

University of Thessaly  
Department of Civil Engineering  
Traffic, Transportation and Logistics Laboratory - TTLog

Doctoral Dissertation

# Intelligent transport systems with usage of big data for management of sustainable mobility

**Maria E. Karatsoli**

Dipl. Civil Engineer - UTH  
Transportation Engineer - TUM

Volos, Greece 2023

«This research is co-financed by Greece and the European Union (European Social Fund- ESF) through the Operational Programme «Human Resources Development, Education and Lifelong Learning» in the context of the project “Strengthening Human Resources Research Potential via Doctorate Research” (MIS-5000432), implemented by the State Scholarships Foundation (IKY)»



**“Intelligent transport systems with usage of big data for management of sustainable mobility”**

A DISSERTATION

Submitted to University of Thessaly, Department of Civil Engineering

For the degree of

DOCTOR OF PHILOSOPHY

by

Maria Karatsoli

Dissertation Committee

**Eftihia Nathanail** | Professor, University of Thessaly, Greece, Supervisor

---

**Socrates Basbas** | Professor, Aristotle University of Thessaloniki, Greece

---

**Oded Cats** | Professor, TU Delft, The Netherlands

---

**Ioannis Politis** | Assistant Professor, Aristotle University of Thessaloniki, Greece

---

**Panteleimon Kopelias** | Assistant Professor, University of Thessaly, Greece

---

**Nikolaos Gavanas** | Assistant Professor, University of Thessaly, Greece

---

**Athanasios Theofilatos** | Assistant Professor, University of Thessaly, Greece

---

© 2023 Maria E. Karatsoli

Η έγκριση της παρούσας Διδακτορικής διατριβής από το Τμήμα Πολιτικών Μηχανικών της Πολυτεχνικής Σχολής του Πανεπιστημίου Θεσσαλίας δεν υποδηλώνει αποδοχή των απόψεων του συγγραφέα (Ν. 5343/32 αρ. 202 παρ. 2).

*Dedicated to my sons.  
For making me believe that anything is possible*

*And to my husband Ioannis.  
For making everything possible*

“Remember to look up at the stars and not down at your feet. Try to make sense of what you see and wonder about what makes the universe exist. Be curious. And however difficult life may seem, there is always something you can do and succeed at. It matters that you don't just give up.”

— *Stephen Hawking* —

## **Acknowledgements**

I am humbled and grateful to have had the opportunity to pursue a PhD degree. This journey would not have been possible without the unwavering support and encouragement of the many people who have touched my life along the way.

First, my heartfelt appreciation goes to my thesis supervisor Prof. Eftihia Nathanail, who provided invaluable guidance and mentorship throughout my research.

Second, I am indebted to the members of my thesis committee, Prof. Socrates Basbas and Prof. Oded Cats, whose insights and feedback have helped me to refine and improve my work.

I would like to express my gratitude to my family and loved ones, who have supported and encouraged me through the ups and downs of this journey. Especially to my beloved mother Vaia for always standing by my side.

Finally, I would like to extend my deepest appreciation to the participants who generously shared their time, experiences, and perspectives with me, making this research possible.

# Intelligent transport systems with usage of big data for management of sustainable mobility

Maria Karatsoli

University of Thessaly, Department of Civil Engineering, 2021

Supervisor: Eftihia Nathanail, Professor, University of Thessaly, Greece

## Abstract

Urban mobility is a critical component of urban planning and development, and it plays a significant role in shaping a city's economic growth, social equity, and environmental sustainability. The increasing demand for urban mobility in modern cities leads to traffic congestion, air pollution, and other environmental and societal impacts that are detrimental to the well-being of individuals and communities. In response to these challenges, there is a growing need to shift towards more sustainable mobility behavior. Sustainable urban mobility aims to promote transportation systems that are efficient, affordable, safe, and environmentally friendly. Intelligent Transportation Systems (ITS) play a crucial role in achieving sustainable mobility. ITS is a broad field that encompasses a wide range of technologies and applications, such as traffic management systems, intelligent vehicles, and advanced traveler information systems. These technologies provide valuable data in large volumes, with high velocity and different structure, enabling informed decisions and optimization of transportation systems. ITS and mobility services primarily based on big data lead to new possibilities for solving transport problems and creating the background for improvements in the existing services and technologies.

One area of research that has gained attention in recent years is the investigation of the impact of social media on mobility behavior. With the widespread use and popularity of social media platforms, researchers are exploring how transport-related content shared on these platforms can influence people's mobility behavior. By understanding the dynamics of social media and its impact on mobility behavior, targeted strategies can be developed to promote information about sustainable mobility. However, the success of any sustainable mobility strategy ultimately depends on the involvement of people. If people are not convinced to embrace change, any action towards enhancing mobility will remain ineffective. Therefore, it is essential to involve communities and stakeholders in the planning and implementation of sustainable mobility strategies and plans. People's involvement in the process ensures that the developed solutions are inclusive, equitable, and meet the needs of all members of society.

This dissertation aims to investigate the potential applications of big data and social media in transportation, and their impact on travel behavior, decision-making, and promotion of sustainable urban mobility. The introduction sets the stage by highlighting the need for more effective transportation planning and management strategies. The importance of transportation

planning and management is emphasized, and the potential of big data and social media is introduced to support these efforts. The research is divided into several parts, including a focus on big data in transportation studies, exploring the potential of social media use for urban mobility and travel choices, and examining transport-related social media content and its role in urban mobility. GPS and self-reported data are used to evaluate daily trips and the impact of travel information on transportation choices. The impact of information on pedestrians and public transport users after crowding information is investigated in the era of COVID-19. The research concludes by presenting important findings and main conclusions. The potential of big data and social media to support sustainable transportation choices and urban mobility is highlighted. Guiding principles for policymakers and transportation professionals are also presented, including the need for better data management, the use of social media for targeted communication, and the development of innovative transportation services and technologies. In summary, this dissertation contributes to the growing body of literature on the potential of big data and social media in transportation studies.



## Περίληψη

Η αστική κινητικότητα αποτελεί βασικό στοιχείο του αστικού σχεδιασμού και ανάπτυξης, και διαδραματίζει σημαντικό ρόλο στο σχηματισμό της οικονομικής ανάπτυξης, της κοινωνικής ισότητας και της περιβαλλοντικής βιωσιμότητας μιας πόλης. Η αυξανόμενη ζήτηση για αστική κινητικότητα στις σύγχρονες πόλεις οδηγεί σε συμφόρηση της κυκλοφορίας, ατμοσφαιρική ρύπανση και άλλες περιβαλλοντικές και κοινωνικές επιπτώσεις που είναι επιζήμιες για την ευημερία των ατόμων και των κοινοτήτων. Ως απάντηση σε αυτές τις προκλήσεις, υπάρχει μια αυξανόμενη ανάγκη για μετάβαση προς μία πιο βιώσιμη συμπεριφορά κινητικότητας. Η βιώσιμη αστική κινητικότητα στοχεύει στην προώθηση συστημάτων μεταφοράς που είναι αποδοτικά, προσιτά, ασφαλή και φιλικά προς το περιβάλλον. Τα Έξυπνα Συστήματα Μεταφοράς (ITS) παίζουν βασικό ρόλο στην επίτευξη της βιώσιμης κινητικότητας. Τα ITS περιλαμβάνουν ένα ευρύ πεδίο από πολλές τεχνολογίες και εφαρμογές, όπως συστήματα διαχείρισης κυκλοφορίας, έξυπνα οχήματα και προηγμένα συστήματα πληροφόρησης για τους ταξιδιώτες. Αυτές οι τεχνολογίες παρέχουν χρήσιμα δεδομένα σε μεγάλες ποσότητες, με υψηλή ταχύτητα και διαφορετική δομή, επιτρέποντας ενημερωμένες αποφάσεις και την βελτιστοποίηση των συστημάτων μεταφοράς. Τα ITS και οι υπηρεσίες κινητικότητας που βασίζονται κυρίως στα μεγάλα δεδομένα οδηγούν σε νέες δυνατότητες για την επίλυση των προβλημάτων στις μεταφορές και αποτελούν υπόβαθρο για βελτιώσεις στις υπάρχουσες υπηρεσίες και τεχνολογίες.

Μια περιοχή έρευνας που έχει κερδίσει προσοχή τα τελευταία χρόνια είναι η διερεύνηση της επίδρασης των κοινωνικών μέσων στη συμπεριφορά κινητικότητας. Με τη διαδεδομένη χρήση και δημοτικότητα των πλατφορμών κοινωνικής δικτύωσης, είναι σημαντική η διερεύνηση του αντίκτυπου της πληροφορίας που σχετίζεται με τις μεταφορές και κοινοποιείται σε αυτές τις πλατφόρμες στην κινητικότητα των ανθρώπων. Μέσω της κατανόησης της δυναμικής των κοινωνικών μέσων και της επίδρασής τους στη μετακίνηση, μπορούν να αναπτυχθούν στοχευμένες στρατηγικές για την προώθηση πληροφοριών σχετικά με τη βιώσιμη κινητικότητα. Ωστόσο, η επιτυχία οποιασδήποτε στρατηγικής εξαρτάται τελικά από τη συμμετοχή των ανθρώπων, οι οποίοι εάν δεν πειστούν να αποδεχτούν την αλλαγή, οποιαδήποτε ενέργεια για την βελτίωση της κινητικότητας θα παραμείνει αναποτελεσματική. Επομένως, είναι ουσιώδες να εμπλακούν οι κοινότητες και οι ενδιαφερόμενοι φορείς στον σχεδιασμό και την υλοποίηση των στρατηγικών και σχεδίων για τη βιώσιμη κινητικότητα. Η συμμετοχή των ανθρώπων στη διαδικασία εξασφαλίζει ότι οι αναπτυσσόμενες λύσεις είναι περιεκτικές, δίκαιες και ανταποκρίνονται στις ανάγκες όλων των μελών της κοινωνίας.

Η διατριβή αυτή στοχεύει στην διερεύνηση της δυναμικής των μεγάλων δεδομένων και των κοινωνικών μέσων για την προώθηση των βιώσιμων επιλογών μεταφορών και την κατανόηση της αστικής κινητικότητας. Η εισαγωγή θέτει το πλαίσιο, τονίζοντας την ανάγκη για πιο αποτελεσματικές στρατηγικές σχεδιασμού και διαχείρισης των μεταφορών. Εισάγεται η σημασία του σχεδιασμού και διαχείρισης των μεταφορών, και παρουσιάζεται η δυναμική των μεγάλων δεδομένων και των κοινωνικών μέσων για την υποστήριξη αυτών των προσπαθειών. Η έρευνα περιλαμβάνει την διερεύνηση της χρήσης των μεγάλων δεδομένων στις μελέτες μεταφορών, την εξερεύνηση της δυναμικής της χρήσης των κοινωνικών μέσων για την αστική κινητικότητα και τις επιλογές ταξιδιού, καθώς και την διερεύνηση του σχετικού με τις μεταφορές περιεχομένου στα κοινωνικά μέσα και του ρόλου του στην αστική κινητικότητα. Τα δεδομένα GPS και δεδομένα δεδηλωμένων προτιμήσεων χρησιμοποιούνται για να αξιολογηθούν οι καθημερινές διαδρομές και ο αντίκτυπος των πληροφοριών ταξιδιού στις μετακινήσεις. Εξετάζεται επίσης ο αντίκτυπος των πληροφοριών σε πεζούς και χρήστες μέσων

μαζικής μεταφοράς μετά την παροχή πληροφοριών σχετικά με τον συνωστισμό κατά τη διάρκεια της πανδημίας COVID-19. Η έρευνα καταλήγει στην παρουσίαση σημαντικών ευρημάτων και κύριων συμπερασμάτων και τονίζεται η δυναμική των μεγάλων δεδομένων και των μέσων κοινωνικής για την υποστήριξη βιώσιμων επιλογών μεταφοράς και την αστική κινητικότητα. Επιπλέον, παρουσιάζονται καθοδηγητικές αρχές για τους φορείς και του τομέα των μεταφορών, συμπεριλαμβανομένης της ανάγκης καλύτερης διαχείρισης δεδομένων, της χρήσης κοινωνικών μέσων για στοχευμένη πληροφόρηση και της ανάπτυξης καινοτόμων υπηρεσιών και τεχνολογιών μεταφοράς. Συνολικά, αυτή η διατριβή συνεισφέρει στην αναπτυσσόμενη βιβλιογραφία που σχετίζεται με τη δυναμική των μεγάλων δεδομένων και των κοινωνικών μέσων στις μελέτες των μεταφορών.

## Table of Contents

<b>1</b>	<b>Introduction .....</b>	<b>18</b>
1.1	Problem statement and motivation .....	20
1.2	Research objectives & gaps .....	21
1.3	Scientific contribution .....	23
1.4	Research methodology and dissertation’s outline .....	25
1.5	Publications from this dissertation .....	29
<b>2</b>	<b>Big data applications and sustainability in urban mobility.....</b>	<b>32</b>
2.1	Big data in transport studies .....	32
2.1.1	Quantitative big data sources .....	33
2.1.2	Qualitative big data sources .....	34
2.2	Big data applications in transportation research .....	35
2.2.1	Transportation planning studies .....	35
2.2.2	Traffic management studies .....	37
2.2.3	Public transport management .....	39
2.2.4	Incident management and safety .....	41
2.2.5	Summary of big data applications in transport research .....	42
2.3	Sustainability in urban mobility .....	48
2.3.1	Real-time traffic management .....	48
2.3.2	Intelligent Transport Systems (ITS).....	49
2.3.3	Transport demand management .....	49
2.3.4	Travel information.....	50
<b>3</b>	<b>Potential of social media use for influencing travel and activity choices .....</b>	<b>52</b>
3.1	Introduction .....	53
3.2	Social media in transport studies .....	54
3.3	Methodology.....	57
3.3.1	Survey design .....	57
3.3.2	Survey communication.....	60
3.3.3	Sample characteristics and social media use.....	60
3.3.4	Data analysis .....	64
3.3.5	Research limitations .....	64
3.4	Social media use before an activity/trip .....	65
3.4.1	Social media use before an activity/trip .....	65
3.4.2	Examining gender differences of social media use .....	73
3.4.3	Impact of users’ characteristics and social media information on mobility decisions .....	80
3.5	Social media use during an activity/trip.....	89
3.5.1	Comparison of social media use before and during an activity .....	89
3.5.2	Impact of social media during an activity and shared content .....	91
3.6	Social media use after an activity/trip .....	95
3.7	Concluding discussion .....	97
<b>4</b>	<b>Harnessing social media content for enhancement and effective promotion of sustainable urban mobility .....</b>	<b>99</b>
4.1	Introduction .....	100
4.2	Methodology.....	101
4.3	Social media content for detection of transport-related activities .....	103
4.3.1	Data description.....	104
4.3.2	Preliminary Grading Results .....	106
4.3.3	Classification.....	107
4.4	Campaigns and awareness-raising strategies on sustainable urban mobility: How a transport-related content could be more influential in social media? .....	108
4.4.1	Sustainable urban mobility awareness campaigns and strategies .....	109
4.4.2	How a transport-related content could be more influential in social media? .....	113
4.5	Concluding discussion .....	136
<b>5</b>	<b>Use of GPS and self-reported data to evaluate daily trips and the impact of travel information .....</b>	<b>139</b>
5.1	Introduction .....	139

<b>5.2</b>	<b>Travel information and mobility behavior .....</b>	<b>140</b>
<b>5.3</b>	<b>Methodological approach .....</b>	<b>141</b>
5.3.1	Phase 1: Collection and analysis of GPS data.....	142
5.3.2	Phase 2: Stated preference survey and behavioral modelling.....	146
<b>5.4</b>	<b>Phase 1: Pre-Interview and GPS data analysis.....</b>	<b>146</b>
5.4.1	Pre-interview data analysis.....	146
5.4.2	GPS data analysis.....	153
5.4.3	Creation of the “Digital travel file card.....	156
<b>5.5</b>	<b>Conclusions .....</b>	<b>158</b>
<b>6</b>	<b>A Stated Preference study to explore the impact of travel information on motorized vehicle users .....</b>	<b>160</b>
<b>6.1</b>	<b>Stated preference survey design.....</b>	<b>160</b>
<b>6.2</b>	<b>Choice model estimation .....</b>	<b>164</b>
6.2.1	Phase 2: Stated preference survey analysis.....	164
<b>6.3</b>	<b>Conclusions .....</b>	<b>168</b>
<b>7</b>	<b>A Stated Preference study of pedestrians’ and public transport–users’ mobility choices in the era of COVID-19 .....</b>	<b>170</b>
<b>7.1</b>	<b>Introduction .....</b>	<b>171</b>
<b>7.2</b>	<b>Crowdedness and social distancing in the era of COVID-19 .....</b>	<b>172</b>
7.2.1	Walking and social distancing.....	172
7.2.2	Public transport and crowding.....	173
7.2.3	Study contributions .....	174
<b>7.3</b>	<b>Survey timeline .....</b>	<b>175</b>
<b>7.4</b>	<b>Methodological approach .....</b>	<b>175</b>
7.4.1	Survey design .....	176
7.4.2	Data collection - Sample recruitment.....	182
7.4.3	Data analysis .....	183
<b>7.5</b>	<b>Descriptive and inferential statistics.....</b>	<b>190</b>
<b>7.6</b>	<b>Model estimation results .....</b>	<b>195</b>
7.6.1	Pedestrians.....	195
7.6.2	Public transport users .....	197
<b>7.7</b>	<b>Discussion .....</b>	<b>200</b>
<b>8</b>	<b>Conclusions and future research .....</b>	<b>203</b>
<b>8.1</b>	<b>Main findings and conclusions .....</b>	<b>203</b>
<b>8.2</b>	<b>Practical implications of main findings.....</b>	<b>208</b>
<b>8.3</b>	<b>Research limitations and recommendations for future research.....</b>	<b>209</b>
<b>References</b>	<b>211</b>	
<b>Annexes</b>	<b>236</b>	

**List of Tables**

Table 1-1. Dissertation’s objectives and corresponding research questions .....22

Table 1-2. Scientific contribution.....24

Table 2-1. Counts of quantitative big data applications in transport research .....42

Table 2-2. Counts of qualitative big data applications in transport research .....43

Table 2-3. Summary of transport studies with two or three big data sources .....47

Table 3-1. Sample characteristics .....61

Table 3-2. Use of social media .....62

Table 3-3. Social media use before an activity/trip .....66

Table 3-4. Impact of social media use before an activity/trip .....68

Table 3-5. Preferable social media post and appealing message approach .....71

Table 3-6. Social media content shared before an activity/trip .....72

Table 3-7. List of tested variables before an activity .....74

Table 3-8. Summary of test results for comparisons between women and men regarding social media use .....75

Table 3-9. Summary of test results for comparisons between women and men regarding influence of social media on activity planning.....77

Table 3-10. Influence of social media content on women’s and men’s decisions .....77

Table 3-11. Summary of test results on preferable social media type about traveling possibilities. ....79

Table 3-12. Abbreviations of the examined variables .....81

Table 3-13. Pseudo R- squares of Models I, II, III and IV .....84

Table 3-14. Parameter estimates for Model IV .....85

Table 3-15. Pseudo R- squares of Models V, VI, VII, and VIII.....87

Table 3-16. Parameter estimates for Model VIII.....88

Table 3-17. Summary of test results for comparisons between changes to travel arrangements before and during an activity .....90

Table 3-18. Summary of test results for comparisons between social media use before and during an activity .....91

Table 3-19. Impact of social media use during an activity/trip .....92

Table 3-20. Social media content shared during an activity/trip .....94

Table 3-21. Social media use after an activity/trip .....95

Table 4-1. Population and Twitter statistics of study areas.....104

Table 4-2. Descriptive statistics of Twitter corpuses. ....105

Table 4-3. Classification accuracy statistics.....107

Table 4-4. Overview of European Union campaigns and strategies. ....	111
Table 4-5. Search query.....	114
Table 4-6. Catalogues of records.....	117
Table 4-7. Transport related social media accounts. ....	131
Table 5-1. Pre-interview sample characteristics.....	147
Table 5-2. Trip characteristics of the initial pre-interview sample.....	147
Table 5-3. Parameters’ rating between non-sustainable and sustainable mode users. ....	150
Table 5-4. Trip characteristics of GPS group. ....	152
Table 5-5. Number of trips and travel time (minutes) per transport mode.....	153
Table 5-6. Number of trips based on the trip purposes. ....	154
Table 5-7. Purpose of missed trips. ....	155
Table 5-8. Frequencies of overestimated and underestimated trips. ....	156
Table 6-1. Alternatives, attributes, and attributes’ levels.....	161
Table 6-2. Choice sets .....	162
Table 6-3. Model estimation results. ....	168
Table 7-1. Alternatives, attributes, and attributes’ levels for pedestrians. ....	179
Table 7-2. Alternatives, attributes, and attributes’ levels for public transport users- change of departure time. ....	180
Table 7-3. Alternatives, attributes, and attributes’ levels for public transport users- use of different public transport stop.....	181
Table 7-4. Sample characteristics.....	183
Table 7-5. List of tested variables. ....	184
Table 7-6. List of tested variables for pedestrians.....	186
Table 7-7. List of tested variables for public transport users. ....	187
Table 7-8. Factor analysis for pedestrians (COVIDIMP and COVIDPERP variables). ....	188
Table 7-9. Factor analysis for public transport users (COVIDIM and TRIPPER variables). ....	189
Table 7-10. Descriptive statistics of pedestrians and public transport users.....	190
Table 7-11. Trip characteristics of pedestrians and public transport users. ....	192
Table 7-12. Tested ordinal variables: pedestrians vs public transport users .....	193
Table 7-13. Model estimation results- pedestrians.....	196
Table 7-14. Model estimation results: public transport users- change of departure time .....	198
Table 7-15. Model estimation results: public transport users- change of public transport stop .....	199

**List of Figures**

Figure 1-1. Dissertation’s methodological approach.....26

Figure 1-2. Conducted surveys.....27

Figure 1-3. Dissertation’s outline .....28

Figure 2-1. Big data sources percentage use per transportation field.....45

Figure 2-2. Big data sources used in each subcategory .....46

Figure 2-3. Percentage of transportation studies per field based on the number of big data sources used.....47

Figure 3-1. Decision making of an activity/trip through social media use (Dwityas and Briandana, 2017) .....58

Figure 3-2. Social media content in decision-making process regarding an activity/ trip (Dwityas & Briandana, 2017).....60

Figure 3-3. Number of responses in selecting the most important criteria for activity choice (per gender and mode user).....79

Figure 3-4. Most appealing approaches of transport related messages .....80

Figure 3-5. Histogram of impact of social media use in activity and mobility planning .....83

Figure 3-6. Histogram of impact of the proposed transport mode by social media information, on mode choice .....87

Figure 4-1. Methodological approach .....102

Figure 4-2. Tweets’ language distribution.....105

Figure 4-3. Daily patterns of Twitter activity. A: total number of tweets; B: number of transport-related tweets; C: word cloud of transport-related tweets. ....107

Figure 4-4. Word cloud produced by the keywords of the initial search (n=431). ....115

Figure 4-5. Number of records per source type and publication year. ....129

Figure 4-6. Scope of social media records. ....130

Figure 5-1. Methodological approach. ....142

Figure 5-2. Google Distance Matrix API result. ....145

Figure 5-3. Importance of commuting characteristics and rating of current situation. ....149

Figure 5-4. Impact of travel information on participants’ travel choices.....151

Figure 5-5. Weekdays and trip purposes. ....155

Figure 5-6. Example of “Digital travel file card”.....158

Figure 6-1. Post appearance of the designated account related to sustainable urban transport on a mobile phone of a vehicle user. ....163

Figure 6-2. Example of a Stated Preference experiment addressed to a vehicle user. ....164

Figure 6-3. Travel information-seeking before/ during commute.....165

Figure 6-4. Impact of travel information. ....166

Figure 6-5. Travel information seeking in Volos city. .... 166

Figure 7-1. COVID-19 restrictions in Greece and experiment timeline ..... 175

Figure 7-2. Methodological approach ..... 176

Figure 7-3. Flowchart based on survey’s logic sequence. .... 177

Figure 7-4. Post appearance of the designated account related to sustainable urban transport on a mobile phone of (a) a pedestrian; (b) a public transport user. .... 178

Figure 7-5. Example of a Stated Preference experiment addressed to public transport users (the specific example advises to take the previous itinerary). The original text of the experiment was in Greek. .... 181



## List of Abbreviations

Abbreviation	Description
AI	Artificial Intelligence
AID	Automatic Incident Detection
ANN	Artificial Neural Networks
ANPR	Automatic Number Plate Recognition
API	Application Programming Interface
BT	Bluetooth
EC	European Commission
GMS	Google Mobile Services
GPS	Global Positioning Systems
ICT	Information and Communication Technologies
iOS	iPhone Operating System
IoT	Internet of Things
IPA	Importance Performance Analysis
ITS	Intelligent Transport Systems
JSON	JavaScript Object Notation
MAC	Media Access Control
MMNL	Mixed Multinomial Logit Models
MSP	Minneapolis – Saint Paul
OD	Origin - Destination
PoI	Points of Interest
PRISMA	Preferred Reporting Items for Systematic reviews and Meta-Analysis
PuT	Public Transport
Q&A	Question & Answers
QR	Quick Response
RO	Research Objectives
RQ	Research Question
SD	Standard Deviation
SP	Stated Preference
UGC	User-generated content
URL	Uniform Resource Locators
UTH	University of Thessaly
VMS	Variable Message Signs

# 1 Introduction

Transportation plays a critical role in connecting communities and enabling individuals to access opportunities and participate in economic, social, and cultural activities. Transportation has evolved over time to a growing array of options including electric vehicles, ridesharing, and bike-sharing. With the increasing demand for mobility, transportation systems must be designed to meet the needs of individuals and communities in an efficient, safe, and sustainable manner. The development of transportation infrastructure and services has significant impacts on the environment, economy, and quality of life, and must be managed in a responsible manner that prioritizes the well-being of individuals and the planet.

Sustainable mobility refers to a transportation system that prioritizes environmentally sustainable and economically feasible modes of transportation, such as cycling, walking, public transportation, and electric vehicles. The goal of sustainable mobility is to decrease greenhouse gas emissions, air pollution, and traffic congestion, while improving mobility and access to health and well-being. This can be achieved through sustainable transportation infrastructure, and promotion of active transportation, and clean energy technologies. Similarly, sustainable urban mobility aims to integrate eco-friendly and socially responsible transportation within cities, through investment in public transportation, active transportation, and low-emission vehicles, while ensuring equitable access to mobility for all residents. To achieve sustainable urban mobility, cities must balance the needs of all stakeholders by considering transportation, land use, and urban design in their planning. By prioritizing sustainable mobility, cities and countries can create healthier communities and a more sustainable future.

Intelligent Transportation Systems (ITS) play a crucial role in achieving sustainable mobility. ITS are a combination of information and telecommunication technologies applied to transportation sector, aiming at an efficient, safe, and economical mobility of people and goods. A plethora of transport related problems of urban centers such as traffic congestion and high travel times, ineffective parking management, environmental pollution and deterioration of urban space are increasingly complicated problems, in which ITS have the potential to offer effective and direct solutions. By leveraging advanced technologies, such as data analytics and real-time monitoring, ITS can help cities optimize their transportation systems to reduce congestion, emissions, and energy use. For instance, ITS can enable smart traffic management systems that regulate traffic flow and reduce congestion by adjusting traffic signals in real-time. This can lead to more efficient use of existing transportation infrastructure and less need for road expansion, which can be expensive and environmentally damaging. In addition, ITS can promote sustainable modes of transportation, such as public transit and active transportation, by providing real-time information on transit schedules, bike sharing options, and pedestrian routes. This can encourage people to choose sustainable modes of transportation and reduce reliance on private vehicles. Overall, ITS can help cities and communities achieve sustainable urban mobility by optimizing their transportation systems, reducing emissions and energy use, and promoting sustainable transportation options.

Modern ITS are strictly related to the use of various types of sensors and new technologies. The benefits of an applied intelligent transport system arise mainly from important information gathered from sources that offer data in large volumes, with high velocity and different structure. These data are the so-called big data. The term big data is used to describe all those data whose scale, diversity and complexity require specific methods in order to be transformed into value (De Mauro, et al., 2016) and new techniques and algorithms in order to be analyzed (Chandrasekar, 2015). Big data are characterized by high Volume,

Velocity and Variety, and in order to be reliable and accurate, they demand Value and Veracity (Emani, et al., 2015; Jagadish, et al., 2014). The five Vs are described further below:

- Volume: is one of the basic dimensions of big data and has to do with the amount of data that are available. Big data are datasets that characterized by the huge volume of data generated by different sources (Watson, 2014).

- Velocity: measures the speed in which the data are generated, retrieved, aggregated and stored (Arun & Jabasheela, 2014).

- Variety: refers to the structure of data which can be structured, semi structured, unstructured or mixed (Sharma, 2016).

- Value: is related to the extraction of useful data from a set of data from different sources (Kemp, et al., 2015).

- Veracity: refers to the uncertainty of the data which should be eliminated from any abnormalities and outliers for a more reliable and accurate dataset (Arun & Jabasheela, 2014).

Big data has been postulated as a new important technology for transport and mobility sector. In the last years, big data paradigm has become a core building block for transport studies and ITS focusing on resolving transport problems and on offering new opportunities and services by using new data sources and technologies. The developed services and tools can collect, manage, and analyze the huge volumes of big data to enhance the transportation industry and solve the aforementioned transport challenges. The answer includes the improvement or the development of new ITS and mobility services, primarily based on the principle of big data paradigm and on the extraction of valuable information from the huge new amount of available data. The extracted information leads to new possibilities for solving transport problems and creates the background for improvements in the existing services and technologies.

According to Abdulhai & Katann (2003) the core of smart information systems and ITS lies in the real time transport interventions. The dynamic monitoring and control are important for the ITS implementation. Hence, the collection and processing of big data and the use of the extracted information in real time is mandatory.

Big data has become a widely recognized and impactful trend over the last decade, with implications in a broad range of industries and sectors, including transportation. In the field of transportation, big data offers numerous benefits for planning and management. One of the key advantages is the ability to support decision-making processes by providing a vast amount of information, resulting in improved decision outcomes. Big data can also enhance traffic forecasting, which is essential for optimizing transportation networks. Furthermore, big data can be used to monitor traffic patterns and identify potential safety risks, enabling proactive measures to reduce accidents and improve safety. Additionally, big data can optimize routes and schedules, leading to more efficient transportation systems. The utilization of big data in transportation can contribute to sustainable mobility by collecting, analyzing, and leveraging large amounts of transportation-related data. This data can be obtained from various sources such as GPS systems, traffic sensors, and mobile devices, and can provide insights into travel patterns, behavior, and preferences. By analyzing big data, cities can identify areas where congestion and emissions can be reduced and allocate resources more effectively to promote sustainable modes of transportation. Moreover, big data can be used to evaluate the effectiveness of sustainability initiatives and adjust them as needed to promote sustainability continuously in the transportation sector. Big data can support sustainable mobility through

traffic management, mobility planning, public transport optimization, emissions reduction, and the promotion of sustainable transportation options.

The use of big data in transport studies presents several challenges that must be overcome to ensure its effective use. The quality of the collected data can be inconsistent and unreliable, leading to inaccurate results and to lack of quality on the data sets. A big challenge in ITS is not only on how to collect reliable big data, but also how to process the large volumes of these unstructured data, which cannot be handled effectively by traditional approaches. Analyzing big data requires specialized technical skills and resources, which can be a challenge for organizations without the necessary expertise. It is of crucial need the development of innovative applications and methodological approaches that can process and store the large volume of data generated by transportation systems. Adding to that, the challenge that comes from the fusion and harmonization of data from many sources at the same time can be a complex and time-consuming process that requires careful planning and execution. Finally, the use of big data in transportation raises concerns about privacy and the protection of personal information, which must be addressed to ensure the responsible use of data (Neilson, et al., 2019).

The use of big data and ITS in collecting, analyzing, and disseminating travel information can significantly contribute to promoting sustainable mobility. Travel information refers to the data and resources that help individuals plan, execute, and manage their trips. It encompasses a wide range of information such as route planning, transportation options, schedules, ticket pricing, and real-time updates. Travel information plays a crucial role in facilitating mobility and enhancing the overall travel experience. By providing travelers with accurate, accessible, and up-to-date information, they can make informed decisions and navigate the transportation system with ease and confidence. By harnessing the vast amount of data generated from various transportation sources, such as GPS systems, traffic sensors, and mobile devices, cities can gain insights into travel patterns, behavior, and preferences. This data can be used to optimize routes, improve traffic flow, reduce congestion, and promote sustainable mobility. The integration of ITS technologies, such as real-time travel information systems and advanced traffic management systems, can provide commuters with up-to-date information on travel times, delays, and alternative routes. This can lead to a reduction in travel times, emissions, and energy consumption, promoting a more sustainable and efficient travel. The availability of travel information also helps to improve transportation efficiency, reduce congestion, and minimize environmental impacts. In today's fast-paced world, where people are constantly on the move, access to reliable travel information has become increasingly important. It has the potential to transform the way people travel and make mobility more sustainable, accessible, and enjoyable for everyone. By combining big data, ITS and travel information, cities can create more livable communities, reduce dependence on fossil fuels, and towards a more sustainable future.

