant and soil systems to capture, retain, and gradually release stormwater, thereby delaying the flow to sewer systems [95]. In doing so, these practices help moderate peak flows and reduce the burden on conventional drainage networks. This metric indicates the additional delay in stormwater runoff achieved through permeable surfaces or green infrastructure.

- *Stormwater Cleaning (mm/h)*

  Stormwater cleaning is defined as the amount of rainfall that can be infiltrated and purified per hour, assuming green areas function as grass areas. Decentralized green infrastructure uses soil and plants to absorb, disperse, and retain stormwater, while also offering additional environmental, social, and economic advantages [96]. In this context, it becomes essential to evaluate how such elements function within urban streetscapes. This metric indicates the extent to which trees and green spaces along the street contribute to filtering and managing stormwater.

- *Temperature Reduction (°C)*

  Temperature reduction is defined as the decrease in temperature caused by the cooling and shading effects of trees, assuming a linear relationship between canopy coverage and temperature reduction, ranging from five degrees at full canopy coverage to zero on a treeless street. Urban trees help lower temperatures in cities, alleviating negative effects on human health, energy use, and infrastructure [97]. In this context, it is essential to assess the cooling benefits provided specifically by trees and vegetation. This metric captures how much urban trees contribute to reducing ambient temperatures and mitigating urban heat island effects.

- *Storable Snow (cm)*

  Storable snow is defined as the amount of snowfall that can be stored in snowbanks within the street's flex zone, assuming specific plowed widths for sidewalks, bike lanes, transit lanes, and travel lanes. In urban environments, the accumu-

lation and removal of snow, along with the resulting meltwater and associated pollutants, are among the major issues encountered during winter [98]. In this context, it is important to assess how snow management practices interact with street functionality. This metric measures the volume of snow that can be retained or stored along the street without obstructing mobility.

3.2. Methods Used in Analysis

3.2.1. Multiple Linear Regression

Multiple linear regression is a statistical technique employed to examine the linear relationship between a continuous dependent variable and multiple independent variables. It allows for the simultaneous estimation of the unique effect of each predictor while controlling for the potential confounding influence of others. This approach is widely valued for its capacity to quantify the relative contribution of different variables, test hypotheses regarding associations, and generate predictive models. One of the principal advantages of multiple linear regression is its interpretability, as it provides clear coefficients indicating the expected change in the dependent variable per unit change in each predictor. However, the method assumes linearity, homoscedasticity, independence of errors, and the absence of multicollinearity among predictors. Violations of these assumptions can compromise the validity of results. The general form of the multiple linear regression equation is expressed in (3.1) [99]:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_m X_m + \varepsilon \tag{3.1}$$

where,

- Y is the dependent variable (outcome),
- $X_1, X_2, \ldots, X_m$ are the independent variables (predictors),
- β_0 is the intercept (constant term),
- $\beta_1, \beta_2, \ldots, \beta_m$ are the coefficients associated with each independent variable,
- ε is the error term, representing the unexplained variation.

3.2.2. Stepwise Regression

Stepwise regression is an automated variable selection procedure that iteratively adds or removes predictors from the regression model based on predefined statistical criteria, such as significance levels. The process may follow a forward selection approach, where predictors are entered sequentially starting with the most significant variable, a backward elimination approach, which begins with all predictors and removes the least significant, or a combination of both methods. The primary advantage of stepwise regression lies in its ability to identify a parsimonious set of predictors that optimally explain variance in the dependent variable while reducing model complexity. However, this method has been criticized for increasing the risk of overfitting, capitalizing on chance associations in the data, and producing results that may not generalize well to other samples. In the present study, stepwise regression was employed to explore which demographic and attitudinal variables contributed most substantially to the prediction of the outcome variables, facilitating the identification of the most relevant predictors among a large set of potential factors. Although stepwise regression applies an iterative selection procedure to determine which predictors enter the model, the underlying regression equation remains identical to the standard multiple linear regression formulation as expressed in (3.1) [99]:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_m X_m + \varepsilon \tag{3.1}$$

where,

- Y is the dependent variable (outcome),
- $X_1, X_2, \ldots, X_m$ are the independent variables (predictors),
- β_0 is the intercept (constant term),
- $\beta_1, \beta_2, \ldots, \beta_m$ are the coefficients associated with each independent variable,
- ε is the error term, representing the unexplained variation.

3.2.3. Hierarchical Regression

Hierarchical regression is a statistical approach in which independent variables are entered into the regression equation in a predetermined sequence based on theoretical considerations or prior empirical evidence. This method enables researchers to examine the unique and incremental variance explained by specific blocks of predictors, allowing for the assessment of how much additional explanatory power is gained when new variables are introduced after accounting for the effects of earlier blocks. For example, demographic factors can be entered in the first block, followed by psychological or behavioral predictors in subsequent steps. The change in R^2 and F-statistics between models provides insight into whether each block significantly improves model fit. Unlike automated selection methods, hierarchical regression relies on the researcher's judgment to determine the order of entry, ensuring that the analysis remains grounded in conceptual rationale. In this study, hierarchical regression was employed to evaluate the incremental contributions of different groups of variables to the prediction of the outcome measures. Although hierarchical regression determines the order in which predictors are entered into the model based on theoretical considerations, the underlying regression equation remains identical to the standard multiple linear regression formulation as expressed in (3.1) [99]:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_m X_m + \varepsilon \tag{3.1}$$

where,

- Y is the dependent variable (outcome),
- $X_1, X_2, \ldots, X_m$ are the independent variables (predictors),
- β_0 is the intercept (constant term),
- $\beta_1, \beta_2, \ldots, \beta_m$ are the coefficients associated with each independent variable,
- ε is the error term, representing the unexplained variation.

3.2.4. Ordinal Regression

Ordinal regression is a statistical technique used when the dependent variable is ordinal, meaning it reflects ordered categories rather than continuous measurements. This method models the probability that an observation falls into or below a particular category as a function of one or more predictor variables. The approach estimates threshold parameters that separate adjacent outcome categories, along with regression coefficients describing the effect of predictors on the odds of higher versus lower outcomes. A key advantage of this technique is that it does not assume equal intervals between categories, making it well-suited for survey items measured on Likert-type scales. In this study, ordinal regression was applied to analyze variables where the outcome was ordered but not continuous, allowing for the interpretation of how predictors influenced the likelihood of respondents reporting higher levels of the target construct. In SPSS, ordinal regression models typically employ the logit link function, which is used to estimate the cumulative odds of an outcome variable falling at or below a given category. The logit link transforms a linear combination of predictors into a probability by mapping it onto the logistic (S-shaped) curve. The mathematical form of the function is expressed in (3.2) [100]:

$$logit(\theta_i) = \ln\left(\frac{\theta_i}{1-\theta_i}\right) = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_U x_{iU} \tag{3.2}$$

where,

- θ_i is the probability of the event of interest for the ith observation (e.g., the cumulative probability of selecting category j or lower).
- $x_{i1}, x_{i2}, \ldots, x_{iU}$ represent the values of the predictor variables for the ith unit.
- β_0 is the intercept.
- $\beta_1, \beta_2, \ldots, \beta_U$ are the regression coefficients that measure the effect of each corresponding predictor variable on the log-odds.

4. METHODOLOGY

This study employed a survey-based quantitative research design to investigate how demographic characteristics and attitudes toward pedestrian-oriented improvements influence individuals' transportation preferences. The methodology section describes the data collection process carried out in Caferağa Neighborhood, including the sampling strategy, survey implementation details, and the structure of the measurement instrument. It also presents how the collected variables were coded and analyzed using descriptive and inferential statistical methods.

4.1. Data Collection

The data collection phase focused on gathering firsthand information from individuals located in Caferağa Neighborhood, Kadıköy. A face-to-face survey approach was adopted to ensure clarity and contextual relevance, with a total of 401 valid responses collected over a five-day period in March 2025. This section outlines the spatial context of the study area, the fieldwork conditions, and the strategy followed for participant recruitment, alongside a justification of the sample size and the non-probabilistic sampling method employed.

4.1.1. Location

Caferağa was selected as the study area due to its social and physical characteristics that make it responsive to pedestrian-oriented transformation processes. The neighborhood offers a suitable context for this type of research with its walkable urban layout, a population inclined toward participatory planning practices, and previous exposure to similar urban interventions. Moreover, the area's accessibility and the high response rate of its residents contributed to the feasibility of data collection. The map shown in the Figure 4.1 provides a general overview of the administrative districts within the metropolitan area of Istanbul. It is included to situate the study site geographically within the city context. The highlighted section indicates the Kadıköy

district, where the specific neighborhood under investigation is located.



Figure 4.1. Districts of Istanbul [1].

Figure 4.2 shows the boundaries and relative population distribution of neighborhoods within Kadıköy, offering a clearer reference point for locating the research area. This intermediate scale map helps illustrate how Caferağa Neighborhood is positioned within the district's urban fabric.

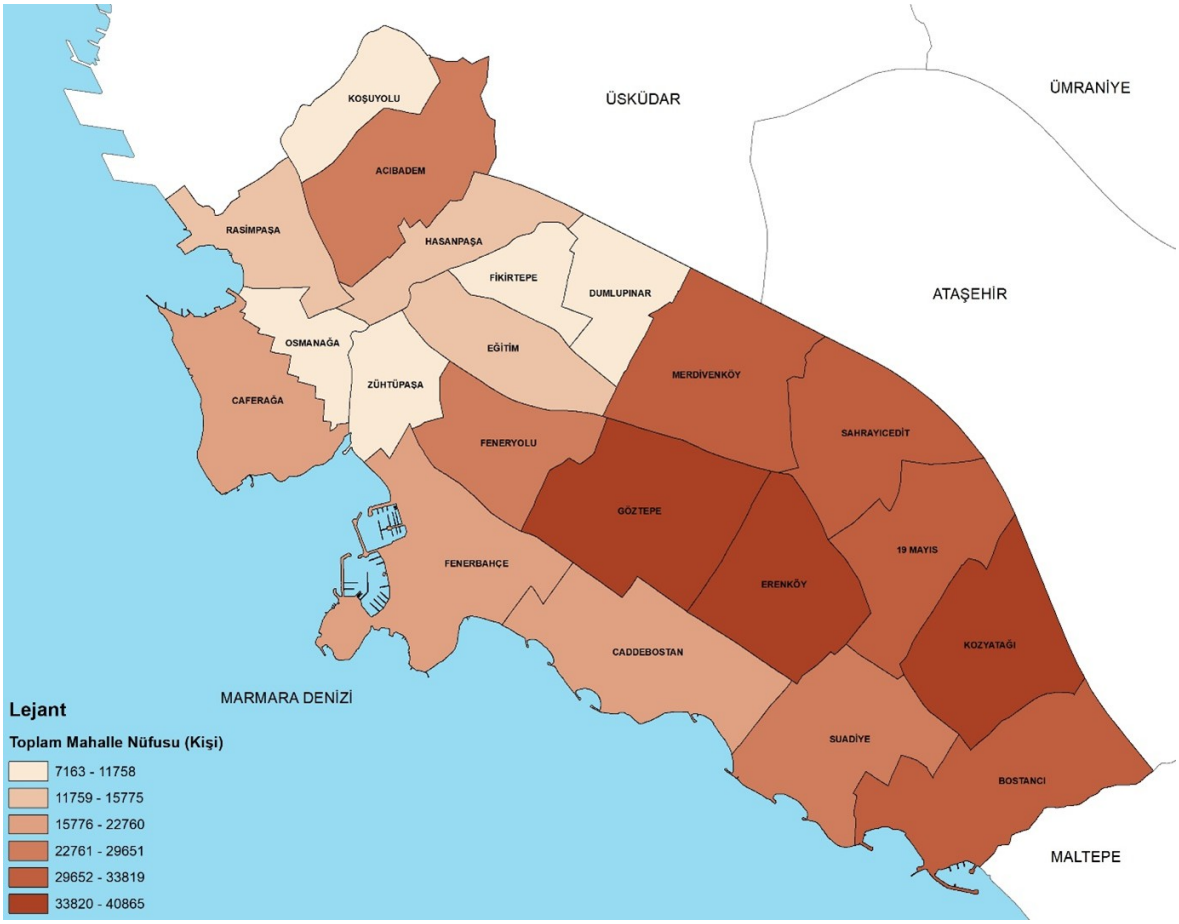

Figure 4.2. Colored political map of Kadıköy district showing population distribution [2].

Figure 4.3 shows a detailed map of the Caferağa Neighborhood, delineating the precise area in which all survey data were collected. As the exclusive focus of this study, Caferağa is characterized by a mix of residential and commercial uses and serves as the spatial context for examining respondents' perspectives on pedestrian-oriented improvements

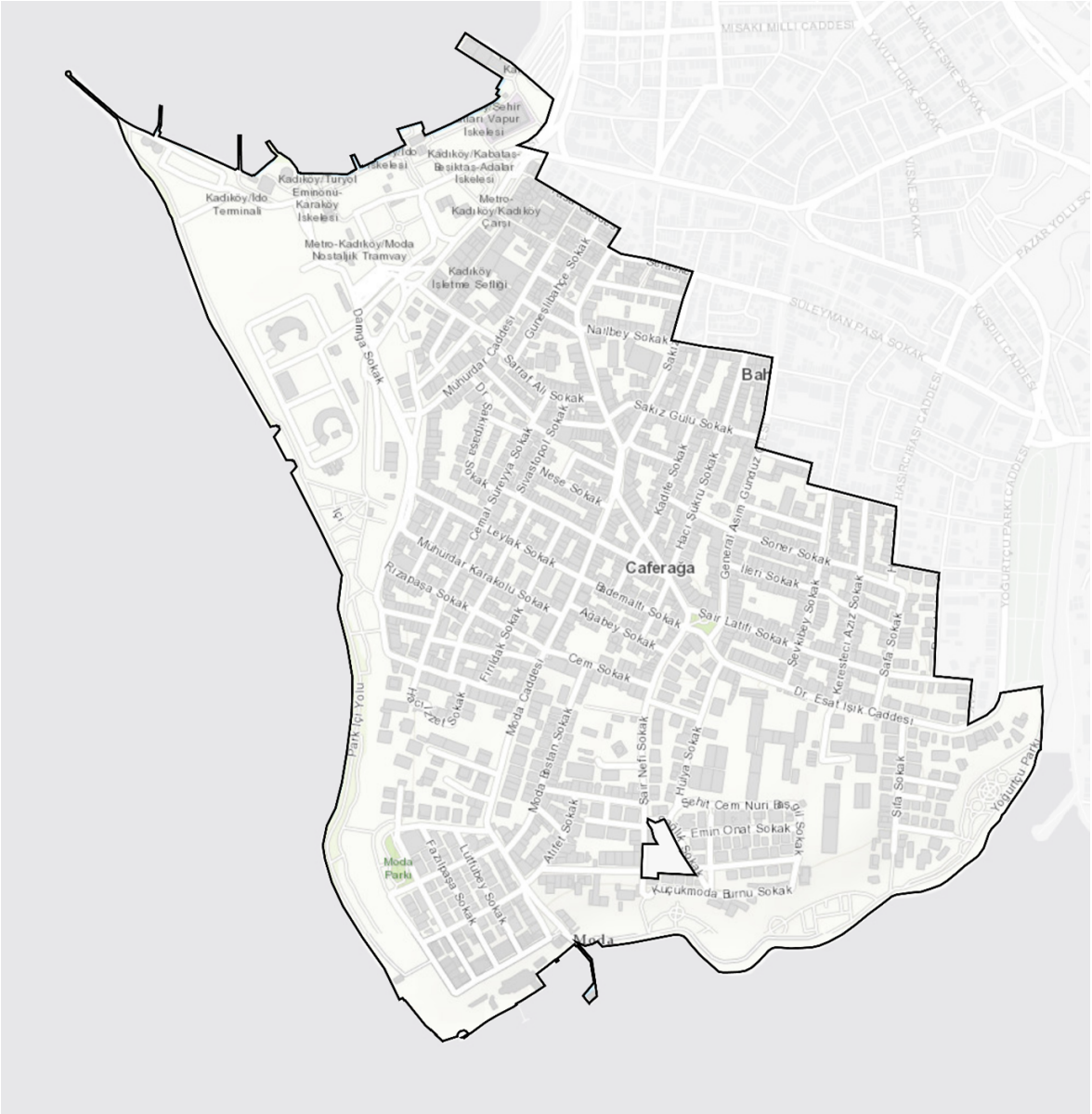

Figure 4.3. Detailed boundary map of Caferağa neighborhood [3].

Figure 4.4 shows Location 1, where a broad road with multiple lanes dominates the urban space. The lanes appear excessively wide and there is no visible pedestrian crossing despite the presence of a nearby bus stop, park, and commercial activity. This lack of dedicated pedestrian infrastructure makes it difficult and unsafe for individuals to cross the street. The oversized lane design also encourages higher vehicle speeds, increasing the risk for pedestrians and reducing the overall walkability of the area.



Figure 4.4. Location 1 – A wide multi-lane road lacking pedestrian crossing infrastructure.

Figure 4.5 captures Location 2, a compact urban street that suffers from circulation difficulties. Although there are only a few vehicles, the area still experiences noticeable spatial congestion. The combination of narrow sidewalks, irregular vehicle movement, and insufficient pedestrian infrastructure creates a challenging environment for walking. Moving from one side of the street to the other becomes difficult due to the disorganized layout and limited pedestrian priority, reducing the sense of safety and comfort for users.



Figure 4.5. Location 2 – A narrow urban street with circulation problems and limited pedestrian accessibility.

4.1.2. Survey Implementation

The survey was conducted through face-to-face interviews with individuals in Caferağa neighborhood. Data collection took place between March 18 and March 22, 2025, during which 401 valid responses were obtained. Participation in this study was voluntary, with respondents informed of the research purpose and assured anonymity, providing verbal consent before participation. No personal data were collected, data were securely stored with restricted access, and formal ethics committee approval was not required due to the non-sensitive, public, and voluntary nature of the research. Participants were approached both in public spaces, such as sidewalks and squares, and at local businesses. A considerable proportion of respondents were shop owners

and employees who spend substantial time in the area and actively shape its street life. Data collection conditions varied throughout the period. On March 18, rainy weather contributed to reduced willingness among passersby to participate in the survey. On the morning of March 19, public sentiment was noticeably affected by the news that the diploma of Ekrem İmamoğlu, the mayor of Istanbul, had been revoked the previous night, which led to visible sadness and tension in the area. In the following days, the situation escalated when İmamoğlu was taken into custody, creating an atmosphere of frustration, anxiety, and anger among many residents and business owners. Each survey took approximately 3 to 4 minutes to complete. However, in cases where respondents wished to share additional comments or elaborate on their opinions, the duration occasionally extended by a few minutes. Responses were initially recorded on printed questionnaire forms and subsequently transferred to Google Forms for digitization. Finally, the data were organized and prepared for analysis using Microsoft Excel.

4.1.3. Sampling Method

A convenience sampling approach was adopted for this study, as participants were selected based on their accessibility and willingness to participate during the survey period. There were no specific eligibility restrictions beyond the requirement that respondents be present in Caferağa Neighborhood and willing to complete the questionnaire voluntarily. The minimum target sample size was determined using the Yamane equation as expressed in (4.1), considering three different error margins ($e = 0.01$, $e = 0.05$, and $e = 0.1$) to evaluate the most appropriate level of precision. Although calculations were performed for all districts of Kadıköy to illustrate potential variations across neighborhoods, the primary focus was on Caferağa, which served as the main area of interest. Assuming a 95% confidence level and the estimated population size for Caferağa, an error margin of 0.05 was identified as the most suitable choice, balancing feasibility and statistical reliability. According to this calculation, a minimum of 393 responses were required. To account for potential incomplete or invalid questionnaires, additional surveys were conducted, resulting in a final total of 401 valid

responses included in the analysis.

$$n = \frac{N}{1 + Ne^2} \tag{4.1}$$

where,

n : The required sample size

N : The total population size of the target group

e : The margin of error

The calculated sample sizes for each margin of error are shown in the Tables 4.1 4.2,4.3.