## **1.1 Problem statement and motivation**

The integration of big data into transportation planning and decision-making processes has the potential to revolutionize the transportation sector by supporting sustainable urban mobility, reducing congestion, and enhancing the travel experience. However, there is a significant knowledge gap in the application and integration of big data in many cities, leading to underutilization of its full potential. This is due to limited understanding of the scope and challenges associated with integrating big data into transportation planning and decision-

making processes, which hinders the effective implementation of sustainable mobility strategies. Additionally, promoting the use of travel information to facilitate mobility and enhance the travel experience presents major challenges. The lack of comprehensive data on the utilization of travel information and its impact on travel behavior, along with limited understanding of the factors influencing its adoption and use, especially in the context of sustainable urban mobility, exacerbate these challenges. Therefore, bridging this knowledge gap is essential to harnessing the full potential of big data and travel information in promoting sustainable urban mobility and addressing the pressing transportation challenges of the present era.

The effective use of big data and the promotion of travel information towards sustainable urban mobility are critical for creating livable, healthy, and efficient cities. By gaining a deeper understanding of the use of big data in the transportation sector and the use of travel information, cities can develop targeted strategies to leverage the full potential of big data and encourage the adoption and use of travel information among their residents. This, in turn, can help to reduce congestion, improve transportation efficiency, and promote the use of environmentally friendly modes of transportation. The use of big data can enhance the accuracy and timeliness of transportation planning and decision-making, making it easier for cities to respond to changing mobility needs and support sustainable urban mobility. Additionally, access to accurate and up-to-date travel information can improve the travel experience and make it easier for individuals to access opportunities and participate in economic, social, and cultural activities.

Many cities face challenges in promoting travel information use among residents. Therefore, there is a need for a deeper understanding of the use of big data and promotion of travel information towards sustainable urban mobility. This survey aims to investigate the potential applications of big data and social media in transportation, and their impact on travel behavior, decision-making, and promotion of sustainable urban mobility.

## **1.2 Research objectives & gaps**

The research process, for addressing the research questions in this study, involved a literature review of previous studies and research papers related to big data, social media, and transportation. The review focused on identifying the potential applications of big data in transportation and mobility, the most frequent big data sources used in transportation studies during the last years, and the influence of social media on travel behavior and decision-making among commuters. Additionally, the review explored the potential of social media as a source of transport-related information and as a tool for promoting awareness and engagement in sustainable urban mobility initiatives, and the impact of transport-related information provision through social media on mobility choices of commuters in urban areas. After conducting the literature review, critical research gaps have emerged in the intersection of transportation, mobility, and digital communication platforms. These gaps underline the need for further investigation and exploration to enhance our understanding of the complexities within these domains.

One research gap that emerged from literature is the less-explored impact of digital technological advancements on the end-users: the commuters. The onset of digital technological advancements, ranging from smartphone apps to smart ticketing systems, has undeniably transformed the transport sector. However, while there has been a notable focus on the technological and infrastructural implications of these advancements (Ju, et al., 2015; Anda,

et al., 2017; Liao & Yeh, 2018; Muresan, et al., 2019), there is a comparative lack of rigorous academic inquiry into their impact on the primary stakeholders – the commuters. This intensifies the need to explore how these technologies are affecting the user experience, both in terms of perceived advantages and potential challenges.

Furthermore, the literature has revealed another research gap focused on limited understanding of the impact of transport-related information sharing and factors that affect the decision-making process and traveling preference. With the proliferation of digital platforms, there has been a surge in transport-related information sharing, from real-time traffic updates to shared user experiences on specific routes (Lin & Wang, 2020; Borowski, et al., 2020; Chen & Deng, 2019). However, the relationship between this information sharing and the choices that commuters make remains under-researched. This points to a gap in the current literature that centers on a thorough exploration of the mechanisms through which social media impacts commuters' travel behavior and choices, along with a comprehensive examination of the factors such as demographic and trip characteristics; social media usage; familiarity with traveling, that moderate or mediate this impact.

Additionally, the literature review has unveiled lack of insights into how transport systems can further evolve to meet the dynamic needs of the digitally empowered traveler. The modern traveler is increasingly digitally empowered, expecting a seamless, efficient, and customized travel experience. While many transport systems have begun adapting to this new reality (Salas, et al., 2017; Wang, et al., 2017; Zhang, et al., 2018; van Essen, et al., 2020), there is a knowledge gap regarding the long-term evolution of these systems. Moreover, as technology continues to advance at an unprecedented rate, it is crucial to understand how transport systems can stay ahead of the curve, ensuring they not only respond to but anticipate the needs of future commuters, ensuring that as these systems evolve, they remain inclusive, equitable, and environmentally responsible.

The primary Research Objectives (ROs) and the relevant Research Questions (RQs) that this dissertation seeks to answer are given below:

Table 1-1. Dissertation’s objectives and corresponding research questions

<b>Research Objectives (ROs)</b>	<b>Corresponding Research Questions (RQs)</b>
RO1: To explore the potential applications of big data in the field of transportation and mobility. To identify the most frequent big data sources used in transport studies and disclose to which application field these sources have contributed the most.	<i>RQ1: What are the most frequent big data sources used in transport studies, in which application field have these sources contributed the most, and how can they be utilized to minimize congestion, improve traveler information and assistance, fulfill commuters' needs, and increase road safety?</i>
RO2: To examine the influence of social media on travel behavior and decision-making among commuters, and to identify the key factors that contribute to this influence.	<i>RQ2: How does social media use affect the travel choices and mobility decisions of commuters, and what specific types of social media content are most influential in this process? How is it associated with gender and social media usage aspects?</i>

Research Objectives (ROs)	Corresponding Research Questions (RQs)
<p>RO3: To explore the potential of social media as a source of transport-related information and as a tool for promoting awareness and engagement in sustainable urban mobility initiatives.</p>	<p><i>RQ3: What is the potential of social media platforms, such as Twitter, as a source of transport-related information across different regions with varying demographics, languages, and infrastructure?</i></p> <p><i>RQ4: What are the challenges of using social media for promoting awareness and engagement in sustainable urban mobility initiatives, and what is an effective scheme for putting a transport-related account and content into practice?</i></p>
<p>RO4: To investigate the impact of transport-related information provision through social media on mobility choices of commuters in urban areas.</p>	<p><i>RQ5: What are the key characteristics that affect the mobility choices of motorized vehicle users, pedestrians, and public transport users? How does the provision of transport-related information influence the mobility choices of different types of travelers, and how do these effects vary across different transport modes and demographic groups?</i></p>

The dissertation will contribute to science by answering the above research questions. The research aims to investigate the potential applications of big data and social media in transportation, and their impact on travel behavior, decision-making, and promotion of sustainable urban mobility. The results will enable the development of targeted and effective strategies that leverage big data to reduce congestion, improve transport efficiency, and promote the use of environmentally friendly modes of transport. Additionally, the research seeks to uncover the factors that influence the adoption and use of travel information, particularly in the context of sustainable urban mobility, promoting its use, enhancing the travel experience, and reducing congestion. Overall, the findings will contribute to the reinforcement of the academically innovative direction, benefiting the transportation systems’ sector.

### 1.3 Scientific contribution

This dissertation contributes to transportation and mobility research by investigating the effectiveness of big data and social media in shaping travel behavior and transportation systems. It explores practical applications of various data sources, provides evidence-based strategies for influencing mobility choices and behavior change through social media, and examines the gender influence on travel decisions. The study also delves into the interplay between social media, travel behavior, and public health concerns like COVID-19, offering insights for optimizing transportation systems and enhancing commuters' experiences. Table 1-2 summarizes the contribution of this dissertation for state-of-the-art in the research domain.

Table 1-2. Scientific contribution

State-of-the-art/ ascertainties	Dissertation’s scientific contribution
<p><i>The advent of big data in transportation sector has led to a reduction of infrastructure costs and service operators and has provided new ways of solving complex transport problems. The vast amount of data and the emerging technologies have opened opportunities to improve transportation and mobility and enhance the system's overall efficiency (Ju, et al., 2015).</i></p>	<p>Specific applications and contributions of different big data sources were investigated within transportation and mobility. The research provides insights into which data sources are more effective for certain types of analyses and decision-making. This knowledge will guide researchers, practitioners, and policymakers in making informed choices about data collection, analysis techniques, and resource allocation for improving transportation systems and mobility services.</p>
<p><i>Studies highlight the potential of social media data as a source of information for transport stakeholders to better understand users' needs and improve transport management (Krumm, et al., 2013; Hawelka, et al., 2014; Jurdak, et al., 2015; Lenormand, et al., 2014).</i></p> <p><i>To promote the adoption of alternative modes of transport, marketing campaigns and awareness-raising strategies are necessary (City of Vancouver, 2016).</i></p>	<p>Insights into the actual effectiveness of using social media as a tool to influence mobility choices are provided, contributing to evidence-based strategies for utilizing social media platforms in urban transportation planning and behavior change campaigns. This knowledge will be of value for urban planners, policymakers, and communication specialists looking to leverage social media to encourage more sustainable and efficient mobility behaviors among commuters in urban environments.</p>
<p><i>Gender may affect the way that people share information on social media and the way they use it to make decisions (Aparicio-Martínez, et al., 2020; Lin &amp; Wang, 2020; Lin &amp; Lu, 2011).</i></p>	<p>Gender differences in social media use for activity planning and travel arrangements before an activity are in depth explored and analyzed.</p>
<p><i>There is a number of ‘big challenges for big data’ that need to be addressed in order to understand and gain most benefit from the transitions that lie ahead. These might be briefly summarized as identifying and measuring the impacts that new data sources have on real transport systems, through the private and commercial use of information and its impacts on travel patterns and related behaviors (Milne &amp; Watling, 2019)</i></p>	<p>The potential for social media to act as a source of information is explored, and furthermore, the ways individuals use this information in their travel choices are thoroughly examined. Overall, it contributes to a deeper understanding of the interplay between social media and travel behavior, shedding light on the complexities of this relationship and helping transportation planners and policymakers harness the potential of social media for improving commuters' experiences and optimizing transportation systems.</p>



<p><i>Previous studies (Shelat, et al., 2022b; Campisi, et al., 2022) revealed that older adults may have a greater sense of personal safety and be more sensitive to issues related to personal space and comfort thus, they are more likely to avoid crowds to reduce the exposure to COVID-19 or other illnesses.</i></p> <p><i>Public transport users are more likely to prioritize its own health and safety (Shelat, et al., 2022b).</i></p> <p><i>The frequency of using public transport before the pandemic along with the travelers' age, influence their behavior in terms of post-pandemic recovery time (Kopsidas, et al., 2021)</i></p>	<p>The route and travel choices of pedestrians and public transport users were examined, with the provisioning of travel information related to crowdedness levels. To that end, a choice experiment was designed to elicit travelers' preferences. Discrete choice models were estimated based on data collected from 465 individuals in Greece. The role of crowd avoidance in shaping mobility decisions for both pedestrians and public transport users was explored. Factors such as place of residence, age, the importance of COVID-19 measures and arrival time were examined to explore the likelihood of switching routes in response to information about high levels of crowdedness.</p>
---	--

### 1.4 Research methodology and dissertation's outline

The research methodology started with a wider search of big data applications in transport studies. To narrow down the research scope one technology was chosen for further analysis. Specifically, social media use for urban mobility and travel choices were further examined. Findings led to the analysis of transport related content during the planning phase before trip. Content was both extracted and shared aiming to investigate the impact of the content on travel behavior and travel preferences. The overall methodology of the dissertation is depicted in Figure 1-1.

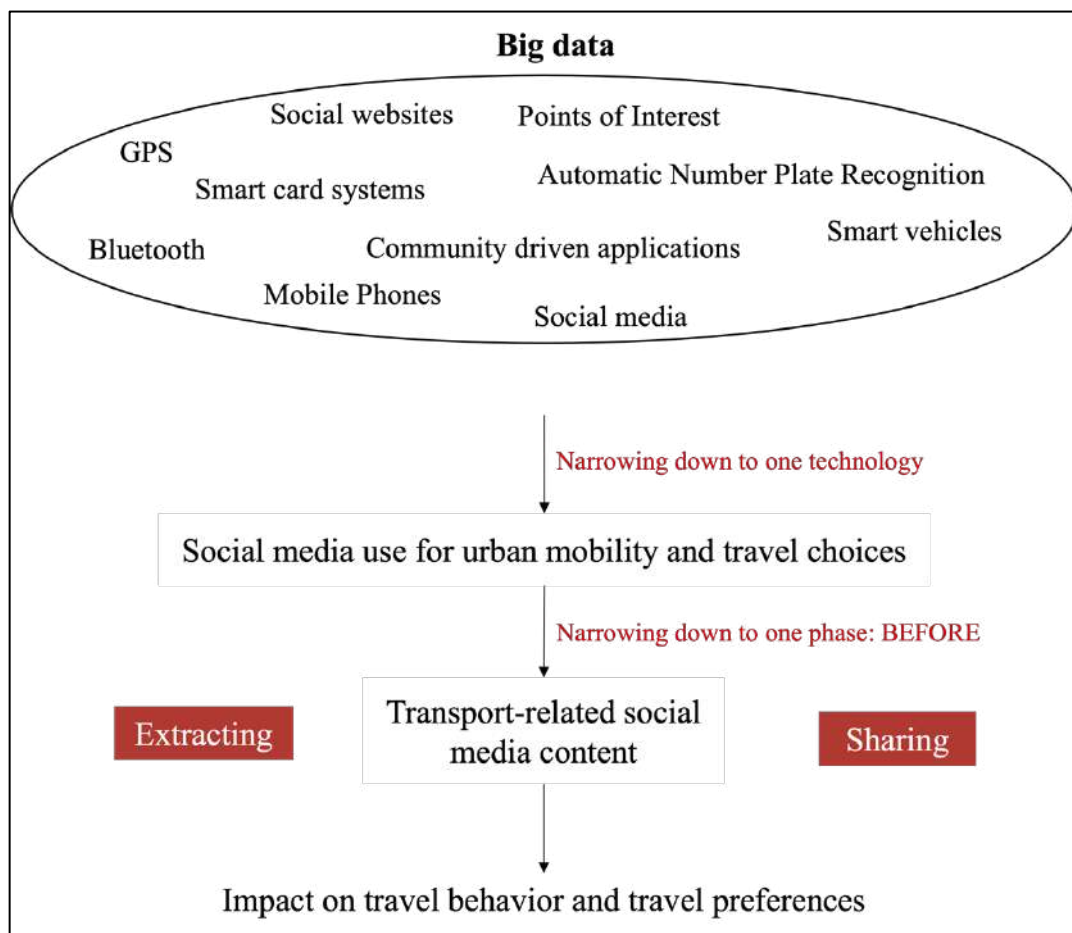


Figure 1-1. Dissertation’s methodological approach

Based on the findings of the literature review, surveys were conducted to address the research gaps by answering the research questions. In total, four surveys were designed and implemented. This involved the collection and analysis of data to explore the potential applications of big data and the influence of social media on travel behavior and decision-making. Additionally, surveys were conducted with commuters to investigate the impact of transport-related information provision through social media on mobility choices and to identify key characteristics that affect the mobility choices of different types of travelers. The research process involved analyzing the data collected using statistical and qualitative analysis methods and results’ interpretation.

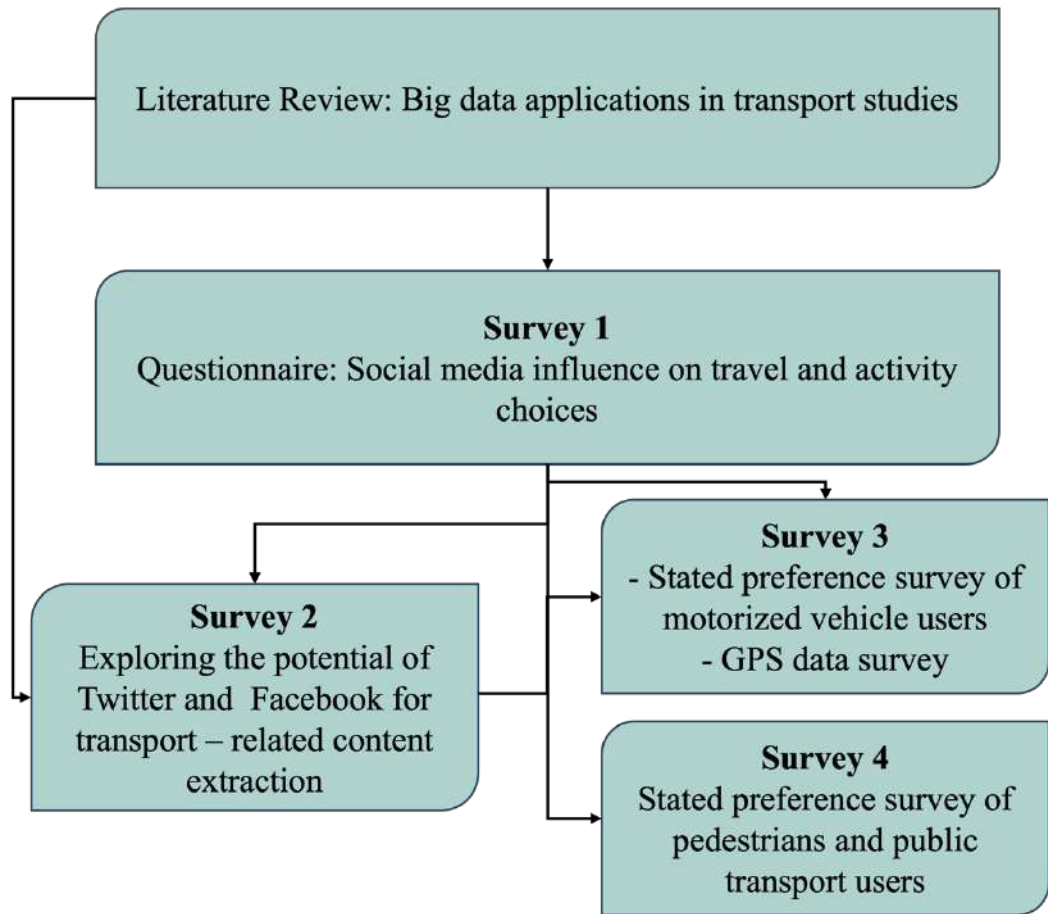


Figure 1-2. Conducted surveys.

The dissertation is organized under eight chapters, schematically outlined in Figure 1-3.

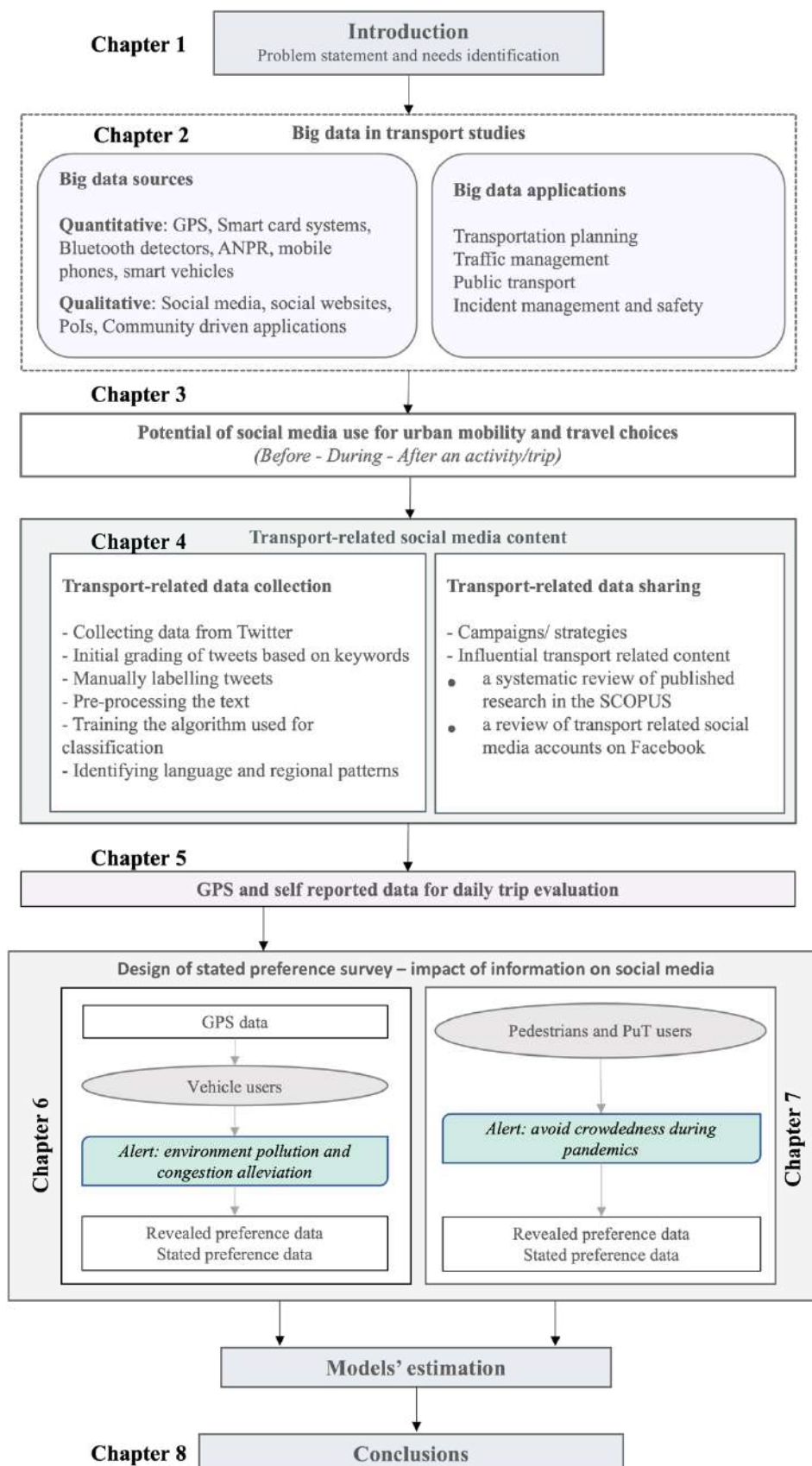


Figure 1-3. Dissertation’s outline

The introduction (Chapter 1) sets the stage by presenting the problem statement and motivation for the research. It highlights the need for more effective transportation planning and management strategies in the face of increasing urbanization and environmental concerns. Moreover, the research objectives, research questions and research methodology are described.

The first part of the research (Chapter 2) focuses on big data in transportation studies, examining both quantitative and qualitative sources of data. This section explores various applications of big data in transportation research, including transportation planning, traffic management, public transport management, incident management, and safety.

Building on this foundation, the next part of the research (Chapter 3) delves into the potential of social media use for urban mobility and travel choices. Specifically, it examines how social media use before, during, and after an activity/trip can affect mobility decisions and considers gender differences in social media use. Additionally, this section explores the impact of users' characteristics and social media information on mobility choices.

The next part (Chapter 4) focuses on the transport-related social media content and its role in urban mobility. This section explores how social media content can be used both for detecting transport-related activities and for sharing transport-related information. It also examines how transport-related content can be made more influential on social media platforms, and reviews previous campaigns and strategies related to sustainable urban mobility implemented in European countries.

In the next section of the research (Chapter 5), GPS and self-reported data are used to evaluate daily trips and the impact of travel information on transportation choices. Specifically, a survey of two phases is performed to evaluate daily trips in terms of travel time, cost, and environmental friendliness. The survey also investigates the extent to which shared information on social media can be used to recommend alternative routes or sustainable modes of transportation to motorized vehicle users (Chapter 6).

An attempt to investigate the impact of information on pedestrians and public transport users is included in the next part (Chapter 7). Specifically, it focuses on pedestrian and public transport users' choices in the era of COVID-19. A Stated Preference study designed to evaluate mobility choices with the provision of travel information related to crowdedness levels. Discrete choice models are estimated based on data collected from individuals in Greece.

Finally, the research concludes by presenting the important findings and main conclusions and provides guiding principles for future research on the topic (Chapter 8). This section summarizes the contributions of the research to the field of transportation studies and highlights future directions for further research.

## 1.5 Publications from this dissertation

The methodology and the results of this dissertation, in combination with the authors' overall scientific work, have been published as follows:

### Scientific Journals

**Karatsoli Maria**, Nathanail Eftihia, Socrates Basbas, Oded Cats, 2023. "A Stated Preference study of pedestrians' and public transport users' choices in the era of COVID-19". Cities (under review)

**Karatsoli Maria**, Nathanail Eftihia, 2022. “Use of GPS and self-reported data to evaluate daily trips and the impact of travel information”. European Transport Research Review (under 2<sup>nd</sup> review).

**Karatsoli Maria**, Nathanail Eftihia, 2021. “Social Influence and Impact of Social Media on Users’ Mobility Decisions”. Journal of Sustainable Development of Transport and Logistics 6 (1), 18-31. <http://dx.doi.org/10.14254/jsdtl.2021.6-1.3>

**Karatsoli Maria**, Nathanail Eftihia, 2020. “Examining gender differences of social media use for activity planning and travel choices”. European Transport Research Review 12, 44. <https://doi.org/10.1186/s12544-020-00436-4>

#### Conference presentations and publications in proceedings

**Karatsoli Maria**, Nathanail Eftihia, 2022. “Use of GPS and self-reported data to evaluate daily trips and the impact of travel information”. Transport Research Arena 2022, November 14-17, Lisbon, Portugal

**Karatsoli Maria**, Nathanail Eftihia, 2023. “Social media and urban mobility choices: How a transport-related content could be influential in social media”. In: Nathanail, E.G., Gavanas, N., Adamos, G. (eds) Smart Energy for Smart Transport. CSUM 2022. Lecture Notes in Intelligent Transportation and Infrastructure. Springer, Cham. [https://doi.org/10.1007/978-3-031-23721-8\\_67](https://doi.org/10.1007/978-3-031-23721-8_67)

**Karatsoli Maria**, Nathanail Eftihia, 2021. “Investigating the travel information-seeking behavior for daily trips in a greek medium sized city”. In: Nathanail E.G., Adamos G., Karakikes I. (eds) Advances in Mobility-as-a-Service Systems. CSUM 2020. Advances in Intelligent Systems and Computing, vol 1278. Springer, Cham, [https://doi.org/10.1007/978-3-030-61075-3\\_66](https://doi.org/10.1007/978-3-030-61075-3_66)

Karakikes Ioannis, Nathanail Eftihia, **Karatsoli Maria**, 2021. “Validating urban freight deliveries through traffic microsimulation: An experimental study”. In: Nathanail E.G., Adamos G., Karakikes I. (eds) Advances in Mobility-as-a-Service Systems. CSUM 2020. Advances in Intelligent Systems and Computing, vol 1278. Springer, Cham, [https://doi.org/10.1007/978-3-030-61075-3\\_77](https://doi.org/10.1007/978-3-030-61075-3_77)

**Karatsoli Maria**, Nathanail Eftihia, 2020. “Analysis of social media use for urban mobility and travel choices”. Transport Research Arena 2020, April 27-30, Helsinki, Finland. (accepted paper; conference canceled due to COVID-19 pandemic)

Pavlyuk Dmitry, **Karatsoli Maria**, Nathanail Eftihia, 2019. “Exploring the potential of social media content for detecting transport-related activities”. In: Kabashkin I., Yatskiv (Jackiva) I., Prentkovskis O. (eds) Reliability and Statistics in Transportation and Communication. RelStat 2018. Lecture Notes in Networks and Systems, vol 68. Springer, Cham, [https://doi.org/10.1007/978-3-030-12450-2\\_13](https://doi.org/10.1007/978-3-030-12450-2_13)

**Karatsoli Maria**, Nathanail Eftihia, 2019. “Investigating the Role and Potential Impact of Social Media on Mobility Behavior”. In: Nathanail E., Karakikes I. (eds) Data Analytics: Paving the Way to Sustainable Urban Mobility. CSUM 2018. Advances in Intelligent Systems and Computing, vol 879. Springer, Cham, [https://doi.org/10.1007/978-3-030-02305-8\\_31](https://doi.org/10.1007/978-3-030-02305-8_31)

**Karatsoli Maria**, Karakikes Ioannis, Nathanail Eftihia, 2019. “Urban Traffic Management Utilizing Soft Measures: A Case Study of Volos City”. In: Nathanail E., Karakikes

I. (eds) *Data Analytics: Paving the Way to Sustainable Urban Mobility*. CSUM 2018. *Advances in Intelligent Systems and Computing*, vol 879. Springer, Cham, [https://doi.org/10.1007/978-3-030-02305-8\\_79](https://doi.org/10.1007/978-3-030-02305-8_79)

Magginas Vissarion, **Karatsoli Maria**, Adamos Giannis, Nathanail Eftihia, 2019. “Campaigns and Awareness-Raising Strategies on Sustainable Urban Mobility”. In: Nathanail E., Karakikes I. (eds) *Data Analytics: Paving the Way to Sustainable Urban Mobility*. CSUM 2018. *Advances in Intelligent Systems and Computing*, vol 879. Springer, Cham, [https://doi.org/10.1007/978-3-030-02305-8\\_32](https://doi.org/10.1007/978-3-030-02305-8_32)

**Karatsoli Maria**, Nathanail Eftihia, Adamos Giannis, 2018. “Studying the influence of social media on activity-travel behavior”. *Proceedings of 5th Panhellenic Planning and Regional Development Conference*, Volos, Greece.

**Karatsoli Maria**, Nathanail Eftihia, 2018. “A Thorough Review of Big Data Sources and Sets Used in Transportation Research”. In: Kabashkin I., Yatskiv I., Prentkovskis O. (eds) *Reliability and Statistics in Transportation and Communication. RelStat 2017. Lecture Notes in Networks and Systems*, vol 36. Springer, Cham, [https://doi.org/10.1007/978-3-319-74454-4\\_52](https://doi.org/10.1007/978-3-319-74454-4_52)

Conference proceedings / presentations with abstract review

Karakikes Ioannis, Nathanail Eftihia, Adamos Giannis, **Karatsoli Maria**, 2018. “Social media users as carriers into the last mile delivery”, *hEART 2018: 7th Symposium of the European Association for Research in Transportation*, Athens, Greece, September 5-7, 2018.

**Karatsoli Maria**, Nathanail Eftihia, 2018. “Intelligent transport systems with usage of big data for management of sustainable mobility: *Investigating the role of social media*”, *COST TU1305 Final Conference*, Milan, Italy, 14-16 February, 2018.

**Karatsoli Maria**, 2017. “Intelligent transport systems with usage of big data for management of sustainable mobility”, *COST TU1305 Young Researchers’ Session*, Krakow, Poland, 29- 30 June, 2017.

## 2 Big data applications and sustainability in urban mobility

The field of transport studies has seen rapid advancements in recent years, with the increasing availability and analysis of big data providing valuable insights into travel patterns, behavior, and preferences. In the context of sustainable urban mobility, these insights are essential for the development of ITS, which use advanced technologies to optimize transport operations, reduce emissions, and improve the travel experience for passengers. One important application of big data in ITS is the use of travel information, which can be shared through a variety of channels, including social media, public announcements, and mobile applications. By providing real-time information on service disruptions, delays, and other relevant information, travel information can help reduce congestion, improve the efficiency of transport networks, and encourage more sustainable modes of transport.

Sections 2.1- 2.2 are an extensive and adaptive version of the following publication:

*Karatsoli Maria, Nathanail Eftihia, 2018. "A Thorough Review of Big Data Sources and Sets Used in Transportation Research". In: Kabashkin I., Yatskiv I., Prentkovskis O. (eds) Reliability and Statistics in Transportation and Communication. RelStat 2017. Lecture Notes in Networks and Systems, vol 36. Springer, Cham, [https://doi.org/10.1007/978-3-319-74454-4\\_52](https://doi.org/10.1007/978-3-319-74454-4_52)*

### 2.1 Big data in transport studies

The advent of big data in transportation sector has led to a reduction of infrastructure costs and service operators and has provided new ways of solving complex transport problems. The vast amount of data and the emerging technologies have opened opportunities to improve transportation and mobility and enhance the system's overall efficiency (Ju, et al., 2015). Minimizing congestion, improvement of traveler's information and traveler's assistance service, fulfillment of commuters' needs and increase of road safety, are mobility challenges that big data applications are dealing with. These applications include the analysis of real-time conditions of a transport network, the optimization of routes and schedules, the analysis of incidents and accidents, as well as the management of public transport data.

In following sections, lies a distinctive classification of big data sources into two key categories: qualitative and quantitative. While the differentiation might seem conventional, it serves as a pivotal framework for comprehending the multifaceted nature of data within the realm of transportation and mobility. Potential sources of quantitative and qualitative big data that can be used in transport analysis and planning are identified. GPS devices, smart card systems, Bluetooth detectors, ANPRs, mobile phones generate large datasets of quantitative big data, while social media and other applications provide a great amount of useful qualitative data. These sources were included within the qualitative group since traditionally are considered as qualitative due to their reliance on textual and multimedia content, without underestimating their quantitative stance through innovative methodologies like natural language processing and sentiment analysis.



### 2.1.1 Quantitative big data sources

This section includes a short description of indicative quantitative big data sources, such as GPS devices, smart card data, Bluetooth detectors, ANPRs, mobile phones and smart vehicles along with some of their advantages and limitations.

#### GPS Devices

GPS devices can be found on vehicles, bicycles and pedestrians and are used to collect location trajectories for the extraction of mobility patterns, through the periodical report of their position and time. The data collection is passive since user participation is not required. The data retrieved from a GPS device consist of the device ID, time stamp, accurate location, speed, and vehicle direction. The datasets are characterized of high sampling frequency and are mainly used for traffic flow analysis, route planning and travel time prediction, and for controlling public transport operations (Anda, et al., 2017). However, a GPS data sample lacks social-economic, demographic, or social network information about users, which necessitates the use of qualitative data for additional information. The small sample size of available GPS data from private vehicles and the high transmission costs are also limitations of this dataset in transport studies.

#### Smart card systems

The smart card system for public transport was introduced for the secure fare collection. However, each transaction offers valuable information regarding the mobility patterns of a city's public transport that is useful in city planning. The data include the card ID, the transportation mode, the route, boarding/ alighting times as well as boarding/ alighting stations (Anda, et al., 2017). This system offers access to large volumes of personal travel data for long periods that reflect credibly the transit demand. However, these datasets are constrained to specific transport modes and sometimes the destination stop is unknown, since passengers are usually required to check in (Karatsoli & Nathanail, 2018).

#### Bluetooth detectors

The Bluetooth detectors collect a sample of traffic data by detecting Bluetooth-enabled devices carried in vehicles. Unique and anonymous IDs (called Media Access Control address, or MAC address) are collected from mobile phones, wireless headsets, tablets, in-vehicle navigation, hands-free systems, laptops, and other Bluetooth devices on vehicles are collected. When an ID and the corresponding timestamps of a Bluetooth device are detected at two different detector sections, the travel time and therefore the travel speed can be determined. Usually, the two sensors do not detect every Bluetooth device so the number of matched IDs is lower than the number of detected devices at each sensor (Karatsoli, et al., 2016). The relative low cost, the simple installation and maintenance of the Bluetooth detectors, the increasing number of vehicles having Bluetooth devices, the anonymity of MAC addresses and the acceptable accuracy of the travel time estimation have resulted in larger datasets and have rendered Bluetooth technology as a reliable method of travel time estimation (Haghani, et al., 2010).

#### Automatic Number Plate Recognition (ANPR)

The Automatic Number Plate Recognition is a collection technique, which incorporates a large sample size and accurate individual data alike. One ANPR system mainly consists of infrared cameras and a digital image-processing device, which can identify number plates on the footage, extracting the letters and numbers and saving them along with a timestamp into a

database. With only two of those ANPR systems, the individual travel time of a detected vehicle between a starting point and an endpoint can be derived easily by just subtracting the two timestamps (Axer, et al., 2012). An ANPR system is characterized of a high reliable collection rate between 70 and 95%. This results in a big sample size, which allows for reliable averaging, i.e., travel time (delay) per vehicle. The high equipment cost and the concerns regarding privacy issues are the main reasons that ANPR technology is not widely used.

### **Mobile Phones**

Network carriers collect mobile phone data for billing and other operational reasons. These datasets include the time and date of each mobile phone activity, the phone number as well as the coordinates of the tower which routes the communication. The broad spatial and temporal coverage of these data lead to a more accurate estimation of the location (home, work, leisure activities' location) for a rich sample of residents (Gonzalez, et al., 2008). However, datasets from mobile phones are based on sparse and noisy measurements with spatial uncertainties since the travel activity between two phone activities is missed making them unsuitable for travel time estimations.

### **Smart vehicles**

Smart vehicles are equipped with GPS devices, Bluetooth sensors, in car sensors and access to Internet. The technology used in a smart vehicle provides constantly data about the vehicle (position, number of stops, travel time, fuel consumption, and speed), the local environment and road (congestion, incidents, and potential dangers, surrounding vehicles, pedestrians) (Vegni, et al., 2013).

## **2.1.2 Qualitative big data sources**

Qualitative data from social media or social websites and community driven applications can shed light on transport analyses, providing supplementary information that enriches the quantitative datasets.

### **Social Media**

The explosive growth of social media use and the amount of time being spent on them has resulted in huge volumes of available and highly active data at low cost. Users share publicly information, ideas, opinions, and experiences on platforms such as Twitter, Facebook, Instagram, LinkedIn rendering them powerful tools, suitable for transport data collection (Karatsoli & Nathanail, 2018). Their widespread encourages the users to share their location more often, leading to an exponential increase of their volume day by day (Morstatter, et al., 2013). In recent years, several studies have analyzed the use of social media for transport related purposes. This analysis opens potential for various applications including accident - incident detection, transport planning and decision making, human mobility analysis and travel behavior (Steiger, et al., 2016).

Check-ins, posts, tweets, photos, and videos provide the exact location of a user along with a large sample of qualitative data i.e., social-economic, demographic, and social network information. However, privacy issues as well as the existence of fake and bot accounts and the share of fake information should be taken under consideration when social media data are used.

### **Social websites, Points of Interest (PoI)**

Points of Interest are businesses and worth visiting places in a city. Yellow pages and Google Places or social websites such as Trip Advisor are the main sources of data regarding

places that people are interested in visiting (Jiang, et al., 2015). Information such as the opening hours, the type and location of a business/ place as well as information how to reach the destination, reviews/ ratings, and crowdedness per hour of a place are some examples of the type of data that can be retrieved. Due to the limited information these datasets cannot be used autonomously; however, they are used as a supplement to other sources enhancing at low cost the quality of quantitative data (Karatsoli & Nathanail, 2018), providing a reasonable explanation of patterns and phenomena discovered in other datasets.

### **Community driven applications**

Data about road conditions are based on reports of the community driven application's users (such as Waze). The shared information is related to incidents such as traffic accidents, construction sites, stopped vehicles or objects on the road (Nurdayat, et al., 2018). Some community driven applications offer also quantitative data by comparing current road conditions with historical data (Walker, 2015).

## **2.2 Big data applications in transportation research**

The widespread usage of the new technologies has marked the beginning of many new and innovative transportation services where big data are applied. A significant number of big data approaches in the existing research has confirmed the important role of big data usage in transportation. The recent trends include the use of new data sources such as GPS devices, smart card systems, Bluetooth detectors, ANPRs, mobile phones, smart vehicles, social media and websites and community driven applications. Based on the literature reviewed, it was attempted to divide the recent applications into four main categories: a) transportation planning b) traffic management c) public transport management d) incident management and safety.

### **2.2.1 Transportation planning studies**

The travel demand studies (understanding of Origin - Destination (OD) data for analysis of the transport system) and the estimation of mobility patterns have been significantly improved by the adoption of the new technologies and the use of big data.

In the case of OD matrix generation, it is noteworthy the work presented by Horn, et al. (2016) that developed a system for OD matrices generation based on cell phone trajectories. Wang, et al. (2012) developed a methodology that uses comprehensive mobile phone data to detect patterns of road usage and the origins of the drivers. Following this approach, Iqbal, et al. (2014) used mobile phone call detail records and traffic count data from video recordings in 13 key locations of Dhaka city, Bangladesh to develop OD matrices. Bekhor, et al. (2013) and Toole, et al. (2015) used also mobile phone data to develop OD matrices in Israel and Massachusetts, respectively. In Alexander, et al. (2015) the authors presented a method for estimation of daily origin-destination trips from mobile phone records. Aim of the work in Michau, et al. (2014) was to propose a method for retrieving the itineraries of individual Bluetooth vehicles to retrieve accurate dynamic OD matrices. Bluetooth technology was used in Carpenter, et al. (2012) for the development of route specific OD matrices in Jacksonville, Florida. A method for OD matrices estimation based on vehicle trajectory data was proposed in Li, et al. (2015). The turning movement and link count are provided by the ANPR data. Wood, et al. (2013) used geotagged photos in Flickr to estimate visitation rates of recreational sites around the world and profiles' information to derive travelers' origins. The research of Caceres, et al. (2020) compares origin-destination (OD) matrices derived from traditional travel

surveys and mobile phone data for mobility studies. Focusing on a specific region, the study reveals significant similarities in trip information between the two sources. Despite concerns about short trips, mobile data's extensive representation captures OD connections, particularly in non-populated areas. The study proposes a data fusion approach for optimal accuracy in heterogeneous sources, emphasizing its applicability for enhancing mobility analyses. The study of Cipriani, et al. (2021) examines the utilization of Bluetooth data from new monitoring devices to enhance Origin-Destination (OD) traffic demand estimation and forecasting. Carried out in a section of Rome, Italy, the research introduces a novel method based on Spiess' formulation for estimating traffic demand using Bluetooth data. Through extensive experiments on test and study networks, including a portion of the city of Rome, the proposed method demonstrates promising results for both off-line and static contexts, contributing to improved OD traffic demand estimation and forecasting capabilities.

A GPS dataset was used in the work Cui, et al. (2016) to develop a method for mobility demand analysis. Mobility patterns were modelled based on the trajectories. The developed model captures traffic characteristics such as travel demand, travel speed and route directness of travel paths. Widhalm, et al. (2015) proposed a method to reveal activity patterns from a sparse sample of mobile phone data by analyzing relational signatures of activity time, duration, and land use. It is worth to mention the work of Schneider, et al. (2013) in which mobile phone billing data from Paris and Chicago were used to reproduce entire daily activity patterns. In 2011, Calabrese, et al. used mobile phone data to estimate travel patterns in Massachusetts. Researchers used trajectory data by simulated mobile phone data to identify activity locations by applying behavior-based algorithms in Chen, et al. (2014). In 2018, Liao & Yeh, captured Twitter user's mobility. Individuals' geotagged activity trajectory was used to predict their mobility. The work of Hasan & Ukkusuri (2014) includes a data-driven modeling approach based on Twitter data to account for missing activities and presents an effective technique to infer individual activity patterns. Cheng, et al. (2011) conducted a study about human mobility patterns and the factors that affect this mobility by using 22 million check-ins. The use of Twitter in European transport networks was investigated by Lenormand, et al. (2014), comparing the daily traffic reports with tweets. In their work, they inferred the type of users' activities in urban centers. In 2016 Nobao, et al. used two big data sources, taxi data and data from Foursquare, to discover and characterize human mobility patterns in urban spaces that cannot be identified in a collective analysis. The activity patterns of large-scale samples of GPS data were investigated in Gennaro, et al. (2016), in order to assess the impact of low-carbon road transport technologies and policies and to underline how challenging is the development of big data applications. Andrienko, et al. (2016) used trajectory data as well as traces from georeferenced tweets to examine people's presence in significant locations (e.g., home, work, or social activity). Noulas, et al. (2013) used mobile phone data, data from social media and PoI in Madrid and Barcelona to infer user activity. In 2017, Eggermond, et al. used georeferenced tweets and Singapore's public transport smart card data to detect locations of activities along with transitions between them. A recent work (Xu & González, 2017) used mobile phone data, Waze data, Airbnb data and hotel information to develop a travel demand model prior to Olympics 2016, in Rio de Janeiro, Brazil. Aim of the research was to evaluate the impact of the Olympic Games to the travel of commuters and propose different route choice scenarios during peak hours.

In 2012, Toole, et al. used mobile phone data to measure spatiotemporal changes in population. Yu, et al. (2014) analyzed the Beijing subway transit smart card data to evaluate the implementation of an urban plan. Previous studies (Cottrill & Derrible, 2015) highlighted

the potential of social media as a source of information for transport stakeholders to understand better users' needs and Jurdak, et al.(2015) found that tweets have similar features with mobile phone records. Hawelka, et al.(2014) correlated tweet locations with socioeconomic characteristics of people. Long, et al. (2015) used datasets from three big data sources, including location check-in data, transit smart card data and taxi trajectories. In their study, they developed four types of measures to evaluate the effectiveness of urban growth boundaries in Beijing. Hu, et al. (2015) proposed a framework for extraction and understanding of urban areas of interest on Flickr's geotagged photos. Such information is very important for city planners, transportation analysts, and location-based service providers.

Furletti, et al. (2013) used mobile phone data to understand the mobility behavior of people based on aggregated calling profiles of the mobile phone users. Regarding human mobility analysis from Twitter data, Krumm, et al. (2013) estimated travel behavior with urban motion patterns. In the aforementioned work of Cheng, et al. (2011) check-ins were used to investigate the factors that affect user's travel behavior.

Lee & Hickman (2014) introduced the use of smart card data for trip purpose estimation. Although the data do not contain information about the commuters and the trip purpose, inferences can be made through the trip purpose assignment process (Lee & Hickman, 2014). Gong, et al. (2016) provided a framework for estimating the trip purposes of taxi passengers such that enriches the semantics of trajectory data. For a more accurate trip purpose detection, Shen & Stopher (2013) proposed an improved process based on GPS data in the Greater Cincinnati region (United States).

## 2.2.2 Traffic management studies

The advent of big data and the changes introduced by big data applications in traffic management are manifold. A plethora of traffic management studies is based on big data usage.

Dewulf, et al. (2015) used GPS data to address the travel time differences between car and public transport during peak and off-peak hours. In 2013, Zhan, et al. used GPS data collected from New York's taxi fleet for travel time estimation. The data included only information about trip's origin and destination and total travel time to reach the destination without the exact trajectory of the taxi. A large dataset of GPS-enabled vehicles in Rome was used to calibrate and validate travel time prediction models (Fusco, et al., 2016). For the data sparsity problem, Sanaullah, et al. (2016) examined and developed practical travel time estimation methods using sparse GPS data. Abedi, et al. (2015) proposed a method for travel time estimation of pedestrians, runners and cyclists by analyzing Wi-Fi and Bluetooth data. Following this approach, Yildirimoglu (2019) proposed a joint method to simultaneously infer vehicle paths and estimate travel times using Bluetooth data. To quantify the accuracy of travel time estimation of GPS data, travel time calculated using ANPR data in (Zhu, et al., 2018).

Muresan, et al. (2019) presented a method to update traffic signal timing plans in real time using travel time data retrieved from Bluetooth and WiFi detectors. The authors in Romancyshyn, et al. (2017) computed the travel delay at signalized intersections with Bluetooth/ WiFi sensor data and validated their accuracy using GPS and manually processed video data.

Pathak, et al. (2015) investigated how transport authorities manage user-generated content for calculation of traffic flow indicators. Using smart card data Roth, et al. (2011) identified multiple centers in London and described the traffic flowing into these centers as a

simple hierarchic decomposition of multiple flows at various scales. The authors stated that the use of data from other big data sources such as GPS devices will help them to better understand and estimate the complex issues of a modern city. Castro, et al. (2012) developed a model for future traffic conditions prediction based on large-scale GPS trajectories of 5000 taxis in Hangzhou, China. The study of (Gore, et al., 2019) was an attempt to develop a methodology to derive vehicle occupancy using Wi-Fi detectors under a heterogeneous traffic environment. Ziolkowski (2018) examined driver's average speed depending on the vehicle and road's geometric characteristics. For this reason the author conducted speed surveys using ANPR cameras. Cici, et al. (2014) used mobile phone data of Madrid and Barcelona and geotagged tweets and foursquare check-ins of New York and Los Angeles to explore the potential of a ride-sharing system in car use reduction. The study of Kan, et al. (2022) employs taxi GPS trajectories and POI data to assess individual exposure to traffic congestion in Wuhan, China. It infers trip purposes, evaluates congestion exposure, and estimates emissions impact, revealing that congestion relates more to traffic rhythms than trip types, emphasizing the need for comprehensive assessments beyond commuting trips.

An important issue related to traffic management is the congestion analysis. In 2012, Møller-Jensen, et al. used GPS-based travel-speed measurements of private and university vehicles in Accra to provide indications of congestion level. An analysis of the traffic flows with respect to speed, time, and direction was also conducted. Also interesting to note the work of Li, et al. (2016), in which crowd-sourced probe vehicle data were used for identification of traffic congestion on limited access roadways. Similarly, in their work Can Diker & Nasibov (2012) used GPS data from probe vehicles to determine the level of traffic congestion during peak hours in Izmir, Turkey. In 2013, Wang, et al. used taxi GPS trajectories in Beijing to detect traffic jams based on relative low speeds. Concerning the evolution of urban recurrent congestion, An, et al. (2016) developed a method for measuring its patterns based on GPS trajectory data collected from taxis in Harbin, China. Following this approach, Gal-Tzur, et al. (2014) investigated the correlation between tweets and traffic congestion. In 2012, Chawla, et al. (2012) used a large GPS dataset to develop a framework for anomaly detection in road traffic data. The authors in Ying, et al. (2018) developed a framework for anomalous trajectory detection between regions by using a dataset of an ANPR system.

In the traffic management sector, a great number of big data research focuses on the assessment of environmental impacts and the development of strategies for more efficient and environmentally friendly operations. Data from GPS devices of 13,586 registered taxis in New York City were used to investigate the potential of sharing taxi trips aiming at the reduction of the negative impacts of taxi services in cities (Santi, et al., 2014). Using data of GPS-equipped vehicles, Chen, et al. (2016) presented a methodology to analyze traffic-related air pollution emissions with multiple traffic-related variables. Considering the impacts of traffic congestion, a framework to quantify air pollution using GPS data in Boston, was presented in Gately, et al. (2017). Luo, et al. (2017) presented an analysis of taxi's energy consumption and emissions and their spatial-temporal distribution in Shanghai, applying big data analysis on GPS data of taxi.

In 2016, Lima, et al. used GPS trajectories of private vehicles to investigate the routing behavior in four cities and check whether these routes are the shortest and lowest-cost paths. Hood, et al. (2011) estimated a route choice model with GPS data of cyclists' routes collected through an application for smartphones in San Francisco, California. In 2016, He, et al. studied two transportation networks to develop routing models. Large-scale mobile phone data in San Francisco and subway card data in Beijing were used to estimate travel demand information

and congestion for the estimation of the routing models. Yang, et al. (2015) proposed a profitable route recommendation algorithm for taxi routes, using GPS taxi data. The authors in Hainen, et al. (2011) used Bluetooth data to estimate the route choice and travel time of vehicles after an unexpected bridge closure in Indiana. The shared experience and information on applications such as Waze is used in Ramos, et al. (2018) to compute the regret of a route choice as a linear combination of local (experience-based) and global (app-based) information.

Mobility and transportation services that provide information to travelers shift to new schemes based on available big data services. Many transport studies focus on traveler information, while studies based on social media data are undoubtedly an upcoming trend in this area. Social media users often use their accounts on platforms (such as Twitter) to share traffic information. That information that stems from Twitter users who can be drivers, pedestrians, or passengers, correspond to larger coverage of traffic conditions as compared to point sensors (Wang, et al., 2017). In fact, due to their nature, it is believed that Twitter data can complement traditional collection method Kokkinogenis, et al., (2015); Zhang, et al., (2018); Wanichayapong, et al. (2011) extracted traffic information from Twitter and classified it. Useful information then was shared to help commuters' planning their routes, avoiding traffic congestion in real-time. The study of Andy Lee, et al. (2011) examined and profiled the reviewers who post helpful reviews on the online travel community of TripAdvisor. The authors in Gal- Tzur, et al. (2018) presented a methodology for automatic categorization of transport related questions posted in Question & Answers (Q&A) TripAdvisor's forums and extracted those questions that seeking travel information. Cottrill, et al. (2017) evaluated how Twitter was used over a large event in Glasgow, Scotland to share transport – related information and respond to information requests. Zhang, et al. (2015) used GPS taxi trace data to detect social events and evaluate their impacts aiming at better travelers' information.

### **2.2.3 Public transport management**

The understanding of passenger demand and commuter's behavior is crucial for the management of a public transport system. A plethora of big data applications aims at better understanding travel demand for the enhancement of public transport network services.

van Oort & Cats (2015) utilized smart card data and vehicle data to improve the public transport system in terms of efficiency, passenger's ridership, and satisfaction. In 2015, van Oort, et al. used smart card data to develop a tool that gives a better understanding to operators of the effects after changes in the public transport system. Schmöcker, et al. (2013) developed a choice model aimed at public transport line choice at stops. The validity of the model was checked with the use of smart card data of a bus network in a local city in Japan. Following this approach, He, et al. (2014) used smart card data to improve the level of service of urban rail transit in Beijing. Eom, et al. (2015) used data collected from Seoul's automatic fare collection system to analyze the public transport services performances. Punctuality, crowdedness, and operational speed are the service performance measures that were addressed in this study. A research in 2016 contributes to the existing literature by presenting a data-driven approach for prediction of bus bunching occurrence by using smart card data from two routes in Beijing (Yu, et al., 2016). Zhou, et al. (2014) used smart card data to conduct detailed research about the efficiency of Beijing's public transport system and how existing bus trips might be optimized. The authors of Berlingerio, et al. (2013) and Li, et al. (2016) developed a system of public transport optimization using mobile phone data. Four new routes were proposed by the optimization system, resulting in a 10% reduction of travel time across the city. The study of Liu, et al. (2021), conducted in Shizuoka, Japan, addresses the dearth of research on

longitudinal variability in public transport usage among different age groups of older adults. Utilizing one-year smart card data, the research examines seasonal and day-to-day patterns of public transport usage. It reveals that older adults in highly developed areas, especially the younger-old group (aged 65-74), exhibit higher-frequency and less variable public transport usage, while day-to-day variability increases with age and urban development.

In 2013, Ma, et al. (2013) used smart card data to model the travel patterns of the public transport commuters in Beijing, China. Long, et al. (2012) also analyzed commuting patterns in Beijing with the use of smart card data. The work presented in Pineda, et al. (2016) compares information of OD matrices, transfers, and passenger flows from two data sources for Santiago: OD survey and smart card data. An approach for identification of commuters' and transit commuting patterns is provided in Ma, et al. (2017). Smart card data were used to measure departure times, travel distances, number of traveling days and home/work distributions. Briand, et al. (2017) used smart card data to analyze year-to-year changes in passengers' behavior and mobility patterns in public transport. In 2014, Gokasar, et al. (2014) used data retrieved from Istanbul's smart card collection system to assess commuters' travel behavior in terms of space and time. The smart card system was evaluated and ways for improvements in planning and management of the public transport system were recommended.

Chen, et al. (2013) used taxi GPS data to locate the places with high numbers of taxi passenger pick-ups and drop offs. Aim of this study was to determine an approach for night bus route planning. An increase in the effectiveness of Santiago's public transport system was attempted in Julio, et al. (2016). Real time GPS data were used to predict the bus travel speeds. In Hurk, et al. (2015) the authors used smart card data to deduce passengers' route choice and to analyze passenger services in terms of travel time. Jalali, et al. (2019) estimated the origin and destination of bus passengers using Bluetooth / Wi- Fi detectors. The detectors collected the MAC addresses and timestamps of passengers on one bus route in Ottawa, Canada for six days.

To assess the quality of public transport services, information regarding commuter's satisfaction can be collected from social media. Casas & Delmelle, (2017) used tweets to capture commuters' perceptions about a Bus Rapid Transit system in Cali, Colombia. The results highlight safety and onboard behavioral issues and problems with the system's infrastructure. In the work of Sarker, et al. (2019) social media data were used to evaluate the walking patterns and willingness of commuters to public transport stations. Collins, et al. (2013) used Twitter keywords to determine users' dissatisfaction in specific metro lines. It is worth noting the work of Nakamura, et al. (2016) in which smart card data were used to analyze the influence of loyalty programs on user travel behavior.

In 2012, Munizaga & Palma used two databases, containing smart card data and GPS data from buses, to obtain OD matrixes for a multimodal public transport system in Santiago, Chile. In 2016, Gschwender, et al. collaborated with public transport authorities to develop tools for public transport planning and operation management with the use of smart card data and data from GPS devices of city buses. The authors in Li, et al. (2017) used GPS trajectory data of taxi and buses and smart card data in Shezhen, China to extract travel information and test the correlation of multi-mode travel characteristics. In 2016, Pinelli, et al. used mobile phone data from half a million phone users in Abidjan to propose an entirely data driven method for transit network design. Furthermore, installed GPS devices inside the buses determined the geographical position of the transfer stations.



## 2.2.4 Incident management and safety

Abnormal data and extreme values that deviate from other observations in a dataset can be used for detection of anomalous events or behaviors that violating the normal traffic situation or put in danger the safety of travelers.

Pang, et al. (2013) used GPS data from taxis to monitor and detect any unexpected incidents in the Beijing metropolitan area aiming to estimate and improve the traffic conditions. Authors in Kong, et al. (2018) proposed a method for long-term traffic anomaly detection using bus GPS datasets in Hangzhou, China. Studies related to incident detection have shown that incidents can be spotted earlier in regular users' social media accounts compared to official transport sources, making traffic related tweets important for real time incident detection (Sakaki, et al., 2010). Analytically, D'Andrea, et al. (2015) classified tweets with accuracy 95.75%, based on traffic event occurrence to present a real-time traffic event system. Gutiérrez, et al. (2015) detected incident relevant tweets by using a classifier to identify traffic event evolution. Gu, et al. (2016) used Twitter data and detected five major incident types employing Naive Bayes classification. The work of Mai & Hranac (2013) showed that there is a correlation between accidents mentioned on tweets and incident records. Schulz, et al. (2013) presented a solution that offers identification of incidents using microblogs with an accuracy of 89%. In another study (Fu, et al., 2015) real-time traffic related twitter data were used for incident management purposes. Pan, et al. (2013) developed a method for traffic incident detection by using GPS trajectories of 30.000 taxis and social media data in Beijing. The study of Kitali, et al. (2019) identified secondary crashes on highways using speed data extracted from Bluetooth detectors. The proposed method could be implemented for the development of active traffic management strategies such as dynamic lane use control to mitigate secondary crashes. In 2016, Karatsoli, et al. analyzed Bluetooth- based travel times for Automatic Incident Detection (AID) purposes and examined the detectors' distance for more efficient incident detection (Karatsoli, et al., 2017). Yuan, et al. (2018) examined the relationship between crash occurrence and real-time traffic and signal timing characteristics using Bluetooth data. The survey's results are important in real-time safety applications in the context of Integrated Active Traffic Management. Kokkinos, et al. (2019) used Twitter data to extract traffic related events and binary classifiers to classify the reasons of occurrence of incidents. In this research, a novel automatic incident detection (AID) method for freeways is introduced, leveraging Bluetooth sensor data and an unsupervised anomaly detection approach. The study of Mercader & Haddad (2020) focuses on Ayalon Highway in Tel Aviv, utilizing a network of Bluetooth sensors to collect real traffic data. The AID system's advantages include the practical benefits of Bluetooth sensors over inductive loop detectors and the unsupervised anomaly detection approach, specifically the isolation forest method. This method's effectiveness is showcased through its high detection performance, simplicity in tuning, and minimal computational demands, contributing to improved incident detection without requiring incident information.

The study of Yuan & Abdel-Aty (2019) aimed to investigate the relationship between crash likelihood at signalized intersections and real time traffic, signaling and weather conditions using Bluetooth data, lane- specific traffic volume and signal timing data, and weather data. Hoque, et al. (2019) proposed a real time alert system of hazardous driving behavior using the technology of connected vehicles.

A large-scale GPS dataset was used to develop a driving behavior framework in Atlanta. This framework addresses how to quantify explicitly volatile driving in a defensible manner

(Wang, et al., 2015). Strauss, et al. (2015) used GPS trajectories of cyclists were used to infer high-risk areas for cycling injuries. The results benefit the bike lane design and cyclist’s safety.

### 2.2.5 Summary of big data applications in transport research

As a manner to summarize the findings of section 2.2, Table 2-1 and Table 2-2 show analytically the number of big data applications per transport field for the aforementioned big data sources. The applications in the four transportation fields were clustered in 17 subcategories. The goal is to identify the most frequent big data source used in the above 127 transportation studies during the last years (2009-2022) and disclose in which application field these sources have contributed the most. Although this is a non-exhaustive list of studies, the author believes that this sample represents adequately the existed trends.

Table 2-1. Counts of quantitative big data applications in transport research

	Quantitative big data sources					
	GPS	Smart Card Systems	BT/Wi-Fi	ANPR	Mobile phones	Smart vehicles
<b>Transportation planning</b>	<b>8</b>	<b>4</b>	<b>3</b>	<b>1</b>	<b>15</b>	<b>0</b>
OD matrix generation	1	0	3	1	7	0
Activity and travel patterns	4	1	0	0	6	0
City planning (opinions, commuters’ needs, land use)	1	2	0	0	1	0
Travel behavior	0	0	0	0	1	0
Trip purpose estimation	2	1	0	0	0	0
<b>Traffic management</b>	<b>23</b>	<b>2</b>	<b>6</b>	<b>3</b>	<b>2</b>	<b>0</b>
Travel time estimation	5	0	2	1	0	0
Traffic flow	2	1	1	1	1	0
Traffic congestion analysis	7	0	0	1	0	0
Environment	4	0	0	0	0	0
Routing	3	1	1	0	1	0
Traveler information	1	0	0	0	0	0
Traffic signaling and control	1	0	2	0	0	0
<b>Public transport</b>	<b>6</b>	<b>19</b>	<b>1</b>	<b>0</b>	<b>2</b>	<b>0</b>

	Quantitative big data sources					
	GPS	Smart Card Systems	BT/Wi-Fi	ANPR	Mobile phones	Smart vehicles
Optimization of PuT services	4	9	0	0	2	0
Commuting patterns estimation	2	9	1	0	0	0
Commuters' opinion, satisfaction	0	1	0	0	0	0
<b>Incident management and safety</b>	<b>5</b>	<b>0</b>	<b>6</b>	<b>0</b>	<b>0</b>	<b>1</b>
Incident detection	3	0	5	0	0	0
Incident prediction	0	0	1	0	0	1
Safety	2	0	0	0	0	0

Table 2-2. Counts of qualitative big data applications in transport research

	Qualitative big data sources		
	Social media	Social websites, PoI	Community driven applications
<b>Transportation planning</b>	<b>15</b>	<b>1</b>	<b>1</b>
OD matrix generation	0	0	0
Activity and travel patterns	8	1	1
City planning (opinions, commuters' needs, land use)	5	0	0
Travel behavior	2	0	0
Trip purpose estimation	0	0	0
<b>Traffic management</b>	<b>7</b>	<b>3</b>	<b>1</b>
Travel time estimation	0	0	0
Traffic flow	1	0	0
Traffic congestion analysis	1	1	0

	Qualitative big data sources		
	Social media	Social websites, PoI	Community driven applications
Environment	0	0	0
Routing	0	0	1
Traveler information	5	2	0
Traffic signaling and control	0	0	0
<b>Public transport</b>	<b>3</b>	<b>0</b>	<b>0</b>
Optimization of PuT services	0	0	0
Commuting patterns estimation	0	0	0
Commuters' opinion, satisfaction	3	0	0
<b>Incident management and safety</b>	<b>8</b>	<b>0</b>	<b>0</b>
Incident detection	8	0	0
Incident prediction	0	0	0
Safety	0	0	0

The most frequent big data source is GPS in traffic management studies and smart card data in PuT operation. Mobility phone data and social media data are mainly used in transportation planning studies (see Figure 2-1).