Table 4.1. Estimated sample sizes for Kadıköy districts calculated using the Yamane equation (error margin = 0.01)

District	**Population Size (N)**	**Sample Size (n)**	**Sample Size (Rounded Up)**
19 Mayıs	31864	7611.31	7612
Acıbadem	28600	7409.33	7410
Bostancı	32415	7642.34	7643
Caddebostan	20209	6689.73	6690
Caferağa	**21350**	**6810.21**	**6811**
Dumlupınar	10170	5042.14	5043
Eğitim	12988	5649.90	5650
Erenköy	34438	7749.67	7750
Fenerbahçe	20571	6728.93	6729
Feneryolu	25300	7167.14	7168
Fikirtepe	12305	5516.70	5517
Göztepe	38613	7942.94	7943
Hasanpaşa	15198	6141.68	6142
Koşuyolu	6660	3997.60	3998
Kozyatağı	36873	7866.58	7867
Merdivenköy	30620	7538.16	7539
Osmanağa	7497	4284.73	4285
Rasimpaşa	12086	5472.24	5473
Sahrayıcedid	30112	7506.98	7507
Suadiye	25697	7198.64	7199
Zühtüpaşa	7903	4414.34	4415

Table 4.2. Estimated sample sizes for Kadıköy districts calculated using the Yamane equation (error margin = 0.05)

District	**Population Size (N)**	**Sample Size (n)**	**Sample Size (Rounded Up)**
19 Mayıs	31864	395.04	396
Acıbadem	28600	394.48	395
Bostancı	32415	395.12	396
Caddebostan	20209	392.24	393
Caferağa	**21350**	**392.64**	**393**
Dumlupınar	10170	384.86	385
Eğitim	12988	388.05	389
Erenköy	34438	395.41	396
Fenerbahçe	20571	392.37	393
Feneryolu	25300	393.77	394
Fikirtepe	12305	387.41	388
Göztepe	38613	395.90	396
Hasanpaşa	15918	390.19	391
Koşuyolu	6660	377.34	378
Kozyatağı	36873	395.71	396
Merdivenköy	30620	394.84	395
Osmanağa	7497	379.74	380
Rasimpaşa	12086	387.19	388
Sahrayıcedid	30112	394.76	395
Suadiye	25697	393.87	394
Zühtüpaşa	7903	380.73	381

Table 4.3. Estimated sample sizes for Kadıköy districts calculated using the Yamane equation (error margin = 0.1)

District	**Population Size (N)**	**Sample Size (n)**	**Sample Size (Rounded Up)**
19 Mayıs	31864	99.69	100
Acıbadem	28600	99.65	100
Bostancı	32415	99.69	100
Caddebostan	20209	99.51	100
Caferağa	**21350**	**99.53**	**100**
Dumlupınar	10170	99.03	100
Eğitim	12988	99.24	100
Erenköy	34438	99.71	100
Fenerbahçe	20571	99.52	100
Feneryolu	25300	99.61	100
Fikirtepe	12305	99.19	100
Göztepe	38613	99.74	100
Hasanpaşa	15918	99.38	100
Koşuyolu	6660	98.52	99
Kozyatağı	36873	99.73	100
Merdivenköy	30620	99.67	100
Osmanağa	7497	98.68	99
Rasimpaşa	12086	99.18	100
Sahrayıcedid	30112	99.67	100
Suadiye	25697	99.61	100
Zühtüpaşa	7903	98.75	99

Although the sampling method was non-probabilistic, the sample size calculation offered a foundation for asserting a reasonable level of representativeness. Nevertheless, contextual factors during data collection, including weather conditions and prevailing public sentiment, resulted in a greater number of responses from local shop owners and employees, who were more readily available and willing to participate at the time. Participants were approached through a combination of recruitment strategies, including intercepting individuals in public spaces (e.g., sidewalks, squares) and visiting commercial establishments to invite shopkeepers and staff to take part in the survey.

4.1.4. Survey Instrument

The survey instrument consisted of two main sections. The first section included demographic questions to collect background information about participants. The second section comprised items developed to assess respondents' attitudes toward various pedestrian-oriented improvements in their neighborhood. All attitude-related items were presented as closed-ended statements accompanied by a five-point Likert scale ranging from "Very Much" to "Very Little." The questions were developed by the researcher, drawing conceptual inspiration from Streetmeter Performance Metrics, though the exact wording and content were original to this study. The survey was administered in Turkish to ensure clarity and accessibility for all participants. No pre-testing or pilot implementation was conducted prior to the main data collection phase.

4.2. Data Description

This section provides an overview of the variables used in the analysis, including their measurement, coding structure, and categorization. Both demographic and attitudinal variables were incorporated, with recoding procedures applied to facilitate statistical analysis. Special attention is given to the operationalization of the key outcome variables, specifically the intentions to shift toward public transportation and active transportation. Descriptive statistics are also presented to summarize the distributional characteristics of the sample.

4.2.1. Variables, Measurement, and Recoding

The study included both demographic and attitudinal variables, which were measured and coded as follows:

Demographic Variables

- *Location:* A numeric variable indicating the location where the survey was conducted.

- *Gender:* Initially recorded as a string variable specifying the respondent's gender (e.g., "Male," "Female"). This variable was later recoded into a numeric binary variable `Gendercode` with 1 = Male and 2 = Female.
- *Age:* A numeric variable reflecting respondents' age in years. This variable was treated as continuous in the analyses.
- *Employment:* A string variable describing the respondent's employment status such as employed or unemployed. For analysis, it was recoded into numeric categories (`Employment_code`).
- *Education Level:* A string variable capturing the highest level of education completed. Recoded into an ordinal numeric variable (`education`) indicating increasing levels of education.
- *Income Level:* A string variable indicating the household's monthly income range. Recoded into an ordinal numeric variable (`incomelevel_code`) reflecting income brackets.
- *Do you have driver license?:* A string variable specifying whether the respondent possessed a driver's license (e.g., "Yes," "No"). Recoded into a numeric binary variable (`license`) with 1 = Yes and 2 = No.
- *Do you have car?:* A string variable indicating vehicle ownership status. Recoded into a numeric binary variable (`ownership`) with 1 = Yes and 2 = No.
- *What frequency:* A string variable assessing the frequency of vehicle use. Recoded into an ordinal numeric variable (`frequency`), where higher values reflected more frequent usage.

Attitudinal Variables

Attitudinal measures consisted of items assessing perceptions of various pedestrian-oriented improvements and active transportation preferences, each presented on a five-point Likert scale ranging from 1 = Very Little to 5 = Very Much:

- *Q1:* Perception of sidewalk widening.
- *Q2:* Perception of lane narrowing.

- *Q3:* Perception of adding green spaces.
- *Q4:* Perception of increasing the number of trees.
- *Q5:* Perception of adding pedestrian crossings.
- *Q6:* Perception of improving street lighting.
- *Q7:* Perception of reducing street parking availability.
- *Q8:* Intention to use public transportation.
- *Q9:* Intention to engage in active transportation (walking or cycling).

All attitudinal variables were treated as ordinal in the analysis. Additionally, in the context of the analyses conducted in this study, Q8 and Q9 were treated as dependent variables. Specifically, Q8 measured respondents' intention to use public transportation, while Q9 assessed their intention to engage in active transportation modes such as walking or cycling. All other variables described above were included as independent variables in the regression models to examine their associations with these outcomes.

4.2.2. Descriptive Statistics

Descriptive statistics were computed separately for continuous/ordinal variables and categorical variables to provide a comprehensive overview of the data. For continuous and ordinal measures, means, standard deviations, minimums, and maximums were reported in Table 4.4. This includes variables such as age and Likert-type survey items assessing attitudes and intentions. For demographic variables other than age, frequency distributions and percentages were calculated to illustrate the composition of the sample across demographic characteristics in they are shown in Table 4.5. This separation facilitates clearer interpretation by aligning statistical summaries with the measurement level of each variable.

Table 4.4. Descriptive statistics for continuous and ordinal variables

Descriptive Statistics					
Variable	**N**	**Minimum**	**Maximum**	**Mean**	**Std. Deviation**
Age	401	17	83	37.92	14.795
Q1	401	1	5	4.08	1.192
Q2	401	1	5	3.21	1.404
Q3	401	1	5	4.77	0.658
Q4	401	1	5	4.75	0.598
Q5	401	1	5	4.31	0.932
Q6	401	1	5	4.46	0.842
Q7	401	1	5	2.81	1.511
Q8	401	1	5	3.73	1.066
Q9	401	1	5	4.03	1.074

Table 2 presents descriptive statistics for participants' age and nine attitudinal items (Q1–Q9), all measured using a five-point Likert scale. These values help illustrate the overall distribution, central tendencies, and variability of responses across the sample (N = 401).

- *Age:* Respondents ranged in age from 17 to 83 years, with a mean of 37.92 (SD = 14.80), indicating that the sample included both younger and older adults with a relatively wide age distribution.
- *Q1 – Sidewalk Widening:* Mean = 4.08, SD = 1.19. This suggests a generally favorable view toward widening sidewalks, though the slightly larger standard deviation indicates moderate variation in opinions.
- *Q2 – Lane Narrowing:* Mean = 3.21, SD = 1.40. This item had a relatively lower mean compared to others, suggesting ambivalence or mixed views among participants.
- *Q3 – Green Space Increase:* Mean = 4.77, SD = 0.66. This was the highest-

scoring item with low variability, indicating strong and consistent support for increasing green areas.

- *Q4 – Tree Planting:* Mean = 4.75, SD = 0.60. Similar to Q3, this item received widespread agreement, again with very low dispersion.
- *Q5 – Pedestrian Crossings:* Mean = 4.31, SD = 0.93. The relatively high average shows general support for installing more pedestrian crossings, with slightly more variation than Q3 and Q4.
- *Q6 – Increasing Street Lighting:* Mean = 4.46, SD = 0.84. This high average shows that improved street lighting is widely viewed as a valuable intervention for safety and comfort.
- *Q7 – Reducing Street Parking Space:* Mean = 2.81, SD = 1.51. This was the lowest-rated item, and the high standard deviation indicates significant disagreement or polarization regarding reducing parking spaces.
- *Q8 – Willingness to Shift Toward Public Transportation:* Mean = 3.73, SD = 1.07. This result shows moderate support for transitioning toward public transportation if pedestrian improvements are made.
- *Q9 – Willingness to Shift Toward Active Transportation:* Mean = 4.03, SD = 1.07. A higher average than Q8, indicating stronger support for walking or cycling in response to pedestrian-friendly changes.

The findings suggest that environmental and safety-related improvements (Q3, Q4, Q5, Q6) received the strongest support, while car-use restricting interventions (Q2, Q7) were more contested. Participants generally showed moderate to strong willingness to consider sustainable transportation modes when supported by street improvements, with stronger support observed for active transportation (Q9) compared to public transportation (Q8).

Table 4.5. Frequency and percentage distributions for demographic variables

Variable	**Category**	**Frequency**	**Percent**	**Valid Percent**	**Cumulative Percent**
Location	1	110	27.4	27.4	27.4
	2	291	72.6	72.6	100.0
	Total	401	100.0	100.0	
Gendercode	Male	283	70.6	70.6	70.6
	Female	118	29.4	29.4	100.0
	Total	401	100.0	100.0	
Employment	Employed	341	85.0	85.0	85.0
	Unemployed	60	15.0	15.0	100.0
	Total	401	100.0	100.0	
Education	Elementary	69	17.2	17.2	17.2
	High School	158	39.4	39.4	56.6
	Bachelor	160	39.9	39.9	96.5
	Master	12	3.0	3.0	99.5
	PhD	2	0.5	0.5	100.0
	Total	401	100.0	100.0	
Income	0–22,500 TL	95	23.7	23.7	23.7
	22,500–45,000 TL	186	46.4	46.4	70.1
	45,000–90,000 TL	92	22.9	22.9	93.0
	90,000–135,000 TL	13	3.2	3.2	96.3
	135,000 TL and above	15	3.7	3.7	100.0
	Total	401	100.0	100.0	
License	Yes	268	66.8	66.8	66.8
	No	133	33.2	33.2	100.0
	Total	401	100.0	100.0	
Ownership	Yes	159	39.7	39.7	39.7
	No	242	60.3	60.3	100.0
	Total	401	100.0	100.0	
Frequency	Never	256	63.8	63.8	63.8
	A few times a month	18	4.5	4.5	68.3
	Once a week	22	5.5	5.5	73.8
	A few times a week	37	9.2	9.2	83.0
	Every day	68	17.0	17.0	100.0
	Total	401	100.0	100.0	

- *Location – Survey Location:* A majority of the participants (72.6%) were surveyed in Location 2, which corresponds to the inner parts of Caferağa neighborhood. The remaining 27.4% were from Location 1, representing the coastal section of Caferağa. This distribution indicates that the sample was more concentrated in the residential inner area than in the waterfront zone.
- *Gendercode – Gender:* The sample was male-dominated, with 70.6% identifying as male and 29.4% as female. Although additional gender options were provided, no participants selected them, nor did anyone choose to withhold their gender identity.
- *Employment – Employment Status:* A large portion of respondents (85%) reported being employed, whereas 15% stated they were unemployed. This imbalance may reflect the characteristics of the sampled population or the times and locations of data collection, suggesting that the survey was more accessible to individuals actively participating in the workforce.
- *Education – Education Level:* Most participants had completed either high school (39.4%) or undergraduate studies (39.9%). A smaller proportion held postgraduate degrees, with 3.0% having a master's degree and 0.5% a doctorate, indicating a relatively well-educated sample.
- *Income – Income Level:* The most common income bracket was 22,500–45,000 TL (46.4%), followed by 0–22,500 TL (23.7%) and 45,000–90,000 TL (22.9%). Higher-income categories (90,000 TL and above) accounted for only a small fraction of the sample. It is worth noting that the minimum wage in Türkiye at the time of data collection was 22,104 TL, placing a substantial portion of respondents around or just above the minimum income threshold.
- *License – Driver's License Ownership:* A majority (66.8%) reported having a driver's license, while 33.2% did not.
- *Ownership – Car Ownership:* 60.3% of respondents indicated they did not own a car, whereas 39.7% were car owners. This suggests a potential reliance on public or alternative forms of transportation.
- *Frequency – Frequency of Car Use:* A significant portion of the sample (63.8%) reported never using a car. Meanwhile, 17% used a car daily, and the rest fell into

varying levels of occasional use. This distribution reflects limited dependence on private vehicles among participants.

The demographic profile of the sample revealed several noteworthy patterns relevant to the interpretation of subsequent analyses. The majority of respondents (72.6%) were surveyed in the inner residential section of the neighborhood, indicating a spatial concentration away from the coastal zone. The sample was predominantly male (70.6%), and the vast majority (85%) reported being employed, suggesting a high rate of workforce participation. Educational attainment was relatively high, with most participants having completed either high school or undergraduate studies. In terms of income, nearly half of the respondents (46.4%) fell within the 22,500–45,000 TL range, which is slightly above the minimum wage at the time of data collection, pointing to a predominantly lower-middle income profile. While two-thirds of the sample (66.8%) reported having a driver's license, a substantial portion (60.3%) did not own a car. Furthermore, 63.8% of participants stated that they never used a car, highlighting a low level of car dependence among the respondents. These findings suggest that the sample largely consisted of working-age, educated individuals who rely on non-automobile transportation options and may thus be more receptive to pedestrian-oriented interventions.

5. RESULTS OF ANALYSIS

This section presents the results of regression analyses conducted to examine the factors influencing participants' responses to Q8 and Q9. Multiple linear regression, stepwise regression, hierarchical regression, and ordinal regression models were employed to assess the predictive roles of demographic, behavioral, and attitudinal variables. The analyses aimed to identify which variables significantly contribute to individuals' reported likelihood of shifting toward public and active transport in response to pedestrian-oriented improvements.

5.1. Multiple Linear Regression Analysis for Q8

5.1.1. Assumption Checks

5.1.1.1. Normality. Visual inspection of the histogram indicated that residuals were approximately normally distributed around the mean of approximately 0 (-5.07×10^{-16}) and had a standard deviation of 0.980. The Normal P–P Plot demonstrated that observed cumulative probabilities closely followed the expected diagonal line. Together, these findings suggest that the normality assumption was adequately satisfied.

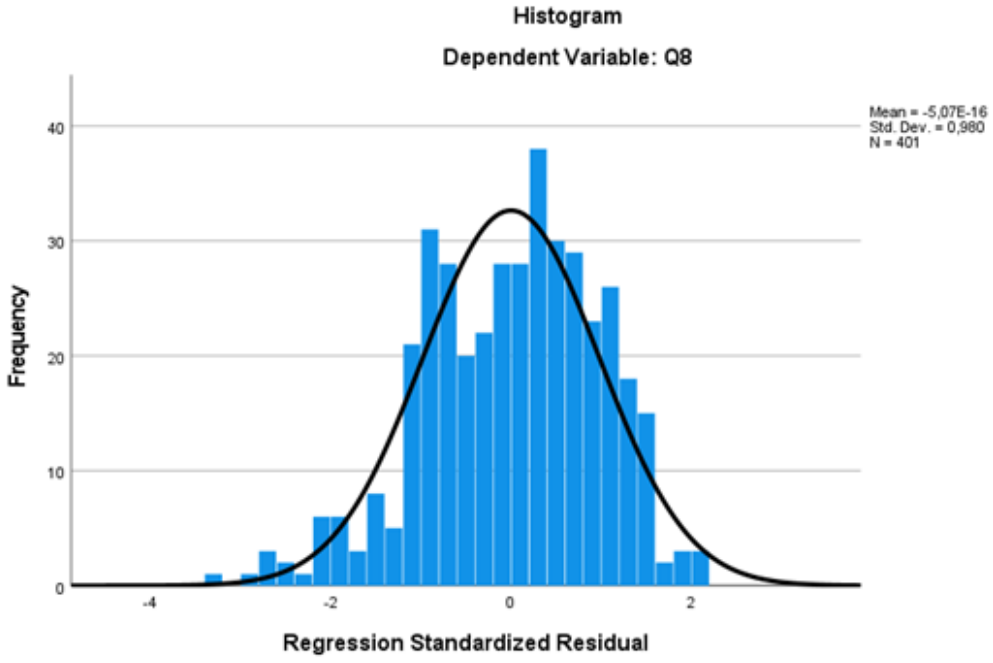

Figure 5.1. Histogram of regression standardized residuals for the multiple linear regression model for Q8.

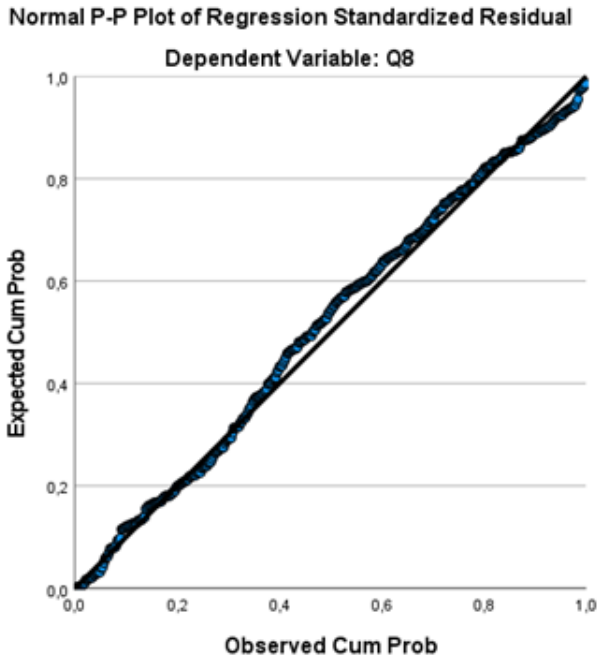

Figure 5.2. Normal P–P of regression standardized residuals for the multiple linear regression model for Q8.

5.1.1.2. Linearity and Homoscedasticity. The scatterplot of standardized residuals against predicted values was reviewed to assess linearity. The absence of discernible curvilinear patterns suggested that the relationship between predictors and the dependent variable was adequately linear.

The same scatterplot also indicated that residuals were evenly and randomly dispersed around the horizontal axis, without evidence of heteroscedasticity. This supports the assumption of constant variance of errors across all levels of predicted values.