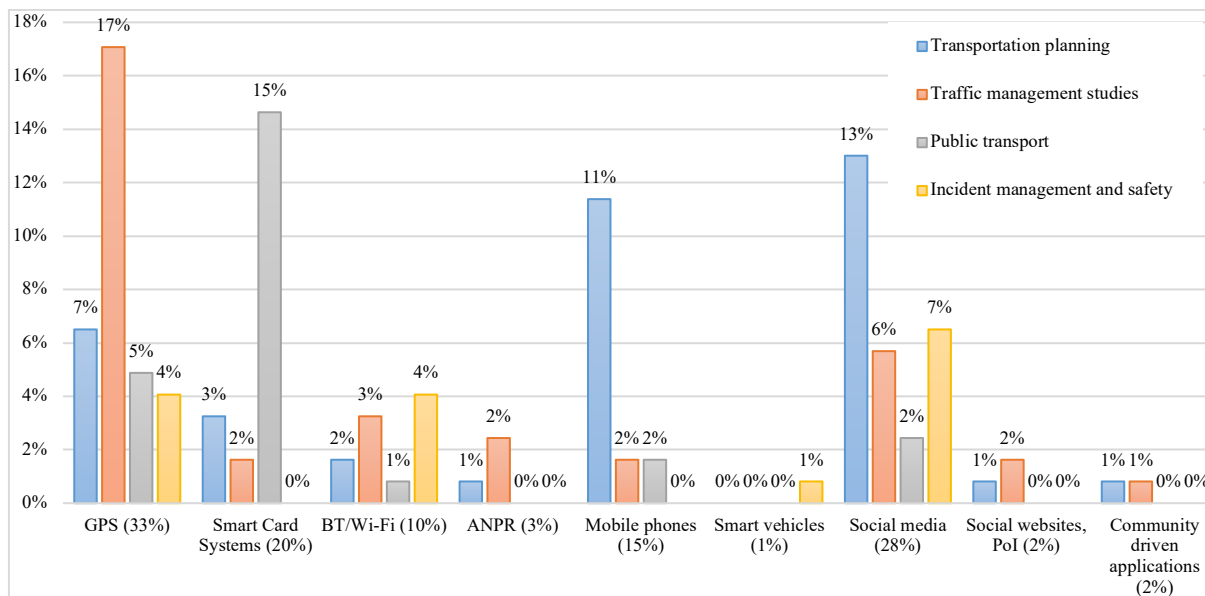


Figure 2-1. Big data sources percentage use per transportation field.

The following graph shows the contribution of each data source in the total 18 subcategories (Figure 2-2). User generated content (UGC) from social media is oriented to enhance incident detection, to estimate activity and travel patterns and contributes to city planning. These platforms have become a popular way for people to share their experiences, report events, and interact with others in real-time. Therefore, researchers have started using UGC data to extract valuable insights about human behavior, activity patterns, and preferences. In addition, social media data can be used to estimate activity and travel patterns by analyzing the content of the posts, such as keywords, geotags, and timestamps. This information can provide insights into the mobility patterns of individuals, groups, and communities, and help planners to identify areas of high demand and plan for future transportation infrastructure. Moreover, data from smart card systems are mainly used for the optimization of PuT services and the estimation of commuting patterns. Smart card data can be used to estimate the number of passengers boarding and alighting at each stop, the frequency and duration of trips, and the modes of transportation used. This information can help to optimize the frequency, routing, and capacity of public transport services, and reduce operating costs. Finally, the contribution of GPS data in transport research is manifold and were used in 14 out of the 17 subcategories.

Finally, GPS data is another valuable source of information for transport research. GPS data can be used to track the location and movement of vehicles, bicycles, and pedestrians. This data can be used to estimate travel times, distances, and speeds, and to identify travel patterns and behavior. GPS data has been used in a wide range of transport research subcategories, including traffic congestion and flow analysis, route optimization, travel time estimation, and estimation of activity and travel patterns.

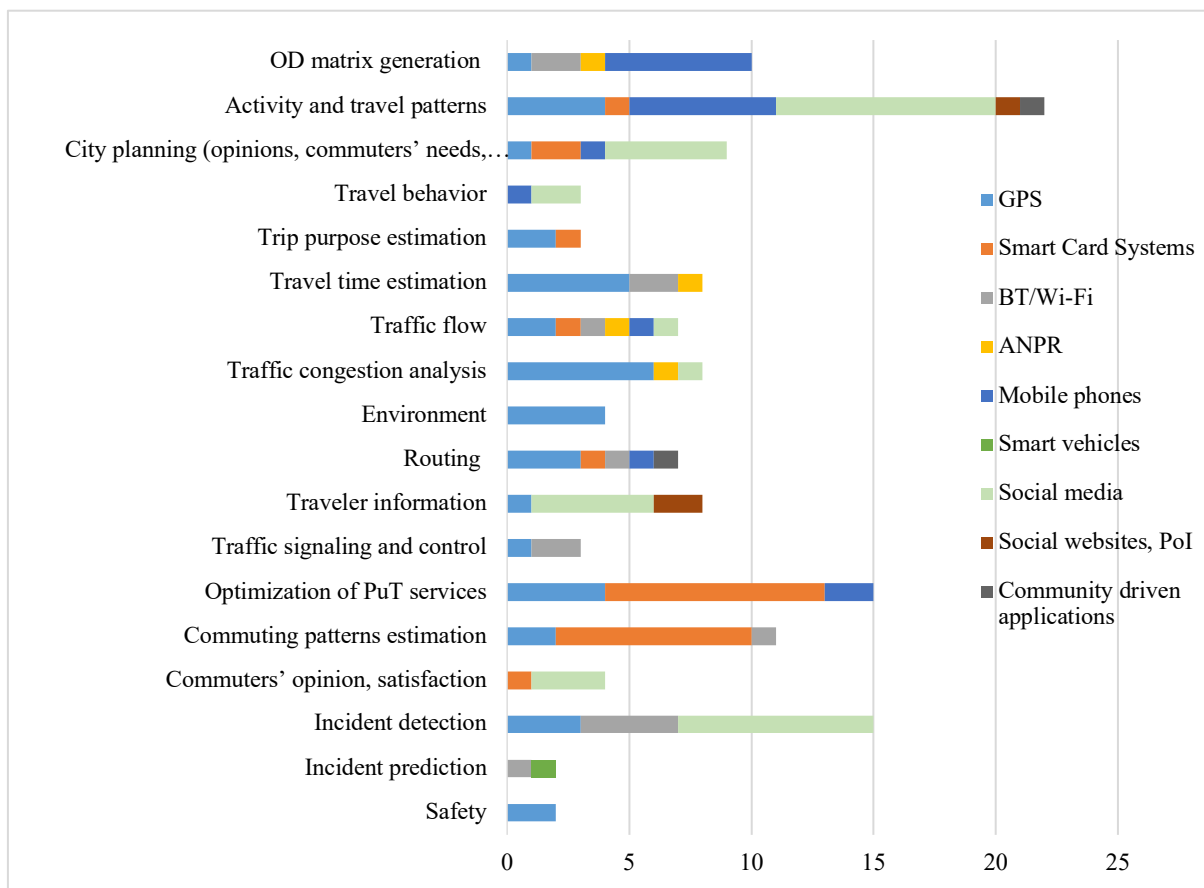


Figure 2-2. Big data sources used in each subcategory

13% of the analyzed transport studies used data from more than one big data source. According to the following graph (Figure 2-3) 11% used data from two big data sources and 2% used data from three.

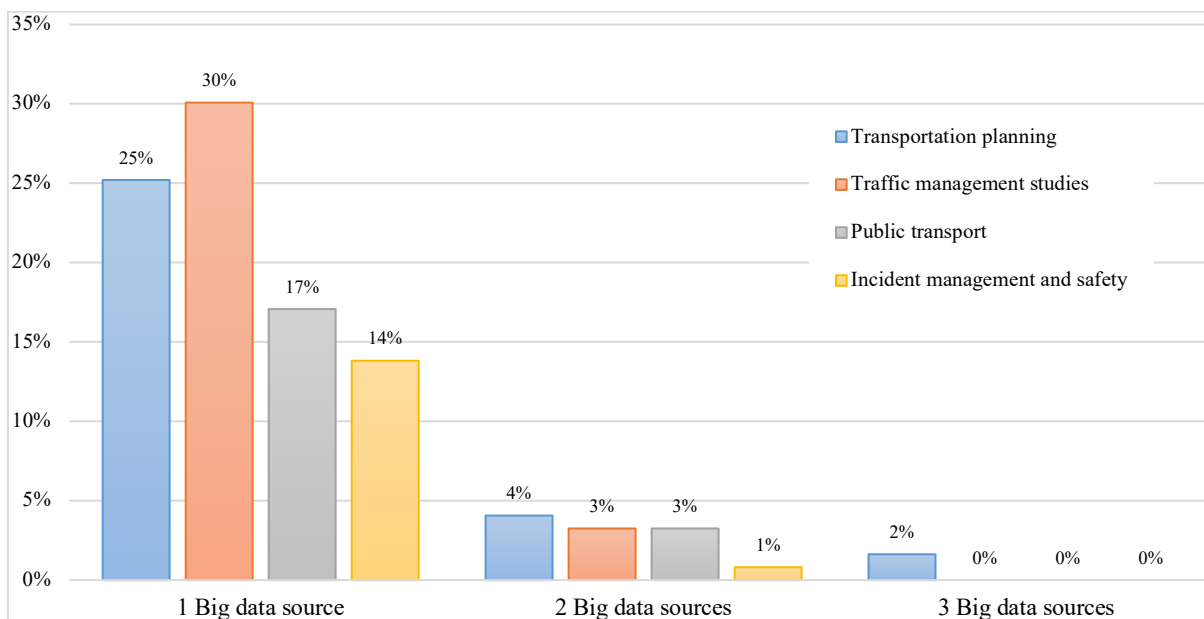


Figure 2-3. Percentage of transportation studies per field based on the number of big data sources used

Table 2-3. Summary of transport studies with two or three big data sources

		Quantitative big data sources					Qualitative big data sources			
		GPS	Smart Card Systems	BT/Wi-Fi	ANPR	Mobile phones	Smart vehicles	Social media	Social websites, PoI	Community driven applications
Transportation planning	(Noboa, et al., 2016)	X						X		
	(Long, et al., 2015)	X	X					X		
	(Andrienko, et al., 2016)	X						X		
	(Noulas, et al., 2013)					X		X	X	
	(Eggermond, et al., 2017)		X					X		
	(Li, et al., 2015)	X			X					
	(Xu & González, 2017)					X				X
Traffic management	(Zhu, et al., 2018)	X			X					
	(Romancyszyn, et al., 2017)	X		X						
	(Cici, et al., 2014)					X		X		
	(He, et al., 2016)		X			X				
	(Kan, et al., 2022)	X							X	
Public transport	(Munizaga & Palma, 2012)	X	X							
	(Gschwender, et al., 2016)	X	X							
	(Li, et al., 2017)	X	X							
	(Pinelli, et al., 2016)	X				X				
Incident management and safety	(Pan, et al., 2013)	X						X		

Big data in transport ensures good knowledge of the system and manages to achieve key objectives, such as increasing travel security and travel comfort and reducing travel time and costs. Big data sources’ development goes in hand with new technologies’ development. In this chapter, the current big data sources and their characteristics in transport were analyzed, revealing the most frequent data source, which is GPS. In most of the cases, the extracted big data were oriented to support traffic management. Mobile phone data and user generated content on social media is mainly used in transportation planning studies.

## 2.3 Sustainability in urban mobility

The increasing levels of urbanization and associated transportation demands have resulted in significant environmental and health impacts, including air pollution, greenhouse gas emissions, traffic congestion and a travel experience of low quality. To address these challenges, urban mobility needs to become more sustainable, and big data can play a critical role in achieving this goal. Sustainable urban mobility aims to provide accessible, safe, and efficient transport options while minimizing environmental impacts, alleviating traffic congestion, and improving the travel experience. It involves promoting active mobility (such as cycling and walking) and public transport, reducing car dependency, and improving the efficiency of existing transport systems. Big data can support sustainable urban mobility by enabling real-time traffic management, developing intelligent transport systems, and managing transport demand. While there are challenges and limitations (data privacy concerns, data quality issues, the need for interoperability, significant investment in infrastructure and expertise,) the potential benefits of using big data for sustainable urban mobility are significant and can help create a more sustainable future for our cities.

### 2.3.1 Real-time traffic management

Real-time traffic management is an essential component of sustainable urban mobility, which aims to reduce emissions by improving the efficiency of transport systems. Big data technologies can enable real-time traffic management by providing real-time information on traffic flows, congestion, and accidents. This information can be used to optimize traffic signals, divert traffic, and reroute vehicles to reduce congestion and emissions. Real-time traffic management involves using data to monitor and manage traffic in real-time. Big data technologies can support real-time traffic management by collecting and analyzing data from various sources, such as traffic sensors, GPS, and social media. This data can provide information on traffic flows, congestion, and accidents in real-time, allowing decision-makers to optimize traffic signals, divert traffic, and reroute vehicles to reduce congestion and emissions. Traffic signals play a critical role in managing traffic flow and optimizing traffic signals can reduce congestion and emissions. Big data can provide real-time information on traffic flows, enabling decision-makers to adjust traffic signals to optimize traffic flow. Diverting traffic to alternative routes can help reduce congestion and emissions. Big data can provide real-time information on traffic flows and congestion, enabling decision-makers to divert traffic to alternative routes. For example, if there is an accident on a particular road, traffic can be diverted to an alternative route, reducing congestion on the affected road, and minimizing emissions. Rerouting vehicles to more efficient routes can also help reduce congestion and emissions. Big data can provide real-time information on traffic flows and travel times, enabling decision-makers to reroute vehicles to more efficient routes.

Real-time traffic management using big data can provide several benefits for sustainable urban mobility. One key advantage is the potential for reduced congestion, which can improve traffic flow and reduce travel times, leading to improved efficiency and productivity. Another benefit is the potential for improved safety, as real-time information on accidents can be used to enable decision-makers to take appropriate action to divert traffic or reroute vehicles. Additionally, real-time traffic management can help optimize the use of existing infrastructure, reducing the need for costly new infrastructure, and minimizing environmental impacts. This



can also provide cost-effective solutions compared to building new infrastructure. However, the effectiveness of real-time traffic management relies on the quality and availability of data, and there may be limitations in collecting and analyzing data in certain areas. Addressing these challenges can help to fully realize the potential of real-time traffic management for sustainable urban mobility.

### **2.3.2 Intelligent Transport Systems (ITS)**

ITS are advanced technologies that optimize transport operations by using real-time data, analytics, and communication technologies. Big data can support ITS by providing large amounts of data that can be analyzed to optimize transport operations. Big data is essential for the development of ITS, as it provides the raw material for data analytics. This data can be analyzed using advanced analytics tools to optimize transport operations, reduce emissions, and improve the overall efficiency of transport networks. ITS can improve traffic flow by using big data to optimize traffic signals, detect incidents, and provide real-time traffic information to drivers. ITS can also detect incidents, such as accidents or road closures, and provide alternative routes to drivers, reducing congestion and emissions. By providing real-time data on traffic flows and network utilization, ITS can enable more efficient use of transport networks. This data can be used to optimize transport routes, reduce travel times, and minimize the environmental impact of transport operations. For example, real-time data on traffic flows can be used to optimize public transport routes, reducing emissions, and improving efficiency.

The development of ITS using big data can result in several benefits, including reduced emissions, improved air quality, and decreased fuel consumption. ITS can also enhance safety by providing real-time information on accidents and enabling timely responses to divert traffic and avoid congestion. However, implementing ITS using big data is not without challenges and limitations. Interoperability and standardization across different transport networks and data sources are major challenges that need to be addressed, along with privacy concerns and data quality issues. Additionally, the cost of implementing ITS can be high, and careful consideration must be given to the cost-benefit analysis of such systems. Addressing these challenges can help to fully realize the potential of ITS for sustainable urban mobility.

### **2.3.3 Transport demand management**

Transport demand management refers to the development and implementation of strategies that aim to influence travel behavior and reduce the demand for private vehicle use. Big data has the potential to play a significant role in transport demand management by providing insights into travel patterns, preferences, and behaviors. Big data can be utilized to develop targeted strategies that encourage active mobility, public transport use, reduce car dependency and enhance the overall travel experience. Big data can provide insight into travel patterns by analyzing travel data from various sources such as GPS, mobile devices, and public transport usage. This data can be used to understand travel patterns, such as the time of day when people travel, the most common routes, and the distance people travel. With this information, targeted strategies towards sustainable mobility can be developed. Analysis of travel patterns and data about car usage can be used to develop targeted travel information that encourages active mobility and reduces car dependency. Additionally, targeted campaigns can be developed to promote the benefits of sustainable modes of transport and encourage people to make the shift.

### 2.3.4 Travel information

Travel information is essential for individuals to plan their trips effectively and efficiently. Access to accurate and timely travel information help travelers to reduce travel time, avoid delays, and minimize costs. Moreover, it can also facilitate the use of sustainable modes of transport, such as public transport, walking, and cycling, and thereby reduce the carbon footprint of the transportation sector.

Furthermore, the availability of travel information is crucial for transport planners and policymakers to design and implement effective transportation policies and infrastructure. Data about travel patterns, preferences, and behaviors can inform the development of transport systems that are safe, efficient, and sustainable. For example, by analyzing travel information, transport planners can identify areas of high demand and optimize public transport services to meet the needs of the population. This can help to reduce congestion and improve air quality in urban areas.

The importance of travel information lies in its ability to support informed decision-making by travelers, facilitate the use of sustainable modes of transport, and inform the development of effective transport policies and infrastructure. By providing access to accurate and timely travel information, we can work towards achieving a more sustainable and efficient transport system. Travel information can be shared through various channels to ensure accessibility and provide travelers with the necessary data to plan their trips effectively. Some common ways in which travel information can be shared include:

*Websites and Mobile Apps:* Travel information can be shared on websites and mobile apps that provide real-time data on transportation modes, schedules, fares, and routes. These platforms can also provide interactive maps, trip planning tools, and other features to facilitate travel planning.

*Public Transport Displays:* Real-time travel information can be displayed at public transport stops and stations, providing travelers with information about the arrival times of trains, buses, and other modes of transport.

*Electronic display panels – Variable Message Signs (VMS):* Signs can be used to provide real-time travel information to motorists, cyclists, and pedestrians. These signs can display information about traffic congestion, travel times, and other relevant information.

*Public Announcements:* Public announcements can be made over public address systems to provide travelers with important travel information. Such announcements can communicate changes to transportation services, updates about service disruptions, or emergency situations to provide travelers with relevant and timely information.

*Social Media:* In recent years, social media has become an increasingly important tool for sharing travel information and updates about transportation services. Social media platforms such as Twitter, Facebook, and Instagram provide a quick and accessible way for transport providers to communicate with travelers and provide real-time information on service disruptions, delays, and other relevant information. Many transport providers use social media platforms to share real-time updates about their services, including information about delays, cancellations, and route changes. This information can be invaluable for travelers, allowing them to adjust their travel plans in real-time to minimize disruption.

Moreover, social media platforms provide a means for two-way communication between transport providers and travelers. By engaging with travelers on social media, transport

providers can gather feedback on their services, respond to customer inquiries, and identify areas where improvements can be made.

However, there are also challenges associated with the use of social media for sharing travel information. One key challenge is the need for transport providers to verify the accuracy of the information they share. Inaccurate or misleading information can have serious consequences for travelers, causing confusion and potentially putting their safety at risk. Despite these challenges, social media represents a powerful tool for sharing travel information and improving the overall travel experience for passengers. As the use of social media continues to grow, it is likely that more transport providers will turn to these platforms as a means of sharing information and engaging with travelers. The potential of social media use for urban mobility and travel choices is investigated in the following chapter (Chapter 3).

### **3 Potential of social media use for influencing travel and activity choices**

Narrowing down the research scope to one technology, social media was chosen for further analysis. The explosive growth of social media has rendered them powerful communication channels. User generated content is an important source of inspiration and often affects the travel choices of a user. This content triggers new activities and affects mobility decisions of others, creating a circle of influence among web friends. A place visit, an event attendance, a change of transport mode or destination or a cancellation of plans are actions that can be triggered through people's interactions on social media. The main objective of this chapter is to investigate the impact of social media use on mobility decisions. A digital questionnaire was formulated to investigate the role of social media use on commuters' mobility and travel choices before - during - after an activity/trip (Annex A) and statistical analysis was performed for the three phases. The potential differences in the impact of social media content on activity planning and travel arrangements between genders was also examined. Additionally, responses were used to formulate ordinal regression models that determine the contribution of users' demographic characteristics, travel characteristics and social media usage to mobility decisions after using social media as a source of information.

Chapter 3 is an extended and adapted version of the following publications:

*Karatsoli Maria, Nathanail Eftihia, 2021. "Social Influence and Impact of Social Media on Users' Mobility Decisions". Journal of Sustainable Development of Transport and Logistics 6 (1), 18-31. <http://dx.doi.org/10.14254/jsdtl.2021.6-1.3>*

*Karatsoli Maria, Nathanail Eftihia, 2020. "Examining gender differences of social media use for activity planning and travel choices". European Transport Research Review 12, 44. <https://doi.org/10.1186/s12544-020-00436-4>*

*Karatsoli Maria, Nathanail Eftihia, 2020. "Analysis of social media use for urban mobility and travel choices". Transport Research Arena 2020, April 27-30, Helsinki, Finland. (accepted paper; conference canceled due to COVID-19 pandemic)*

*Karatsoli Maria, Nathanail Eftihia, 2019. "Investigating the Role and Potential Impact of Social Media on Mobility Behavior". In: Nathanail E., Karakikes I. (eds) Data Analytics: Paving the Way to Sustainable Urban Mobility. CSUM 2018. Advances in Intelligent Systems and Computing, vol 879. Springer, Cham, [https://doi.org/10.1007/978-3-030-02305-8\\_31](https://doi.org/10.1007/978-3-030-02305-8_31)*

*Magginas Vissarion, Karatsoli Maria, Adamos Giannis, 2019. "Campaigns and Awareness-Raising Strategies on Sustainable Urban Mobility". In: Nathanail E., Karakikes I. (eds) Data Analytics: Paving the Way to Sustainable Urban Mobility. CSUM 2018. Advances in Intelligent Systems and Computing, vol 879. Springer, Cham, [https://doi.org/10.1007/978-3-030-02305-8\\_32](https://doi.org/10.1007/978-3-030-02305-8_32)*

*Karatsoli Maria, Nathanail Eftihia, Adamos Giannis, 2018. "Studying the influence of social media on activity-travel behavior". Proceedings of 5th Panhellenic Planning and Regional Development Conference, Volos, Greece.ç*

### 3.1 Introduction

Social media are considered as a major communications channel for information exchange, opinion statement, social network enabling, decisions influencing and business promotion. Social networking affects the users' perceptions and choices regarding their activity planning. The shared content is a valuable source of inspiration and often affects the initial decision of activity planning (Borowski, et al., 2020; Chen & Deng, 2019). A mutual trust on choices is developed during peoples' interactions on social media, resulting in a trigger for new activities (Cho, et al., 2011).

Social networking affects the users' perceptions and choices regarding their traveling. The shared content is a valuable source of mobility related information that can be easily accessible at low cost. Due, also, to their high availability, data from social media is a means

for mobility behavior analysis. Moreover, profiles of social media users offer useful socio-economic and demographic information of travelers, creating potential for investigating relationships between activity patterns and the characteristics of the users (Karatsoli & Nathanail, 2018; Osorio-Arjona & García-Palomares, 2019; Rodríguez, et al., 2020).

The increasing time being spent on social media and the interactions with web friends and followers, have changed dramatically the way that users perceive social relationships. Social networking plays an important role not only in broadening social connections but also affecting users' decisions (Yamagishi, et al., 2016). Social media are used in ways that shape the users' travelling, entertainment and shopping preferences, creating the need for them to participate in activities shared by their web friends or by people they follow. Even though social media allow a communication in which the physical presence is not necessary, reviews, photos, and videos shared via them motivate users to visit a place, attend an event or buy a product. The instantaneous and real-time access to relevant tips and guides, travelling instructions, specific offers and discounts or inspirational photos/videos has ultimately changed the way users plan an activity (Abbasi, et al., 2015; Esztergár-Kiss & Tettamanti, 2019).

The impact of social media in activity planning and mobility decisions is the main objective of this chapter. It investigates how user generated content triggers new activities of other users, creating a circle of influence among web friends. For this reason, a digital questionnaire was formulated to capture the social media usage in terms of type of information searched, reached, and shared, time of information and purpose for which the information was created. It addressed the users' preferences in sharing photos/videos or posts during or upon an experience and the impact on their final decision regarding an activity. The formation of the questionnaire and the analysis is based on the circle of influence that is created between shared content and users in the three phases of an activity before, during and after.

### **3.2 Social media in transport studies**

The uptake of ICT has increased rapidly and changed the way that people plan their activities and mobility. Recent ICT innovations have a positive impact on sustainability, as they resulted in increased interest in sustainable forms of mobility. The growth of ICT, through online platforms, smartphone applications and social media plays an important role in transport contexts by facilitating travel and allowing virtual presence (Germann Molz, 2012). A mobile phone or any device connected to Internet has the potential to bring a significant change in the way people move by providing real-time information about traffic and travel times, appropriate transport modes, shortest routes, and so on. This information can affect people's mobility behavior since it allows better planning of their activities and mobility. The ubiquitous mobile technology and web-based applications enabled the emergence of social media.

Studies have documented that ICT has a significant influence on transport behavior. ICT provides access to travel information, transport modes comparison, work from home, online payments, travel planning tools (Gossling, 2017). Thus, it is considered an important added value to transport systems. Line, et al. (2011) found that there is a cumulative impact of ICT on users' daily lives. The findings were based on a qualitative diary and an interview of students between 18-28 years old and part-time working mums. Cohen-Blankshtain & Rotem-Mindali (2016) examined the integration of ICT with ITS and assessed its impact on travel demand, urban form and urban mobility. A thorough review was done, concluding that ICT have changed the perceptions of distance, accessibility, and availability. The authors noted that the ICT innovations lead to travel substitution since substitution of physical by virtual presence

has grown. ICT-based activities could lead to a reduction in average time and less interest in private car ownership (Delbosc & Currie, 2014; van Wee, 2015; Belgiawan, et al., 2014).

More recent studies as of Varghese & Jana (2019) focused on exploring the potential of ICT to improve access to opportunities. The data showcased the differences in household socio-economic characteristics, individual personal characteristics, ICT use patterns, activity participation, and time allocation patterns, drawing conclusions about the interrelationships between ICT, social disadvantage, and activity participation. Lee & Circella (2019) attempted to understand the relationships of ICT use and travel outcomes among millennials, by clustering them in intense users, moderate users, and light users, however, no conclusions were drawn about how the use of ICT affect their travel choices. Finally, Jamal & Habib (2020) explored the covariates that affect the use of smartphones for trip planning as well as the covariates of perceived impact of smartphone use on travel outcomes. One of their main outcomes was that millennials are more likely to use smartphones for trip planning as well as perceive increase in travel outcomes due to smartphone use.

The shared content on social media and the interaction with other users has intensified changes in users' mobility decisions by setting a new framework for travel behavior. Xiang & Gretzel (2010) were among the first that reported the importance of social media in seeking travel information. The goal of their study was to investigate the extent to which social media appear in search engine results in the context of travel-related engines. The analysis showed that social media constitute a substantial part of the search results, indicating that search engines direct travelers to social media sites. Yoo & Gretzel (2011) in their study, identified social media as an important source of information for travelers, the majority of whom trust their content. The results of their survey indicated that travelers' personality influences perceived barriers to content creation and engagement in generated content creation. In following research, Yoo & Gretzel (2012), argued that social media have a significant impact on travel planning and decision-making, first in terms of accommodation and facilities, and then in terms of activity type and location.

Gao, et al. (2012) explored the role of social association in users' check-ins to improve the accuracy of activity's location prediction. A social-historical model was used to integrate social ties and historical ties. The results showed that users who sustain a level of friendship tend to go to similar locations. A year later Ayeh, et al. (2013) investigated the factors that affect the intention to use social media for specific purposes of travel planning. Through an online survey, they proved that among individuals with Internet access who take often vacation trips, mostly young people use social media to plan their trips. In this direction, Schroeder & Pennington-Gray (2015) used linear regression to explore the relationships of variables with the likelihood of social media use to seek information in the event of a crisis during travel. Results showed that those who travel frequently use social media to get information in the event of a crisis during their trip more often than those who travel less. In the study of Gossling & Stavrinidi (2015) Facebook profiles were analyzed to investigate the presence of mobility aspects on social media, discussing also how individual's mobilities can set in motion competitive travel. A qualitative exploratory research approach was chosen to determine inter-relational dynamics between corporeal and imaginative travel and their importance for society. The study used ethnographic content analysis to structure and evaluate shared content on 50 Facebook profiles. Results showed that Facebook increases sociality and facilitates mobility through advice and invitations.

Keith, et al. (2012) developed a formal model of spatial technology diffusion to capture the information flow through people's social networks. The authors investigated to what extent spatial clustering in social networks could explain observed clusters in adoption patterns of hybrid-electric vehicle ownership. Goetzke & Weinberger (2012) used a binary discrete choice framework to investigate the factors that affect bicycle use in Germany. The analysis showed that social network effects increase bicycle use for shopping and recreational trip purposes, but not for working or educational purposes. Zhang, et al. (2019) studied the route choice behavior in a two-route network under social influence. The effects of social learning on participant's route choice were studied by proposing an instance-based learning theory model with social learning. As an extension of the study, it was shown that the more participants choose the recommended routes, the better the traffic conditions. Social influence has also an impact on driving behavior. A driving simulator study tested the impact of passenger presence who applied peer influence on driving behavior of male teenagers. The findings support the contention that social influence has an impact on driving risk behavior and are in line with social norms theory (Bingham, et al., 2016).

Social networking is characterized by interactivity and encourages users to share opinions, photos, experiences, and locations with their web friends. This content builds awareness and shapes users' activity and mobility preferences (Mohammadreza, 2012). Transit agencies use social media to connect with commuters since the online platforms can be a powerful tool for engaging and communicating with the public. Cottrill, et al. (2017) evaluated a social media strategy for the dissemination of transport information during a large event. The coordination of the multiple services and information providers for the dissemination of a reliable message and the public response to it was also examined. The findings of this survey demonstrated the benefits of social media as a medium for sharing accurate and trusted information.

As per differences between women and men in online activities and use of information technology, Park & Lee (2014) conducted an online survey to investigate gender differences in smartphone application use. Results revealed that women found more useful the smartphone text communications to keep strong their personal relationships as compared to men. Idemudia, et al. (2017) used confirmatory factor analysis and structural equation modeling to analyze 290 datasets from college students. Their results indicated that women had stronger perception of ease of use, compatibility, relative advantage, and risk when using social media when compared to men. More recent studies, as the one of Lin & Wang (2020) aimed at explaining the gender differences in information-sharing behavior on social networking sites. To achieve this, a comparative theoretical model of information sharing between genders was developed. In line with previous studies, results showed that privacy risk, social ties, and commitment are more important for women than men, as attitude towards information sharing, affects people's intention to share information more strongly for women than it does for men. Another recent study by Twenge & Martin (2020) attempted to investigate gender differences in the use of social media by examining 13- to 18-year-old adolescents in the U.S. and UK. Results showed that adolescent girls spent more time on smartphones, social media, texting, general computer use as compared to boys, however, no further investigation was made about how much of this time was spent to plan an activity.

Most of the studies that are related to urban mobility (Fu, et al., 2015; Byon, et al., 2009; Hasan, et al., 2013; Lee, et al., 2017) explore the use of social media data to collect travel information and attributes (i.e. transport mode, activity patterns, traffic incidents). Several studies have shown attention to extract information from social media to track and analyze



human mobility. Information about trip purpose, transport mode, location data, activity duration and sociodemographic characteristics can be obtained directly and at low cost from social media. The study of Manca, et al. (2017) explored the way that social media data can be used to infer knowledge about urban dynamics and mobility patterns in an urban area. A workflow that shows how social media can become a source to reveal these patterns was identified, and then applied into a real case study. Tasse & Hong (2018) presented ways of using geotagged social media data to develop an understanding of urban areas, categorizing the opportunities for a city planner, small business owners and individuals. Lee, et al. (2016) used geotagged Twitter data from the greater area of Los Angeles. A Twitter-based Origin-Destination (OD) matrix was compared with a recent OD matrix provided from the 4-step model output. Regression models were estimated to measure the correlations between the two OD data. The results showed that location-based social media data on large scales have an added value on travel demand modeling. Hasan & Ukkusuri (2015) used Foursquare check-ins in New York City. The study aimed to infer individual lifestyle behavior based on activity-location choices in social media.

Data from social media have been utilized to extract information about traffic conditions for network management purposes. Real-time information about incidents, schedules, fares, and projects are some examples of how transport companies use social media (Bregman, 2012). Tian, et al. (2016) verified traffic incidents that were posted on social media by comparing them with field data from installed cameras. The results showed that users' tweets about true and severe incidents were shared more often compared to false and minor incidents. In the study of Fu, et al. (2015) an approach has been developed for the extraction and analysis of real-time traffic-related data from Twitter. The preliminary results showed that social media can be used as a supplementary source for traffic incident data collection.