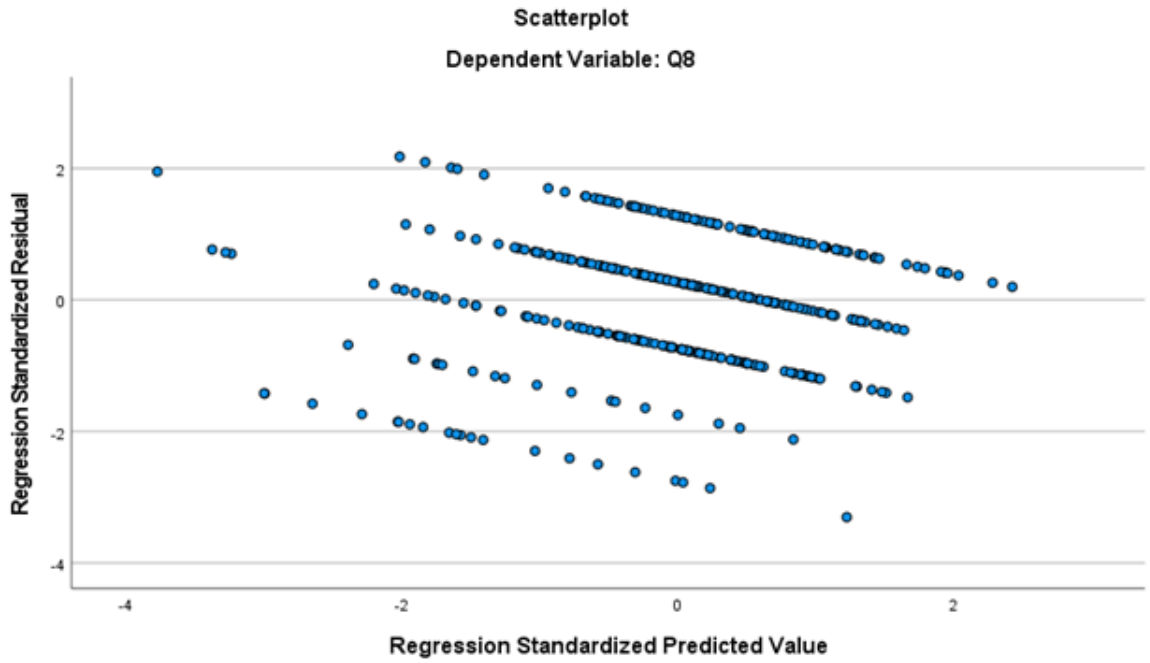

Figure 5.3. Scatterplot of standardized residuals versus predicted values for the multiple linear regression modelfor Q8.

5.1.1.3. Multicollinearity. Multicollinearity was evaluated by examining Variance Inflation Factors (VIF), tolerance values, and the condition index. VIF values ranged from 1.085 to 3.735, remaining below the commonly recommended threshold of 5. Tolerance statistics exceeded the minimum acceptable criterion of .20, indicating an acceptable level of shared variance among predictors. Although the condition index reached 62.225, suggesting some potential collinearity concerns, the overall combination of VIF and tolerance measures indicated that multicollinearity was not severe

enough to compromise the validity of the regression analysis.

Table 5.1. Regression coefficients for the multiple linear regression model for Q8.

Coefficients[a]							
Model	**Unstandardized Coefficients**		**Standardized Coefficients**	**t**	**Sig.**	**Collinearity Statistics**	
	B	Std. Error	Beta			Tolerance	VIF
(Constant)	2.600	0.736	–	3.533	< 0.001	–	–
Location	-0.129	0.116	-0.054	-1.117	0.265	0.921	1.085
Age	0.013	0.004	0.186	3.651	< 0.001	0.835	1.198
Q1	0.011	0.045	0.012	0.241	0.810	0.836	1.196
Q2	0.137	0.038	0.180	3.557	< 0.001	0.844	1.185
Q3	0.208	0.100	0.128	2.084	0.038	0.570	1.756
Q4	-0.180	0.108	-0.101	-1.675	0.095	0.593	1.688
Q5	0.179	0.058	0.156	3.061	0.002	0.827	1.209
Q6	0.050	0.064	0.040	0.789	0.430	0.857	1.167
Q7	0.052	0.035	0.074	1.495	0.136	0.883	1.132
Gendercode	-0.192	0.118	-0.082	-1.633	0.103	0.852	1.173
Employment	-0.118	0.151	-0.040	-0.784	0.434	0.844	1.184
Education	0.104	0.067	0.078	1.543	0.124	0.843	1.186
Income	-0.114	0.063	-0.102	-1.828	0.068	0.693	1.444
License	0.031	0.126	0.014	0.249	0.803	0.698	1.432
Ownership	-0.191	0.195	-0.088	-0.975	0.330	0.268	3.735
Frequency	-0.121	0.058	-0.182	-2.072	0.039	0.280	3.567
[a] Dependent Variable: Q8							

5.1.1.4. Autocorrelation. The Durbin–Watson statistic was 1.916, indicating that there was no evidence of autocorrelation in the residuals.

Table 5.2. Model summary of the multiple linear regression model for Q8.

Model	**R**	**R Square**	**Adjusted R Square**	**Std. Error of the Estimate**	**R Square Change**	**F Change**	**df1**	**df2**	**Sig. F Change**	**Durbin-Watson**
1	0.414[a]	0.172	0.137	0.991	0.172	4.972	16	384	< 0.001	1.916
[a] Predictors: (Constant), frequency, Q4, Location, education, Q1, Employment, Q7, Age, Q6, Gendercode, Q2, Q5, license, income, Q3, ownership										
[b] Dependent Variable: Q8										

5.1.1.5. Outliers and Influential Observations. Standardized residuals ranged between –3.3 and +2.2, with only a small number of observations exceeding ±3. This indicates minimal impact from outliers. In addition, the maximum Cook's Distance was 0.051, which is well below the threshold of 1, indicating no influential observations. Based

on these diagnostics, all key assumptions were judged to be satisfactorily met. Consequently, the regression analysis was considered appropriate and was conducted without further data transformation or variable exclusion.

Table 5.3. Residual statistics for the multiple linear regression model for Q8.

Residuals Statistics[a]	**Minimum**	**Maximum**	**Mean**	**Std. Deviation**	**N**
Predicted Value	2.07	4.80	3.73	0.442	401
Std. Predicted Value	-3.768	2.429	0.000	1.000	401
Standard Error of Predicted Value	0.123	0.414	0.199	0.046	401
Adjusted Predicted Value	1.84	4.79	3.73	0.442	401
Residual	-3.274	2.158	0.000	0.971	401
Std. Residual	-3.304	2.178	0.000	0.980	401
Stud. Residual	-3.362	2.237	-0.001	1.003	401
Deleted Residual	-3.388	2.277	-0.001	1.017	401
Stud. Deleted Residual	-3.408	2.249	-0.001	1.005	401
Mahal. Distance	5.208	68.824	15.960	8.761	401
Cook's Distance	0.000	0.051	0.003	0.005	401
Centered Leverage Value	0.013	0.172	0.040	0.022	401

[a] Dependent Variable: Q8

5.1.2. Multiple Linear Regression Results for Q8

5.1.2.1. Model Summary. The multiple linear regression model accounted for approximately 17.2% of the variance in the dependent variable ($R^2 = .172$), reflecting a modest level of explanatory power. Furthermore, the model was statistically significant overall, as indicated by the F-test ($F(16, 384) = 4.972$, $p < .001$), suggesting that the set of predictors jointly provided a meaningful contribution to the prediction of the outcome variable.

Table 5.4. Model summary of the multiple linear regression model for Q8.

Model	**R**	**R Square**	**Adjusted R Square**	**Std. Error of the Estimate**	**R Square Change**	**F Change**	**df1**	**df2**	**Sig. F Change**	**Durbin-Watson**
1	0.414[a]	0.172	0.137	0.991	0.172	4.972	16	384	< 0.001	1.916

[a] Predictors: (Constant), frequency, Q4, Location, education, Q1, Employment, Q7, Age, Q6, Gendercode, Q2, Q5, license, income, Q3, ownership

[b] Dependent Variable: Q8

5.1.2.2. ANOVA. The ANOVA results confirmed that the regression model significantly improved prediction compared to the intercept-only model ($F(16, 384) = 4.972$, $p < .001$). This finding indicates that all independent variables collectively contributed to explaining perceptions related to Q8.

Table 5.5. ANOVA results of the multiple linear regression model for Q8.

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	78.076	16	4.880	4.972	$< .001$[b]
	Residual	376.837	384	0.981		
	Total	454.913	400			
[a] Dependent Variable: Q8						
[b] Predictors: (Constant), frequency, Q4, Location, education, Q1, Employment, Q7, Age, Q6, Gendercode, Q2, Q5, license, income, Q3, ownership						

5.1.2.3. Regression Coefficients. In Model 1, which included all independent variables entered simultaneously into the regression equation, several predictors were found to be statistically significant in explaining the variance in Q8. *Age* ($B = 0.013$, $\beta = 0.186$, $p < .001$), Q2 ($B = 0.137$, $\beta = 0.180$, $p < .001$), Q3 ($B = 0.208$, $\beta = 0.128$, $p = .038$), and Q5 ($B = 0.179$, $\beta = 0.156$, $p = .002$) were positively associated with the dependent variable, indicating that higher values on these variables predicted increased scores on Q8. Additionally, *frequency* was negatively associated with the outcome ($B = -0.121$, $\beta = -0.182$, $p = .039$), suggesting that more frequent car use was linked to lower scores on Q8. Other predictors did not reach statistical significance at the .05 level.

The findings suggest that attitudes toward specific pedestrian-oriented improvements play a meaningful role in shaping public transport intentions. Positive evaluations of lane narrowing , increasing green areas, and adding more pedestrian crossings were significantly associated with a higher reported willingness to use public transportation. This indicates that interventions aimed at improving both safety and environmental quality can positively influence travel behavior. Additionally, older participants were more inclined to consider shifting to public transport in response to these improvements, while individuals who frequently use private cars were less receptive.

Table 5.6. Regression coefficients for the multiple linear regression model for Q8.

Coefficients[a]							
Model	**Unstandardized Coefficients**		**Standardized Coefficients**	**t**	**Sig.**	**Collinearity Statistics**	
	B	Std. Error	Beta			Tolerance	VIF
(Constant)	2.600	0.736	–	3.533	< 0.001	–	–
Location	-0.129	0.116	-0.054	-1.117	0.265	0.921	1.085
Age	0.013	0.004	0.186	3.651	< 0.001	0.835	1.198
Q1	0.011	0.045	0.012	0.241	0.810	0.836	1.196
Q2	0.137	0.038	0.180	3.557	< 0.001	0.844	1.185
Q3	0.208	0.100	0.128	2.084	0.038	0.570	1.756
Q4	-0.180	0.108	-0.101	-1.675	0.095	0.593	1.688
Q5	0.179	0.058	0.156	3.061	0.002	0.827	1.209
Q6	0.050	0.064	0.040	0.789	0.430	0.857	1.167
Q7	0.052	0.035	0.074	1.495	0.136	0.883	1.132
Gendercode	-0.192	0.118	-0.082	-1.633	0.103	0.852	1.173
Employment	-0.118	0.151	-0.040	-0.784	0.434	0.844	1.184
Education	0.104	0.067	0.078	1.543	0.124	0.843	1.186
Income	-0.114	0.063	-0.102	-1.828	0.068	0.693	1.444
License	0.031	0.126	0.014	0.249	0.803	0.698	1.432
Ownership	-0.191	0.195	-0.088	-0.975	0.330	0.268	3.735
Frequency	-0.121	0.058	-0.182	-2.072	0.039	0.280	3.567

[a] Dependent Variable: Q8

5.2. Stepwise Regression Analysis for Q8

5.2.1. Assumption Checks

5.2.1.1. Normality. Visual inspection of the histogram indicated that residuals were approximately normally distributed. The Normal P–P Plot demonstrated that observed cumulative probabilities closely followed the expected diagonal line. Additionally, the standardized residuals had a mean of approximately 0 (3.42×10^{-16}) and a standard deviation of 0.995, supporting the assumption of normality.

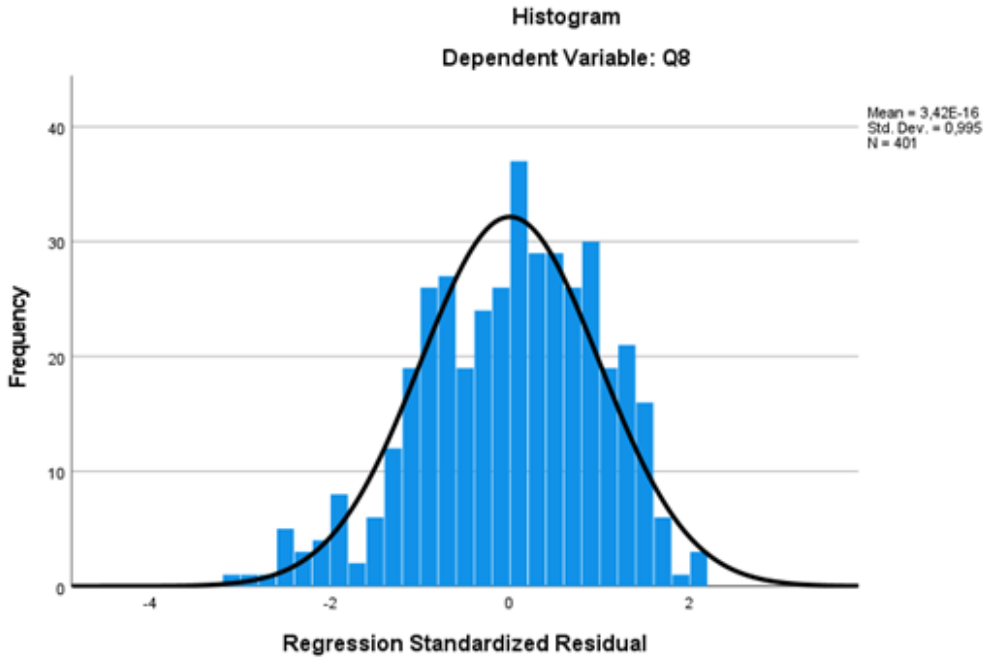

Figure 5.4. Histogram of regression standardized residuals for the stepwise regression model for Q8.

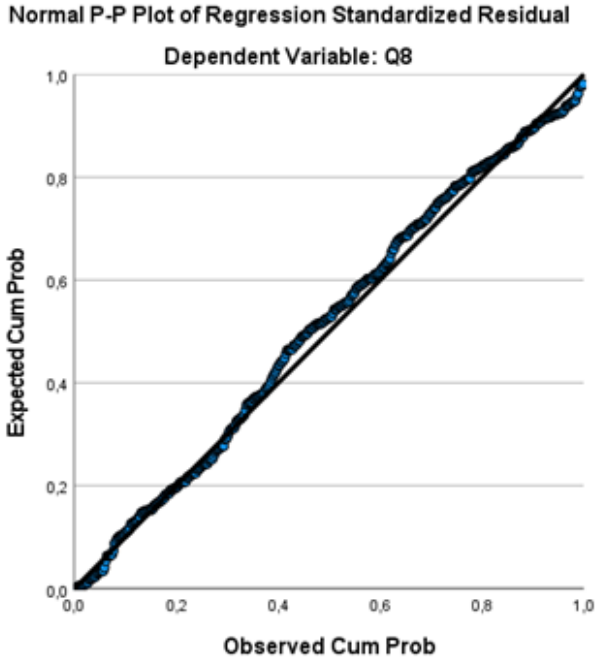

Figure 5.5. Normal P–P Plot of regression standardized residuals for the stepwise regression model for Q8.

5.2.1.2. Linearity and Homoscedasticity. The scatterplot of standardized residuals against predicted values was reviewed to assess linearity. The absence of discernible curvilinear patterns suggested that the relationship between predictors and the dependent variable was adequately linear. The same scatterplot also indicated that residuals were evenly and randomly dispersed around the horizontal axis, without evidence of heteroscedasticity. This supports the assumption of constant variance of errors across all levels of predicted values.

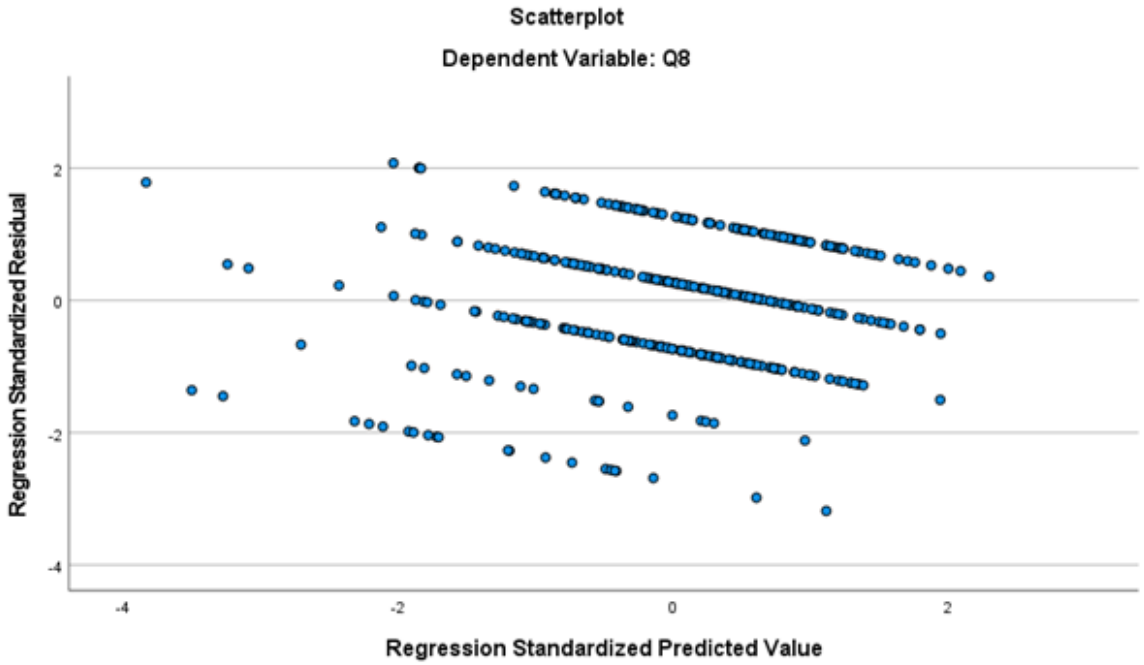

Figure 5.6. Scatterplot of standardized residuals versus predicted values for the stepwise regression model for Q8.

5.2.1.3. Multicollinearity. Multicollinearity was evaluated using Variance Inflation Factors (VIF), tolerance values, and the condition index. VIF values for predictors retained in the stepwise model ranged from approximately 1.085 to 3.735, all below the recommended threshold of 5. Although the condition index exceeded 30 in some dimensions, the combination of acceptable VIF and tolerance measures indicated that multicollinearity was not a substantial concern.

Table 5.7. Regression coefficients for the stepwise regression model for Q8.

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
No		B	Std. Error	Beta			**Tolerance**	**VIF**
1	(Constant)	2.539	0.245	–	10.363	< .001	–	–
	Q5	0.277	0.056	0.242	4.979	< .001	1.000	1.000
2	(Constant)	2.167	0.255	–	8.514	< .001	–	–
	Q5	0.245	0.055	0.214	4.470	< .001	0.982	1.018
	Q2	0.158	0.036	0.208	4.341	< .001	0.982	1.018
3	(Constant)	1.815	0.277	–	6.545	< .001	–	–
	Q5	0.233	0.054	0.204	4.283	< .001	0.977	1.023
	Q2	0.162	0.036	0.213	4.489	< .001	0.981	1.019
	Age	0.010	0.003	0.143	3.034	0.003	0.994	1.006
4	(Constant)	2.071	0.292	–	7.095	< .001	–	–
	Q5	0.212	0.055	0.185	3.876	< .001	0.956	1.046
	Q2	0.150	0.036	0.198	4.172	< .001	0.967	1.034
	Age	0.012	0.003	0.162	3.417	0.001	0.972	1.029
	Frequency	-0.084	0.032	-0.127	-2.635	0.009	0.940	1.064

[a] Dependent Variable: Q8

5.2.1.4. Autocorrelation. The Durbin–Watson statistic was 1.913, indicating that there was no evidence of autocorrelation in the residuals.

Table 5.8. Model summary of stepwise regression model for Q8.

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	.242[a]	.058	.056	1.036	.058	24.788	1	399	< .001	
2	.318[b]	.101	.097	1.014	.043	18.842	1	398	< .001	
3	.348[c]	.121	.115	1.003	.020	9.206	1	397	.003	
4	.370[d]	.137	.128	0.996	.015	6.945	1	396	.009	1.913

[a] Predictors: (Constant), Q5

[b] Predictors: (Constant), Q5, Q2

[c] Predictors: (Constant), Q5, Q2, Age

[d] Predictors: (Constant), Q5, Q2, Age, frequency

[e] Dependent Variable: Q8

5.2.1.5. Outliers and Influential Observations. Standardized residuals ranged between –3.18 and +2.07, suggesting minimal influence from outliers. The maximum Cook's Distance was 0.0495, well below the threshold of 1, indicating no undue influence of individual observations.

Table 5.9. Residual statistics for the stepwise regression model for Q8.

Residuals Statistics[a]					
	Minimum	**Maximum**	**Mean**	**Std. Deviation**	**N**
Predicted Value	2.22	4.64	3.73	0.394	401
Std. Predicted Value	-3.829	2.302	0.000	1.000	401
Standard Error of Predicted Value	0.065	0.227	0.108	0.027	401
Adjusted Predicted Value	2.14	4.63	3.73	0.394	401
Residual	-3.171	2.069	0.000	0.991	401
Std. Residual	-3.184	2.078	0.000	0.995	401
Stud. Residual	-3.197	2.092	0.000	1.002	401
Deleted Residual	-3.198	2.098	0.000	1.005	401
Stud. Deleted Residual	-3.235	2.101	-0.001	1.005	401
Mahal. Distance	0.690	19.794	3.990	2.720	401
Cook's Distance	0.000	0.049	0.003	0.005	401
Centered Leverage Value	0.002	0.049	0.010	0.007	401

[a] Dependent Variable: Q8

5.2.2. Stepwise Regression Results for Q8

5.2.2.1. Variables Entered and Removed. The stepwise procedure selected predictors in four steps, sequentially entering the variables that contributed the greatest incremental explanatory power to the model predicting Q8. In the first step, Q5 was included as the initial predictor. In the second step, Q2 was added to improve the model's fit. Then, in the third step, "Age" was entered. Finally, "frequency" was added as a final variable. No variables were removed during the procedure, and all predictors were retained across steps based on the specified entry and removal criteria.

Variables entered/removed[a]			
Model	**Variables Entered**	**Variables Removed**	**Method**
1	Q5		Stepwise (Criteria: Probability-of-F-to-enter ≤ .050, Probability-of-F-to-remove ≥ .100).
2	Q2		Stepwise (Criteria: Probability-of-F-to-enter ≤ .050, Probability-of-F-to-remove ≥ .100).
3	Age		Stepwise (Criteria: Probability-of-F-to-enter ≤ .050, Probability-of-F-to-remove ≥ .100).
4	frequency		Stepwise (Criteria: Probability-of-F-to-enter ≤ .050, Probability-of-F-to-remove ≥ .100).
[a] Dependent Variable: Q8			

5.2.2.2. Model Summary. The stepwise regression analysis demonstrated that the explanatory power of the models increased incrementally with the addition of new predictors. Model 1 included only Q5 as the predictor and accounted for approximately 5.8% of the variance in the dependent variable ($R^2 = .058$). Model 2 incorporated both Q5 and Q2 as predictors, explaining 10.1% of the variance ($R^2 = .101$). Model 3 added *Age* to the previous predictors, resulting in 12.1% of the variance explained ($R^2 = .121$). Finally, Model 4 included Q5, Q2, *Age*, and *frequency*, achieving the highest explanatory power by accounting for approximately 13.7% of the variance in the outcome variable ($R^2 = .137$).

Table 5.10. Model summary of stepwise regression model for Q8.

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	.242[a]	.058	.056	1.036	.058	24.788	1	399	< .001	
2	.318[b]	.101	.097	1.014	.043	18.842	1	398	< .001	
3	.348[c]	.121	.115	1.003	.020	9.206	1	397	.003	
4	.370[d]	.137	.128	0.996	.015	6.945	1	396	.009	1.913
[a] Predictors: (Constant), Q5										
[b] Predictors: (Constant), Q5, Q2										
[c] Predictors: (Constant), Q5, Q2, Age										
[d] Predictors: (Constant), Q5, Q2, Age, frequency										
[e] Dependent Variable: Q8										

5.2.2.3. ANOVA. The ANOVA results confirmed that each regression model significantly improved the explanation of variance in Q8 compared to the intercept-only model

($p < .001$ in all cases). Model 1, which included only Q5 as a predictor, accounted for a significant proportion of variance ($F(1, 399) = 24.788$, $p < .001$). Model 2, incorporating Q2 alongside Q5, remained statistically significant ($F(2, 398) = 22.369$, $p < .001$). The addition of *Age* in Model 3 further improved the model's explanatory power ($F(3, 397) = 18.289$, $p < .001$). Finally, Model 4, which included *frequency* as an additional predictor, continued to yield a significant overall model ($F(4, 396) = 15.658$, $p < .001$). These results indicate that each successive set of predictors contributed meaningfully to explaining perceptions related to Q8.

Table 5.11. ANOVA results of the stepwise regression model for Q8.

ANOVA[a]						
Model		**Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**
1	Regression	26.609	1	26.609	24.788	$< .001^{b}$
	Residual	428.304	399	1.073		
	Total	454.913	400			
2	Regression	45.969	2	22.984	22.369	$< .001^{c}$
	Residual	408.944	398	1.027		
	Total	454.913	400			
3	Regression	55.237	3	18.412	18.289	$< .001^{d}$
	Residual	399.676	397	1.007		
	Total	454.913	400			
4	Regression	62.125	4	15.531	15.658	$< .001^{e}$
	Residual	392.787	396	0.992		
	Total	454.913	400			
[a] Dependent Variable: Q8						
[b] Predictors: (Constant), Q5						
[c] Predictors: (Constant), Q5, Q2						
[d] Predictors: (Constant), Q5, Q2, Age						
[e] Predictors: (Constant), Q5, Q2, Age, frequency						

5.2.2.4. Regression Coefficients. Across the four regression models predicting Q8, several predictors consistently emerged as significant. In Model 1, support for increasing pedestrian crossings (Q5) was a significant positive predictor. Model 2 showed that both Q5 and support for lane narrowing (Q2) were significantly associated with higher

Q8 scores. Model 3 further demonstrated that age also contributed positively alongside Q5 and Q2. In the final model, Q5, Q2, and age remained significant positive predictors, while frequency of car use was negatively associated with the outcome, indicating that individuals who relied more heavily on private vehicles reported less favorable perceptions. The findings suggest that attitudes toward pedestrian-oriented improvements, particularly increasing pedestrian crossings and narrowing lane widths play a central role in shaping perceptions related to Q8. Positive evaluations of these measures were consistently associated with higher scores, indicating that interventions targeting safety and walkability are likely to be well received. Additionally, age emerged as a significant factor, with older participants expressing more favorable perceptions of such improvements. In contrast, frequent car use was negatively related to the outcome, suggesting that habitual reliance on private vehicles may limit openness to pedestrian-focused changes.

Table 5.12. Regression coefficients for the stepwise regression model for Q8.

Model		**Unstandardized Coefficients**		**Standardized Coefficients**	**t**	**Sig.**	**Collinearity Statistics**	
No		B	Std. Error	Beta			**Tolerance**	**VIF**
1	(Constant)	2.539	0.245	–	10.363	< .001	–	–
	Q5	0.277	0.056	0.242	4.979	< .001	1.000	1.000
2	(Constant)	2.167	0.255	–	8.514	< .001	–	–
	Q5	0.245	0.055	0.214	4.470	< .001	0.982	1.018
	Q2	0.158	0.036	0.208	4.341	< .001	0.982	1.018
3	(Constant)	1.815	0.277	–	6.545	< .001	–	–
	Q5	0.233	0.054	0.204	4.283	< .001	0.977	1.023
	Q2	0.162	0.036	0.213	4.489	< .001	0.981	1.019
	Age	0.010	0.003	0.143	3.034	0.003	0.994	1.006
4	(Constant)	2.071	0.292	–	7.095	< .001	–	–
	Q5	0.212	0.055	0.185	3.876	< .001	0.956	1.046
	Q2	0.150	0.036	0.198	4.172	< .001	0.967	1.034
	Age	0.012	0.003	0.162	3.417	0.001	0.972	1.029
	Frequency	-0.084	0.032	-0.127	-2.635	0.009	0.940	1.064

[a] Dependent Variable: Q8

5.3. Hierarchical Regression Analysis for Q8

5.3.1. Assumption Checks

5.3.1.1. Normality. Visual inspection of the histogram indicated that residuals were approximately normally distributed. The Normal P–P Plot showed that observed cumulative probabilities closely followed the expected diagonal line. Additionally, the standardized residuals had a mean of approximately 0 (-7.48×10^{-16}) and a standard deviation of 0.980, supporting the assumption of normality.

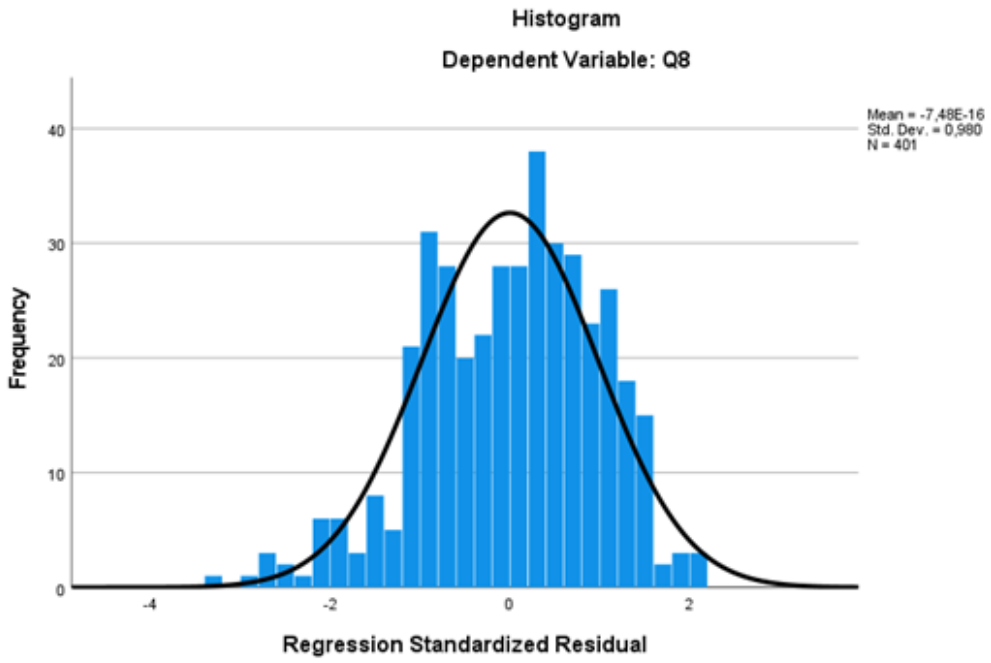

Figure 5.7. Histogram of regression standardized residuals for the hierarchical regression model for Q8.

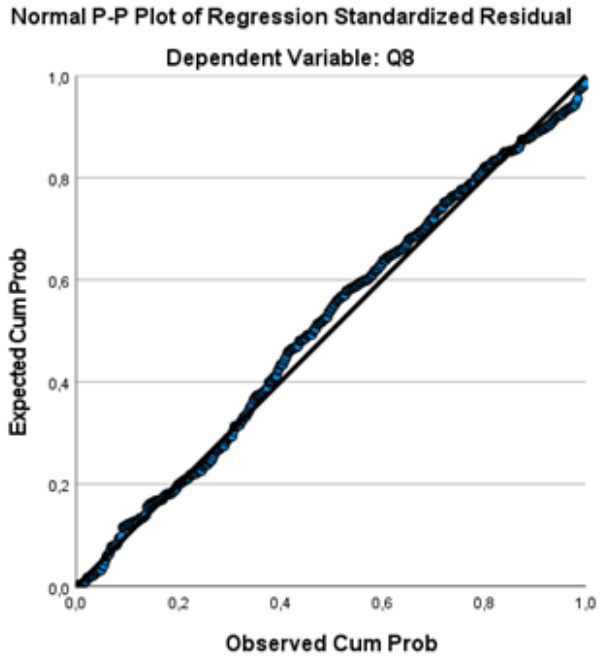

Figure 5.8. Normal P–P plot of regression standardized residuals for the hierarchical regression model for Q8.

5.3.1.2. Linearity and Homoscedasticity. The scatterplot of standardized residuals against predicted values was reviewed to assess linearity. The absence of discernible curvilinear patterns suggested that the relationship between predictors and the dependent variable was adequately linear. The same scatterplot also indicated that residuals were evenly and randomly dispersed around the horizontal axis, without evidence of heteroscedasticity. This supports the assumption of constant variance of errors across all levels of predicted values.

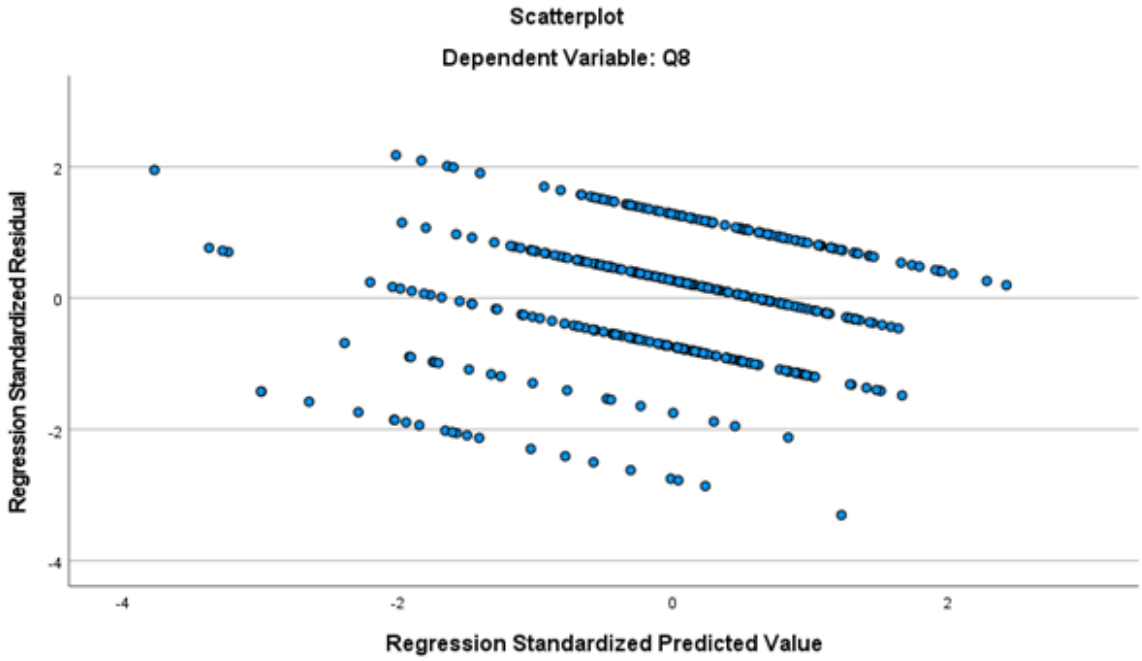

Figure 5.9. Scatterplot of standardized residuals versus predicted values for the hierarchical regression model for Q8.

5.3.1.3. Multicollinearity. Multicollinearity was assessed using Variance Inflation Factors (VIF) and the condition index. VIF values ranged from approximately 1.1 to 3.7, all below the recommended threshold of 5. Although the highest condition index was above 30, the combination of acceptable VIF and tolerance measures suggested that multicollinearity was not severe.

Table 5.13. Regression coefficients for the hierarchical regression model for Q8.

Coefficients[a]								
Model	**Variable**	**Unstandardized Coefficients**		**Standardized Coefficients**	**t**	**Sig.**	**Collinearity Statistics**	
		B	**Std. Error**	**Beta**			**Tolerance**	**VIF**
1	(Constant)	3.845	0.611		6.295	< 0.001		
	Location	-0.041	0.117	-0.017	-0.353	0.724	0.975	1.026
	Gendercode	-0.156	0.122	-0.067	-1.277	0.202	0.867	1.154
	Employment	-0.147	0.157	-0.049	-0.935	0.350	0.855	1.170
	education	0.141	0.069	0.107	2.040	0.042	0.865	1.156
	income	-0.155	0.065	-0.138	-2.384	0.018	0.703	1.422
	license	0.023	0.131	0.010	0.175	0.861	0.708	1.413
	ownership	-0.017	0.199	-0.008	-0.085	0.933	0.282	3.550
	frequency	-0.109	0.060	-0.164	-1.816	0.070	0.288	3.478
	Age	0.015	0.004	0.207	3.927	0.000	0.851	1.175
2	(Constant)	2.600	0.736		3.533	< 0.001		
	Location	-0.129	0.116	-0.054	-1.117	0.265	0.921	1.085
	Gendercode	-0.192	0.118	-0.082	-1.633	0.103	0.852	1.173
	Employment	-0.118	0.151	-0.040	-0.784	0.434	0.844	1.184
	education	0.104	0.067	0.078	1.543	0.124	0.843	1.186
	income	-0.114	0.063	-0.102	-1.828	0.068	0.693	1.444
	license	0.031	0.126	0.014	0.249	0.803	0.698	1.432
	ownership	-0.191	0.195	-0.088	-0.975	0.330	0.268	3.735
	frequency	-0.121	0.058	-0.182	-2.072	0.039	0.280	3.567
	Age	0.013	0.004	0.186	3.651	< 0.001	0.835	1.198
	Q1	0.011	0.045	0.012	0.241	0.810	0.836	1.196
	Q2	0.137	0.038	0.180	3.557	0.000	0.844	1.185
	Q3	0.208	0.100	0.128	2.084	0.038	0.570	1.756
	Q4	-0.180	0.108	-0.101	-1.675	0.095	0.593	1.688
	Q5	0.179	0.058	0.156	3.061	0.002	0.827	1.209
	Q6	0.061	0.064	0.040	0.789	0.430	0.857	1.167
	Q7	0.052	0.035	0.074	1.495	0.136	0.883	1.132

[a] Dependent Variable: Q8

5.3.1.4. Autocorrelation. The Durbin–Watson statistic was 1.916, indicating that there was no evidence of autocorrelation in the residuals.

Table 5.14. Model summary of the hierarchical regression model for Q8.

Model Summary[c]										
Model	**R**	**R Square**	**Adjusted R Square**	**Std. Error of the Estimate**	**Change Statistics**					**Durbin-Watson**
					R Square Change	**F Change**	**df1**	**df2**	**Sig. F Change**	
1	.280[a]	.078	.057	1.036	.078	3.685	9	391	.000	
2	.414[b]	.172	.137	0.991	.093	6.188	7	384	.000	1.916
[a] Predictors: (Constant), Age, Employment, education, Location, frequency, Gendercode, license, income, ownership										
[a] Predictors: (Constant), Age, Employment, education, Location, frequency, Gendercode, license, income, ownership, Q4, Q1, Q6, Q7, Q2, Q5, Q3										
[c] Dependent Variable: Q8										

5.3.1.5. Outliers and Influential Observations. Standardized residuals ranged between –3.07 and +2.16, indicating minimal influence from outliers. The maximum Cook's Distance was 0.083, well below the threshold of 1, indicating no undue influence of individual observations. Leverage values were within acceptable limits.

Table 5.15. Residual statistics for the hierarchical regression model for Q8.

Residuals Statistics[a]	**Minimum**	**Maximum**	**Mean**	**Std. Deviation**	**N**
Predicted Value	2.07	4.80	3.73	0.442	401
Std. Predicted Value	-3.768	2.429	0.000	1.000	401
Standard Error of Predicted Value	0.123	0.414	0.199	0.046	401
Adjusted Predicted Value	1.84	4.79	3.73	0.442	401
Residual	-3.274	2.158	0.000	0.971	401
Std. Residual	-3.304	2.178	0.000	0.980	401
Stud. Residual	-3.362	2.237	-0.001	1.003	401
Deleted Residual	-3.388	2.277	-0.001	1.017	401
Stud. Deleted Residual	-3.408	2.249	-0.001	1.005	401
Mahal. Distance	5.208	68.824	15.960	8.761	401
Cook's Distance	0.000	0.051	0.003	0.005	401
Centered Leverage Value	0.013	0.172	0.040	0.022	401
[a] Dependent Variable: Q8					

5.3.2. Hierarchical Regression Results for Q8

5.3.2.1. Model Summary. The hierarchical regression analysis demonstrated that the explanatory power of the models increased with the addition of attitudinal variables. Model 1 accounted for approximately 7.8% of the variance in the dependent variable ($R^2 = .078$). Model 2 explained 17.2% of the variance ($R^2 = .172$), representing a substantial improvement in explanatory power. This final model was statistically significant ($F(16, 384) = 4.972$, $p < .001$), indicating that the inclusion of all predictors contributed meaningfully to explaining perceptions related to Q8.

Table 5.16. Model summary of the hierarchical regression model for Q8.

Model Summary[c]										
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.280[a]	.078	.057	1.036	.078	3.685	9	391	< .001	
2	.414[b]	.172	.137	0.991	.093	6.188	7	384	< .001	1.916
[a] Predictors: (Constant), Age, Employment, education, Location, frequency, Gendercode, license, income, ownership										
[a] Predictors: (Constant), Age, Employment, education, Location, frequency, Gendercode, license, income, ownership, Q4, Q1, Q6, Q7, Q2, Q5, Q3										
[c] Dependent Variable: Q8										

5.3.2.2. ANOVA. The ANOVA results confirmed the overall significance of both regression models compared to intercept-only models. Model 1 produced an F-statistic of 3.685 ($p < .001$), showing that the initial set of demographic and behavioral predictors contributed significantly to explaining the variance in Q8. Model 2 demonstrated an even higher F-statistic of 4.972 ($p < .001$), further supporting that the addition of attitudinal variables significantly improved model fit. The increase in the regression sum of squares from 35.568 in Model 1 to 78.076 in Model 2 also highlights this improvement in explanatory power.

Table 5.17. ANOVA results of the hierarchical regression model for Q8.