### **3.3 Methodology**

This chapter attempts to identify the importance of social media use in activity planning, collection of information and mobility decisions. In view of these objectives a survey was set up and implemented, where photos/ videos, reviews, promoted places were considered as influencers of the travelers' choices regarding activities and traveling decisions.

#### **3.3.1 Survey design**

An online survey in the English language was hosted on Survey Monkey to investigate the influence of social media use in activity planning and travel arrangements. In the context of the survey, the term "activity planning" is used to describe the preparatory actions and set of conditions to perform an activity, such as going to a restaurant, visiting a museum, participating in an outdoor yoga class, visiting a doctor, or going to a shopping mall. Such preparatory actions include decisions about which activity to do next, who to do the activity with, always based on information concerning reviews and ratings, photos, and videos of alternative destinations, as shared by previous visitors on social media. The term "travel arrangements" refers to decisions on how to reach the selected destination, and specifically departure time, mode of travel, route, ticket purchasing and other. This survey focused on the influence of information or advice for using a specific transport mode to reach the destination, as most social media accounts of businesses, events etc. include in their description the proposed transport mode to reach the location. In addition, social media friends share or propose a transport mode to reach a destination of an activity either based on their own experience or knowledge.

The questionnaire consisted of five parts. The first part recorded the socio-demographic and travel characteristics of the respondents. Demographics included gender, age, occupation, and country of residence. For the travel characteristics, respondents were asked if they hold a driver’s license and if they mainly use a sustainable or a non-sustainable transport mode for their activities. The category of sustainable mode users includes the participants that use only sustainable modes for their daily commute (public transport, biking or walking), while the category of non-sustainable mode users includes participants that use at least one non-sustainable mode of transport for their mobility (car or motorbike). The frequency of public transport use was reported on a 5- point scale (Never 1, Seldom 2, Sometimes 3, Often 4, Always 5).

The second part referred to the use of social media and recorded the number of days per week that participants use social media, the average minutes spending when using a social platform and the time of the day that they use more frequently social media. They were also asked whether they use a supplementary source, except for social media to facilitate them for the mobility/activity planning. Then, the respondents answered if they believe that social media help them with their mobility decisions. Finally, in the last part, respondents were asked if social media affects their activity and mobility planning, and if advice from social media about transportation modes affects their mode choice. All these last questions were rated using the 5-point scale (Never 1, Seldom 2, Sometimes 3, Often 4, Always 5).

The questions of the last three parts was based on the model (Figure 3-1) which was presented in the work of Dwityas & Briandana, (2017), adapted from Travel Decision Making Model (Mathieson & Wall, 1982).

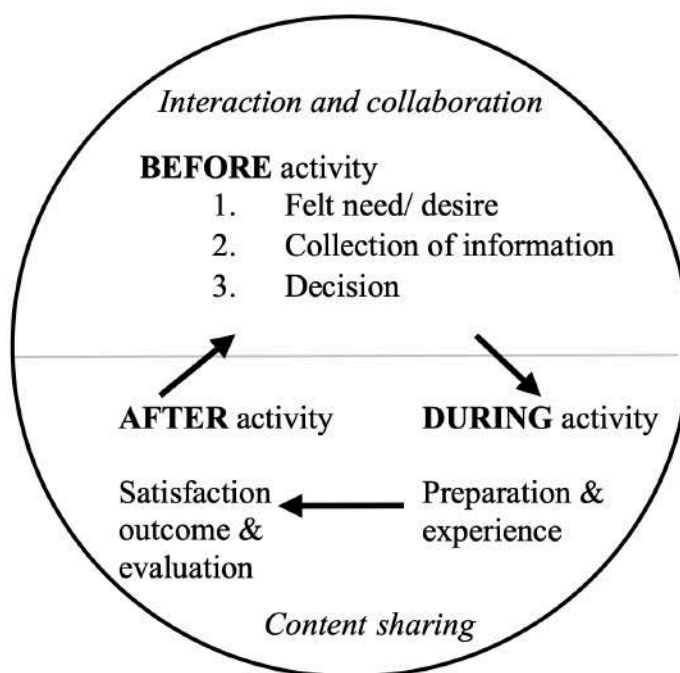


Figure 3-1. Decision making of an activity/trip through social media use (Dwityas and Briandana, 2017)

The third and fourth parts constitute the main core of the survey, highlighting the influence of social media as stated by the respondents. In particular, the third part of the survey

investigated the impact of social media content on “activity planning” and “travel arrangements”, before performing an activity. Specifically, it was examined whether reviews and ratings, photos/videos, and proposed transport mode affect “activity planning” and “travel arrangements” (categorical variables), and the degree of such influence (ordinal variables). It also investigated the post type that would mostly affect decisions, such as a post by a famous person, a sponsored post or a post by a designated account related to transport.

“Before activity” phase includes:

(1) The desire and need of performing an activity. Social media content such as photos, videos, text, or a combination of them influence the users, by creating the need to perform the shared activity.

(2) The collection of information regarding the activity, such as activity type, location of the activity, instructions to reach the destination, public transport timetable, reviews, and ratings. At this stage, the users look for information about activities performed by others and visit the appropriate social media accounts to get precise data as a basis for right decision-making.

(3) The decision-making. In this phase, the user evaluates the collected information. Reviews, ratings, and comments uploaded by other users play an important role on the evaluation stage and on the final decision. After evaluating the collected information and making the final decision, the user usually shares content on social media about the upcoming performance of the activity.

The fourth part focused both on the type of user-generated content and on the reasons of social media use during an activity. In this phase, social media are used for sharing live the experience with web friends or for searching additional information regarding the ongoing/ next activity (reviews and ratings, opening/ closing hours, how to reach next destination, public transport timetable etc.).

The survey’s last part referred to the phase when a series of activities have been accomplished and the experiences are evaluated. In this phase users share not only their satisfaction/ dissatisfaction about an activity, but also information and sources that have been used throughout their decision-making process. Hence, the fifth part of the survey aims to investigate the feedback that a user provides upon a completed activity, as it undoubtedly affects the mobility decisions and activity planning of other users and influences the way that someone acts in daily life (Dwityas & Briandana, 2017).

Figure 3-2 depicts the circle of influence of the shared social media content in the three phases of an activity (before - during - after). It shows that the content, which is shared by social media users, based on its type, can affect other users before and during an activity. Users make their final decision by seeking additional information on social media evaluating at the same time the information sources. After the completion of the activity, the user shares the experience and provides feedback that triggers or enriches the activities of other users.

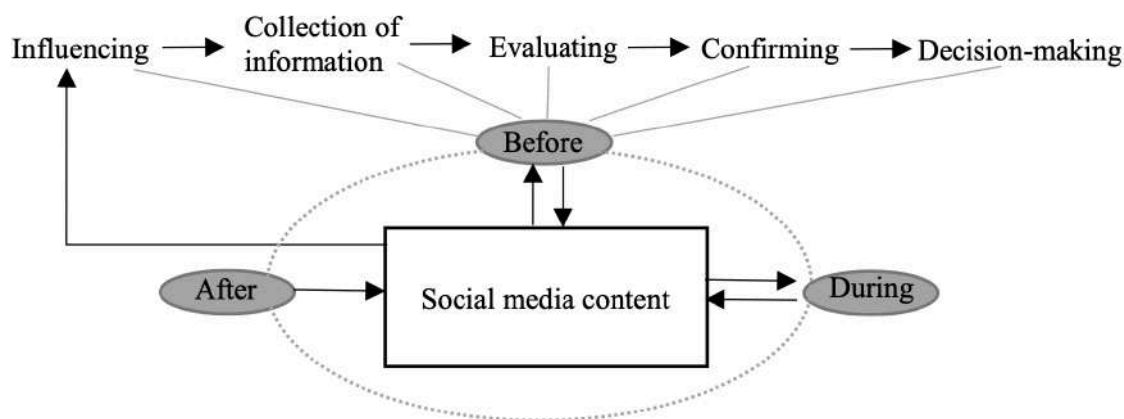


Figure 3-2. Social media content in decision-making process regarding an activity/ trip (Dwityas & Briandana, 2017)

### 3.3.2 Survey communication

The online survey was targeted to social media users across the world. Social media users were reached through email and posting on first author’s Instagram and Facebook accounts. As a first step, emails were sent to 3436 contacts of Traffic, Transportation and Logistics (TTLog) laboratory of University of Thessaly contact list comprised of research institutions, ministries, municipalities, associations, groups, companies, actions, projects, and postgraduate students around the world. The emails were sent from the email account of TTLog laboratory. As a second step, the questionnaire link was shared on first author’s personal social media accounts. The link of the questionnaire was active from January 2018 and remained opened till January 2019. Along with the invitation to participate, information about the purpose and the design of the survey were sent. The participants were chosen by chance without any specific screening process during the recruitment period. The final sample size comprised 888 users, who fully completed the questionnaire. However, as the aim of the study dictates, the analysis was made based on the 91% of the respondents, who use social media. The 804 participants that gave a positive response to this question were able to proceed to the next parts of the survey. The rest 9% were redirected at the end of the survey since the following sections were to be responded by social media users.

### 3.3.3 Sample characteristics and social media use

Descriptive statistics were used to demonstrate socio-demographic and general characteristics of the 804 respondents. Table 3-1 summarizes the socio-demographic and general characteristics of the respondents. Analytically, 61% of them are women and the rest 39% are men. Most of the respondents belong to the age groups of 18–25years old (38% of the respondents) and 26–35 years old (36% of the respondents). In addition, 38% of the survey respondents are students and 51% have a full-time job. 70% of the respondents live in Greece and the rest 30% live in Germany (5%), the United States of America (3%), the United Kingdom, France, and Italy (2% each) and other countries (16%). Regarding the travel characteristics, 76% of the participants hold a driver’s license, 47% use only sustainable transport modes in their daily life, while 8.1% stated that they never use public transport.

Table 3-1. Sample characteristics

Variables	Level	%
Gender	Female	61
	Male	39
Age	<18	1
	18-25	38
	26-35	36
	36-45	14
	>45	11
Occupation	Student	38
	Full-time job	51
	Part-time job	6
	Unemployed	4
	Other	1
Country of residence	Greece	70
	Germany	5
	USA	3
	UK	2
	France	2
	Italy	2
	Other	16
Driver's License	Yes	76
	No	24
Transport mode users	Sustainable transport mode users	47
	Non- sustainable transport mode users	53
Use of public transport	Always	8
	Often	22

Variables	Level	%
	Sometimes	21
	Seldom	31
	Never	18
Mean=3.34, SD=1.202		

The social media usage of respondents appears in Table 3-2. The results show that 87% of the participants use social media every day, 34% spend 6 to 15 minutes online every time they check their social media accounts and 66% use more frequently social media between 17:00 and midnight. As 8% of social media users stated that they never use social media for their mobility/ activity planning, the last four parameters in Table 3-2 refer to the rest of 738 participants who use social media for their travel arrangements and activity planning. Moreover, 91% stated that except for social media use a supplementary source of information during the mobility/ activity planning phase. Most of the respondents answered that social media help them with their final decision sometimes (46%) and often (30%). 47% of the respondents stated that social media influences their activity and mobility planning sometimes. 36% of the participants stated that their mode choice is influenced sometimes by social media information.

According to users' statements, Facebook and Instagram are the most used social media platforms. Analytically, 90.2% stated that they use Facebook, 73.4% Instagram, 42.8% LinkedIn, 29.5% Pinterest and 22.3% Twitter. It is noted that participants could select multiple choices.

Table 3-2. Use of social media

Variables	Level	%
How many days per week do you use social media	Everyday	87
	5-6	7
	4-3	3
	2-1	2
	More rarely	1
How many minutes do you spend on average per time	0-5	21
	6-15	34
	16-30	21

Variables	Level	%
	31-60	10
	>60	14
What time of the day do you use most frequently social media	07:00-12:00	13
	12:00-14:00	5
	14:00-17:00	11
	17:00-00:00	66
	00:00-07:00	5
Do you use any other sources of information except for social media	Yes	91
	No	9
Do you consider that social media help you in your final decision	Never	2
	Seldom	13
	Sometimes	46
	Often	30
	Always	9
	Mean=3.31, SD=0.892	
Does social media use affect your activity and mobility planning	Never	9
	Seldom	32
	Sometimes	47
	Often	11
	Always	1
	Mean=2.64, SD=0.832	
Does the proposed transport mode by social media information affect your mode choice?	Never	11
	Seldom	26

Variables	Level	%
	Sometimes	36
	Often	21
	Always	6
	Mean=2.86, SD=1.058	

### 3.3.4 Data analysis

The analysis of the data was done through descriptive and inferential statistics. In the first case, sample characteristics, such as age, gender and occupation were addressed by estimating the frequency distribution per characteristic (section 3.3.3). Furthermore, the mean values and standard deviations, and medians were calculated. In the second case, the statistical analysis of the responses was carried out using non-parametric tests which are regarded as particularly powerful for analyzing data collected through questionnaire surveys (Park, 2009; Siegel & Castellan, 1988). Specifically, chi-square test for homogeneity ( $\chi^2$  test) was used to test differences in characteristics measured by categorical variables. The Mann-Whitney U-test was performed to assess differences between the samples in characteristics measured on the 5-point scale (Never 1, Seldom 2, Sometimes 3, Often 4, Always 5) (Park, 2009)

Ordinal regression analysis was conducted to analyze the influence of social media use in activity and mobility planning and mode choice, as affected by explanatory variables associated with demographic information (Simms, 2012), travel characteristics (Gunnarsson, 2000) and social media usage (Chung & Koo, 2015; Milioti, et al., 2019) that contribute to users' final decisions after social media use. The applied methods are presented in more details in the respective sections below.

### 3.3.5 Research limitations

This study may entail limitations related to the sample used. Due to authors' nationality, most of the respondents (70%) are from Greece. In addition, 74% of the respondents belong to young age groups (18–35 years old), as they are more familiar with technology and social media use. Elderly individuals and those with limited access to these platforms might be underrepresented due to various challenges, including technological barriers, socio-economic constraints, and personal preferences. Such underrepresentation can potentially skew the results, limiting their generalizability. Considering these challenges, the analyzed sample size, derived primarily from online platforms, reflects primarily the views and behaviors of those active on social media. For future studies, it might be beneficial to employ a mixed-methods approach, combining both online and on-site surveys, to ensure a broader representation. Collaborations with community organizations and offering alternative ways of participation can also enhance inclusivity. Researchers should be cognizant of these limitations when interpreting the findings from online-only datasets.



After a thorough research on global related figures, the authors concluded that this does not affect the present research's validity. Both sample's age distribution and social media usage are in line with the global population age distribution, initially documented in US Census Bureau (Bureau, 2017) and in Martin, et al. (2019) for US, and supported worldwide by Ferrer (2018) and world social media users per age group (Jaffray, 2019; Viens, 2019). Also, all participating countries share similar social media usage (Statcounter, 2020). Another possible limitation of the study could be the abstract understanding of the term "social media use" by the respondents. However, this study investigated social media use only related to information searching, which was explicitly stated in the respective questions of the questionnaire and not for any other reason that social media could be used and could confuse respondents.

In the ordinal regression analysis, the definition of some independent variables such as "average minutes spending when using a social media platform", might limit the scope of the study. Although the responses measured the average time accurately, it is uncertain whether users are active all the reported time. Thus, the definition of "social media use" might not reflect the complexity of someone's use patterns.

### **3.4 Social media use before an activity/trip**

The third part of the survey focused on examining the influence of social media content on individuals' behavior in terms of activity planning and travel arrangements prior to engaging in an activity (Section 3.4.2). The purpose of this investigation was to gain a better understanding of how social media content can shape people's decision-making processes when it comes to planning their trips. By exploring this topic, we can gain insights into the potential impact of social media on individuals' daily activities and travel patterns, which can have implications for various fields, including tourism, marketing, and social psychology. An examination of the potential differences in the impact of social media content on activity planning and travel arrangements between genders was done (Section 3.4.3). This analysis aimed to explore potential gender-based variations in the effects of social media on individuals' behavior and decision-making processes. Additionally, responses of the 738 participants that stated that they use social media for their activity and mobility planning, were used to formulate ordinal regression models. The developed models determine the contribution of users' demographic characteristics, travel characteristics and social media usage to mobility decisions after using social media as a source of information. These decisions were expressed in two dependent variables; (i) the impact of social media use in activity and mobility planning; (ii) the impact of the proposed transport mode by social media information, on mode choice (Section 3.4.3).

#### **3.4.1 Social media use before an activity/trip**

Social media platforms have become an increasingly popular source of information for individuals before engaging in activities or trips. According to the results, 82% of participants reported that they use social media platforms to get information before their trip or activity, with 37.4% reporting that they use it often, and 14.2% reporting that they use it always. The mean score for frequency of use was 2.63 out of 5, with a standard deviation of 1.119, indicating that the use of social media in trip planning is relatively common but can vary widely among individuals. When it comes to the type of activity, social media is used most for entertainment (84%) and travel arrangements (74%). In contrast, social media is used less frequently for business/job (39%) and shopping activities (52%). Moreover, 91% of participants reported

using complementary sources of information other than social media. Among other sources of information, friends and/or relatives were the most reported (80%), followed by tourism-related social websites (71%) and blogs/forums (53%). This highlights the importance of personal recommendations and word-of-mouth when it comes to gathering information for the planning phase.

Regarding the use of social media in the phase of planning, participants reported that they use it for various purposes. For instance, 81% reported using social media to search for reviews, while 73% used it to search for the location of a place and how to reach the destination. Additionally, 58% reported that they use social media to get inspired through photos/videos. Despite the widespread use of social media in trip planning, the perception of its usefulness varied among participants. Only 9.1% of participants reported that social media always helped them in planning their trip or activity, while 45.7% reported that it sometimes helped them. The mean score for usefulness was 2.69 out of 5, with a standard deviation of 0.892, indicating that the usefulness of social media in trip planning can vary among individuals.

Table 3-3. Social media use before an activity/trip

Variables	Level	%
Do you use social media platforms before your trip/activity to get any sort of information for it?	Never	8.2
	Seldom	12.1
	Sometimes	28.1
	Often	37.4
	Always	14.2
		Mean=2.63, SD=1.119
What type of activity do you plan by using social media		
Travel arrangements	Yes	74
	No	26
Entertainment	Yes	84
	No	16
Business/ Job	Yes	39
	No	61
Shopping activities	Yes	52
	No	48
Except for social media, do you use any other sources of information	Yes	91
	No	9

Variables	Level	%
Which other sources of information do you use?		
Friends and/or relatives	Yes	80
	No	20
Tourism related social websites (such as Tripadvisor)	Yes	71
	No	29
Blogs and forums	Yes	53
	No	47
How do you use social media when planning an activity		
Get inspired through photos/videos	Yes	58
	No	42
Search for reviews	Yes	81
	No	19
Search for parks/ outdoor activities	Yes	36
	No	64
Search the location of a place and how to reach the destination	Yes	73
	No	27
Search the appropriate transport mode / search the timetable in case you choose public transport	Yes	54
	No	46
Check opening hours/ crowdedness of a place	Yes	54
	No	46
Do you consider that social media help you in before an activity/trip	Never	2.4
	Seldom	12.7
	Sometimes	45.7
	Often	30.1
	Always	9.1
	Mean=2.69, SD=0.892	

The study found that most respondents reporting that they visit places or perform activities they have seen on social media at least sometimes. Specifically, 53.4% of respondents reported that they sometimes visit places or perform activities shared on social media. This suggests that social media can act as a source of inspiration for individuals seeking new experiences. In terms of the influence of reviews and ratings, it was found that they are a moderately important factor in decision-making, with 40.2% of respondents reporting that they

often consider reviews and ratings when planning an activity or trip. Photos and videos are also important, with 47.8% of respondents reporting that they often consider them when deciding. Interestingly, negative reviews were found to have a greater impact on decision-making than positive or neutral reviews, with 47.4% of respondents reporting that negative reviews influence their decision-making process. This highlights the importance of managing negative feedback for businesses/organizations that rely on positive word-of-mouth to attract audience.

The study also found that the proposed transport mode on social media has a moderate impact on individuals' final decision, with 35.9% of respondents reporting that they sometimes consider the transport mode when planning an activity or trip. When it comes to making changes to activity plans after using social media, most respondents reported that they sometimes make changes (46.9%). This suggests that social media can have a significant impact on individuals' activity planning even after the initial decision has been made.

In terms of the criteria for activity choice, the study found that positive reviews were the most important factor, with 75% of respondents reporting that they consider them when deciding. Low cost was also a significant factor for 54% of respondents. The proximity of the activity to home or workplace and accessibility to public transport were also moderately important, with 32% and 37% of respondents reporting that they consider them, respectively.

Table 3-4. Impact of social media use before an activity/trip

Variables	Level	%
How often do you visit a place/perform an activity shared on social media?	Never	2.6
	Seldom	22.2
	Sometimes	53.4
	Often	20.7
	Always	1.1
	Mean=3.04, SD=0.758	
Do reviews and ratings affect this decision?	Never	2.4
	Seldom	9.3
	Sometimes	36.0
	Often	40.2
	Always	11.9
	Mean=2.5, SD=0.907	
Do photos/videos affect this decision?	Never	1.8
	Seldom	6.5
	Sometimes	27.8

Variables	Level	%
	Often	47.8
	Always	16.1
	Mean=2.3, SD=0.877	
What kind of review affects more this decision?	Negative review	47.4
	Neutral review	8.3
	Positive review	38.2
	None	6.1
Does the proposed transport mode on social media affect your final decision?	Never	10.7
	Seldom	25.9
	Sometimes	35.9
	Often	21.7
	Always	5.8
	Mean=3.14, SD=1.058	
Do you make changes to all or parts of your activity plans after using social media?	Never	8.8
	Seldom	32.0
	Sometimes	46.9
	Often	11.4
	Always	0.9
	Mean=3.36, SD=0.832	
To what extent social media influence your activity planning?		
Change destination	Yes	37
	No	63
Change purpose/ activity	Yes	33
	No	67
Change time or date of activity	Yes	53
	No	47
Change of transport mode	Yes	32

Variables	Level	%
	No	68
Cancel your activity	Yes	20
	No	80
Which are for you the most important criteria for the activity choice?		
Positive reviews	Yes	75
	No	25
Low cost	Yes	54
	No	46
Close to your home/workplace	Yes	32
	No	68
Accessibility to public transport	Yes	37
	No	63
Available parking	Yes	16
	No	84
It is a trend on social media	Yes	13
	No	87

The understanding of the social media preferences and effective messaging approaches of potential users is crucial for promotion of travel possibilities. The percentages related to the preferable social media post and the most appealing message approach regarding travel possibilities can be found in Table 3-5. The findings reveal that a message by a designated account related to transport is the most effective way to raise awareness on traveling possibilities (61.0%). This result suggests that travelers are more likely to trust information provided by official transport accounts rather than sponsored posts or celebrity endorsements. This can be explained by the fact that designated accounts are perceived as having more reliable and credible information. Sponsored messages were ranked as the least effective way to raise awareness on travel possibilities (11.7%). This result can be explained by the fact that sponsored messages are often perceived as inauthentic and lacking credibility. Celebrity endorsements were ranked as the second most effective way to raise awareness on travel possibilities (22.1%). This can be attributed to the influence and trust that people have in celebrities. However, it is important to note that this approach is less effective than designated transport accounts.

The findings also reveal that the most appealing message approach to potential travelers is the informative approach (79%). This result suggests that travelers prefer messages that provide them with relevant and useful information that can help them plan their trip effectively. This is consistent with the result that designated transport accounts are the most effective way to raise awareness on traveling possibilities. The humorous approach was ranked as the second

most appealing approach (65%). This can be attributed to the fact that humor is an effective way to engage with potential travelers and create a positive and memorable experience. However, it is important to note that this approach may not be appropriate for all types of travel. The encouraging approach was ranked as the third most appealing approach (48%) which suggests that travelers appreciate messages that motivate and inspire them to travel. However, it is important to note that this approach should be balanced with providing accurate and relevant information. The confronting approach was ranked as the least appealing approach (15%). This suggests that potential travelers are less likely to respond positively to messages that use fear or negative emotions to motivate them to travel. This approach can be perceived as manipulative and may have a negative impact.

Table 3-5. Preferable social media post and appealing message approach

Variables	Level	%
What would raise mostly your awareness on traveling possibilities?		
	A message post by a famous person/account that you follow	22.1
	A sponsored message	11.7
	A message by a designated account related to transport	61.0
	Other	5.3
Select up to three approaches of the message that would appeal more to you.		
hard socking, fear	Yes	11
	No	89
confronting	Yes	15
	No	85
informative	Yes	79
	No	21
encouraging	Yes	48
	No	52
emotional	Yes	31
	No	69
humorous	Yes	65
	No	35

It is also examined the extent to which individuals post information before their activities and trips on social media, the platforms they use for this posting, and the types of information they share. The results indicate that most individuals (81.3%) post information about their activities on social media before their occurrence. Most individuals post information about their activities seldom (55.8%) or sometimes (20.1%), while a smaller percentage of individuals post information about their activities often (5.4%) or always (0.8%). The mean score for posting activity information on social media was 3.85, with a standard deviation of 0.804. Regarding the platforms used for posting activity information, the findings suggest that Facebook and Instagram are the most used platforms, with 53% and 51% of respondents indicating that they use these platforms, respectively. Twitter is less commonly used, with only 3% of respondents indicating that they use it. In terms of the types of information shared, our results indicate that individuals are most likely to share photos and videos (65%), followed by stories (41%), posts with comments (23%), like posts (29%), and share posts (15%).

Table 3-6. Social media content shared before an activity/trip

Variables	Level	%
Do you post any information on social media about your activity before its occurrence?	Never	17.9
	Seldom	55.8
	Sometimes	20.1
	Often	5.4
	Always	0.8
	Mean=3.85, SD=0.804	
In continuation to the above question, which social media platform do you use for this posting?(you can select more than one answer)		
Facebook	Yes	53
	No	47
Instagram	Yes	51
	No	49
Twitter	Yes	3
	No	97
What kind of information do you post? (you can select more than one answer)		
Photos/videos	Yes	65
	No	35
Posts with comments	Yes	23



Variables	Level	%
	No	77
Stories	Yes	41
	No	59
Share posts	Yes	15
	No	85
Like posts	Yes	29
	No	71

### 3.4.2 Examining gender differences of social media use

According to literature, gender may affect the way that people share information on social media and the way they use it to make decisions (Aparicio-Martínez, et al., 2020; Lin & Lu, 2011; Lin & Wang, 2020). However, an extended literature review in this study, revealed that there are no published studies that have examined the gender differences of social media use for activities and travel choices. To address this gap, this study aims at explaining gender differences in social media use for activity planning and travel arrangements before an activity. As Dwityas & Briandana (2017) stated in their research, before an activity, social media content such as photos, videos, or text, influence the user by creating the need to perform a shared activity. Furthermore, the user collects information regarding the activity, such as activity type, destination, instructions to reach the destination, public transport timetable, reviews, and ratings, looks for information about activities performed by others and visits the appropriate social media accounts to get precise data as a basis for right decision-making.

As it is already mentioned 66% of users, split in 41% women and 25% men, use social media between 17:00-00:00, with the results being statistically significant. In addition, 54% of the respondents, split in 37% women and 17% men, stated that they use social media for travel arrangements. In a multiple choices question about which social media is used, Facebook and Instagram are the mostly used platforms for both women (57% use Facebook and 53% use Instagram) and men (33% use Facebook and 21% Instagram). Twenty percent of men are also interested in job-related social media such as LinkedIn, while 25% of women are more interested in inspirational image-based platforms such as Pinterest.

Acknowledging the amount of shared information on social media platforms today and the current growth rate of social media users, the following sections discuss the gender differences in social media use for planning an activity and for making travel arrangements in an urban environment.

#### 3.4.2.1 Applied methods

The statistical analysis of the responses was carried out using non-parametric tests which are regarded as particularly powerful for analyzing data collected through questionnaire surveys (Park, 2009; Siegel & Castellan, 1988). Specifically, chi-square test for homogeneity

( $\chi^2$  test) was used to test differences in characteristics measured by categorical variables. In total, nine categorical variables were examined. One variable that refers to the general use of social media, four variables that refer to reasons for social media use before an activity, three variables that are related to the influence of social media content on activity planning and the responses of variable “type of post that would mostly affect users’ travel arrangements” were compared through chi-square ( $\chi^2$ ) tests to detect any differences between the two genders. Furthermore, the Mann-Whitney two-sample U-test was performed to assess differences between the two genders of ordinal variables measured on the 5-point scale (1: never, 2: seldom, 3: sometimes, 4: often, 5: always). This scale was used as it increases the variance in the measurements and allows a greater differentiation in the results (Krosnick & Presser, 2009). The list of the tested variable is included in Table 3-7.

Table 3-7. List of tested variables before an activity

Variables	Type	Description
General use of social media	Categorical	Yes/No
Use of social media for:		
• activity planning	Categorical	Yes/No
• travel arrangements	Categorical	Yes/No
• searching information regarding an activity location and how to reach the destination	Categorical	Yes/No
• searching the appropriate transport mode and the public transport timetable	Categorical	Yes/No
Influence of ... on activity planning:		
• reviews and ratings	Categorical	Yes/No
• photos/ videos	Categorical	Yes/No
• proposed transport mode	Categorical	Yes/No
Influence of ... on activity planning:		
• reviews and ratings	Ordinal	1–5 <sup>a</sup>
• photos/ videos	Ordinal	1–5 <sup>a</sup>
• proposed transport mode	Ordinal	1–5 <sup>a</sup>
Post type that would mostly affect users’ travel arrangement:	Categorical	Multiple Choice

• a post by a famous person/ account that you follow		
• a sponsored post		
• a post by a designated account related to transport		
• other		
*1: never, 2: seldom, 3: sometimes, 4: often, 5: always		

### 3.4.2.2 Reasons for social media use before an activity

Results showed that women are more likely to use social media compared to men with the result being statistically significant. Table 3-8 shows the proportion of Women’s (W) and Men’s (M) positive responses applied to social media use for activity planning, travel arrangements, searching information regarding an activity location and how to reach the destination and searching the appropriate transport mode and the public transport timetable. Both genders indicate interest in receiving information from social media, more when planning an activity (94.5% for women and 87% for men) as compared to making travel arrangements (76.4% for women and 53.4% for men). Moreover, the responses were compared through chi-square ( $\chi^2$ ) tests to detect any effect of the gender on social media use. The fifth column of the table contains the test p-values that indicate the strength of the respective evidence. In this case, four out of five p-values are smaller than 0.05, thus, the null hypothesis for those four that asserts the two variables are independent of each other is rejected. The significant results show that the variables gender and social media use for activity planning, travel arrangements and searching the appropriate transport mode and the public transport timetable are associated with each other. Results showed that the percentages of positive responses of women are higher than men for all the examined variables and the differences were statistically significant to four out of five examined variables (p-value < 0.05). This finding indicates that women are keener than men on reaching out for information provided by social media. In the variable “Use of social media for travel arrangements”, the large chi-square statistic (45.006) and its small significance level (p < 0.05) indicate that it is very likely that these variables are dependent of each other. Thus, it is concluded that there is a relationship between gender and use of social media for travel arrangements.

Table 3-8. Summary of test results for comparisons between women and men regarding social media use

Variables		Proportion of positive responses (p)		p-value	Test parameters relation
		W	M	W vs M	
General use of social media	$\chi(1)=22.953$	94.3%	84.6%	< 0.05*	pW > pM

Use of social media for:					
• activity planning	$\chi(1) = 14.048$	94.5%	87%	< <b>0.05*</b>	pW> pM
• travel arrangements	$\chi(1) = 45.006$	76.4%	53.4%	< <b>0.05*</b>	pW> pM
• searching information regarding an activity location and how to reach the destination	$\chi(1)=2.950$	68.9%	63%	0.086	pW > pM
• searching the appropriate transport mode and the public transport timetable	$\chi(1)=13.741$	54.7%	41.1%	< <b>0.05*</b>	pW> pM
*statistically significant (p-value < 0.05)					

### 3.4.2.3 Influence of social media content on activity planning

The gender effect on the influence of social media content on activity planning was examined through three chi-square ( $\chi^2$ ) tests; one related to reviews and ratings, the second, to photos/videos and the last, to a proposed transport mode. The proportion of positive responses applied to the examined variables, by Women (W) and Men (M), are shown in Table 3-9. In all examined cases of social media content, respondents indicated influence on activity planning. Photos/videos seem to be slightly more influential (92.8% of women and 85.6% of men) than reviews and ratings (92.2% of women and 84.9% of men). Proposed transport mode by social media influences less than the previous contents, however, still in high proportions in both women (85.5%) and men (75.7%). The fifth column of Table 3-9 contains the test p- values that indicate the strength of the evidence of the effect of gender on social media content. Results showed that statistically significant differences were observed in all three variables. The significant results indicate that the influence of reviews and ratings, photos/ videos and proposed transport mode on activity planning are associated with gender. This finding is reasonable and supports the previous results, according to which women are more receptive to the information provided by social media.

Table 3-9. Summary of test results for comparisons between women and men regarding influence of social media on activity planning

Variables		Proportion of positive responses (p)		p-value	Test parameters relation
		W	M	W vs M	
Influence of ... on activity planning					
• reviews and ratings	$\chi(1) = 10.464$	92.2%	84.9%	< 0.05*	pW> pM
• photos/videos	$\chi(1) = 10.750$	92.8%	85.6%	< 0.05*	pW> pM
• proposed transport mode	$\chi(1) = 12.234$	85.5%	75.7%	< 0.05*	pW> pM
*statistically significant (p-value < 0.05)					

For the same variables, the participants were asked to rate on a 1–5 scale (1: never, 2: seldom, 3: sometimes, 4: often, 5: always) the frequency that social media use affects activity planning. Table 3-10 presents an overview of the average values (m), medians (mdn) and standard deviations (sd) of the three variables and the test results of the gender effect on the attributed ratings. Results are described through Mann-Whitney U statistic and p-value, indicating the strength of the respective evidence. Statistically significant differences between women and men were reported in all the examined variables. Table 3-10 shows that women rate higher than men all three contents (p-value<0.05). Photos/ videos influence more often both women (m = 3.47) and men (m = 3.00) than reviews and ratings (m = 3.21 for women and 2.94 for men). Both these contents influence more than proposed transport mode (m = 2.62 and 2.37 for women and men). It is concluded that social media content is more influential when providing visual information or feedback based on experience and less when the information is more formal, as in the case of a proposed transport mode.

Table 3-10. Influence of social media content on women’s and men’s decisions

Variables	Groups						Test parameters relation	W vs M	
	Women			Men				U	p-value
	m	mdn	sd	m	mdn	sd			
• reviews and ratings	3.21	3	1.217	2.94	3	1.373	$r_W > r_M$	51,934	0.047*

• photos/ videos	3.47	4	1.253	3.00	3	1.453	$r_W > r_M$	45,831	<b>0.000*</b>
• proposed transport mode	2.62	3	1.225	2.37	3	1.365	$r_W > r_M$	51,599	<b>0.037*</b>
m: average rating, sd: standard deviation, mdn: median, r: rating median. *statistically significant (p-value < 0.05)									

The participants responded about the most important criteria for their final decision regarding their activity choice. Specifically, Figure 3-3 shows the responses of women and men who could select more than one of the seven available criteria. The responses also include the separation of each gender in non- sustainable and sustainable mode users. The separation was done to check to what extent the parameters related to mobility (distance from home/ work, public transport accessibility, parking availability) affect the sustainable and non- sustainable mode users. The light orange and gray colors were used to show the responses of female and male sustainable mode users, respectively. The category of sustainable mode users includes the participants that use only sustainable modes for their daily commute. In this survey, public transport, cycling, and walking were considered as sustainable modes of transport. The category of non- sustainable mode users includes participants that use at least one non- sustainable mode of transport for their mobility (car or motorbike). In the context of this survey there was not any further separation of cars and motorbikes into conventional (gasoline or diesel powered) and green types (electric, hybrid etc.), thus all cars and motorbikes were considered as non-sustainable modes of transport.

The results showed that the final decision of both women and men is affected more by a positive review or low cost of an activity, compared to the distance from home/ work or the trending activities on social media. Both cost and accessibility to public transport, which is one of the top three criteria selected by women, showed to be more important to female sustainable mode users compared to female non-sustainable mode users. Parking availability affects more the non- sustainable mode users of both genders compared to sustainable mode users. However, in absolute numbers, parking availability is one of the least selected criteria.

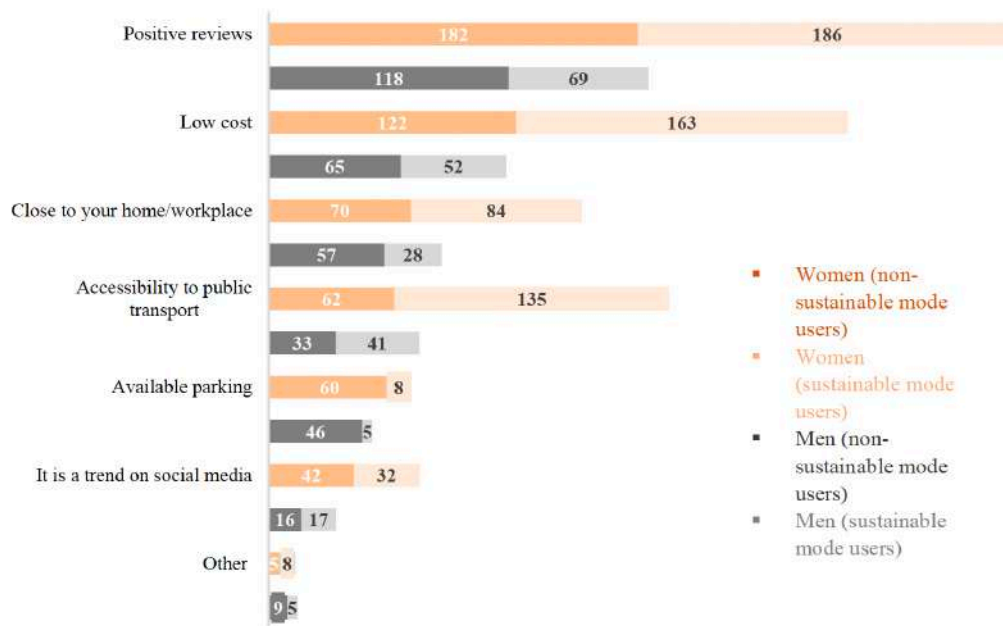


Figure 3-3. Number of responses in selecting the most important criteria for activity choice (per gender and mode user).

3.4.2.4 Influence of social media post on travel arrangements

This section includes the analysis of the responses that focused on the investigation of the influence of social media post on travel arrangements, as an engaging content affects peoples’ mobility decisions. Specifically, participants were asked what would mostly affect their travel arrangements, see Table 3-11. The p-value (0.051) is larger than 0.05 and consequently there is not enough evidence to conclude that the gender and type of post that would affect travel arrangements are associated. Most of the participants answered that a post by a designated account related to transport would affect the most their arrangements. The potential of social media as means for sharing transport information has been already indicated in research (Cottrill, et al., 2017). Respondents pointed out that the account behind social media post plays an important role on final decision regarding travel arrangements and is independent of gender. In general, social media users hardly trust information if they don’t know where it comes from. A sponsored post is harder to affect travel arrangements since social media users are more skeptical about the transparency and credibility of such content. Hence, it is a challenge to discern if the information is reliable or simply an advertisement (Stebbins, 2015). Results of a previous study showed that women are more inclined to trust the content on social media, perceiving information from others as more trustworthy than men (Warner-Søderholm, et al., 2018).

Table 3-11. Summary of test results on preferable social media type about traveling possibilities.

Variables				p-value W vs M	Test parameters relation

Categorical		W	M		
Type of content that would mostly affect users' travel arrangements:	$X(3) = 7.777$			0.051	
• a post by a famous person/ account that you follow		15.6%	6.5%		$p_W > p_M$
• a sponsored post		7.0%	4.6%		$p_W > p_M$
• a post by a designated account related to transport		40.4%	20.6%		$p_W > p_M$
• other		2.6%	2.7%		$p_W < p_M$

Furthermore, the participants were asked to select up to three most appealing approaches of this transport related post, from a given list of approaches, see Figure 3-4. Results showed that an informative or a humorous post would be more appealing for both genders compared to an emotional, encouraging, confronting or hard socking/ fear post. These findings are in line with previous literature in which the shortcomings of a fear-based messages (Hastings, et al., 2004) and the adverse results of other negative appealing messages such as shame or guilt (Brennan & Binney, 2010) have been pointed out.

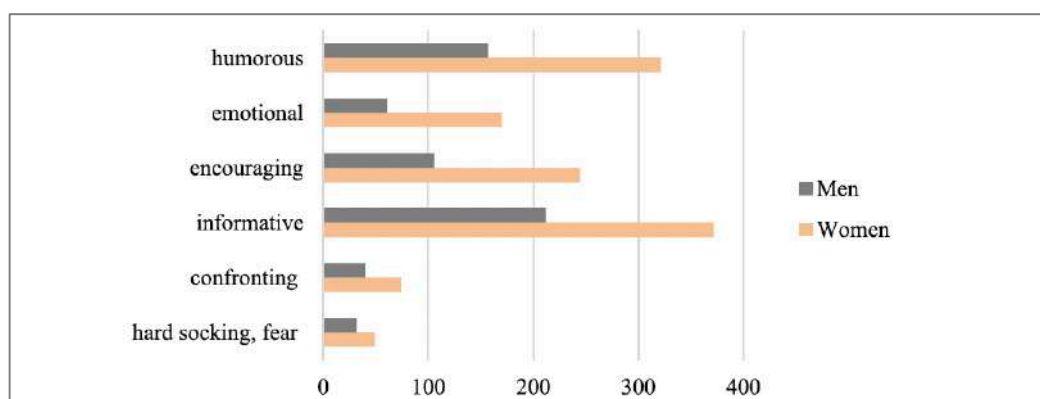


Figure 3-4. Most appealing approaches of transport related messages

### 3.4.3 Impact of users' characteristics and social media information on mobility decisions

Responses of the 738 participants that stated that they use social media for their activity and mobility planning, were used to formulate ordinal regression models. The developed models determine the contribution of users' demographic characteristics, travel characteristics



and social media usage to mobility decisions after using social media as a source of information. These decisions were expressed in two dependent variables; (i) the impact of social media use in activity and mobility planning; (ii) the impact of the proposed transport mode by social media information, on mode choice.

A preliminary analysis was done to identify the independent variables that were not highly correlated with each other, to be used in the same model. Multicollinearity arises when two or more independent variables in a model are highly correlated, meaning one can be linearly predicted from the others with a significant degree of accuracy. The potential for multicollinearity was assessed in the developed models by examining the correlation matrixes of the predictors. The correlation matrixes were employed to detect multicollinearity among the independent variables of the models. The matrixes provide a pairwise correlation coefficient for each pair of variables, allowing for quick identification of linear relationships. It was checked if two predictors have a correlation coefficient close to the extremes -1 and 1, or greater than 0.8, since this would suggest high multicollinearity, making them potentially redundant in the model.

The ordinal regression approach was chosen because it is more appropriate for data measured on a Likert scale compared to common statistical models which may simplify the collected data by assuming equal intervals between the scoring categories. Ordinal regression analysis, based on the cumulative-odds principle, treats the dependent variables as an ordered categorical variable (Stewart, et al., 2019; Gutiérrez, et al., 2016; Osborne, 2015; Hosmer, et al., 2013). The results of ordinal regression can be easily interpreted and are straightforward regarding the occurrence probability of an event. This method was also used in several studies and aims at identifying the strength of the effect that the independent variables have on a dependent variable (D'Ambra, et al., 2021; Booth, et al., 2019; van den Berg, et al., 2017).

The selection of the link function that would be more appropriate for the model is another important decision in the formulation of the ordinal regression models. Logit, Complementary log-log, Negative log-log, Probit and Cauchit are link functions that allow the estimation of the models. The selection of the link function depends on the distribution of the dependent variable values. Logit function is applied when the values are evenly distributed. The Complementary and Negative log-log are more suitable when the higher or the lower categories of the dependent variable are more probable, respectively. The Probit link function provides better predictions of the dependent variable when the responses are normally distributed. Finally, the Cauchit link function is mainly used when the dependent variable has many extreme values (Staus, 2008).

Two sets of four ordinal regression models were developed. For each dependent variable, the first model used as explanatory variables the demographic characteristics, the second considered the travel characteristics, the third implemented those characteristics regarding the social media usage, and the fourth comprised all variables. Table 3-12 includes a list of the examined variables and their abbreviations for a better understanding of the analysis.

Table 3-12. Abbreviations of the examined variables

<b>Variables</b>	<b>Abbreviation</b>
<b>Dependent Variables</b>	
Impact of social media use	ISMU

Variables	Abbreviation
Impact of the proposed transport mode based on information provided by social media	IPTM
<b>Explanatory Variables</b>	
<i>-Demographic characteristics</i>	
Gender	GEN
Age	AGE
Occupation	OCC
Country of residence	RES
<i>-Travel characteristics</i>	
Driver’s license	DL
Transport mode	TM
Public transport use	PTU
<i>-Social media usage</i>	
Days/week of social media use	DSMU
Average minutes of social media use	MSMU
Time of the day of social media use	TSMU
Supplementary source of information	SSOI
Help of social media use on the planning phase	HOSM

3.4.3.1 *Impact of social media use on activity/mobility plans*

The first developed model (Model I) examines the relationship between the impact of social media use (ISMU) on activity and mobility planning and the demographic characteristics.

Model I:  $(ISMU)=f (GEN,AGE,OCC,RES)$ , where GEN is the gender, AGE the age of participants, OCC the occupation and RES the country of residence. The research hypothesis 1 (H1) is that the demographic characteristics are good determinants of the impact of social media use on activity/mobility planning.

The second model investigates whether travel characteristics of participants are predictors of the impact of social media use on mobility/ activity plans.

Model II:  $(ISMU)=f (DL,TM,PTU)$ , where DL shows if the user holds a driver’s license, TM is the most preferred transport mode (sustainable or non-sustainable transport mode) and PTU depicts the use of public transport. The second research hypothesis (H2) is that the travel characteristics are good determinants of the impact of social media use on activity/mobility planning.

The third model includes as independent variables the participants’ responses that are related to social media use.

Model III:  $(ISMU)=f(DSMU,MSMU,TSMU,SSOI,HOSM)$ , where DSMU is the days per week that a participant uses social media, MSMU the average minutes spending when using a social platform, TSMU the time of the day that a participant uses more frequently social media. SSOI is the use of a supplementary source, except for social media for better mobility/activity planning and HOSM is related to the respondents' statement regarding the overall help of social media use on the planning phase. The third research hypothesis (H3) is that characteristics related to social media use predict the impact of social media use on activity/mobility planning.

The fourth model includes all the independent variables of the previous models.

Model IV:

$$(ISMU)=f(GEN,AGE,OCC,RES,DL,TM,PTU,DSMU,MSMU,TSMU,SSOI,HOSM)$$

The fourth research hypothesis (H4) is that the impact of social media use on activity/mobility planning is predicted by all the characteristics.

To decide which link function gives good fits for the examined data, the distribution of values for the outcome variable was examined based on the histogram for the dependent variable. Based on (Staus, 2008) the Logit link function was selected to run the ordinal regression analysis of our models, since the middle category of the dependent variable was more probable. The higher and lower categories recorded less responses (see Figure 3-5).

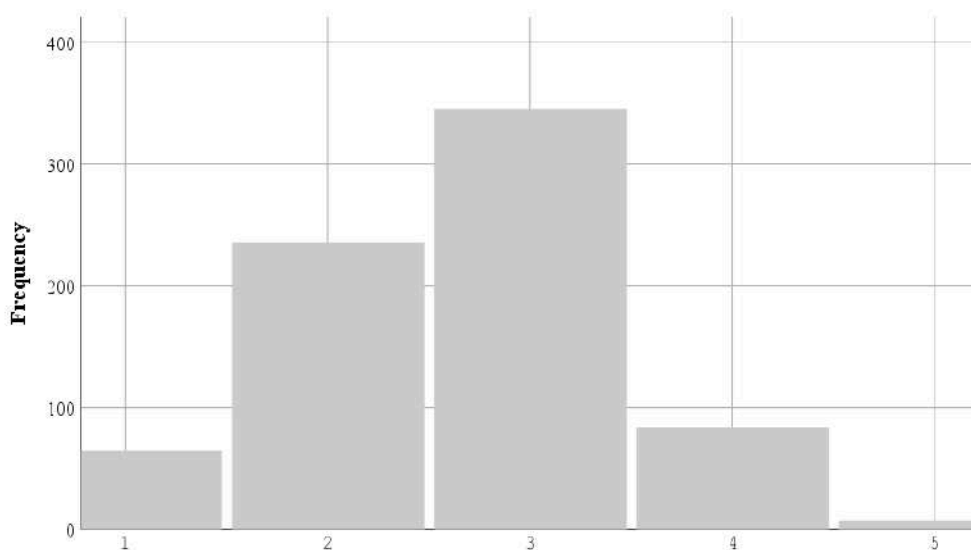


Figure 3-5. Histogram of impact of social media use in activity and mobility planning

As there were cells with zero frequencies, the interpretation of fit statistics is difficult to be done and thus chi-square based fit statistics had to be evaluated very carefully.

The Model Fitting Information of the four models were examined to find out if the models give adequate predictions. The significant chi-square statistic (Sig.=0.000) indicates that Models III and IV give a significant improvement over the baseline intercept-only model. Model I (Sig.=0.304>0.0005) and Model II (Sig.=0.119>0.0005) do not give adequate and better predictions than those we could infer from the marginal probabilities for the outcome categories.

The Goodness- of- Fit includes the Pearson's chi-square statistic of a model and a chi-square statistic based on deviance. Large significant values show that the observed data and the

model predictions are similar. However, the Model Fitting Information and the Goodness-of-Fit statistics are not appropriate when estimating models with continuous covariates, since they are too sensitive to empty cells (Spais & Vasileiou, 2006). Due to the existence of empty cells in the current study, it is uncertain if these statistics follow the chi-square distribution and the significant values could be inaccurate. For this reason, the pseudo R-squares ( $R^2$ ) were used to assess the overall goodness of fit of the four models. In ordinal regression models, the pseudo  $R^2$  are based on likelihood ratios. The following three methods are used to estimate the coefficient of determination. A generalization of the measure designed to apply when maximum likelihood estimation is used as with ordinal regression is Cox and Snell's  $R^2$  (Cox & Snell, 1989). Nagelkerke  $R^2$  (Nagelkerke, 1991) modifies the index to take values from 0 to 1. The log-likelihood ratio of McFadden  $R^2$  (McFadden, 1973) is one minus the ratio of the full-model log-likelihood to the intercept-only log-likelihood. A low  $R^2$  indicates that the model is likely to be a poor predictor of the outcome for any user.

Table 3-13 indicates that Model IV, including all explanatory variables, predicts better the impact of social media use on the participants' activity/mobility plans than the rest three models. Also, Model III, which includes the participants' social media usage characteristics, predicts better the impact of social media use on activity/mobility plans compared to Model I, which includes the demographic characteristics, and Model II, which includes the travel characteristics. Models III and IV have demonstrated higher values of Nagelkerke  $R^2$  than previous research (Milioti, et al., 2019).

Table 3-13. Pseudo R- squares of Models I, II, III and IV

	<b>Model I</b>	<b>Model II</b>	<b>Model III</b>	<b>Model IV</b>
Cox and Snell	0.016	0.014	0.176	0.204
Nagelkerke	0.017	0.015	0.193	0.223
McFadden	0.006	0.006	0.079	0.093

For the four models, the test of parallel lines compares the estimated model with one set of coefficients for all categories to a model with a separate set of coefficients for each category. The Null Hypothesis refers to the constrained model, which assumes that the lines are parallel. If the lines are parallel, the observed significance level for the change should be large, since the general model does not improve the fit very much. In the four models, the null hypothesis that the lines are parallel is not rejected since Sig. >0.05 in all models. If Sig. <0.05 then the null hypothesis would be rejected which means that the selected link function is incorrect or the relationships between the independent variables and logits are not the same for all logits.

The parameter estimates for Model IV are given in Table 3-14 and are the core of the output that shows the relationship between the explanatory variables and the outcome. The column "Estimate" contains the logit regression coefficients. The last category of each input variable was used as reference value and due to the zero values are not included in the table. The significance values that are less than 0.05, suggesting that their observed effect is not random.

Participants who are younger than 18 years old are less likely to change their mobility plans based on social media information than older participants. An explanation regarding this

finding could be related to the fact that this group is more dependent on other members of the household for their travel needs compared to older participants. Furthermore, students and full-time employees are more likely to change their plans after social media use compared to others. The rare public transport use and the minimum time spent on social media has a negative impact on changing mobility plans after using social media as a source of information. According to the results, participants who stated that social media do not help them with the mobility-planning phase have a decreased probability to change their mobility plans upon social media use.

Table 3-14. Parameter estimates for Model IV

Input Variable	Estimate	Sig.
<b>GEN</b>		
Female	-0.077	0.641
<b>AGE</b>		
<18	-1.524	<b>0.036</b>
18-25	-0.179	0.643
26-35	-0.160	0.627
36-45	0.067	0.851
<b>OCC</b>		
Student	2.639	<b>0.037</b>
Part- time job	2.254	0.077
Full- time job	2.584	<b>0.038</b>
Unemployed	2.071	0.109
<b>RES</b>		
Greece	-0.126	0.482
<b>DL</b>		
Yes	0.106	0.600
<b>TM</b>		
Sustainable transport mode users	-0.102	0.562
<b>PTU</b>		
Never	0.085	0.810
Seldom	-0.515	<b>0.038</b>
Sometimes	0.231	0.376
Often	-0.100	0.634
<b>DSMU</b>		
Everyday	0.449	0.612
5-6	0.308	0.542
4-3	0.270	0.562
2-1	-0.542	0.071
<b>MSMU</b>		
0-5	-0.558	<b>0.030</b>
6-15	-0.364	0.117
16-30	-0.284	0.251
31-60	-0.251	0.390

Input Variable	Estimate	Sig.
<b>TSMU</b>		
07:00-12:00	-0.267	0.503
12:00-14:00	-0.390	0.390
14:00-17:00	-0.492	0.212
17:00-00:00	-0.337	0.327
<b>SSOI</b>		
Yes	-0.267	0.304
<b>HOSM</b>		
Never	-3.973	<b>0.000</b>
Seldom	-2.960	<b>0.000</b>
Sometimes	-1.910	<b>0.000</b>
Often	-0.954	<b>0.001</b>

3.4.3.2 *Impact of proposed transport mode based on information provided by social media on mode choice*

The next four models were developed to explore the relationship among the impact of the proposed transport mode based on information provided by social media (IPTM) on users’ final decision and the i) demographic characteristics ii) travel characteristics iii) social media usage. The dependent ordinal variable was measured on a 5-point scale (Never 1, Seldom 2, Sometimes 3, Often 4, Always 5) and according to descriptive statistics, the mean value was 2.86 (SD= 1.058).

The fifth developed model (Model V) examines the relationship between the impact of the information provided by social media regarding a transport mode on mode choice and the demographic characteristics.

Model V:  $(IPTM)=f (GEN,AGE,OCC,RES)$ . The fifth research hypothesis (H5) is that each of the demographic characteristics is a good determinant of the impact of the proposed transport mode on mode choice.

The next model investigates whether travel characteristics of participants can predict the impact of the proposed transport mode based on information provided by social media on mode choice.

Model VI:  $(IPTM)=f (DL,TM,PTU)$ . The sixth research hypothesis (H6) is that each of the users’ travel characteristics is a good determinant of the impact of the proposed transport mode on the final decision.

The seventh model includes as independent variables the participants’ responses that are related to social media use. The research hypothesis (H7) is that each of the users’ characteristics that are related to social media use predicts better the impact of the proposed transport mode on mode choice.

Model VII:  $(IPTM)=f (DSMU,MSMU,TSMU,SSOI,HOSM)$

The final model includes all the independent variables of the above-mentioned models.

The last research hypothesis (H8) is that the impact of the proposed transport mode based on information provided by social media on mode choice is predicted by all the characteristics.

Model VIII:

$$(IPTM)=f (GEN,AGE,OCC,RES,DL,TM,PTU,DSMU,MSMU,TSMU,SSOI,HOSM)$$

The Logit link function was selected to run the ordinal regression analysis of the models since the responses were evenly distributed (see Figure 3-6). Cells with zero frequencies were detected for these models too. The Model Fitting Information of the four models were examined to find out if the models give adequate predictions. The significant chi-square statistics indicate that all the four models give a significant improvement over the baseline intercept-only model. The pseudo R- squares ( $R^2$ ) were used to assess the overall goodness of fit of the four models.

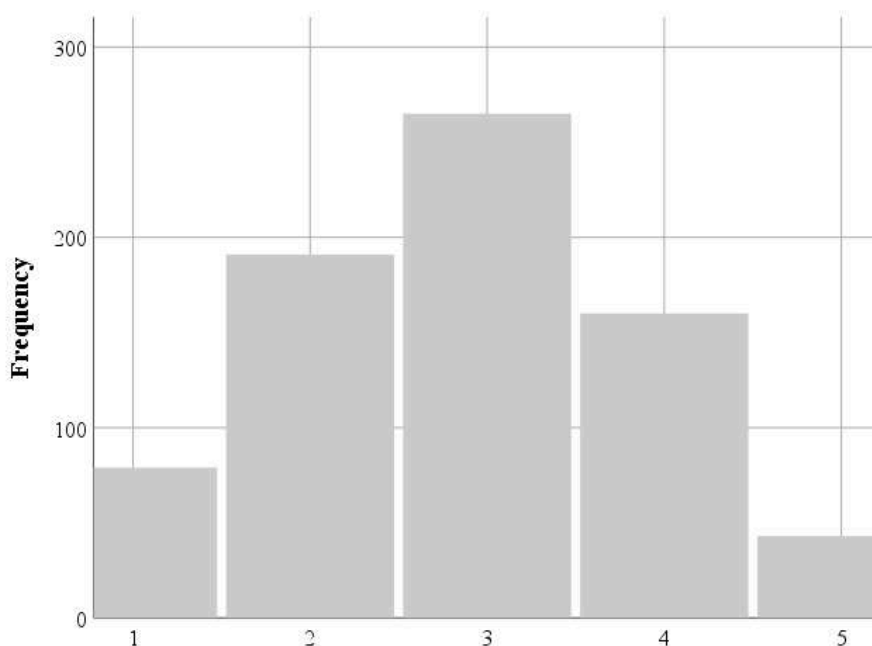


Figure 3-6. Histogram of impact of the proposed transport mode by social media information, on mode choice

According to Table 3-15, the last model predicts better the impact of the proposed transport mode based on information provided by social media on mode choice. More analytically, the demographic (Model V) and travel (Model VI) characteristics of a user and the social media usage (Model VII) cannot predict the impact of the proposed transport mode on activity/mobility plans as well as the last model (VIII) does, where all the characteristics are considered. A close Nagelkerke  $R^2$  value to a relevant study was achieved for Model VIII (11).

Table 3-15. Pseudo R- squares of Models V, VI, VII, and VIII

	Model V	Model VI	Model VII	Model VIII
Cox and Snell	0.027	0.040	0.131	0.171
Nagelkerke	0.028	0.043	0.128	0.181

	Model V	Model VI	Model VII	Model VIII
McFadden	0.009	0.014	0.048	0.064

For the four models, the test of parallel lines showed that the proportional odds assumption has been held, as all the Sig. values were higher than 0.05. The parameter estimates for Model VIII are given in Table 3-16. These parameters show the relationship between the explanatory variables and the outcome. Significance values less than 0.05 were observed in DL, PTU and HOSM independent variables. More specifically, participants that hold a driver’s license are less likely to change their mobility plans based on social media information about a proposed transport mode. Furthermore, respondents that use public transport rarely or sometimes are less likely to change their mobility plans compared to those who use public transport always. As expected, the proposed transport mode has a significantly high negative impact on participants who stated that social media never help them with the mobility-planning phase compared to those who stated that social media always help them. It is noted that the absolute values of the parameter estimates for HOSM are decreasing as the ordinal scale increases. This finding is in line with previous researches who stated that respondents who rate highly the social media use are more likely to change their trip plans based on the information provided on social media (Milioti, et al., 2019).

Table 3-16. Parameter estimates for Model VIII

Input Variable	Estimate	Sig.
<b>GEN</b>		
Female	-0.115	0.462
<b>AGE</b>		
<18	-0.964	0.165
18-25	0.130	0.724
26-35	-0.079	0.802
36-45	-0.005	0.988
<b>OCC</b>		
Student	-0.854	0.452
Part- time job	-0.792	0.489
Full- time job	-0.713	0.523
Unemployed	-0.196	0.866
<b>RES</b>		
Greece	0.306	0.072
<b>DL</b>		
Yes	-0.443	<b>0.022</b>
<b>TM</b>		
Sustainable transport mode users	-0.131	0.436
<b>PTU</b>		
Never	-0.588	0.080
Seldom	-0.917	<b>0.000</b>
Sometimes	-0.518	<b>0.024</b>



Input Variable	Estimate	Sig.
Often	-0.325	0.105
<b>DSMU</b>		
Everyday	0.615	0.467
5-6	0.534	0.267
4-3	0.639	0.149
2-1	-0.085	0.767
<b>MSMU</b>		
0-5	-0.215	0.379
6-15	-0.312	0.157
16-30	-0.314	0.181
31-60	-0.396	0.154
<b>TSMU</b>		
07:00-12:00	-0.010	0.978
12:00-14:00	0.072	0.869
14:00-17:00	0.250	0.506
17:00-00:00	0.297	0.364
<b>SSOI</b>		
Yes	-0.154	0.533
<b>HOSM</b>		
Never	-3.058	<b>0.000</b>
Seldom	-2.113	<b>0.000</b>
Sometimes	-1.328	<b>0.000</b>
Often	-0.542	<b>0.040</b>

### 3.5 Social media use during an activity/trip

#### 3.5.1 Comparison of social media use before and during an activity

Based on the Travel Decision Making Model (Mathieson & Wall, 1982), and its adaptation by Dwityas & Briandana (2017), users could be affected both before and during an activity. Social media content can cause changes to users’ travel arrangements before and during the activity occurrence. Table 3-17 presents an overview of the average rating and standard deviation of the two variables and the test results of the comparisons between men and women. Results are described through U and p-value. Social media use affects the travel arrangements of both genders before and during an activity with almost the same frequency (before: m= 3.48 for women, m= 3.5 for men, during: m= 2.86 for women, m= 2.84 for men). Changes to travel arrangements after social media use before an activity can occur more often for both women (m = 3.48) and men (m = 3.50) than during an activity (m = 2.86 and m= 2.84 for women and men). Changes to travel arrangements during the activity occurrence may happen due to changes in public transport timetable, unpredictable events, or changes of next activity’s plans, hence, it is not so probable compared to changes before an activity, when someone seeks the information to make his/ her final decision. As Dwityas & Briandana (2017)

stated in their research, before an activity the user collects plenty of information regarding the activity and gets a precise set of data as a basis for right decision-making.

Table 3-17. Summary of test results for comparisons between changes to travel arrangements before and during an activity

Parameters	Groups						Test parameters relation	W vs M	
	Women			Men				U	p-value
	m	mdn	sd	m	mdn	sd			
• Changes to travel arrangements <b>after</b> social media use before an activity	3.48	4	0.669	3.50	4	0.619	$r_W < r_M$	21,090	0.983
• Changes to travel arrangements after social media use <b>during</b> an activity	2.86	3	0.690	2.84	3	0.647	$r_W > r_M$	22,592	0.926

m: average rating, sd: standard deviation, mdn: median, r: rating median.  
 \*statistically significant (p-value < 0.05)

To detect any difference between the before (B) and during (D) phases of an activity, five variables were compared through chi-square ( $\chi^2$ ) tests. The examined variables are related to the social media use for information searching and the impact of it on the final decision. Table 3-18 shows the proportion of positive responses between the two phases.

Results showed statistically significant differences in three out of five relative variables. More specifically, the variable that addresses the use of social media for searching the appropriate transport mode and the timetable of public transport shows that more commuters search this information before their activity rather than during (p<0.05). The participants responded that parts or all of their activity plans are affected more by social media use before the activity compared to social media use during the activity. (p<0.05). Social media users search information regarding the activity location and instructions of how to reach the destination, more likely during the activity occurrence and not before it, with the results being statistically significant.