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	35.568	9	3.952	3.685	$< .001^{b}$
	Residual	419.344	391	1.072		
	Total	454.913	400			
2	Regression	78.076	16	4.880	4.972	$< .001^{c}$
	Residual	376.837	384	0.981		
	Total	454.913	400			

[a] Dependent Variable: Q8

[b] Predictors: (Constant), Age, Employment, education, Location, frequency, Gendercode, license, income, ownership

[c] Predictors: (Constant), Age, Employment, education, Location, frequency, Gendercode, license, income, ownership, Q4, Q1, Q6, Q7, Q2, Q5, Q3

5.3.2.3. Regression Coefficients. In Model 1, age and education level emerged as significant positive predictors, with higher age ($B = 0.015$, $\beta = 0.207$, $p < .001$) and higher education ($B = 0.141$, $\beta = 0.069$, $p = .042$) associated with increased scores on Q8, while income level showed a significant negative relationship ($B = -0.155$, $\beta = -0.138$, $p = .018$). In Model 2, age remained a significant positive predictor ($B = 0.013$, $\beta = 0.186$, $p < .001$), and positive evaluations of lane narrowing (Q2, $B = 0.137$, $\beta = 0.180$, $p < .001$), increasing green areas (Q3, $B = 0.208$, $\beta = 0.128$, $p = .038$), and adding pedestrian crossings (Q5, $B = 0.179$, $\beta = 0.156$, $p = .002$) were also associated with higher outcomes. Frequency of car use showed a significant negative association in Model 2 ($B = -0.121$, $\beta = -0.182$, $p = .039$). Other predictors did not reach statistical significance in either model.

The findings suggest that both demographic characteristics and attitudes toward specific pedestrian improvements contributed meaningfully to explaining perceptions related to Q8. Age consistently emerged as a significant positive predictor, indicating that older participants were more likely to report favorable perceptions. Positive evaluations of lane narrowing, increasing green areas, and adding pedestrian crossings were also associated with higher scores, highlighting the relevance of supportive attitudes toward safety and environmental enhancements. Conversely, higher frequency of car use was negatively related to the outcome, suggesting that habitual reliance on private vehicles may reduce openness to pedestrian-oriented measures.

Table 5.18. Regression coefficients for the hierarchical regression model for Q8.

Coefficients[a]								
Model	**Variable**	**Unstandardized Coefficients**		**Standardized Coefficients**	**t**	**Sig.**	**Collinearity Statistics**	
		B	**Std. Error**	**Beta**			**Tolerance**	**VIF**
1	(Constant)	3.845	0.611		6.295	< 0.001		
	Location	-0.041	0.117	-0.017	-0.353	0.724	0.975	1.026
	Gendercode	-0.156	0.122	-0.067	-1.277	0.202	0.867	1.154
	Employment	-0.147	0.157	-0.049	-0.935	0.350	0.855	1.170
	education	0.141	0.069	0.107	2.040	0.042	0.865	1.156
	income	-0.155	0.065	-0.138	-2.384	0.018	0.703	1.422
	license	0.023	0.131	0.010	0.175	0.861	0.708	1.413
	ownership	-0.017	0.199	-0.008	-0.085	0.933	0.282	3.550
	frequency	-0.109	0.060	-0.164	-1.816	0.070	0.288	3.478
	Age	0.015	0.004	0.207	3.927	0.000	0.851	1.175
2	(Constant)	2.600	0.736		3.533	< 0.001		
	Location	-0.129	0.116	-0.054	-1.117	0.265	0.921	1.085
	Gendercode	-0.192	0.118	-0.082	-1.633	0.103	0.852	1.173
	Employment	-0.118	0.151	-0.040	-0.784	0.434	0.844	1.184
	education	0.104	0.067	0.078	1.543	0.124	0.843	1.186
	income	-0.114	0.063	-0.102	-1.828	0.068	0.693	1.444
	license	0.031	0.126	0.014	0.249	0.803	0.698	1.432
	ownership	-0.191	0.195	-0.088	-0.975	0.330	0.268	3.735
	frequency	-0.121	0.058	-0.182	-2.072	0.039	0.280	3.567
	Age	0.013	0.004	0.186	3.651	< 0.001	0.835	1.198
	Q1	0.011	0.045	0.012	0.241	0.810	0.836	1.196
	Q2	0.137	0.038	0.180	3.557	0.000	0.844	1.185
	Q3	0.208	0.100	0.128	2.084	0.038	0.570	1.756
	Q4	-0.180	0.108	-0.101	-1.675	0.095	0.593	1.688
	Q5	0.179	0.058	0.156	3.061	0.002	0.827	1.209
	Q6	0.061	0.064	0.040	0.789	0.430	0.857	1.167
	Q7	0.052	0.035	0.074	1.495	0.136	0.883	1.132

[a] Dependent Variable: Q8

5.4. Ordinal Regression Analysis for Q8

5.4.1. Assumption Checks

5.4.1.1. Model Fit. The model fitting information indicates that the final model significantly improved over the intercept-only model. The reduction in -2 Log Likelihood from 1100.632 to 1018.960 resulted in a Chi-Square statistic of 81.672 ($df = 25$, $p < .001$). This finding confirms that the inclusion of the predictor variables contributed significantly to improving model fit.

Table 5.19. Model fitting information for ordinal regression model for Q8.

Model Fitting Information				
Model	**-2 Log Likelihood**	**Chi-Square**	**df**	**Sig.**
Intercept Only	1100.632			
Final	1018.960	81.672	25	< 0.001
Link function: Logit.				

5.4.1.2. Goodness of Fit. Goodness-of-fit statistics showed that the model adequately fit the data. The Pearson Chi-Square ($\chi^2 = 1466.569$, $p = .966$) and Deviance ($\chi^2 = 1018.960$, $p = 1.000$) tests were both non-significant, suggesting no evidence of poor fit and indicating that the model's predicted probabilities closely matched the observed outcomes.

Table 5.20. Goodness-of-fit statistics for ordinal regression model for Q8.

Goodness-of-Fit			
	Chi-Square	**df**	**Sig.**
Pearson	1466.569	1567	0.966
Deviance	1018.960	1567	1.000
Link function: Logit.			

5.4.1.3. Pseudo R-square. The pseudo R-square statistics demonstrated that the model explained a modest proportion of variance in the dependent variable. The Cox and Snell R^2 was .184, indicating that approximately 18.4% of the variance could be accounted for by the predictors. The Nagelkerke R^2 was slightly higher at .197, corresponding to about 19.7% of explained variance. In contrast, the McFadden R^2 was more conservative, with a value of .074, suggesting that roughly 7.4% of the variance was explained by the model. These results collectively indicate that, while the model improved prediction relative to the null model, its overall explanatory power was moderate.

Table 5.21. Pseudo R-square values for ordinal regression model for Q8.

Pseudo R-Square	
Cox and Snell	0.184
Nagelkerke	0.197
McFadden	0.074
Link function: Logit.	

5.4.1.4. Test of Parallel Lines. In this analysis, the test produced a Chi-Square value of 138.580 with 75 degrees of freedom ($p < .001$). The significant result indicates that the assumption of parallel lines was violated, suggesting that the relationship between the predictors and the outcome variable is not consistent across the levels of the dependent variable. This violation implies that the estimated coefficients may vary across outcome categories, and interpretations should be made with caution.

Table 5.22. Test of parallel lines for the ordinal regression model for Q8.

Test of Parallel Lines[a]				
Model	**−2 Log Likelihood**	**Chi-Square**	**df**	**Sig.**
Null Hypothesis	1018.960			
General	880.379[b]	138.580[c]	75	< 0.001
The null hypothesis states that the location parameters (slope coefficients) are the same across response categories.				
[a] Link function: Logit.				
[b] The log-likelihood value cannot be further increased after maximum number of step-halving.				
[c] The Chi-Square statistic is computed based on the log-likelihood value of the last iteration of the general model. Validity of the test is uncertain.				

5.4.2. Ordinal Regression Results for Q8

5.4.2.1. Parameter Estimates. The parameter estimates indicated that several predictors were significantly associated with higher outcome levels. Age emerged as a significant positive predictor (Estimate = 0.025, $p = .001$), suggesting that older individuals were more likely to report higher scores. Positive evaluations of lane narrowing (Estimate = 0.239, $p = .001$) and pedestrian crossings (Estimate = 0.335, $p = .003$) also contributed significantly to increased odds of higher responses. Among categorical variables, respondents in income level 1 showed higher odds compared to the reference group (Estimate = 1.177, $p = .045$). Additionally, reporting the highest frequency of car use was positively associated with the outcome (Estimate = 1.305, $p = .001$). Other predictors were not statistically significant at the .05 level.

The findings indicate that both attitudinal and demographic factors played a meaningful role in predicting higher levels of the outcome variable. Positive evaluations of lane narrowing and the addition of pedestrian crossings were consistently associated with increased odds of reporting higher responses, highlighting the importance of perceptions related to safety-oriented improvements. Age also emerged as a significant factor, suggesting that older individuals were more supportive of these interventions. Furthermore, respondents in the lowest income category and those who reported the highest frequency of car use demonstrated higher odds of endorsing higher outcome levels.

Table 5.23. Parameter estimates for the ordinal regression model for Q8.

Parameter Estimates								
		Estimate	**Std. Error**	**Wald**	**df**	**Sig.**	**95% Confidence Interval**	
							Lower Bound	**Upper Bound**
Threshold	[Publictransport = 1]	-16.253	1.422	130.559	1	< 0.001	-19.041	-13.465
	[Publictransport = 2]	-15.505	1.420	119.177	1	< 0.001	-18.289	-12.722
	[Publictransport = 3]	-13.489	1.437	88.063	1	< 0.001	-16.307	-10.672
	[Publictransport = 4]	-11.825	1.453	66.215	1	< 0.001	-14.674	-8.977
Location	Age	0.025	0.007	11.352	1	0.001	0.011	0.039
	Sidewalk widening	0.006	0.086	0.006	1	0.941	-0.161	0.174
	Lane narrowing	0.239	0.073	10.593	1	0.001	0.095	0.382
	Green space	0.366	0.187	3.809	1	0.051	-0.002	0.733
	Tree number	-0.278	0.201	1.913	1	0.167	-0.673	0.116
	Pedestrian crossing	0.335	0.111	9.066	1	0.003	0.117	0.553
	Street lamp	0.119	0.120	0.994	1	0.319	-0.115	0.354
	Parking space	0.096	0.066	2.115	1	0.146	-0.033	0.225
	[Location=1]	0.105	0.219	0.232	1	0.630	-0.323	0.533
	[Location=2][a]	0						
	[Gender_code=1]	0.435	0.225	3.739	1	0.053	-0.006	0.876
	[Gender_code=2][a]	0						
	[Employment_code=1]	0.236	0.310	0.581	1	0.446	-0.371	0.843
	[Employment_code=2][a]	0						
	[education_code=1]	-19.785	0.608	1059.85	1	< 0.001	-20.976	-18.594
	[education_code=2]	-19.491	0.581	1124.47	1	< 0.001	-20.631	-18.352
	[education_code=3]	-19.253	0.582	1093.12	1	< 0.001	-20.395	-18.112
	[education_code=4]	-19.018	0		1	< 0.001	-19.018	-19.018
	[education_code=5][a]	0						
	[income_level_code=1]	1.177	0.587	4.016	1	0.045	0.026	2.328
	[income_level_code=2]	0.715	0.542	1.741	1	0.187	-0.347	1.777
	[income_level_code=3]	0.847	0.546	2.412	1	0.120	-0.222	1.917
	[income_level_code=4]	0.357	0.728	0.241	1	0.624	-1.074	1.784
	[income_level_code=5][a]	0						
	[license_code=1]	-0.021	0.236	0.008	1	0.928	-0.484	0.441
	[license_code=2][a]	0						
	[ownership_code=1]	-0.002	0.478	0.001	1	0.997	-0.938	0.935
	[ownership_code=2][a]	0						
	[frequency_code=1]	0.783	0.517	2.295	1	0.130	-0.230	1.795
	[frequency_code=2]	0.829	0.506	2.683	1	0.101	-0.163	1.822
	[frequency_code=3]	0.547	0.475	1.330	1	0.249	-0.383	1.477
	[frequency_code=4]	1.305	0.393	11.002	1	0.001	0.534	2.076
	[frequency_code=5][a]	0						

Link function: Logit.

[a] This parameter is set to zero because it is redundant.

5.5. Multiple Linear Regression Analysis for Q9

5.5.1. Assumption Checks

5.5.1.1. Normality. Visual inspection of the histogram indicated that residuals were approximately normally distributed. The Normal P–P Plot demonstrated that observed cumulative probabilities closely followed the expected diagonal line. Additionally, the standardized residuals had a mean of approximately 0 (3.27×10^{-16}) and a standard deviation of 0.980, supporting the assumption of normality.

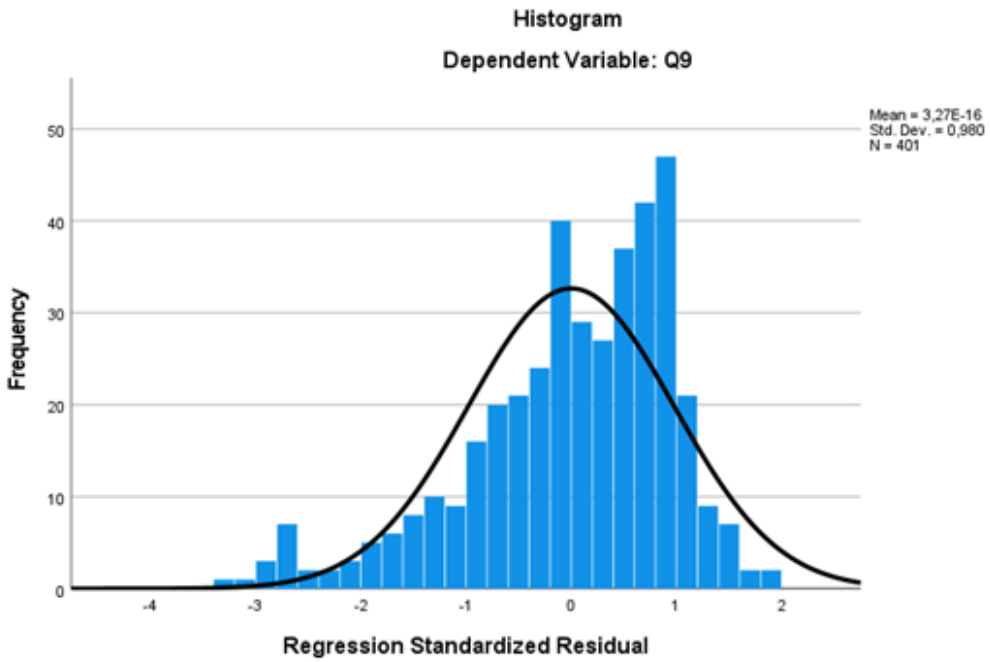

Figure 5.10. Histogram of regression standardized residuals for the multiple linear regression model for Q9.

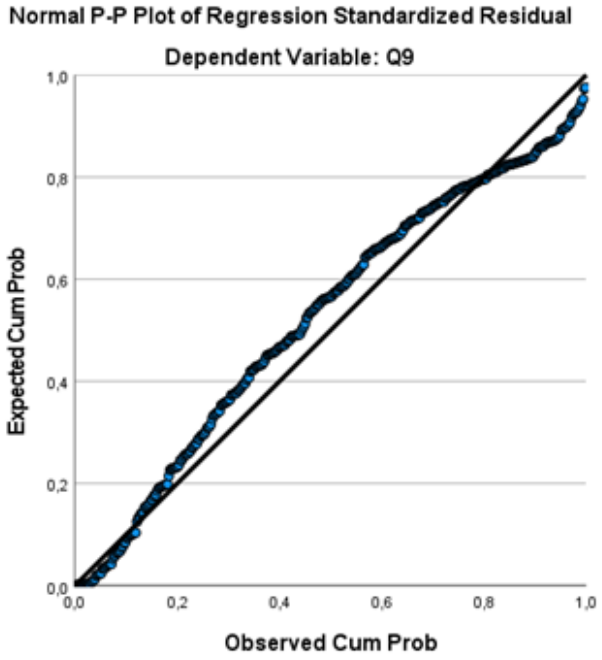

Figure 5.11. Normal P–P plot of regression standardized residuals for the multiple linear regression model for Q9.

5.5.1.2. Linearity and Homoscedasticity. The scatterplot of standardized residuals against predicted values was reviewed to assess linearity. The absence of discernible curvilinear patterns suggested that the relationship between predictors and the dependent variable was adequately linear. The same scatterplot also indicated that residuals were evenly and randomly dispersed around the horizontal axis, without evidence of heteroscedasticity. This supports the assumption of constant variance of errors across all levels of predicted values.

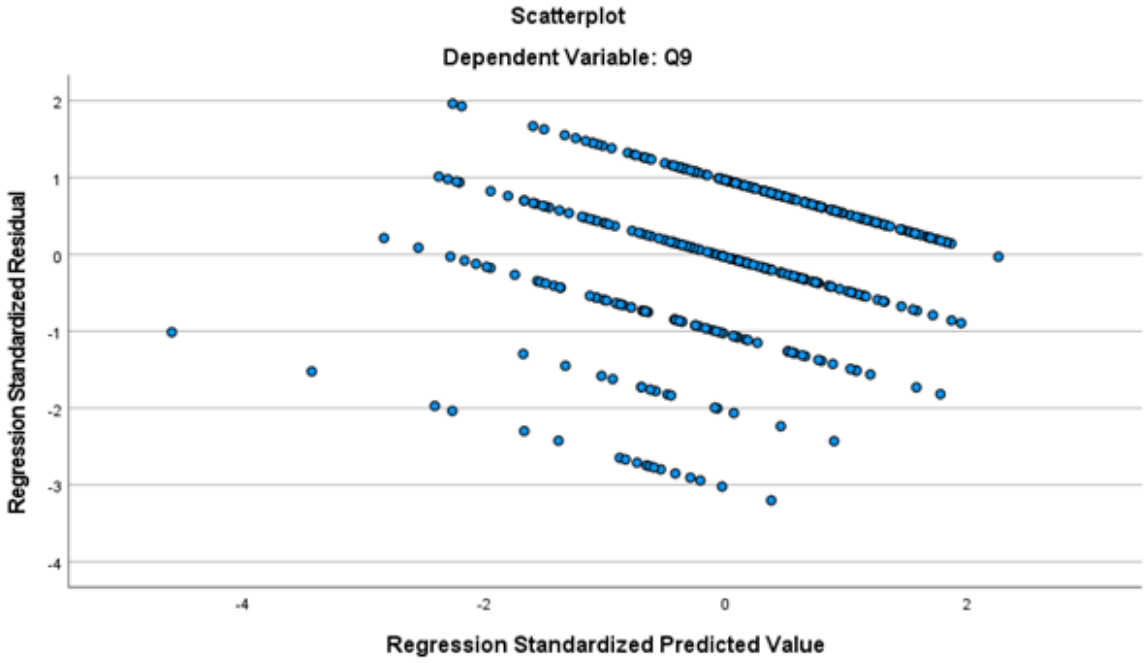

Figure 5.12. Scatterplot of standardized residuals versus predicted values for the multiple linear regression model for Q9.

5.5.1.3. Multicollinearity. Multicollinearity was assessed using Variance Inflation Factors (VIF), tolerance statistics, and the condition index. VIF values ranged from 1.085 to 3.735, all below the recommended threshold of 5, indicating acceptable levels of collinearity. Although the condition index exceeded 30 in some dimensions, the combination of VIF and tolerance measures suggested that multicollinearity did not pose a substantial concern.

Table 5.24. Regression coefficients for the multiple linear regression model for Q9.

Coefficients[a]							
Model	**Unstandardized Coefficients**		**Standardized Coefficients**	**t**	**Sig.**	**Collinearity Statistics**	
	B	Std. Error	Beta			Tolerance	VIF
(Constant)	1.830	0.743	–	2.463	0.014	–	–
Location	-0.201	0.117	-0.084	-1.728	0.085	0.921	1.085
Age	0.010	0.004	0.133	2.607	0.009	0.835	1.198
Q1	0.056	0.046	0.062	1.217	0.224	0.836	1.196
Q2	0.171	0.039	0.223	4.406	< 0.001	0.844	1.185
Q3	0.030	0.101	0.018	0.296	0.767	0.570	1.756
Q4	-0.063	0.109	-0.035	-0.578	0.563	0.593	1.688
Q5	0.132	0.059	0.114	2.233	0.026	0.827	1.209
Q6	0.110	0.064	0.086	1.709	0.088	0.857	1.167
Q7	0.077	0.035	0.109	2.194	0.029	0.883	1.132
Gendercode	0.114	0.119	0.048	0.960	0.338	0.852	1.173
Employment	0.006	0.152	0.002	0.040	0.968	0.844	1.184
Education	0.053	0.068	0.039	0.779	0.437	0.843	1.186
Income	-0.011	0.063	-0.010	-0.174	0.862	0.693	1.444
License	0.165	0.127	0.072	1.298	0.195	0.698	1.432
Ownership	-0.044	0.197	-0.020	-0.221	0.825	0.268	3.735
Frequency	-0.050	0.059	-0.075	-0.855	0.393	0.280	3.567

[a] Dependent Variable: Q9

5.5.1.4. Autocorrelation. The Durbin–Watson statistic was 1.738, indicating that there was no evidence of autocorrelation in the residuals.

Table 5.25. Model summary of the multiple linear regression model for Q9.

Model Summary[b]										
Model	**R**	**R Square**	**Adjusted R Square**	**Std. Error of the Estimate**	**Change Statistics**					**Durbin-Watson**
					R Square Change	**F Change**	**df1**	**df2**	**Sig. F Change**	
1	.410[a]	0.168	0.134	1.000	0.168	4.860	16	384	< 0.001	1.738

[a] Predictors: (Constant), frequency, Q4, Location, education, Q1, Employment, Q7, Age, Q6, Gendercode, Q2, Q5, license, income, Q3, ownership

[b] Dependent Variable: Q9

5.5.1.5. Outliers and Influential Observations. Standardized residuals ranged between –3.20 and +1.96, suggesting minimal influence from outliers. The maximum Cook's Distance was 0.075, well below the threshold of 1, indicating no undue influence of individual observations. Leverage values were also within acceptable limits.

Table 5.26. Residual statistics for the multiple linear regression model for Q9.

Residuals Statistics[a]					
	Minimum	**Maximum**	**Mean**	**Std. Deviation**	**N**
Predicted Value	2.01	5.03	4.03	0.441	401
Std. Predicted Value	-4.59	2.257	0	1	401
Standard Error of Predicted Value	0.125	0.418	0.201	0.047	401
Adjusted Predicted Value	2.13	5.03	4.04	0.442	401
Residual	-3.2	1.963	0	0.98	401
Std. Residual	-3.201	1.963	0	0.98	401
Stud. Residual	-3.277	2.092	-0.001	1.005	401
Deleted Residual	-3.353	2.228	-0.001	1.031	401
Stud. Deleted Residual	-3.319	2.101	-0.002	1.009	401
Mahal. Distance	5.208	68.824	15.96	8.761	401
Cook's Distance	0	0.075	0.003	0.007	401
Centered Leverage Value	0.013	0.172	0.04	0.022	401
[a] Dependent Variable: Q9					

5.5.2. Multiple Linear Regression Results for Q9

5.5.2.1. Model Summary. The regression model explained approximately 16.8% of the variance in the dependent variable ($R^2 = .168$), with an adjusted R^2 of .134, indicating moderate explanatory power. The model was statistically significant ($F(16, 384) = 4.860$, $p < .001$).

Table 5.27. Model summary of the multiple linear regression model for Q9.

Model Summary[b]										
Model	**R**	**R Square**	**Adjusted R Square**	**Std. Error of the Estimate**	**Change Statistics**					**Durbin-Watson**
					R Square Change	**F Change**	**df1**	**df2**	**Sig. F Change**	
1	.410[a]	0.168	0.134	1.000	0.168	4.860	16	384	< 0.001	1.738
[a] Predictors: (Constant), frequency, Q4, Location, education, Q1, Employment, Q7, Age, Q6, Gendercode, Q2, Q5, license, income, Q3, ownership										
[b] Dependent Variable: Q9										

5.5.2.2. ANOVA. The ANOVA confirmed that the regression model significantly improved prediction compared to the intercept-only model ($p < .001$), indicating that the set of predictors contributed meaningfully to the outcome.

Table 5.28. ANOVA results of the multiple linear regression model for Q9.

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	77.715	16	4.857	4.860	$< .001^{b}$
Residual	383.796	384	0.999		
Total	461.511	400			
[a] Dependent Variable: Q9					
[b] Predictors: (Constant), frequency, Q4, Location, education, Q1, Employment, Q7, Age, Q6, Gendercode, Q2, Q5, license, income, Q3, ownership					

5.5.2.3. Regression Coefficients. In the model, age ($B = 0.010$, $\beta = 0.133$, $p = .009$), Q2 ($B = 0.171$, $\beta = 0.223$, $p < .001$), Q5 ($B = 0.132$, $\beta = 0.114$, $p = .026$), and Q7 ($B = 0.077$, $\beta = 0.109$, $p = .029$) emerged as significant positive predictors of Q9. These results suggest that higher age and more favorable evaluations of lane narrowing, additional pedestrian crossings, and reducing parking spaces were associated with increased scores on the dependent variable. Other predictors did not reach statistical significance at the 0.05 level.

The findings indicate that both demographic and attitudinal factors contributed to explaining perceptions related to Q9. Age was positively associated with higher scores, suggesting that older participants were more supportive of the evaluated improvements. Positive evaluations of lane narrowing, increasing pedestrian crossings, and reducing parking spaces also emerged as significant predictors, highlighting the importance of safety and accessibility-oriented measures.

Table 5.29. Regression coefficients for the multiple linear regression model for Q9.

Coefficients[a]							
Model	**Unstandardized Coefficients**		**Standardized Coefficients**	**t**	**Sig.**	**Collinearity Statistics**	
	B	Std. Error	Beta			Tolerance	VIF
(Constant)	1.830	0.743	–	2.463	0.014	–	–
Location	-0.201	0.117	-0.084	-1.728	0.085	0.921	1.085
Age	0.010	0.004	0.133	2.607	0.009	0.835	1.198
Q1	0.056	0.046	0.062	1.217	0.224	0.836	1.196
Q2	0.171	0.039	0.223	4.406	< 0.001	0.844	1.185
Q3	0.030	0.101	0.018	0.296	0.767	0.570	1.756
Q4	-0.063	0.109	-0.035	-0.578	0.563	0.593	1.688
Q5	0.132	0.059	0.114	2.233	0.026	0.827	1.209
Q6	0.110	0.064	0.086	1.709	0.088	0.857	1.167
Q7	0.077	0.035	0.109	2.194	0.029	0.883	1.132
Gendercode	0.114	0.119	0.048	0.960	0.338	0.852	1.173
Employment	0.006	0.152	0.002	0.040	0.968	0.844	1.184
Education	0.053	0.068	0.039	0.779	0.437	0.843	1.186
Income	-0.011	0.063	-0.010	-0.174	0.862	0.693	1.444
License	0.165	0.127	0.072	1.298	0.195	0.698	1.432
Ownership	-0.044	0.197	-0.020	-0.221	0.825	0.268	3.735
Frequency	-0.050	0.059	-0.075	-0.855	0.393	0.280	3.567

[a] Dependent Variable: Q9

5.6. Stepwise Regression Analysis for Q9

5.6.1. Assumption Checks

5.6.1.1. Normality. Visual inspection of the histogram indicated that residuals were approximately normally distributed. The Normal P–P Plot demonstrated that observed cumulative probabilities closely followed the expected diagonal line. Additionally, the standardized residuals had a mean of approximately 0 (-3.70×10^{-16}) and a standard deviation of 0.996, supporting the assumption of normality.

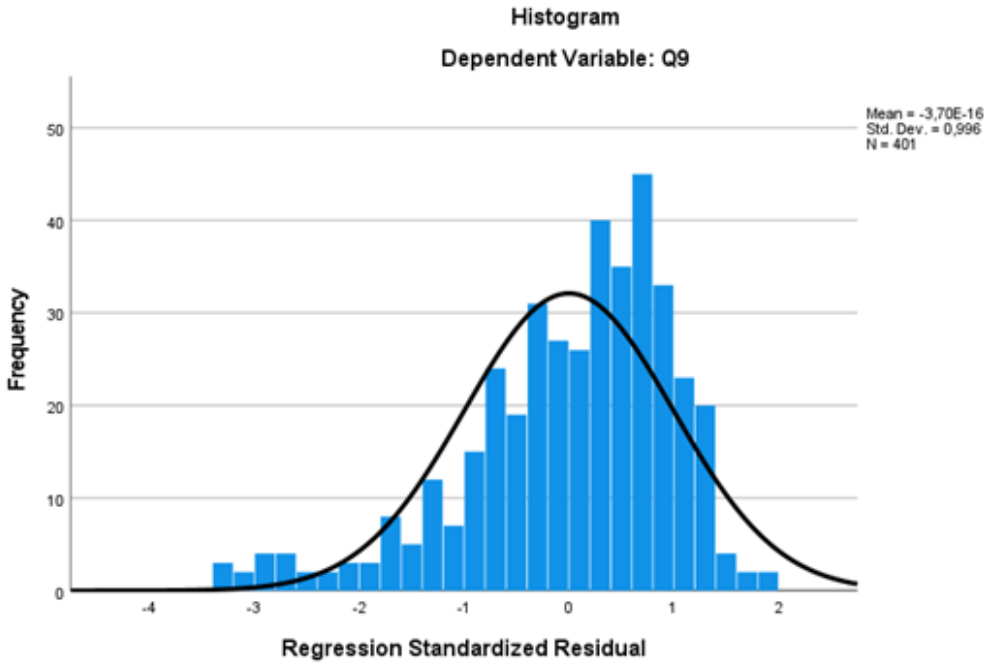

Figure 5.13. Histogram of regression standardized residuals for the stepwise regression model for Q9.

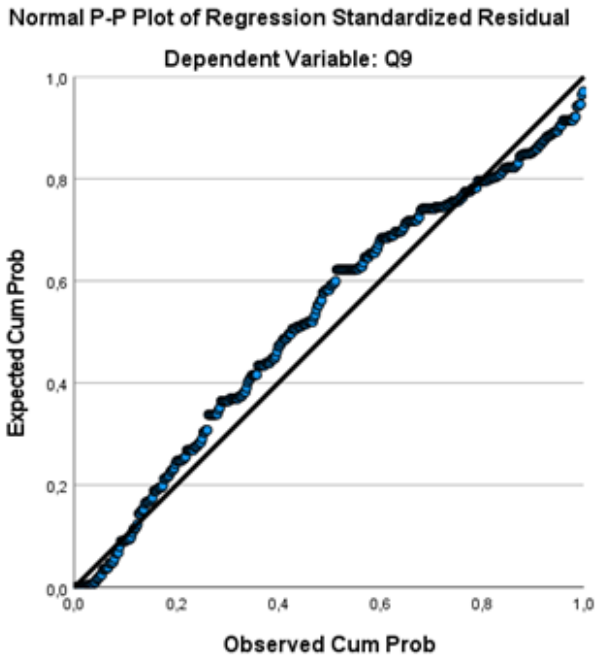

Figure 5.14. Normal P–P plot of regression standardized residuals for the stepwise regression model for Q9.

5.6.1.2. Linearity and Homoscedasticity. The scatterplot of standardized residuals against predicted values was reviewed to assess linearity. The absence of discernible curvilinear patterns suggested that the relationship between predictors and the dependent variable was adequately linear. The same scatterplot also indicated that residuals were evenly and randomly dispersed around the horizontal axis, without evidence of heteroscedasticity. This supports the assumption of constant variance of errors across all levels of predicted values.

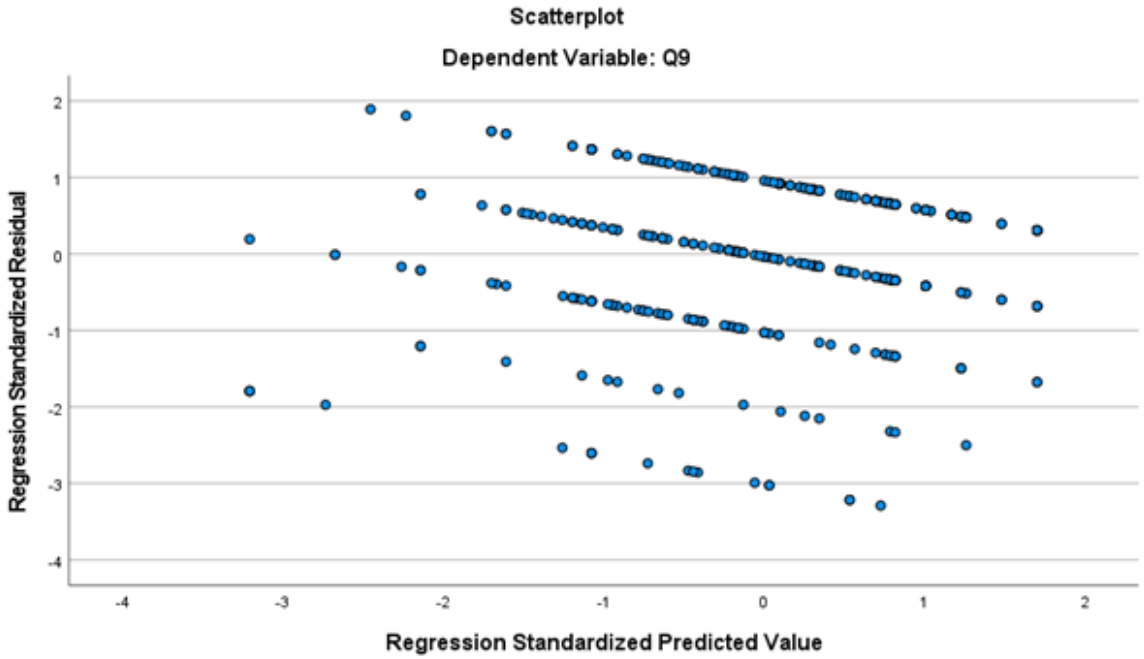

Figure 5.15. Scatterplot of standardized residuals versus predicted values for the stepwise regression model for Q9.

5.6.1.3. Multicollinearity. Multicollinearity was evaluated by examining Variance Inflation Factors (VIF), tolerance values, and the condition index. VIF values ranged from 1.000 to 1.059, remaining well below the commonly recommended threshold of 5. Tolerance statistics exceeded the minimum acceptable criterion of .20, indicating an acceptable level of shared variance among predictors. Although the condition index reached 13.000, suggesting some potential collinearity concerns, the overall combination of VIF and tolerance measures indicated that multicollinearity was not severe

enough to compromise the validity of the regression analysis.

Table 5.30. Regression coefficients for the stepwise regression model for Q9.

Coefficients[a]								
Model		**Unstandardized Coefficients**		**Standardized Coefficients**	**t**	**Sig.**	**Collinearity Statistics**	
		B	**Std. Error**	**Beta**			**Tolerance**	**VIF**
1	(Constant)	3.334	0.129		25.933	< 0.001		
	Q2	0.218	0.037	0.285	5.945	< 0.001	1.000	1.000
2	(Constant)	2.490	0.255		9.783	< 0.001		
	Q2	0.200	0.036	0.261	5.486	< 0.001	0.982	1.018
	Q5	0.210	0.055	0.182	3.824	< 0.001	0.982	1.018
3	(Constant)	2.334	0.261		8.957	< 0.001		
	Q2	0.182	0.037	0.237	4.919	< 0.001	0.944	1.059
	Q5	0.204	0.055	0.177	3.745	< 0.001	0.981	1.019
	Q7	0.085	0.034	0.119	2.488	0.013	0.956	1.046
[a] Dependent Variable: Q9								

5.6.1.4. Autocorrelation. The Durbin–Watson statistic was 1.698, indicating that there was no evidence of autocorrelation in the residuals.

Table 5.31. Model summary of the stepwise regression model for Q9.

Model Summary[d]										
Model	**R**	**R Square**	**Adjusted R Square**	**Std. Error of the Estimate**	**Change Statistics**					**Durbin-Watson**
					R Square Change	**F Change**	**df1**	**df2**	**Sig. F Change**	
1	.285[a]	0.081	0.079	1.031	0.081	35.343	1	399	< 0.001	
2	.338[b]	0.114	0.109	1.014	0.033	14.622	1	398	< 0.001	
3	.357[c]	0.128	0.121	1.007	0.014	6.191	1	397	0.013	1.698
[a] Predictors: (Constant), Q2										
[b] Predictors: (Constant), Q2, Q5										
[c] Predictors: (Constant), Q2, Q5, Q7										
[d] Dependent Variable: Q9										

5.6.1.5. Outliers and Influential Observations. Standardized residuals ranged between –3.29 and +1.89, suggesting minimal influence from outliers. The maximum Cook's Distance was 0.038, well below the threshold of 1, indicating no undue influence of individual observations.

Table 5.32. Residual statistics for the stepwise regression model for Q9.

Residuals Statistics[a]					
	Minimum	**Maximum**	**Mean**	**Std. Deviation**	**N**
Predicted Value	2.80	4.69	4.03	0.384	401
Std. Predicted Value	-3.208	1.701	0.000	1.000	401
Standard Error of Predicted Value	0.054	0.217	0.097	0.026	401
Adjusted Predicted Value	2.80	4.71	4.04	0.382	401
Residual	-3.313	1.906	0.000	1.003	401
Std. Residual	-3.290	1.893	0.000	0.996	401
Stud. Residual	-3.302	1.914	0.000	1.002	401
Deleted Residual	-3.338	1.949	0.000	1.014	401
Stud. Deleted Residual	-3.344	1.920	-0.001	1.005	401
Mahal. Distance	0.149	17.492	2.993	2.358	401
Cook's Distance	0.000	0.038	0.003	0.007	401
Centered Leverage Value	0.000	0.044	0.007	0.006	401

[a] Dependent Variable: Q9

5.6.2. Stepwise Regression Results for Q9

5.6.2.1. Variables Entered and Removed. The stepwise procedure selected predictors in three steps, sequentially entering the variables that contributed the greatest incremental explanatory power to the model predicting Q9. In the first step, Q2 was included as the initial predictor. In the second step, Q5 was added to improve the model's fit. Finally, in the third step, Q7 was entered. No variables were removed during the procedure, and all predictors were retained across steps based on the specified entry and removal criteria.

Table 5.33. List of Variables Entered and Removed of Stepwise Regression Model of Q9.

Variables entered/removed[a]			
Model	**Variables Entered**	**Variables Removed**	**Method**
1	Q2		Stepwise (Criteria: Probability-of-F-to-enter ≤ .050, Probability-of-F-to-remove ≥ .100).
2	Q5		Stepwise (Criteria: Probability-of-F-to-enter ≤ .050, Probability-of-F-to-remove ≥ .100).
3	Q7		Stepwise (Criteria: Probability-of-F-to-enter ≤ .050, Probability-of-F-to-remove ≥ .100).
[a] Dependent Variable: Q9			

5.6.2.2. Model Summary. The stepwise regression analysis revealed that the explanatory power of the models increased incrementally with the inclusion of additional predictors. Model 1 included Q2 as the sole predictor and accounted for 8.1% of the variance in the dependent variable ($R^2 = .081$). Model 2 incorporated both Q2 and Q5, explaining 11.4% of the variance ($R^2 = .114$). Model 3 added Q7 to the previous predictors, resulting in 12.8% of the variance explained ($R^2 = .128$).

Table 5.34. Model summary of the stepwise regression model for Q9.

Model Summary[d]										
Model	**R**	**R Square**	**Adjusted R Square**	**Std. Error of the Estimate**	**Change Statistics**					**Durbin-Watson**
					R Square Change	**F Change**	**df1**	**df2**	**Sig. F Change**	
1	.285[a]	0.081	0.079	1.031	0.081	35.343	1	399	< 0.001	
2	.338[b]	0.114	0.109	1.014	0.033	14.622	1	398	< 0.001	
3	.357[c]	0.128	0.121	1.007	0.014	6.191	1	397	0.013	1.698
[a] Predictors: (Constant), Q2										
[b] Predictors: (Constant), Q2, Q5										
[c] Predictors: (Constant), Q2, Q5, Q7										
[d] Dependent Variable: Q9										

5.6.2.3. ANOVA. The ANOVA results confirmed that each regression model significantly improved the explanation of variance in Q9 compared to the intercept-only model ($p < .001$ in all cases). Model 1, which included only Q2 as the predictor, accounted for a significant proportion of variance ($F(1, 399) = 35.343$, $p < .001$). Model 2 incorporated both Q2 and Q5, remaining statistically significant ($F(2, 398) = 25.586$,

$p < .001$). The addition of Q7 in Model 3 further improved the model's explanatory power ($F(3, 397) = 19.343$, $p < .001$). These results indicate that each successive set of predictors contributed meaningfully to explaining perceptions related to Q9.

Table 5.35. ANOVA results of the stepwise regression model for Q9.