Table 3-18. Summary of test results for comparisons between social media use before and during an activity

Variables		Proportion of positive responses		p- value	Test parameters relation
		B	D	B vs D	
<i>Categorical</i>					
<b>Use of social media:</b>					
for activity planning	$\chi(1)=1.281$	91.8%	91%	0.258	$p_B > p_D$
for searching information regarding an activity location and how to reach the destination	$\chi(1)=7.490$	83.7%	88.4%	<b>&lt;0.05*</b>	$p_B < p_D$
for searching the appropriate transport mode and the public transport timetable	$\chi(1)=44.004$	66.8%	50.5%	<b>&lt;0.05*</b>	$p_B > p_D$
<b>Impact of:</b>					
Social media use to all or parts of activity plans	$\chi(1)=18.631$	49.8%	39.1%	<b>&lt;0.05*</b>	$p_B > p_D$
<b>Help of social media on activity planning</b>	$\chi(1)=0.901$	89.6%	88.1%	0.343	$p_B > p_D$
*statistically significant ( $p\text{-value} < 0.05$ )					

### 3.5.2 Impact of social media during an activity and shared content

The impact and use of social media during an activity or trip have been studied the collection of data on the frequency of social media use during an activity or trip, the changes made to the activity after using social media content, the type of activity, and the ways in which social media is used during the activity/trip. Additionally, the participants' perception of the usefulness of social media during the trip was assessed.

The results showed that a considerable number of participants (37.3%) sometimes used social media platforms to obtain information related to their activity, while 27.9% often used social media. A smaller proportion of participants reported never (9.8%), seldom (15.7%), or always (9.3%) using social media during their activity. The mean score for social media use during the activity was 2.89, with a standard deviation of 1.091. The following parameters in Table 3-19 refer to the 725 participants who use social media during an activity/trip (the 9.8% of participants that answered never in the first presented question are excluded).

Regarding changes made to the activity after using social media content, 50.8% of participants reported sometimes making changes, while 34.3% reported seldom making changes. Only 1.9% of participants reported never making changes, while 11.7% of participants reported often making changes. The mean score for changes made to the activity after using social media content was 3.24, with a standard deviation of 0.729.

The survey also assessed the type of activity, and the results showed that most participants (64%) used social media for travel arrangements, followed by entertainment (78%) and business/job (22%). The ways in which social media was used during the activity/trip varied, with 48% of participants searching for uploaded photos/videos, 33% planning the next activity, 56% searching for the location of the next activity and how to reach there, and 43% searching for the appropriate transport mode to get to the new location/searching the timetable in case of public transport.

Finally, the survey aimed to assess the participants' perception of the usefulness of social media during the trip, and the results showed that 32.7% of participants often found social media helpful, while 37.5% found it helpful sometimes. Only a small proportion of participants reported never (2.37%) or always (13.8%) finding social media helpful during their trip. The mean score for the usefulness of social media during the trip was 3.31, with the standard deviation of 1.067.

Table 3-19. Impact of social media use during an activity/trip

Variables	Level	%
Do you use social media platforms during your activity to get any sort of information for it?	Never	9.8
	Seldom	15.7
	Sometimes	37.3
	Often	27.9
	Always	9.3
	Mean=2.89, SD=1.091	
Do you make changes to all or part of your activity after using the content provided on social media?	Never	1.9
	Seldom	34.3
	Sometimes	50.8
	Often	11.7
	Always	1.2
	Mean=3.24, SD=0.729	
In continuation to the above question, what is the type of the activity		
Travel arrangements	Yes	64
	No	36
Entertainment	Yes	78
	No	22
Business/ Job	Yes	22

Variables	Level	%
	No	78
How do you use social media during your activity/trip?		
Search uploaded photos/videos	Yes	48
	No	52
Plan your next activity	Yes	33
	No	67
Search the location of the next activity you are going to visit after and how to reach there	Yes	56
	No	44
Search the appropriate transport mode to get to the new location/ search the timetable in case you choose public transport	Yes	43
	No	57
Do you consider social media help you during your trip?	Never	2.37
	Seldom	13.7
	Sometimes	37.5
	Often	32.7
	Always	13.8
	Mean=3.31, SD=1.067	

The extent to which participants engage in sharing information on social media during their activity or trip is also investigated. Results revealed that 17.2% of participants often and 34.8% sometimes post information on social media during their activity or trip, while 14.8% of participants never do so. Additionally, the mean score for this behavior was 2.58, with a standard deviation of 0.967, indicating that the frequency of posting information on social media during an activity or trip varies among participants.

The social media platforms used for posting information during activities or trips are also examined. Results showed that most participants used Instagram (61%) and Facebook (52%) for this purpose, while only 3% used Twitter. Interestingly, some participants did not use any social media platform for posting information during their activity or trip.

Furthermore, the study explored the types of information shared on social media during activities or trips. Findings showed that the most common type of information shared was photos/videos (76%), followed by stories (49%) and posts with comments (27%). Additionally, a smaller proportion of participants shared check-ins (25%), shared posts (9%), and walking/running route maps (4%).

Table 3-20. Social media content shared during an activity/trip

Variables	Level	%
Do you post any information on social media during your activity/trip?	Never	14.8
	Seldom	28.6
	Sometimes	34.8
	Often	17.2
	Always	4.7
		Mean=2.58, SD=0.967
Which social media platform do you use for this posting?		
Facebook	Yes	52
	No	48
Instagram	Yes	61
	No	39
Twitter	Yes	3
	No	97
What kind of information do you post		
Photos/videos	Yes	76
	No	24
Posts with comments	Yes	27
	No	73
Stories	Yes	49
	No	51
Check-ins	Yes	25
	No	75
Share posts	Yes	9
	No	91
Walking/running route maps	Yes	4
	No	96

### 3.6 Social media use after an activity/trip

In this section it is explored how individuals provide feedback or write reviews of their experiences on social media, the frequency with which they do so, and the platforms they use. Additionally, it is examined whether individuals are more likely to provide feedback upon positive, negative, or neutral experiences, and the types of information they share in their posts.

The results indicate that 83.5% of individuals provide feedback or write reviews on social media after their experiences. Of these, 16.5% always provide feedback, while 5.8% never provide feedback. The mean frequency of providing feedback was 3.28 with a standard deviation of 1.121. When examining the likelihood of providing feedback upon positive, negative, or neutral experiences, we found that individuals were most likely to provide feedback upon positive experiences (81%), followed by neutral experiences (78%), and negative experiences (49%).

Regarding the platforms used for providing feedback, most individuals (67%) used Facebook, while 49% used Instagram. Only 5% used Twitter. When asked about the types of information shared in their posts, 73% of individuals shared photos or videos, while 43% shared posts with comments. Only 39% wrote reviews, 36% provided ratings, and 34% shared stories. The parameters in Table 3-21 refer to the 671 participants who use social media after an activity/trip to give feedback about their experience (the 5.8% of participants that answered never in the first presented question are not included).

The findings demonstrate that individuals are more likely to provide feedback on social media upon positive or neutral experiences compared to negative experiences. Although individuals are deeply influenced by negative reviews, they are more inclined to share positive moments on social media by sharing photos and videos after having a satisfactory experience. When it comes to posting reviews, they're compelled more by negative experiences. This dual behavior suggests that people use social media to predominantly share and amplify positive experiences within their networks but resort to reviews primarily to express dissatisfaction. This suggests that individuals may use social media to share positive experiences with their social networks, while avoiding negative experiences. Additionally, the results highlight the importance of visual content, with most individuals sharing photos or videos in their posts. Finally, the findings indicate that Facebook and Instagram are the most popular platforms for providing feedback and writing reviews.

Table 3-21. Social media use after an activity/trip

Variables	Level	%
Once your activity is over, do you provide feedback (i.e photos, posts etc.) and/or write a review of your experience	Never	5.8
	Seldom	18.7
	Sometimes	33.8
	Often	25.1
	Always	16.5
		Mean=3.28, SD=1.121

Variables	Level	%
Do you provide feedback (i.e photos, posts)/ review upon a:		
Negative experience	Yes	49
	No	51
Neutral experience	Yes	78
	No	22
Positive experience	Yes	81
	No	19
Which social media platform do you use for this feedback (i.e photos, posts)/review?		
Facebook	Yes	67
	No	33
Instagram	Yes	49
	No	51
Twitter	Yes	5
	No	95
What kind of information do you post		
Photos/videos	Yes	73
	No	27
Posts with comments	Yes	43
	No	57
Reviews	Yes	39
	No	61
Ratings	Yes	36
	No	64
Stories	Yes	34
	No	66
Share posts	Yes	10
	No	90



### 3.7 Concluding discussion

During the last years there has been an increased usage of social media platforms when planning an activity which denotes the high intrusion rates of such platforms in our social lives. Decisions of almost nine out of ten individuals who use social media are affected on “what to do” (activity plans), while almost 75% of women and 50% of men are affected on “how to do it” (travel arrangements of the activity).

Social media content and interaction with other users has intensified changes in users’ activity and mobility plans by setting a new framework for travel behavior. Based on ordinal regression analysis, the current study explored (i) the impact of social media use on activity and mobility planning and (ii) the impact of the proposed transport mode based on information provided by social media on mode choice. According to models’ results, participants under 18 years old are not likely to adjust their activity and mobility plans based on social media information as compared to older users. On the contrary, students and full-time employees have an increased probability to change their plans based on information provided by social media. Respondents who seldom or sometimes use public transport are affected less by social media information as related to the proposed transport mode compared to those who always use public transport. Finally, participants that stated that social media always help them with their activity and mobility planning are affected more by social media information.

Social media usage aspects are better associated with estimating their influence in activity and mobility planning and mode choice. Also, prediction power increases as more independent variables are considered. This is a direction to which future work should be oriented.

Moreover, the significant results showed that the variables gender and social media use for activity planning and travel arrangements are associated with each other. Results have also indicated that the influence of reviews and ratings, photos/ videos and proposed transport mode on activity planning is gender dependent. Consistent with previous studies, women are affected at a higher degree than men and are more receptive to the information provided by social media. Specifically, women reported that social media content such as reviews and ratings, often affect their activity planning decisions. Social media use affects travel arrangements of both women and men more before performing an activity rather than during. However, this is believed to change shortly, as usage rates of smart phones coupled with rich applications and mobile data services are increasing, allowing us staying more connected.

In conclusion, the use of social media platforms before, during, and after an activity or trip has a significant impact on individual behavior and decision-making. While social media can be a valuable source of information, it should be used in conjunction with other sources to ensure a successful trip or activity. Positive reviews, photos/videos, and proposed transport mode are influential factors in decision-making.

Travel arrangements of most respondents would be influenced by a post of a designated account related to transport. This finding is in line with previous studies, which showed that users trust in social media content is strongly related to who shares it and they are willing to share this information to others if it comes from an account they trust. Another useful conclusion stemming from this research, was that social media users selected informative transport related messages over other appealing approaches, when they are asked about the type of content that would mostly affect their travel choices. Although shocking related content is believed to have greater impact on getting our attention, informative messages seem to establish

a high-quality level of information shared on social media platforms, which could help transport authorities and decisions makers to adopt effective policies and promote awareness campaigns towards sustainable mobility.

Facebook and Instagram are the most used platforms for sharing personal experiences and activities, with photos and videos being the most common types of information shared. These findings have important implications for individuals and organizations seeking to leverage social media for personal and promotional purposes. During activities and trips, social media plays a significant role in providing information and guiding decisions. Social media content can influence travelers' decisions and behavior, indicating the potential impact of social media on travel-related decision-making. Transportation services can leverage social media platforms to reach and engage with commuters. After an activity or trip, individuals are more likely to provide feedback on social media upon positive or neutral experiences compared to negative experiences. Visual content, such as photos and videos, is crucial for feedback posts. Facebook and Instagram are the most popular platforms for providing feedback and writing reviews.

The survey sheds light on the significant role of social media in the decision-making process of individuals before, during, and after their activities and trips. It highlights that social media is a popular platform for sharing personal experiences and activities, with Facebook and Instagram being the most commonly used platforms. The study emphasizes the importance of managing the online presence of designated transport related accounts to attract and affect travelers' decisions. The findings also suggest that social media can play a vital role in promoting sustainable urban mobility, as it is an effective way to reach many people and spread awareness and transport-related information. Future research can further explore the potential impact of social media on travelers' experiences and behaviors and how to leverage social media to enhance sustainable urban mobility.

Future work should investigate how the impact of social media on mobility decisions is affected by other factors such as the trip purpose and the commuter type. A recommended framework to set up a campaign or to share transport related information on social media towards sustainable urban mobility is of great importance. Focus should be given on a strategical approach for social media use in producing a reliable network of communication with users about their daily trips. A challenge of using social media as a supporting tool is the constant development of them, which requires staying abreast of every new change. Privacy concerns continue to be a threat to social media use, and it is still unknown to what extent and how these security issues will affect the way that people use social media. Moreover, a clear understanding of gender differences on users' information-sharing behavior could contribute to promoting travel services more efficiently.

## **4 Harnessing social media content for enhancement and effective promotion of sustainable urban mobility**

Social media are online communities where people share information, experiences and connect with other users. The use of these platforms is not limited to the exchange of thoughts and content among the users. Social media can play a double role in urban mobility by both extracting and sharing information that can promote sustainable mobility. On the one hand, social media can be used as a tool for gathering information about urban mobility patterns, such as traffic congestion, public transport options, and cycling infrastructure. This information can be used by city planners, transportation engineers, and policymakers to design more sustainable mobility solutions. On the other hand, social media can represent opportunities for designated accounts and local authorities that can use them both to inform and engage proactively with users. The shared information on social media can reach quickly a larger audience compared to traditional media channels, however, the use of such technologies should be filtered, as there are cases in which the usability and the reliability of the gathered information is doubtful (CIVITAS, 2020). Moreover, social media platforms can facilitate communication and collaboration among citizens, businesses, and local governments, fostering partnerships that can lead to more sustainable mobility solutions. For instance, social media platforms can be used to organize community events, campaigns, or petitions that raise awareness about sustainable mobility and advocate for policy changes.

This chapter investigates the potential of social media use for collection of transport-related data and for promotion of sustainable mobility and share of information. In Section 4.3 data from Twitter are retrieved and processed to explore their potential for providing transport related data. Section 4.4 reviews and analyses previous campaigns and strategies related to sustainable urban mobility implemented in European countries and investigates to what extent social media have an impact on the mobility choices of people.

Chapter 4 is an extended and adapted version of the following publications:

*Pavlyuk Dmitry, Karatsoli Maria, Nathanail Eftihia, 2019. "Exploring the potential of social media content for detecting transport-related activities". In: Kabashkin I., Yatskiv (Jackiva) I., Prentkovskis O. (eds) Reliability and Statistics in Transportation and Communication. RelStat 2018. Lecture Notes in Networks and Systems, vol 68. Springer, Cham, [https://doi.org/10.1007/978-3-030-12450-2\\_13](https://doi.org/10.1007/978-3-030-12450-2_13)*

*Magginas Vissarion, Karatsoli Maria, Adamos Giannis, Nathanail Eftihia, 2019. "Campaigns and Awareness-Raising Strategies on Sustainable Urban Mobility". In: Nathanail E., Karakikes I. (eds) Data Analytics: Paving the Way to Sustainable Urban Mobility. CSUM 2018. Advances in Intelligent Systems and Computing, vol 879. Springer, Cham, [https://doi.org/10.1007/978-3-030-02305-8\\_32](https://doi.org/10.1007/978-3-030-02305-8_32)*

*Karatsoli, M., Nathanail, E. 2023. "Social Media and Urban Mobility Choices: How a Transport-Related Content Could Be Influential in Social Media.". In: Nathanail, E.G., Gavanas, N., Adamos, G. (eds) Smart Energy for Smart Transport. CSUM 2022. Lecture Notes in Intelligent Transportation and Infrastructure. Springer, Cham. [https://doi.org/10.1007/978-3-031-23721-8\\_67](https://doi.org/10.1007/978-3-031-23721-8_67)*

## 4.1 Introduction

The increase of traffic volumes and public transport use in modern cities makes important the optimization of the existing mobility systems. The continuous collection of traffic data is necessary for decision making, prediction of changes in a transport system as well as objective analysis of commuters' expectations and needs (Kuflik, et al., 2017). The wide spread of social media encourages the users to share more often their activities as well as their location, leading to a rapid growth of the data volume. This data is highly available for researchers and public, and this fact creates a potential for using them as a supporting tool for traffic-related decisions (Zheng, et al., 2016).

Several studies have investigated the use of social media for transport-related purposes, presenting various potential applications such as accident detection, transport planning and decision-making, human mobility analysis, and travel behavior (Steiger, et al., 2016). Social media users, particularly on Twitter, frequently share traffic information, providing broader coverage of traffic conditions compared to point sensors (Wang, et al., 2017). Twitter data has been shown to complement traditional collection methods (Kokkinogenis, et al., 2015; Zhang, et al., 2018), although tweets may contain errors, resulting in 60% useful content (Pearanalytics, 2010). Additionally, Twitter has limitations in retrieving real-time data (Salas, et al., 2017). Incidents can be detected earlier through social media users' accounts compared to official transport sources (Sakaki, et al., 2010). Various studies have shown the potential of using Twitter data for real-time incident detection, such as D'Andrea, et al. (2015), Gutiérrez, et al., (2015), Wanichayapong, et al. (2011), Gal-Tzur, et al. (2014), and Gu, et al. (2016), who employed different approaches such as classification and Natural Language Processing (NLP).

Mai & Hranac (2013) found a correlation between accidents mentioned on tweets and incident records, while Collins, et al. (2013) used Twitter keywords to identify users' dissatisfaction with specific metro lines. Twitter data has also been utilized for mobility analysis, with studies conducted by Krumm, et al. (2013), Hawelka, et al. (2014), and Jurdak, et al. (2015) estimating travel behavior, correlating tweet locations with socioeconomic characteristics of the population, and showing that tweets can be used similarly to mobile phone tracks, respectively. Additionally, Lenormand, et al. (2014) investigated the use of Twitter in European transport networks by comparing daily traffic reports with tweets. Overall, these studies highlight the potential of social media data as a source of information for transport stakeholders to better understand users' needs and improve transport management.

Cities are rapidly growing worldwide, and over 70% of people now live in urban areas. This trend has led to the development of Sustainable Urban Mobility Plans (SUMPs), which aim to support sustainable urban mobility schemes, such as soft modes, public transport, car-sharing, and carpooling systems (European Commission, 2013). To promote the adoption of these alternative modes of transport, marketing campaigns and awareness-raising strategies are necessary (City of Vancouver, 2016). Such campaigns typically involve defining objectives, identifying target groups, crafting messages, and evaluating results (Pressl & Kollinger, 2012). The explosive growth of social media use and its impact on how people interact with information has reshaped the way a campaign interacts with users and considering the amount of time being spent on them, a shift from traditional campaigns to campaigns on digital channels should be considered.

In transport planning, engagement of different stakeholders – so as to contribute to the decision-making process – is increasingly requested. Engagement and, thus participation within the transport planning process, not only empowers consultation and yields more representative and comprehensive results, but it also offers a sense of ownership to those who participate, increasing in this way a wider acceptance and understanding. Social media along with various other interacting technologies, i.e., Internet forums, social networks, e-magazines, rating, wikis, podcasts, photographs or pictures, video, social blogs, etc., have the capacity to increase engagement, while facilitating social interaction with the users, affecting in this way their daily decisions, and as per the scope of this article, their urban mobility decisions. This interaction is to be seriously considered, as it increases direct communication with citizens and it can provide valuable feedback, which can be used as an input back in the transport planning process.

Considering social media's crucial role towards creating, sharing, and exchanging ideas and information, this chapter provides also a comprehensive systematic literature review on exploring to what extent social media have an impact on the mobility choices of people and analyzes several transport related accounts/groups on social media platforms, based on their scope, type, content and engagement metrics, to reveal their impact.

## 4.2 Methodology

The following figure shows the chapter's methodological approach which is organized into two parts.

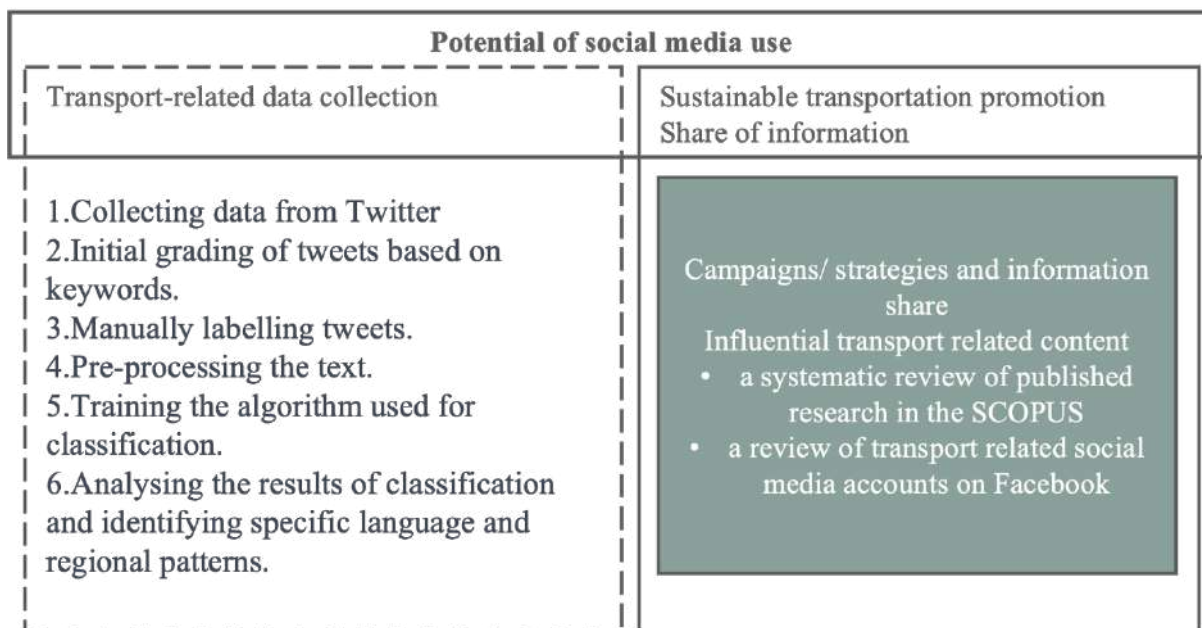


Figure 4-1. Methodological approach

The first part investigates the reliability of the transport related content retrieved from Twitter and the transferability of findings analytics methods to smaller other cities and other languages. Twitter was selected as a social media platform for the research experiment because of its widespread international usage and advanced automated access to source data through the Twitter Application Programming Interface (API). First, tweet data collection was conducted using the Twitter API. Each tweet was considered as a separate document, and collected information included (i) tweet submission date and time, (ii) message text, (iii) author's nickname, and (iv) geo-reference (if available). Preliminary grading was performed based on a predefined keyword list to identify potentially transport-related tweets. The preliminary grading of collected tweets enabled the identification of tweets that may be related to transport, which were then analyzed further. The authors created lists of transport-related keywords in English, Latvian, Russian, and Greek, based on the findings of Kuflik, et al. (2017). Each keyword was assigned a grade from 0 (not related to transport) to 5 (highly related to transport), depending on its relevance to transport (Annex D). Finally, each tweet was assigned a score based on the sum of its related keywords. A set of tweets was manually labelled for transport domain classes, including (i) general transport-related information, (ii) real-time transport-related information, (iii) transport-related complaints, (iv) transport-related advice/questions, and (v) unrelated tweets (Annex E). Data pre-processing was carried out to translate text data into machine-readable format using text mining techniques such as text stemming, removal of stop words, punctuation, numbers, and other uninformative symbols. The document-term matrix representation of corpuses was applied using a term frequency-based matrix, considering tf-idf (term frequency—inverse document frequency) as an alternative (Kuflik, et al., 2017; Khan, et al., 2017). Classification was conducted using three different techniques: Naive Bayes classifier, decision tree, and artificial neural network, separately examined for 4-class and 2-class cases. Evaluation of classifiers was performed with classical accuracy and Cohen's kappa metrics, cross-validated for 10 resampling iterations with a training sample size of 75% of the labelled tweets.

The second part includes the review and analysis of European campaigns and strategies addressing sustainable urban mobility. For each campaign/strategy, data were collected about

the country of implementation, the responsible organization, time period, scope (local, regional or national), target groups (general or specific), main objectives, theme, media plan (i.e. internet, brochures, local events) and type of approach (i.e. informative, positive, etc.). In those cases, that the campaign or strategy was evaluated, the research design, the data collection technique, and the evaluation outcomes (impacts) were also recorded.

Furthermore, a systematic review of published research in the SCOPUS database was performed to retrieve any record that is related to social media and urban mobility. Only records with an important and relevant contribution to the topic were kept. The selection of the SCOPUS database was made as it contains high-quality core journals and books with content depth related to social media and transport. The papers were screened following the PRISMA (PRISMA) guidelines (Liberati, et al., 2009).

In addition, a thorough review of transport-related social media accounts and content on Facebook was performed to retrieve relevant groups or pages. The selection of specifically, Facebook – and not of other popular online social networks – was decided as Facebook is the most used social networking site worldwide, with roughly 2.93 billion active users as of the first quarter of 2022 (Statista, 2022), covering the widest range of social media accounts' profiles. Another reason that Facebook was selected, was that it incorporates many different media aspects from photos, videos, links, and location sharing to status updates and messenger to text. The search strategy for the identification of the social media accounts to be included in the analysis did not follow any specific protocol, however, a consistent methodological approach was adopted; first, keywords associated to the research scope– based on authors' knowledge – were specified. The initial set of keywords was consisting of the following terms: Green Mobility, Urban Mobility, Sustainable Mobility, Sustainable Transportation. Second, a snowball sampling type search was performed in the following way: for any identified social media group or page addressing the research scope, relevant recommended pages or groups were visited to check their content and their relevance. From the second step, only groups and pages whose last post was in 2021 or later were kept, to ensure that only active accounts are considered. Groups and pages in any other language other than English and Greek were left out. Beyond the latter, not any other filter or exclusion criteria were applied.

It is noted that in public groups, anyone can add himself/herself as a member without any invite or approval. Thus, the name of the group, location, member list and posts can be shown up in the group's member News Feed. On the contrary, a page is a public profile aiming at promoting the account publicly. A user of Facebook can either like or follow a page.

### **4.3 Social media content for detection of transport-related activities**

In this section, the potential of Twitter as a source of transport-related data is examined by retrieving and processing data. The aim of this research is to assess the reliability of transport-related content obtained from tweets and the applicability of analytical methods in different cities and languages. The study gathered data from thousands of tweets in three cities: Minneapolis-Saint Paul twin cities (USA), Riga (Latvia), and Volos (Greece) during May-June 2018. The selection of these cities was based on their significant differences in terms of population, language, and transport infrastructure. The collected data were classified into five categories, including: (i) general transport-related information, (ii) real-time transport-related information, (iii) transport-related complaints, (iv) transport-related advice/questions, and (v) unrelated tweets. Based on the results, a cross-comparison was made to determine the efficiency of Twitter as a social media source of transport-related information in various urban settings.

According to Kokkinogenis, et al. (2015), Twitter has gained popularity among social media users due to the 140-character limit on tweets, which makes it easy to consume retrieved information. Twitter users often share information on traffic conditions and incidents as well as their opinions and complaints about transport services (Salas, et al., 2017; Rusitschka & Curry, 2016; van Oort, et al., 2015).

### 4.3.1 Data description

This research collected tweets from three cities, Minneapolis-Saint Paul twin cities (USA), Riga (Latvia), and Volos (Greece), between May 22 and June 1, 2018. The selection of these cities reflects the main research question, which is whether methodologies successfully applied in monolingual English-speaking areas can be used for the analysis of social media data in smaller English-speaking (Minneapolis-Saint Paul), non-English speaking (Volos), and multilingual (Riga) environments.

The first study area, Minneapolis-Saint Paul, has a population of 3,600,618 residents and is in east central Minnesota with two urban central business districts. The region has a multi-modal transportation network that includes a Metro Transit bus fleet with over 100 routes, two light rail lines, commuter and intercity rail service, bus rapid transit on city arterials, bicycle trails, and car share services (U.S. Department of Transportation, 2016). According to the Texas A&M University Transportation Institute, the region is one of the least congested major metropolitan areas in the US (Schrank, et al., 2015).

The second study area, Riga, has a population of 641,423 residents, and the road network consists of 1,778 streets with a total length of 1,173 km. The public transport system includes trams, trolleybuses, and buses. The narrow street network in the urban core and the crossing of the river Daugava are the main problems of Riga's transportation system, leading to a congested city core due to dense traffic.

The third study area, Volos, is the sixth-largest city in Greece, with a population of 144,000 inhabitants. Roads in the city center are organized as a grid and serve intensive vehicle traffic during peak season. The lack of parking areas and the illegal parking of private or UFT vehicles are the main reasons for congestions in the city center.

Bounding boxes were set for the three study areas, obtaining 372,077 tweets in MSP, 35,206 tweets in Riga, and 6,851 tweets in Volos during the period from May 22 to June 1, 2018. Most tweets in MSP were in English (88.7%), and the rest were in other languages that were not further analyzed. Regarding Riga's tweets, 36.4% were in Latvian, 27% were in English, and 19.8% were in Russian. Most tweets collected in Volos were in Greek (87.6%), with only 4.5% in English (Figure 4-2).

Table 4-1. Population and Twitter statistics of study areas.

City	Country	Population	Collected tweets	Tweets per week per thousand inhabitants
Minneapolis – Saint Paul (MSP)	USA	3,600,618 <sup>a</sup>	372,077	120



City	Country	Population	Collected tweets	Tweets per week per thousand inhabitants
Riga	Latvia	641,423 <sup>b</sup>	35,206	55
Volos	Greece	144,449 <sup>c</sup>	6851	47

<sup>a</sup> Data source: US Census Bureau (2017)  
<sup>b</sup> Data source: Central Statistical Bureau of Latvia (2017)  
<sup>c</sup> Data source: Hellenic Statistical Authority (2011)



Figure 4-2. Tweets' language distribution

Table 4-2 includes the tweets that are categorized based on the language used along with the grade per document. The number of tweets for the analyzed classes based on the manual labelling can be found in Figure 4-3.

Table 4-2. Descriptive statistics of Twitter corpuses.

Corpus	Number of documents	Number of terms	Grade per document	Labelled documents				Total
				(i)general	(ii)real-time	(iii)complaints	(v)urelated	
MSP (en)	330,082	428,478	0.995	87	379	60	474	1000
Riga (en)	9846	25,795	1.096	9	255	4	232	500

Corpus	Number of documents	Number of terms	Grade per document	Labelled documents				Total
				(i)general	(ii)real-time	(iii)complaints	(v)unrelated	
Riga (lv)	12,814	42,361	0.615	31	167	0	382	580
Riga (ru)	6963	19,138	0.341	16	37	3	444	500
Volos (el)	6000	21,607	0.460	5	89	2	404	500
Volos (en)	306	1580	0.605	0	2	0	304	306

#### 4.3.2 Preliminary Grading Results

The initial selection of transport-related tweets using keyword-based grading provided an early indication of social media's potential as a source of transport-related data. The keyword lists used were designed to be similar across all the examined languages, allowing for comparable grading results. First, a percentage of graded tweets with at least one transport-related word for different research areas was identified and found significant differences: 15% for Volos, 22% for Riga, and 27% for MSP. Two area-specific characteristics were identified that could explain these differences: Twitter popularity, which is higher in Riga and MSP (as shown in Table 4-1, and language distribution (as shown in Figure 4-2). We tested the hypothesis about language-specifics by comparing the intensity of graded tweets for Volos and Riga across different languages (Table 4-2). The results supported the hypothesis that tweets in English have higher potential as a source of transport-related information. For example, in Riga, the average grade per document for tweets in English was higher (1.096) than for tweets in Latvian and Russian (0.615 and 0.341) and was comparable to that for tweets in English in MSP (0.995). Similarly, in Volos, the average grade for tweets in English was higher (0.605) than for tweets in Greek (0.460). However, the average grades were lower for Volos, leading us to a preliminary conclusion that areas with smaller populations may have lower Twitter potential.