ANOVA[a]						
Model		**Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**
1	Regression	37.553	1	37.553	35.343	< .001[b]
	Residual	423.958	399	1.063		
	Total	461.511	400			
2	Regression	52.577	2	26.288	25.586	< .001[c]
	Residual	408.934	398	1.027		
	Total	461.511	400			
3	Regression	58.856	3	19.619	19.343	< .001[d]
	Residual	402.655	397	1.014		
	Total	461.511	400			
[a] Dependent Variable: Q9						
[b] Predictors: (Constant), Q2						
[c] Predictors: (Constant), Q2, Q5						
[d] Predictors: (Constant), Q2, Q5, Q7						

5.6.2.4. Regression Coefficients. Across the three regression models predicting Q9, several predictors consistently emerged as significant. In Model 1, support for narrowing traffic lanes (Q2) was a significant positive predictor. Model 2 showed that both Q2 and support for additional pedestrian crossings (Q5) were significantly associated with higher Q9 scores. Model 3 further demonstrated that attitudes toward reducing parking spaces (Q7) also contributed positively alongside Q2 and Q5. In the final model, three predictors were statistically significant: Q2 ($\beta = .223$, $p < .001$), reflecting positive attitudes toward narrowing traffic lanes; Q5 ($\beta = .177$, $p < .001$), associated with support for additional pedestrian crossings; and Q7 ($\beta = .119$, $p = .013$), related to attitudes about reducing parking availability. No other predictors were retained in the model.

The findings suggest that attitudes toward pedestrian-oriented improvements, particularly narrowing lane widths, increasing pedestrian crossings, and reducing parking spaces play a central role in shaping perceptions related to Q9. Positive evaluations of these measures were consistently associated with higher scores, indicating that in-

terventions aimed at improving safety and reallocating street space can be effective in fostering supportive attitudes. Additionally, the results highlight that such preferences may be influenced by individuals' broader views on prioritizing pedestrian infrastructure over car-oriented uses.

Table 5.36. Regression coefficients for the stepwise regression model for Q9.

Coefficients[a]								
Model		**Unstandardized Coefficients**		**Standardized Coefficients**	**t**	**Sig.**	**Collinearity Statistics**	
		B	**Std. Error**	**Beta**			**Tolerance**	**VIF**
1	(Constant)	3.334	0.129		25.933	< 0.001		
	Q2	0.218	0.037	0.285	5.945	< 0.001	1.000	1.000
2	(Constant)	2.490	0.255		9.783	< 0.001		
	Q2	0.200	0.036	0.261	5.486	< 0.001	0.982	1.018
	Q5	0.210	0.055	0.182	3.824	< 0.001	0.982	1.018
3	(Constant)	2.334	0.261		8.957	< 0.001		
	Q2	0.182	0.037	0.237	4.919	< 0.001	0.944	1.059
	Q5	0.204	0.055	0.177	3.745	< 0.001	0.981	1.019
	Q7	0.085	0.034	0.119	2.488	0.013	0.956	1.046

[a] Dependent Variable: Q9

5.7. Hierarchical Regression Analysis for Q9

5.7.1. Assumption Checks

5.7.1.1. Normality. Visual inspection of the histogram indicated that residuals were approximately normally distributed. The Normal P–P Plot demonstrated that observed cumulative probabilities closely followed the expected diagonal line. Additionally, the standardized residuals had a mean of approximately 0 (-5.88×10^{-16}) and a standard deviation of 0.980, supporting the assumption of normality.

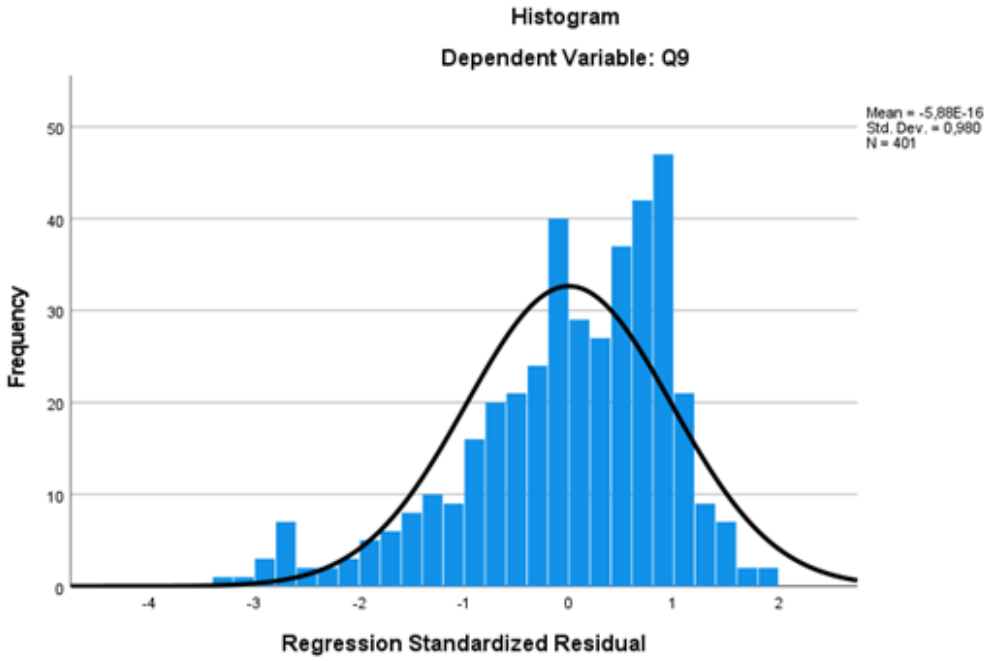

Figure 5.16. Histogram of regression standardized residuals for the hierarchical regression model for Q9..

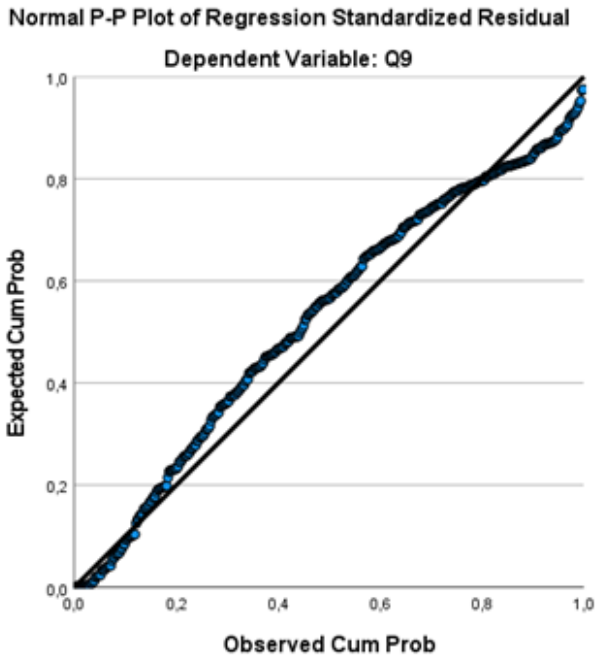

Figure 5.17. Normal P–P Plot of regression standardized residuals for the hierarchical regression model for Q9.

5.7.1.2. Linearity and Homoscedasticity. The scatterplot of standardized residuals against predicted values was reviewed to assess linearity. The absence of discernible curvilinear patterns suggested that the relationship between predictors and the dependent variable was adequately linear. The same scatterplot also indicated that residuals were evenly and randomly dispersed around the horizontal axis, without evidence of heteroscedasticity. This supports the assumption of constant variance of errors across all levels of predicted values.

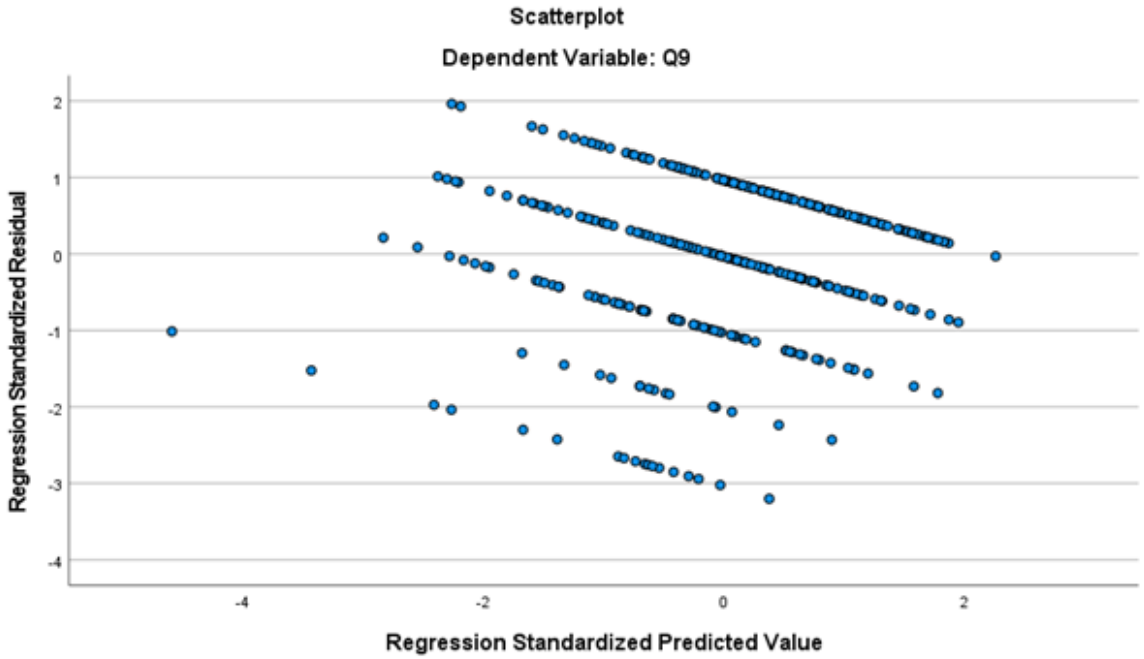

Figure 5.18. Scatterplot of standardized residuals versus predicted values for the hierarchical regression model for Q9.

5.7.1.3. Multicollinearity. Multicollinearity was assessed using Variance Inflation Factors (VIF) and the condition index. VIF values ranged from approximately 1.1 to 3.7, all below the recommended threshold of 5. Although the highest condition index exceeded 30, the combination of acceptable VIF and tolerance measures suggested that multicollinearity was not severe.

Table 5.37. Regression coefficients for the hierarchical regression model for Q9.

Coefficients[a]								
Model	**Variable**	**Unstandardized Coefficients**		**Standardized Coefficients**	**t**	**Sig.**	**Collinearity Statistics**	
		B	**Std. Error**	**Beta**			**Tolerance**	**VIF**
1	(Constant)	3.051	0.623		4.896	< 0.001		
	Location	-0.076	0.120	-0.032	-0.637	0.525	0.975	1.026
	Gendercode	0.145	0.124	0.062	1.167	0.244	0.867	1.154
	Employment	-0.016	0.160	-0.005	-0.102	0.919	0.855	1.170
	Education	0.100	0.071	0.075	1.409	0.160	0.865	1.156
	Income	0.066	0.066	0.051	0.993	0.321	0.703	1.422
	License	0.135	0.063	0.103	2.151	0.032	0.707	1.413
	Ownership	0.166	0.203	0.060	0.817	0.415	0.283	3.530
	Frequency	-0.043	0.061	-0.041	-0.707	0.480	0.857	1.168
	Age	0.011	0.004	0.157	2.940	0.003	0.851	1.175
2	(Constant)	1.830	0.743		2.463	0.014		
	Location	-0.201	0.117	-0.084	-1.728	0.085	0.921	1.085
	Gendercode	0.114	0.119	0.048	0.958	0.338	0.852	1.173
	Employment	0.006	0.161	0.002	0.038	0.970	0.844	1.185
	Education	0.101	0.070	0.076	1.439	0.151	0.843	1.186
	Income	0.061	0.065	0.047	0.928	0.354	0.693	1.444
	License	0.163	0.062	0.124	2.628	0.009	0.702	1.425
	Ownership	0.090	0.204	0.033	0.440	0.660	0.270	3.706
	Frequency	-0.050	0.059	-0.075	-0.853	0.394	0.835	1.197
	Age	0.010	0.004	0.143	2.307	0.022	0.830	1.205
	Q1	0.056	0.046	0.062	1.217	0.224	0.864	1.158
	Q2	0.106	0.041	0.138	2.607	0.009	0.364	2.748
	Q3	0.030	0.041	0.036	0.727	0.468	0.569	1.758
	Q4	0.063	0.039	0.103	1.602	0.110	0.466	2.145
	Q5	0.132	0.064	0.104	2.070	0.039	0.518	1.930
	Q6	0.110	0.058	0.100	1.903	0.058	0.521	1.918
	Q7	0.077	0.035	0.109	2.194	0.029	0.883	1.132

[a] Dependent Variable: Q9

5.7.1.4. Autocorrelation. The Durbin–Watson statistic was 1.738, indicating that there was no evidence of autocorrelation in the residuals.

Table 5.38. Model summary of the hierarchical regression mdel for Q9

Model Summary[c]									
Model	**R**	**R Square**	**Adjusted R Square**	**Std. Error of the Estimate**	**Change Statistics**				**Durbin-Watson**
					R Square Change	**F Change**	**df1**	**df2**	
1	.233[a]	0.054	0.032	1.057	0.054	2.485	9	391	1.738
2	.410[b]	0.168	0.134	1.000	0.114	7.540	7	384	
[a] Predictors: (Constant), Age, Employment, education, Location, frequency, Gendercode, license, income, ownership									
[b] Predictors: (Constant), Age, Employment, education, Location, frequency, Gendercode, license, income, ownership, Q1, Q4, Q6, Q7, Q2, Q5, Q3									
[c] Dependent Variable: Q9									

5.7.1.5. Outliers and Influential Observations. Standardized residuals ranged between –3.07 and +2.16, indicating minimal influence from outliers. The maximum Cook's Distance was well below the threshold of 1, suggesting no undue influence of individual observations. Leverage values were within acceptable limits.

Table 5.39. Residual statistics for the hierarchical regression model for Q9.

Residuals Statistics[a]					
	Minimum	**Maximum**	**Mean**	**Std. Deviation**	**N**
Predicted Value	2.01	5.03	4.03	0.441	401
Std. Predicted Value	-4.590	2.257	0.000	1.000	401
Standard Error of Predicted Value	0.125	0.418	0.201	0.047	401
Adjusted Predicted Value	2.13	5.03	4.04	0.442	401
Residual	-3.200	1.963	0.000	0.980	401
Std. Residual	-3.201	1.963	0.000	0.980	401
Stud. Residual	-3.277	2.092	-0.001	1.005	401
Deleted Residual	-3.353	2.228	-0.001	1.031	401
Stud. Deleted Residual	-3.319	2.101	-0.002	1.009	401
Mahal. Distance	5.208	68.824	15.960	8.761	401
Cook's Distance	0.000	0.075	0.003	0.007	401
Centered Leverage Value	0.013	0.172	0.040	0.022	401
[a] Dependent Variable: Q9					

5.7.2. Hierarchical Regression Results for Q9

5.7.2.1. Model Summary. The hierarchical regression analysis demonstrated that the explanatory power of the models increased with the addition of attitudinal variables. Model 1 accounted for 5.4% of the variance in the dependent variable ($R^2 = .054$). Model 2 explained 16.8% of the variance ($R^2 = .168$), representing a substantial improvement in explanatory power. This final model was statistically significant, indicating that the inclusion of attitudinal predictors contributed meaningfully to explaining perceptions related to Q9.

Table 5.40. Model summary of the hierarchical regression model for Q9.

Model Summary[c]									
Model	**R**	**R Square**	**Adjusted R Square**	**Std. Error of the Estimate**	**Change Statistics**				**Durbin-Watson**
					R Square Change	**F Change**	**df1**	**df2**	
1	.233[a]	0.054	0.032	1.057	0.054	2.485	9	391	1.738
2	.410[b]	0.168	0.134	1.000	0.114	7.540	7	384	
[a] Predictors: (Constant), Age, Employment, education, Location, frequency, Gendercode, license, income, ownership									
[b] Predictors: (Constant), Age, Employment, education, Location, frequency, Gendercode, license, income, ownership, Q1, Q4, Q6, Q7, Q2, Q5, Q3									
[c] Dependent Variable: Q9									

5.7.2.2. ANOVA. The ANOVA results confirmed the overall significance of both regression models compared to intercept-only models. Model 1 produced an F-statistic of 2.485 ($p = .009$), showing that the initial set of demographic and behavioral predictors contributed significantly to explaining the variance in Q9. Model 2 demonstrated a higher F-statistic of 4.860 ($p < .001$), further supporting that the addition of attitudinal variables significantly improved model fit. The increase in the regression sum of squares from 24.965 in Model 1 to 77.715 in Model 2 also highlights this improvement in explanatory power.

Table 5.41. ANOVA results of the hierarchical regression model for Q9.

ANOVA[a]						
Model		**Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**
1	Regression	24.965	9	2.774	2.485	.009[b]
	Residual	436.546	391	1.116		
	Total	461.511	400			
2	Regression	77.715	16	4.857	4.860	< .001[c]
	Residual	383.796	384	0.999		
	Total	461.511	400			
[a] Dependent Variable: Q9						
[b] Predictors: (Constant), Age, Employment, education, Location, frequency, Gendercode, license, income, ownership						
[c] Predictors: (Constant), Age, Employment, education, Location, frequency, Gendercode, license, income, ownership, Q4, Q1, Q6, Q7, Q2, Q5, Q3						

5.7.2.3. Regression Coefficients. In Model 1, age emerged as the only significant positive predictor ($B = 0.011$, $\beta = 0.157$, $p = .003$), indicating that higher age was associated with increased scores on Q9. In Model 2, age remained a significant predictor ($B = 0.010$, $\beta = 0.133$, $p = .009$). Additionally, positive evaluations of lane narrowing (Q2, $B = 0.171$, $\beta = 0.223$, $p < .001$), adding pedestrian crossings (Q5, $B = 0.132$, $\beta = 0.114$, $p = .026$), and reducing parking spaces (Q7, $B = 0.077$, $\beta = 0.109$, $p = .029$) were significantly associated with higher scores. Other predictors did not reach statistical significance in either model.

The findings indicate that both demographic characteristics and attitudes toward specific pedestrian improvements played a meaningful role in predicting higher levels of the outcome variable. Age consistently emerged as a significant positive predictor, suggesting that older individuals were more likely to express supportive perceptions. Positive evaluations of lane narrowing, increasing pedestrian crossings, and reducing parking spaces were also associated with higher scores, highlighting the importance of safety-oriented and space reallocation measures in shaping attitudes.

Table 5.42. Regression coefficients for the hierarchical regression model for Q9.

Coefficients[a]								
Model	**Variable**	**Unstandardized Coefficients**		**Standardized Coefficients**	**t**	**Sig.**	**Collinearity Statistics**	
		B	**Std. Error**	**Beta**			**Tolerance**	**VIF**
1	(Constant)	3.051	0.623		4.896	< 0.001		
	Location	-0.076	0.120	-0.032	-0.637	0.525	0.975	1.026
	Gendercode	0.145	0.124	0.062	1.167	0.244	0.867	1.154
	Employment	-0.016	0.160	-0.005	-0.102	0.919	0.855	1.170
	Education	0.100	0.071	0.075	1.409	0.160	0.865	1.156
	Income	0.066	0.066	0.051	0.993	0.321	0.703	1.422
	License	0.135	0.063	0.103	2.151	0.032	0.707	1.413
	Ownership	0.166	0.203	0.060	0.817	0.415	0.283	3.530
	Frequency	-0.043	0.061	-0.041	-0.707	0.480	0.857	1.168
	Age	0.011	0.004	0.157	2.940	0.003	0.851	1.175
2	(Constant)	1.830	0.743		2.463	0.014		
	Location	-0.201	0.117	-0.084	-1.728	0.085	0.921	1.085
	Gendercode	0.114	0.119	0.048	0.958	0.338	0.852	1.173
	Employment	0.006	0.161	0.002	0.038	0.970	0.844	1.185
	Education	0.101	0.070	0.076	1.439	0.151	0.843	1.186
	Income	0.061	0.065	0.047	0.928	0.354	0.693	1.444
	License	0.163	0.062	0.124	2.628	0.009	0.702	1.425
	Ownership	0.090	0.204	0.033	0.440	0.660	0.270	3.706
	Frequency	-0.050	0.059	-0.075	-0.853	0.394	0.835	1.197
	Age	0.010	0.004	0.143	2.307	0.022	0.830	1.205
	Q1	0.056	0.046	0.062	1.217	0.224	0.864	1.158
	Q2	0.106	0.041	0.138	2.607	0.009	0.364	2.748
	Q3	0.030	0.041	0.036	0.727	0.468	0.569	1.758
	Q4	0.063	0.039	0.103	1.602	0.110	0.466	2.145
	Q5	0.132	0.064	0.104	2.070	0.039	0.518	1.930
	Q6	0.110	0.058	0.100	1.903	0.058	0.521	1.918
	Q7	0.077	0.035	0.109	2.194	0.029	0.883	1.132

[a] Dependent Variable: Q9

5.8. Ordinal Regression Analysis for Q9

5.8.1. Assumption Checks

5.8.1.1. Model Fit. The comparison between the intercept-only model and the final model demonstrated that including predictors significantly improved model fit. The -2 Log Likelihood decreased from 1040.54 to 957.60, resulting in a Chi-Square statistic of 82.93 ($df = 25$, $p < .001$). This indicates that the model with predictors provided a significantly better fit than the intercept-only model.

Table 5.43. Model fitting information for ordinal regression model for Q9.

Model Fitting Information				
Model	**−2 Log Likelihood**	**Chi-Square**	**df**	**Sig.**
Intercept Only	1040.536			
Final	957.604	82.932	25	< .001
Link function: Logit.				

5.8.1.2. Goodness of Fit. The model demonstrated acceptable fit to the data. The Pearson Chi-Square statistic was 1478.01 ($p = .946$) and the Deviance statistic was 957.60 ($p = 1.000$). As both tests were non-significant ($p > .05$), there was no evidence of poor fit, indicating that the model's predicted probabilities closely matched the observed outcomes.

Table 5.44. Goodness-of-fit statistics for ordinal regression model for Q9.

Goodness-of-Fit			
	Chi-Square	**df**	**Sig.**
Pearson	1478.013	1567	0.946
Deviance	957.604	1567	1.000
Link function: Logit.			

5.8.1.3. Pseudo R-square. The pseudo R-square measures suggested that the model accounted for a moderate proportion of variance in the dependent variable. The Cox and Snell R^2 was 0.187, indicating that approximately 18.7% of the variance could be explained by the predictors. The Nagelkerke R^2 was slightly higher at 0.202, corre-

sponding to about 20.2% of explained variability. The McFadden R^2 was more conservative, with a value of 0.080, suggesting that roughly 8.0% of the variance was accounted for by the model. These results indicate that, while the model improved prediction compared to the null model, its overall explanatory power remained moderate.

Table 5.45. Pseudo R-square values for ordinal regression model for Q9.

Pseudo R-Square	
Cox and Snell	0.187
Nagelkerke	0.202
McFadden	0.080
Link function: Logit.	

5.8.1.4. Test of Parallel Lines. The proportional odds assumption was evaluated using the Test of Parallel Lines. The analysis produced a Chi-Square value of 84.90 with 75 degrees of freedom ($p = .203$). Since the p-value exceeded .05, there was no evidence of a violation, indicating that the proportional odds assumption was met and the relationship between predictors and the outcome was consistent across response categories.

Table 5.46. Test of parallel lines for the ordinal regression model for Q9.

Test of Parallel Lines[a]				
Model	**−2 Log Likelihood**	**Chi-Square**	**df**	**Sig.**
Null Hypothesis	957.604			
General	872.701[b]	84.903[c]	75	0.203
The null hypothesis states that the location parameters (slope coefficients) are the same across response categories.				
[a] Link function: Logit.				
[b] The log-likelihood value cannot be further increased after maximum number of step-halving.				
[c] The Chi-Square statistic is computed based on the log-likelihood value of the last iteration of the general model. Validity of the test is uncertain.				

5.8.2. Ordinal Regression Results for Q9

5.8.2.1. Parameter Estimates. The parameter estimates indicated that several predictors were significantly associated with higher outcome levels. Age showed a significant

positive effect (Estimate = +0.015, $p = .048$), suggesting that older individuals were more likely to report higher scores. Positive evaluations of lane narrowing (Estimate = +0.341, $p < .001$), pedestrian crossings (Estimate = +0.229, $p = .041$), and reducing parking spaces (Estimate = +0.183, $p = .007$) also contributed significantly to increased odds of higher responses. Other predictors were not statistically significant at the .05 level.

The findings indicate that both attitudinal and demographic factors played a meaningful role in predicting higher levels of the outcome variable. Positive evaluations of lane narrowing, pedestrian crossings, and reducing parking spaces were significantly associated with increased odds of reporting higher responses, underscoring the importance of supportive perceptions toward safety and accessibility improvements. Age also emerged as a significant predictor, suggesting that older individuals were more inclined to express favorable attitudes toward these interventions. Overall, these results highlight that targeted infrastructural measures and demographic characteristics jointly contribute to shaping more supportive views of pedestrian-oriented changes.

Table 5.47. Parameter estimates for the ordinal regression model for Q9.

Parameter Estimates								
		Estimate	**Std. Error**	**Wald**	**df**	**Sig.**	**95% Confidence Interval**	
							Lower Bound	**Upper Bound**
Threshold	[cyclewalk = 1]	-17.975	1.432	157.502	1	< 0.001	-20.782	-15.168
	[cyclewalk = 2]	-17.272	1.427	146.499	1	< 0.001	-20.068	-14.475
	[cyclewalk = 3]	-15.747	1.431	121.075	1	< 0.001	-18.551	-12.942
	[cyclewalk = 4]	-14.155	1.441	96.454	1	< 0.001	-16.98	-11.33
Location	Age	0.015	0.007	3.914	1	0.048	0	0.029
	Sidewalk widening	0.045	0.087	0.262	1	0.609	-0.126	0.215
	Lane narrowing	0.341	0.075	20.601	1	< 0.001	0.194	0.489
	Green space	0.003	0.189	0	1	0.985	-0.366	0.373
	Tree number	0.002	0.204	0	1	0.994	-0.399	0.402
	Crossing	0.229	0.112	4.189	1	0.041	0.01	0.449
	Street lamb	0.185	0.121	2.322	1	0.128	-0.053	0.423
	Parking space	0.183	0.068	7.192	1	0.007	0.049	0.317
	[Location=1]	0.308	0.225	1.885	1	0.17	-0.132	0.748
	[Location=2]	0a			0			
	[Gender_code=1]	-0.32	0.233	1.875	1	0.171	-0.777	0.138
	[Gender_code=2]	0a			0			
	[Employment_code=1]	0.037	0.319	0.013	1	0.908	-0.588	0.662
	[Employment_code=2]	0a			0			
	[education_code=1]	-18.631	0.618	907.944	1	< 0.001	-19.843	-17.419
	[education_code=2]	-18.669	0.591	997.005	1	< 0.001	-19.828	-17.51
	[education_code=3]	-18.519	0.593	974.29	1	< 0.001	-19.682	-17.356
	[education_code=4]	-18.651	0		1		-18.651	-18.651
	[education_code=5]	0a			0			
	[incomelevel_code=1]	0.543	0.586	0.859	1	0.354	-0.605	1.69
	[incomelevel_code=2]	0.249	0.538	0.214	1	0.644	-0.806	1.304
	[incomelevel_code=3]	0.776	0.544	2.034	1	0.154	-0.29	1.841
	[incomelevel_code=4]	0.35	0.728	0.232	1	0.63	-1.077	1.777
	[incomelevel_code=5]	0a			0			
	[license_code=1]	-0.321	0.245	1.705	1	0.192	-0.802	0.161
	[license_code=2]	0a			0			
	[ownership_code=1]	-0.571	0.484	1.392	1	0.238	-1.52	0.378
	[ownership_code=2]	0a			0			
	[frequency_code=1]	-0.203	0.52	0.153	1	0.696	-1.223	0.816
	[frequency_code=2]	0.946	0.531	3.173	1	0.075	-0.095	1.987
	[frequency_code=3]	0.619	0.482	1.653	1	0.199	-0.325	1.563
	[frequency_code=4]	0.234	0.39	0.36	1	0.548	-0.53	0.997
	[frequency_code=5]	0a			0			

Link function: Logit.

[a] This parameter is set to zero because it is redundant.

5.9. Discussion of Theoretical and Practical Implications of the Results

To facilitate a comprehensive interpretation of the findings, the regression models predicting intentions to use public transportation (Q8) and active transportation (Q9) are presented together in an integrated set of tables. Displaying these results side by side enables a clear comparison of the relative strength and consistency of predictors across the two behavioral outcomes. This approach also allows for the identification of common factors that simultaneously influence both types of sustainable mobility intentions, as well as unique determinants that are more specific to one mode of travel.

Table 5.48. Regression model estimates and model fit statistics for predictors of public transportation intentions

Regression Model	**Dependent Variable: Q8 — Regression Results**				**Model Fit**	
	Predictor Variable	**B Coefficient**	**Beta (Standardized)**	**Sig. (p-value)**	**R^2**	**ANOVA**
Multiple Linear Regression	Age	0.013	0.186	<0.001	0.172	F = 4.972 (p < 0.001)
	Q2	0.137	0.180	<0.001		
	Q5	0.179	0.156	0.002		
	Q3	0.208	0.128	0.038		
	Frequency	-0.121	-0.182	0.039		
Stepwise Regression	Q5	0.212	0.185	<0.001	0.137	F = 15.568 (p < 0.001)
	Q2	0.150	0.198	<0.001		
	Age	0.012	0.162	0.001		
	Frequency	-0.084	0.032	0.009		
Hierarchical Regression	Age	0.013	0.186	<0.001	0.172	F = 4.972 (p < 0.001)
	Q2	0.137	0.180	<0.001		
	Q5	0.179	0.156	0.002		
	Q3	0.208	0.128	0.038		
	Frequency	-0.121	-0.182	0.039		

Table 5.49. Ordinal regression model estimates and model fit statistics for predictors of public transportation intentions

Dependent Variable: Q8								
Regression Model	**Predictor Variable**	**Regression Results**				**Model Fit**		
		Estimate (B)	**Std. Error**	**Wald χ^2**	**p-value**	**−2 Log Likelihood**	**Model χ^2 (df=25, p<.001)**	**Nagelkerke R^2**
Ordinal Regression	Age	0.027	0.007	15.557	< 0.001	1018.960	81.672	0.197
	Q2	0.259	0.072	12.903	< 0.001			
	Q5	0.317	0.109	8.465	0.004			

Regarding intentions to use public transportation, the findings consistently demon-

strate that both demographic characteristics and attitudes toward pedestrian-oriented improvements played a significant role. In the multiple linear regression model ($R^2 = 0.172$), positive perceptions of lane narrowing (Q2: $B = 0.137$, $\beta = 0.180$, $p < 0.001$) and the addition of pedestrian crossings (Q5: $B = 0.179$, $\beta = 0.156$, $p = 0.002$) were significantly associated with higher reported willingness to use public transport. Age was also a strong positive predictor ($B = 0.013$, $\beta = 0.186$, $p < 0.001$), indicating that older individuals were more inclined toward adopting sustainable mobility behaviors. Additionally, favorable views of increasing green areas (Q3: $B = 0.208$, $\beta = 0.128$, $p = 0.038$) contributed to stronger intentions, though with a slightly smaller standardized effect size. Frequency of car use exhibited a negative relationship ($B = -0.121$, $\beta = -0.182$, $p = 0.039$), suggesting that habitual reliance on private vehicles may impede openness to modal shift.

The stepwise regression model ($R^2 = 0.137$) reinforced the importance of pedestrian crossings (Q5: $B = 0.212$, $\beta = 0.185$, $p < 0.001$) and lane narrowing (Q2: $B = 0.150$, $\beta = 0.198$, $p < 0.001$), which emerged as the most influential predictors retained in the final selection process. Age ($B = 0.012$, $\beta = 0.162$, $p = 0.001$) and car use frequency ($B = -0.084$, $\beta = -0.032$, $p = 0.009$) remained statistically significant, although their effect sizes were relatively smaller compared to the perceptions of infrastructural improvements.

In the hierarchical regression analysis ($R^2 = 0.172$), positive evaluations of lane narrowing (Q2: $B = 0.137$, $\beta = 0.180$, $p < 0.001$) and pedestrian crossings (Q5: $B = 0.179$, $\beta = 0.156$, $p = 0.002$) again demonstrated consistent positive associations. Age ($B = 0.013$, $\beta = 0.186$, $p < 0.001$) retained a strong effect comparable to the multiple regression results. Green area improvements (Q3: $B = 0.208$, $\beta = 0.128$, $p = 0.038$) also contributed significantly to increased intentions to use public transport. Car use frequency ($B = -0.121$, $\beta = -0.182$, $p = 0.039$) remained negatively associated, further highlighting the role of established travel habits.

In the ordinal regression model (Nagelkerke $R^2 = 0.197$), consistent patterns were observed. Lane narrowing was a significant positive predictor (Estimate = 0.259,

$p < 0.001$), as was the addition of pedestrian crossings (Estimate = 0.317, $p = 0.004$), underscoring the importance of safety-focused improvements. Age also showed a robust positive effect (Estimate = 0.027, $p < 0.001$), indicating that increasing age was associated with a higher likelihood of reporting stronger intentions to use public transport. The −2 Log Likelihood value of 1,018.960 and significant model chi-square test ($\chi^2(25) = 81.672$, $p < 0.001$) confirmed that the model fit was acceptable and the predictors collectively contributed to explaining variance in the outcome.

Table 5.50. Regression model estimates and model fit statistics for predictors of active transportation intentions

Regression Model	**Regression Results (Dependent Variable: Q9)**				**Model Fit**	
	Predictor Variable	**B Coefficient**	**Beta (Standardized)**	**Sig. (p-value)**	**R^2**	**ANOVA**
Multiple Linear Regression	Age	0.010	0.133	0.009	0.168	F = 4.860 ($p < 0.001$)
	Q2	0.171	0.223	< 0.001		
	Q5	0.132	0.114	0.026		
Stepwise Regression	Q2	0.200	0.223	< 0.001	0.128	F = 25.586 ($p < 0.001$)
	Q5	0.204	0.177	< 0.001		
	Q7	0.085	0.119	0.013		
Hierarchical Regression	Age	0.010	0.133	0.009	0.134	F = 4.860 ($p < 0.001$)
	Q2	0.171	0.223	< 0.001		
	Q5	0.132	0.114	0.026		
	Q7	0.077	0.109	0.029		

Table 5.51. Ordinal regression model estimates and model fit statistics for predictors of active transportation intentions

Dependent Variable: Q9								
Regression Model	**Predictor Variable**	**Regression Results**				**Model Fit**		
		Estimate (B)	**Std. Error**	**Wald χ^2**	**p-value**	**−2 log Likelihood**	**Model χ^2 (df=25, p<.001)**	**Nagelkerke R^2**
Ordinal Regression	Age	0.015	0.007	3.914	0.048	957.604	82.932	0.202
	Q2	0.341	0.075	20.601	< 0.001			
	Q5	0.229	0.112	4.189	0.041			
	Q7	0.183	0.068	7.192	0.007			

Regarding intentions to use active transportation, the findings consistently demonstrate that perceptions of pedestrian-oriented improvements and selected demographic factors were significant predictors. In the multiple linear regression model ($R^2 = 0.168$), positive evaluations of lane narrowing (Q2: $B = 0.171$, $\beta = 0.223$, $p < 0.001$) and the addition of pedestrian crossings (Q5: $B = 0.132$, $\beta = 0.114$, $p = 0.026$) were positively

associated with stronger intentions to engage in active travel. Age was also significant ($B = 0.010$, $\beta = 0.133$, $p = 0.009$), indicating that older individuals expressed greater willingness to adopt active transportation behaviors.

The stepwise regression model ($R^2 = 0.128$) further highlighted the importance of these factors. Lane narrowing (Q2: $B = 0.200$, $\beta = 0.223$, $p < 0.001$) and pedestrian crossings (Q5: $B = 0.204$, $\beta = 0.177$, $p < 0.001$) emerged as the most influential predictors retained during variable selection. Additionally, favorable perceptions of pedestrian safety and comfort (Q7: $B = 0.085$, $\beta = 0.119$, $p = 0.013$) contributed significantly, underscoring the importance of subjective evaluations of safety in motivating active transportation choices.

In the hierarchical regression analysis ($R^2 = 0.134$), lane narrowing (Q2: $B = 0.171$, $\beta = 0.223$, $p < 0.001$) and pedestrian crossings (Q5: $B = 0.132$, $\beta = 0.114$, $p = 0.026$) again demonstrated positive associations with active transport intentions. Age ($B = 0.010$, $\beta = 0.133$, $p = 0.009$) remained a consistent demographic predictor. Perceptions of pedestrian safety and comfort (Q7: $B = 0.077$, $\beta = 0.109$, $p = 0.029$) were also significant contributors, further supporting the role of perceived improvements in shaping behavior.

The ordinal regression model (Nagelkerke $R^2 = 0.202$) corroborated these results. Lane narrowing demonstrated a strong positive effect (Estimate = 0.341, $p < 0.001$), as did pedestrian crossings (Estimate = 0.229, $p = 0.041$). Perceptions of pedestrian safety and comfort (Q7: Estimate = 0.183, $p = 0.007$) also retained significance. Age again emerged as a positive factor (Estimate = 0.015, $p = 0.048$), reinforcing the pattern observed in the multiple linear regression analyses. The model chi-square statistic confirmed the predictors' collective contribution to explaining variance in intentions ($\chi^2(25) = 82.932$, $p < 0.001$).

Overall, across all regression models, positive perceptions of lane narrowing (Q2) and the addition of pedestrian crossings (Q5) consistently emerged as the most robust and significant determinants of intentions to use active transportation. Favorable views

of pedestrian safety and comfort (Q7) and higher age were also important predictors that contributed significantly in several models, although their effects were not uniformly retained across every specification. These results underscore the central role of safety-focused design improvements in promoting active mobility behaviors, while also highlighting that demographic characteristics such as age and perceptions of comfort can meaningfully enhance individuals' willingness to shift away from car use when present.

6. CONCLUSION

This thesis investigated how socioeconomic and environmental factors influence individuals' preferences toward public transport and active transportation following pedestrianization initiatives in the Caferağa neighborhood of Kadıköy, Istanbul. A total of 401 face-to-face surveys were conducted, and the collected data were analyzed using multiple linear regression, stepwise regression, hierarchical regression, and ordinal regression models. Participants' attitudes toward pedestrian-focused improvements were examined in detail, revealing statistically significant relationships between these attitudes and intentions to adopt more sustainable mobility behaviors.

Successfully implementing pedestrian-oriented planning in urban areas requires not only physical interventions but also public acceptance and behavioral change. This study contributes to the literature by offering a comprehensive approach that connects spatial improvements with social vulnerabilities and perceptions. It provides scientific evidence on how human-centered design resonates within the local context.

The primary aim of the research was to understand the potential of pedestrianization interventions to motivate individuals to shift toward more sustainable transport options. The findings demonstrated that positive perceptions of measures such as narrowing vehicle lanes and increasing pedestrian crossings significantly increased intentions to use both public transport and active modes of travel. Additionally, age emerged as a positive demographic factor, while individuals who frequently relied on private cars exhibited more resistant attitudes.

These findings emphasize the need to develop urban mobility strategies that take into account demographic differences and current travel behaviors, rather than applying uniform approaches. The data showing that interventions aimed at safety and accessibility can enhance public perception highlights their key role in encouraging shifts toward more sustainable transportation choices.

Limitations of the study include the restriction of data collection to a single neighborhood, which limits generalizability; the timing of the survey within March 2025; and the potential influence of concurrent socio-political events on participants' attitudes. Additionally, the use of convenience sampling and reliance on self-reported measures

mean that actual behaviors may not fully align with the expressed intentions.

Future research could expand the scope by replicating similar studies in different districts and socioeconomic contexts, conducting longitudinal studies to observe long-term behavioral change, and integrating spatial analyses to explore causal relationships between built environment interventions and mobility choices. Moreover, before-and-after evaluations of pilot pedestrianization projects could offer valuable insights for evidence-based policy development. From a not-so-far-fetched perspective, this kind of consensus may even be necessary between humans and robots in the future. Set in a futuristic Detroit in 2038 where androids are deeply integrated into society, the video game called Detroit: Become Human portrays a world in which the peaceful path to android liberation depends on public support for genuine acceptance, whereas the violent path leads only to coerced recognition lacking true consensus [101].

After all the work done, not just this thesis but all the papers published throughout history, the inventions that transformed societies, and the mysteries that were discovered, one must realize that it all comes down to human beings. Whether in good times or bad times, somewhere, someone tries to move forward or achieve something for people. From revolutionary upheavals to individual acts of courage, these efforts are linked by a shared aspiration to create a more just world. The words "Liberté, Égalité, Fraternité!" did not become the official motto of France until 1848, when the Second Republic was proclaimed. Over time, they became more than just a motto, emerging as a republican principle incorporated into the preamble of the Constitution [102]. This spirit found one of its earliest and most powerful expressions in the events that transformed the course of French history. When calendars showed July 14, 1789, the Storming of the Bastille marked an event that would be remembered as the death of the old regime [103]. In the same way, contemporary events remind us that the struggle for rights and justice continues in every society, becoming new chapters in the story of humanity.

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