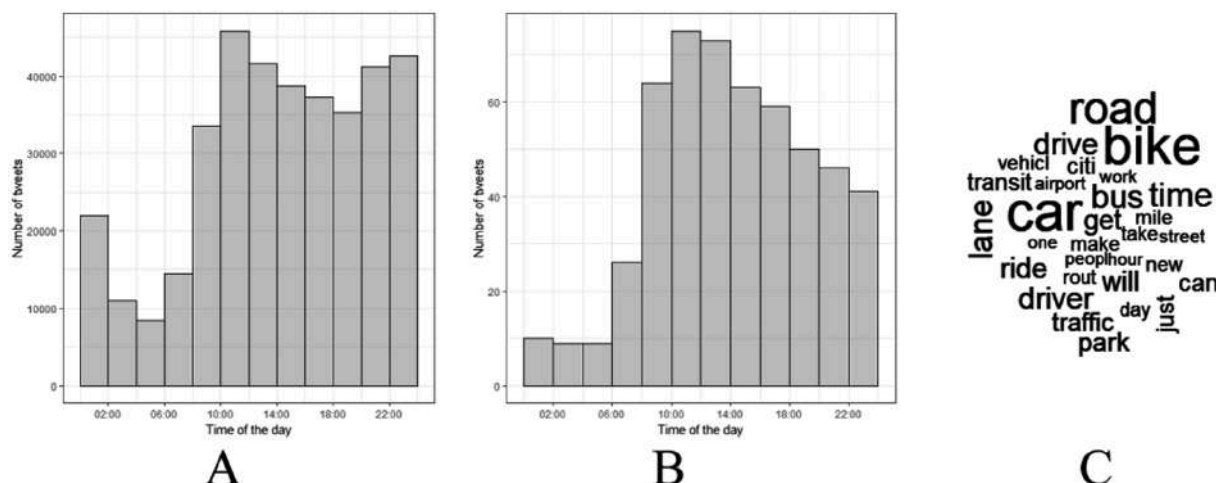


Figure 4-3. Daily patterns of Twitter activity. A: total number of tweets; B: number of transport-related tweets; C: word cloud of transport-related tweets.

The collected tweets of each city were manually classified into the four classes (i) general transport-related information, (ii) real-time transport-related information, (iii) transport-related complaints, and (v) unrelated tweets. The class (iv) transport-related advice/questions was merged to general information due to the limited number of related tweets.

It is important to note that more than half of the manually analyzed tweets in MSP (52.6%) and Riga (53.6%) are related to transportation, which is consistent with the higher average grades reported in Table 4-2. Conversely, the low percentage of analyzed tweets related to transportation in Volos (0.65% in English and 19.2% in Greek) and Riga (11.2% in Russian) are also reflected in the lower average grades reported above. The limited number of collected tweets in Volos, along with the low average grades, contribute to the high number of tweets unrelated to transportation. This suggests that the potential of Twitter data is higher in areas with larger populations, such as MSP.

### 4.3.3 Classification

The research's classification stage focuses on the automated association of transport-related classes with tweets, rather than a thorough examination of classification techniques. As a result, various classifiers from different groups, such as Naive Bayes, decision tree, and Artificial Neural Networks (ANN), were utilized for classifying 2 and 4 classes. Using multiple classification techniques enhances the dependability of the conclusions and eliminates the reliance on a single technique. Table 4-3 displays the classification accuracy.

Table 4-3. Classification accuracy statistics.

Corpus	Classifier	Binomial classification (2 classes)		Multinomial classification (4 classes)	
		Accuracy	Kappa	Accuracy	Kappa
MSP (en)	Naïve Bayes	0.622	0.257	0.626	0.265
	Decision tree	0.613	0.248	0.609	0.238
	ANN	0.653	0.309	0.658	0.320

Corpus	Classifier	Binomial classification (2 classes)		Multinomial classification (4 classes)	
		Accuracy	Kappa	Accuracy	Kappa
Riga (en)	Naïve Bayes	0.806	0.617	0.750	0.523
	Decision tree	0.792	0.590	0.780	0.576
	ANN	0.790	0.585	0.806	0.624
Riga (lv)	Naïve Bayes	0.729	0.338	0.698	0.158
	Decision tree	0.730	0.158	0.736	0.308
	ANN	0.745	0.372	0.723	0.316
Riga (ru)	Naïve Bayes	0.886	0.000	0.888	0.000
	Decision tree	0.878	0.106	0.884	0.031
	ANN	0.886	0.262	0.890	0.184
Volos (el)	Naïve Bayes	0.808	0.000	0.812	0.000
	Decision tree	0.798	0.115	0.802	0.137
	ANN	0.808	0.020	0.800	0.137

Initially, a general consistency of results for different classifiers is noted, which allows us to presume that the findings are not solely dependent on any classifier. Secondly, accuracies are higher for 2-class classification, than for 4-class. It is easier to segregate related and unrelated tweets than it is to differentiate between different classes within transport-related tweets, such as general information, real-time information, and complaints. Lastly, the overall accuracy of classification is low, with an average Cohen's kappa of 0.275, indicating that the potential for automated classification of tweets is limited. Only the corpus of English tweets from Riga showed significantly better results, with an average Cohen's kappa of 0.597, corroborating our hypothesis that tweets in English (even as a second language) have a higher potential as a source of transport-related information.

#### 4.4 Campaigns and awareness-raising strategies on sustainable urban mobility: How a transport-related content could be more influential in social media?

As it is already discussed in the previous section the emergence of social media resulted in a high number of people using them. Thus, data from Twitter were retrieved to explore their potential for providing transport related data. The collected data can offer information about mobility patterns and can be used for the design of more sustainable mobility solutions.

To raise awareness on sustainability, various techniques may be used, such as designated educational programs, training sessions, seminars and campaigns. To this direction, social media can be used for information -sharing. Their flexibility makes them more popular compared to conventional methods of information sharing. Transport-related information can be shared cost-efficiently and timely on platforms such as Facebook, Instagram, and Twitter. The shared content’s form can be a text, a photo, or a video enabling more accurate transport-related information.

Firstly, this section reviews and analyses previous campaigns and strategies related to sustainable urban mobility implemented in European countries. Analysis includes the organization, which was responsible for initiating the campaign, the time period, theme, scope, target group and type of approach. In those cases, that evaluation of the campaign was conducted, impacts on attitudes and behavior are also identified and the success attributes of

the campaigns are selected. Secondly, the section investigates to what extent social media have an impact on the mobility choices of people. A systematic literature review was performed to identify any record that is related to social media and urban mobility. In addition, a thorough review of transport-related social media accounts and content was performed to investigate their influence. The analysis ends up with an appropriate scheme and form of a transport-related account and content that would be more influential in today's social media landscape.

#### 4.4.1 Sustainable urban mobility awareness campaigns and strategies

To understand sustainable mobility awareness campaigns and strategies, in this section ten cases implemented in various EU countries are examined and their approaches are analyzed (Table 4-4). These campaigns were part of broader projects that aimed to promote sustainable mobility behavior in specific target groups, highlighting the need for tangible strategies alongside awareness campaigns to make the concept of sustainable mobility more explicit. The European Commission (EC) co-funded many of these projects, emphasizing the significance of sustainable urban mobility in the EU and encouraging member states to cooperate towards this common goal. Eight out of ten campaigns/strategies were implemented in multiple European countries (ASTUTE consortium, 2009; di Nunzio, et al., 2010; Moscholidou & Colclough, 2017; Buningham, et al., 2016; Fiedler & Fenton, 2011; Swennen, et al., 2016; MoMa.BIZ Consortium, 2013; Thormann & Dotter, 2010), with participating organizations comprising academic and EU institutions, public bodies, and private entities (ASTUTE consortium, 2009); (di Nunzio, et al., 2010) (Moscholidou & Colclough, 2017); (Buningham, et al., 2016); (Fiedler & Fenton, 2011); (Swennen, et al., 2016); (MoMa.BIZ Consortium, 2013); (Thormann & Dotter, 2010); (Ribeiro, et al., 2013). According to sources (ASTUTE consortium, 2009); (di Nunzio, et al., 2010) (Moscholidou & Colclough, 2017); (Buningham, et al., 2016); (Fiedler & Fenton, 2011); (Swennen, et al., 2016); (Thormann & Dotter, 2010); (Meloni, et al., 2012), the promotion of sustainable mobility and alternative transport modes was the central theme of most campaigns and strategies. Most campaigns were locally focused, except for the Traffic Snake Game Network, which was implemented in primary schools across eighteen European countries. In this case, schools played a role in collecting and registering data (Buningham, et al., 2016). While many campaigns promoted a combination of cycling, walking, and public transport (ASTUTE consortium, 2009; Moscholidou & Colclough, 2017; Buningham, et al., 2016; Fiedler & Fenton, 2011; Swennen, et al., 2016; Thormann & Dotter, 2010), some focused specifically on public transport (Meloni, et al., 2012), car-sharing, and bike-sharing schemes (di Nunzio, et al., 2010). Target groups varied widely, ranging from residents of cities where the campaigns were implemented (Swennen, et al., 2016; Thormann & Dotter, 2010; Meloni, et al., 2012) to more specific groups such as commuters to business and industrial zones (MoMa.BIZ Consortium, 2013), primary school students and their parents (Moscholidou & Colclough, 2017), university students and faculty (di Nunzio, et al., 2010), company employees (Buningham, et al., 2016), and people over a certain age (Fiedler & Fenton, 2011). Despite some variations in topics, the primary objective of most campaigns was to promote the adoption of sustainable urban mobility among their target audiences (di Nunzio, et al., 2010; Moscholidou & Colclough, 2017; Swennen, et al., 2016; Thormann & Dotter, 2010; Meloni, et al., 2012; Ribeiro, et al., 2013). Some campaigns focused on overcoming organizational barriers and improving communication (ASTUTE consortium, 2009; Fiedler & Fenton, 2011; MoMa.BIZ Consortium, 2013), while others highlighted the environmental impacts of urban mobility to encourage behavior change (di Nunzio, et al., 2010).

All the campaigns used informative and positive messaging to inform the public of the benefits of sustainable mobility and the consequences of the current situation. The campaigns utilized various means of communication such as the internet, printed materials, local events, and the press. However, social media use was limited. There could be several reasons why the use of social media for the promotion of sustainable urban mobility awareness campaigns and strategies is limited. The complexity of the topic, the lack of engagement, the limited resources may be some of them.

The campaigns' impact was evaluated by measuring performance indicators such as the reduction of CO<sub>2</sub> emissions and the increase in the use of sustainable transport modes. The reduction in CO<sub>2</sub> emissions ranged from 51 (Buningh, et al., 2016) kilograms to 4695.74 tons (Thormann & Dotter, 2010), while the increase in the use of alternative transport modes ranged from about 1.5% (Ribeiro, et al., 2013) to about 25% (Fiedler & Fenton, 2011). Some evaluations used a qualitative approach, with positive impacts estimated based on the general acceptance of the sustainable mobility concept by target groups (MoMa.BIZ Consortium, 2013; Ribeiro, et al., 2013).

Table 4-4. Overview of European Union campaigns and strategies.

Campaign/strategy	Country	Objective	Media plan	Evaluation	Theme	Target group	Ref.
ASTUTE	Several	Overcoming organizational barriers	Internet, brochures, local events	Longitudinal study	Cycling, walking	City inhabitants	(ASTUTE consortium, 2009)
Today and Tomorrow	Cyprus, Portugal, Italy	University mobility impacts reduction	Internet	Questionnaires, interviews	Carpooling, bikesharing	Students and faculty	(di Nunzio, et al., 2010)
The Traffic Snake Game Network	18 EU countries	Travel behavior change	Internet, local events, posters	Before-after analysis, longitudinal study	Cycling, walking, car-sharing, public transport	Primary school children and parents	(Moscholidou & Colclough, 2017)
MOBI	Several	Travel behavior change	Internet	Longitudinal study, after analysis	Cycling, walking, car-sharing, gamification	23,400 employers of 117 companies	(Buningh, et al., 2016)
AENEAS	Several	Alternatives to car use	Internet, brochures, newsletters	Questionnaires	Walking, cycling, public transport	Senior citizens	(Fiedler & Fenton, 2011)
SWITCH	Several	Soft modes promotion for short trips	Internet, local media	Before-after analysis	Walking, cycling	City inhabitants	(Swennen, et al., 2016)

<b>Campaign/strategy</b>	<b>Country</b>	<b>Objective</b>	<b>Media plan</b>	<b>Evaluation</b>	<b>Theme</b>	<b>Target group</b>	<b>Ref.</b>
MoMa.BIZ	Several	Business & industrial zones mobility issues	Internet, local events	Before analysis	Mobility issues	Business & industrial zones commuters	(MoMa.BIZ Consortium, 2013)
PRO.MOTION	12 EU countries	Influencing travel decisions at home	Several	SUMO evaluation method, Before-after behavioral analysis	Public transport, car-sharing, walking	City inhabitants	(Thormann & Dotter, 2010)
Casteddu Mobility Styles	Italy	Light metro service promotion	Internet	Before-after analysis	Metro service	Car users	(Meloni, et al., 2012)
CIVITAS	Portugal	Sustainable transport behavior	Internet, local events, posters, flyers, local press	Questionnaires, interviews	Eco-driving, school mobility, public transport	Residents, students	(Ribeiro, et al., 2013)



#### 4.4.2 How a transport-related content could be more influential in social media?

In this section it is investigated to what extent social media have an impact on the mobility choices of people, filling the gap of previous studies that paid little attention to the influence of social media on transport-related purposes. A systematic literature review was performed in SCOPUS database to identify any record that is related to social media and urban mobility. Only records with an important and relevant contribution to the topic were kept. In addition, a thorough review of transport-related social media accounts and content was performed to investigate their influence. Social media metrics such as reactions, comments and shares of posts are measured to determine the real influence of the accounts and their content. The analysis ends up with an appropriate scheme and form of a transport-related account and content that would be more influential in today's social media landscape.

##### 4.4.2.1 Systematic literature review results.

The review examined articles, conference papers, books and book chapters published between 1 January 2015 and 1 March 2022 in the English language. This period of almost 7 years was selected to guarantee inclusion of recent research contributions. First, the search terms were determined based on keywords, classified in two groups. The one group composed of words related to "urban mobility". The other group referred to the data source "social media". The search terms were left on purpose generic at this stage to ensure that no record with contribution is left out, see Table 4-5. Both groups of keywords were adapted to ensure appropriate database search syntax. Moreover, the search query was progressively enriched with additional options provided by the "advanced search" of SCOPUS database aiming at filtering out records that were captured wrongly under the set keywords.

Table 4-5. Search query.

Database	Search query
SCOPUS	TITLE-ABS-KEY ( {social media} AND ( transport* OR mobility OR travel* ) AND NOT ( wildlife ) AND NOT ( forest ) ) AND NOT ( logistics ) AND NOT ( freight ) AND NOT ( food ) AND NOT ( political ) AND NOT ( neural ) AND NOT ( career* ) AND NOT ( migrat* ) AND NOT ( hotel ) AND NOT ( racism ) AND NOT ( cyberattack* ) AND NOT ( mountain ) AND NOT ( medical ) AND NOT ( nurse* ) AND NOT ( livestream* ) AND NOT ( terrorism ) AND ( EXCLUDE ( SUBJAREA , "MEDI" ) OR EXCLUDE ( SUBJAREA , "ARTS" ) OR EXCLUDE ( SUBJAREA , "EART" ) OR EXCLUDE ( SUBJAREA , "PHYS" ) OR EXCLUDE ( SUBJAREA , "BIOC" ) OR EXCLUDE ( SUBJAREA , "AGRI" ) OR EXCLUDE ( SUBJAREA , "MATE" ) OR EXCLUDE ( SUBJAREA , "NURS" ) OR EXCLUDE ( SUBJAREA , "HEAL" ) OR EXCLUDE ( SUBJAREA , "NEUR" ) OR EXCLUDE ( SUBJAREA , "IMMU" ) OR EXCLUDE ( SUBJAREA , "PHAR" ) OR EXCLUDE ( SUBJAREA , "CENG" ) OR EXCLUDE ( SUBJAREA , "CHEM" ) OR EXCLUDE ( SUBJAREA , "VETE" ) OR EXCLUDE ( SUBJAREA , "DENT" ) ) AND ( LIMIT-TO ( DOCTYPE , "ar" ) OR LIMIT-TO ( DOCTYPE , "cp" ) OR LIMIT-TO ( DOCTYPE , "ch" ) OR LIMIT-TO ( DOCTYPE , "bk" ) ) AND ( LIMIT-TO ( PUBYEAR , 2022 ) OR LIMIT-TO ( PUBYEAR , 2021 ) OR LIMIT-TO ( PUBYEAR , 2020 ) OR LIMIT-TO ( PUBYEAR , 2019 ) OR LIMIT-TO ( PUBYEAR , 2018 ) OR LIMIT-TO ( PUBYEAR , 2017 ) OR LIMIT-TO ( PUBYEAR , 2016 ) OR LIMIT-TO ( PUBYEAR , 2015 ) ) AND ( LIMIT-TO ( LANGUAGE , "English" ) ) AND ( EXCLUDE ( EXACTKEYWORD , "Tourism" ) OR EXCLUDE ( EXACTKEYWORD , "Tourist Destination" ) OR EXCLUDE ( EXACTKEYWORD , "Tourist Behavior" ) OR EXCLUDE ( EXACTKEYWORD , "Air Transportation" ) OR EXCLUDE ( EXACTKEYWORD , "Tourism Market" ) OR EXCLUDE ( EXACTKEYWORD , "Intelligent Vehicle Highway Systems" ) OR EXCLUDE ( EXACTKEYWORD , "Consumption Behavior" ) OR EXCLUDE ( EXACTKEYWORD , "Economics" ) OR EXCLUDE ( EXACTKEYWORD , "Tourism Development" ) OR EXCLUDE ( EXACTKEYWORD , "Migration" ) OR EXCLUDE ( EXACTKEYWORD , "Support Vector Machines" ) OR EXCLUDE ( EXACTKEYWORD , "Airline Industry" ) OR EXCLUDE ( EXACTKEYWORD , "Tourism Industry" ) OR EXCLUDE ( EXACTKEYWORD , "Data Mining" ) OR EXCLUDE ( EXACTKEYWORD , "Sentiment Analysis" ) OR EXCLUDE ( EXACTKEYWORD , "Machine Learning" ) OR EXCLUDE ( EXACTKEYWORD , "Semantics" ) OR EXCLUDE ( EXACTKEYWORD , "Forecasting" ) OR EXCLUDE ( EXACTKEYWORD , "Text Mining" ) OR EXCLUDE ( EXACTKEYWORD , "Spatiotemporal Analysis" ) OR EXCLUDE ( EXACTKEYWORD , "Population Statistics" ) OR EXCLUDE ( EXACTKEYWORD , "Deep Learning" ) OR EXCLUDE ( EXACTKEYWORD , "Location Based Services" ) OR EXCLUDE ( EXACTKEYWORD , "Search Engines" ) OR EXCLUDE ( EXACTKEYWORD , "Learning Algorithms" ) OR EXCLUDE ( EXACTKEYWORD , "Natural

Database	Search query
	Language Processing" ) OR EXCLUDE ( EXACTKEYWORD , "Photography" ) OR EXCLUDE ( EXACTKEYWORD , "Sales" ) OR EXCLUDE ( EXACTKEYWORD , "Complex Networks" ) OR EXCLUDE ( EXACTKEYWORD , "Hotels" ) OR EXCLUDE ( EXACTKEYWORD , "Prediction" ) OR EXCLUDE ( EXACTKEYWORD , "Crime" ) OR EXCLUDE ( EXACTKEYWORD , "Health" ) OR EXCLUDE ( EXACTKEYWORD , "Collaborative Filtering" ) OR EXCLUDE ( EXACTKEYWORD , "Epidemiology" ) OR EXCLUDE ( EXACTKEYWORD , "Artificial Intelligence" ) OR EXCLUDE ( EXACTKEYWORD , "Augmented Reality" ) OR EXCLUDE ( EXACTKEYWORD , "Trajectories" ) OR EXCLUDE ( EXACTKEYWORD , "Virtual Reality" ) OR EXCLUDE ( EXACTKEYWORD , "Mobile Computing" ) OR EXCLUDE ( EXACTKEYWORD , "Clustering Algorithms" ) OR EXCLUDE ( EXACTKEYWORD , "Human Engineering" ) OR EXCLUDE ( EXACTKEYWORD , "Numerical Model" ) OR EXCLUDE ( EXACTKEYWORD , "Cloud Computing" ) OR EXCLUDE ( EXACTKEYWORD , "Cluster Analysis" ) OR EXCLUDE ( EXACTKEYWORD , "Risk Management" ) OR EXCLUDE ( EXACTKEYWORD , "Body Image" ) OR EXCLUDE ( EXACTKEYWORD , "Image Segmentation" ) OR EXCLUDE ( EXACTKEYWORD , "Natural Language Processing Systems" ) OR EXCLUDE ( EXACTKEYWORD , "Netnography" ) OR EXCLUDE ( EXACTKEYWORD , "Data Handling" ) OR EXCLUDE ( EXACTKEYWORD , "Spatial Analysis" ) OR EXCLUDE ( EXACTKEYWORD , "Text Processing" ) OR EXCLUDE ( EXACTKEYWORD , "Tourist Attractions" ) )

The search query of Table 4-5 yielded a total of 431 records. The reported keywords of the captured articles are given in the word cloud of Figure 4-4.



Figure 4-4. Word cloud produced by the keywords of the initial search (n=431).

As a next step, the 431 records were further screened to exclude those that do not address the research question or have a marginal relevance. To perform this process, we relied on the

titles and abstracts of the records which reduced the number of potential articles to 42. These 42 were considered eligible to be thoroughly reviewed due to their high relevance to the research question. The last screening step – reading the full text of the record – yielded 25 records which were included in the analysis.

#### *4.4.2.2 Research articles on social media and mobility choices*

This section analyzes and discusses the identified records in terms of the scope of the study, which method of data collection and analysis was employed, and which are the main findings in terms of quantitative results or qualitative findings output/findings.

The following table gives a summary of all heading levels.

Table 4-6. Catalogues of records.

No.	Scope	Data collection method // Social media platform used (if applic.)	Data analysis	Output / findings	Reference
1	Investigate the impact of social media marketing on sustainable attitudes and behaviors of tourists	Questionnaire	<ul style="list-style-type: none"> <li>- exploratory factor analysis</li> <li>- descriptive statistics</li> <li>- multiple linear regression analysis</li> </ul>	<ul style="list-style-type: none"> <li>- younger travelers are more likely to use social media in making their travel plans</li> <li>- social media have the most significant influence on promoting sustainable behaviour in leisure travelers</li> </ul>	(Walsh & Dodds, 2022)
2	Investigate if and under which circumstances exposure to travel-related content posted by professional influencers affects their followers' travel intentions	(Online) Questionnaire // Instagram	- partial least squares structural equation modeling	- online social identity does not change the strength of the effect between content exposure and travel intention. Instead, the content someone is exposed fosters a sense of belonging and identification with the platform, increasing the intention to imitate the behavior displayed	(Asdecker, 2022)
3	Examine the differences on the acceptability of persuasive strategies (i.e. adoption of more environmental-	(Paper & pencil) Questionnaire	<ul style="list-style-type: none"> <li>- cross sectional survey</li> <li>- cluster analysis</li> </ul>	- social media is the strategy with the lowest	(dos Reis, et al., 2022)

No.	Scope	Data collection method // Social media platform used (if applic.)	Data analysis	Output / findings	Reference
	friendly modes of transport) of different psychological profiles			overall scores on all acceptance indicators. - ‘non-motorized lovers’ and ‘autonomous environmentalists’ are particularly less resistant to it when compared to the car-predisposed, who shows significantly lower scores even when compared to the bus-dependent cluster	
4	Identify whether a smiling vs. a non-smiling face is superior for social media success of a destination	(Online) Questionnaire (with video and photo included) combined with AI // Facebook	- two-way ANCOVA (ANOVA & Regression) - EMFACS (Emotional Facial Action recognition)	- smiling (vs. non-smiling) endorser in a destination's social media post influences more positively travelers’ intention to visit	(Schoner-Schatz, et al., 2021)
5	Explore the potential of social media to enact new forms of surveillance and control	Netnography, Gamification // Foursquare	Big data analytics	- potential importance and complementarity of surprising elements of control in terms of fun, excitement and game playing, by drawing on the concept of seduction.	(Chapman, et al., 2021)
6	- Analyse the relations between sex, personality, and the way social media is used  - Run a campaign that encourages and advise travelers on how congestion	Questionnaire	Statistical methods	- the use of social media has a significant impact on the motivation to act	(Król & Zdonek, 2021)

No.	Scope	Data collection method // Social media platform used (if applic.)	Data analysis	Output / findings	Reference
	could be avoided if people travelled less by cars				
7	Explore the reduction of negative effects of long-term temporal infrastructural disruptions in urban transport systems	<ul style="list-style-type: none"> <li>- Metanalysis of 2 campaigns (initial collection based on Focus groups and surveys) // Twitter and Facebook</li> <li>- Questionnaire, focus groups interviews, document studies of reports, planning and decision documents</li> </ul>	Descriptive analysis	<ul style="list-style-type: none"> <li>- the inclusion of social media in the information campaign illustrates new approaches to audience targeting to reach certain groups at specific times. The public information become more targeted in both time and space. The audience-targeting advertising on social media sought to reach residents in specific geographic areas and at defined times. Pre-trip information was viewed as crucial for influencing travel behaviour.</li> </ul>	(Tønnesen, et al., 2021)
8	Investigate the influence of social media content on activity planning and travel arrangements for women and men	Questionnaire	Inferential statistics	<ul style="list-style-type: none"> <li>- the influence of reviews and ratings, photos/ videos and proposed transport mode on activity planning is gender dependent</li> <li>- photos/ videos influence more often both women (m=3.47) and men (m=3.00) than reviews and ratings (m=3.21 for women and 2.94 for men).</li> </ul>	(Karatsoli & Nathanail, 2020)

No.	Scope	Data collection method // Social media platform used (if applic.)	Data analysis	Output / findings	Reference
				<p>- before an activity, both women and men tend to use majorly social media for activity planning and travel arrangements, while photos/videos influence women's decisions more often than men</p> <p>- travel arrangements of the majority of respondents would be influenced by a post of a designated account related to transport</p> <p>- social media use affects travel arrangements of both women and men more before performing an activity rather than during.</p>	
9	Investigate the impact of social media on diffusion of sustainable mobility opinions	Previous literature and domain knowledge	- dynamic agent-based simulation (agent-based diffusion modeling)	- a modeling framework for the impact of social media on opinion diffusion. The framework applies different learning mechanisms (e.g., word-of-mouth and mass media) in network architectures to explore the effects of network topology on acceptance of green travel alternatives using	(Borowski, et al., 2020)



No.	Scope	Data collection method // Social media platform used (if applic.)	Data analysis	Output / findings	Reference
				conceptual idealizations of the complex processes involved in diffusion interactions	
10	Examine the official Instagram and Twitter accounts of Bird and Tier Mobility to determine whether these companies promote and demonstrate the use of safety gear in their posts to their consumers	Photo elicitation of social media content // Instagram, Twitter	Visual analysis	<ul style="list-style-type: none"> <li>- modeling and promoting safety is rare on Bird's and Tier Mobility's official social media accounts</li> <li>- social media platforms may offer a potential avenue for public health officials to intervene with rider safety campaigns for public education</li> </ul>	(Dormanesh, et al., 2020)
11	Promote ridesharing and organize a ridesharing scheme	Metanalysis	Descriptive	<ul style="list-style-type: none"> <li>- a framework that highlights the role of information use in ridesharing and identified the needs and harvesting technologies for social data in ridesharing services</li> </ul>	(Tang, et al., 2019)
12	Measure the impact of social media in travel/mobility decisions and investigate the degree of social media usage in terms of type of information searched, reached and shared, time of information and purpose for which the information was created	Questionnaire	Descriptive – Inferential Statistics	<ul style="list-style-type: none"> <li>- users plan an activity and do their travel arrangements based on information and experiences shared online</li> <li>- the mobility decisions of both women and men, as well as of students and</li> </ul>	(Karatsoli & Nathanail, 2019)

No.	Scope	Data collection method // Social media platform used (if applic.)	Data analysis	Output / findings	Reference
				full-time job employees are affected by negative reviews or nice photos/videos and posts. These mobility decisions may be related to changes of the time and the date of an activity, the transport mode or the destination  - survey participants believe that social media help significantly their activity planning	
13	Investigate how a shift in behavior towards more sustainable modes of transportation may be affected by a digital campaign	Metanalysis, Questionnaire	Descriptive – Inferential Statistics	- a message with informative content is more appealing to the users  - a message by a designated account related to transport would raise more the awareness of the majority of respondents towards implementing sustainable solutions for urban mobility	(Magginas, et al., 2019)
14	Investigate the use of social media for travel planning on a transit system with particular attention to travel disruptions and delays	Questionnaire // Twitter, Facebook	Descriptive and Principal Component Analysis (PCA), cross-tabulation analysis	- the vast majority of respondents – in all demographic groups – check the social media sites to gather daily updates before starting	(Douglass, et al., 2018)

No.	Scope	Data collection method // Social media platform used (if applic.)	Data analysis	Output / findings	Reference
				their journeys. Thus, the TW-Metro social media sites have the potential to influence users' travel plans before their journey, such as changing their route, travel mode, and/or departure time	
15	Propose a new approach for traffic safety improvement programs based on citizen participation on social media	Questionnaire, Crash data	Descriptive, Crowdsourcing, Empirical Bayes (EB) method	- resident-reported information on social media has high potential to assess current safety conditions on roadways efficiently	(Chung & Won, 2018)
16	Create opportunities afforded to citizens for accessing information online and the use of apps and social media to engage, participate, co-produce and co-create with Glasgow City Council.	Metanalysis, 'SmartGov' transnational research project, literature review, three projects of 'Future City Glasgow programme': Energy Efficiency, Active Travel and Open Glasgow // Twitter, Facebook	Mixed- methods research approach including document and literature review and semi-structured interviews.	- better informed citizens have more information available about how they can take part in community life, and lead healthier and more active lifestyles	(Leleux & Webster, 2018)
17	Examine the intention of respondents to use real-time information from social media for transportation purposes or post transport-related information on social media	Questionnaire	Descriptive, binary logistic logit models	- 64% of the survey's participants receive information from social media about their trip, especially when they use public transport. They also	(Nikolaidou & Papaioannou, 2017)

No.	Scope	Data collection method // Social media platform used (if applic.)	Data analysis	Output / findings	Reference
				<p>reveal that this information may alter, in a substantial percentage, their route or the period they travel.</p>	
18	<p>Understand patterns of social media use by travelers across the three stages of the trip experience (i.e. pre-, during, post-trip)</p>	<p>Questionnaire</p>	<p>Descriptive, Latent class analysis (LCA) and latent transition analysis (LTA)</p>	<p>Travelers' use of social media is extremely dynamic and depends not only on the decision context they are facing at the time (i.e. trip stage, purpose, internet connection) but also on the features of the social media platform</p>	<p>(Choe, et al., 2017)</p>
19	<p>Evaluate how social media can be used over a large event, to provide and share transport-related information and respond to information requests</p>	<p>Interviews, Tweets // Twitter</p>	<p>Matanalysis, Cross-tabulation</p>	<p>Findings indicate the potential for future applications of social media by transport operators and authorities in producing a more effective network of communication with passengers, i.e.:</p> <ul style="list-style-type: none"> <li>- positive aspects of the experience, particularly regarding positive effects of enabling competing transport operators, who would normally work in separate organizations, to</li> </ul>	<p>(Cottrill, et al., 2017)</p>

No.	Scope	Data collection method // Social media platform used (if applic.)	Data analysis	Output / findings	Reference
				come together for a shared goal under pressured circumstances - challenges associated with coordinating the social media message, the on-ground situation, and user responses in a public forum.	
20	Investigate the impact of a hashtag campaign as a critical tool aimed to design a territorial transmedia storytelling within a digital strategy	Metanalysis of posts on Twitter, Facebook, Instagram	Descriptive, Hand-Ranked Sentiment Analysis, social media on demand analytics and google analytics	The interested parties have used the hashtag and have joined the campaign demonstrating a strong interest for the social media content, which would increase the engagement and visibility	(Paiano, et al., 2017)
21	Understand how a user experience rating and review platform can serve as an information source for activity and trip planning in the pre-trip process	Dataset of 2.2 million reviews downloaded from Yelp.com	Descriptive, Sentiment analysis	- transportation reviews are longer than overall reviews. Within transport-related reviews, multi-modal reviews are the longest, followed by car, walk, rideshare, taxi, transit, and bike. - the results imply that travelers will on average find more information than nontravelers	(Bou Mjahed, et al., 2017)

No.	Scope	Data collection method // Social media platform used (if applic.)	Data analysis	Output / findings	Reference
				- travelers, especially car users, can find access to information for almost every place visited. Furthermore, bikers have access to the most encouraging reviews  - travel recommendations for walking and transit generally conform to walkability and transit supply.	
22	Study the relations between ICT and social media usage, social networks, and social travel. Investigate the effect of ICT on social travel, its interaction with social networks, and, how the perception of its usefulness influences its usage	Questionnaire	Descriptive, Exploratory factor analysis	Regarding the trip planning phase there is a clear substitution between different technologies. A stronger use of phone calls is associated with a lower or inexistent use of social media.	(de Abreu e Silva, et al., 2017)
23	Examine the effect of different social network structures, in terms of both travel choices and transportation system performance	Online experiment (use of experiment website in which participants can input their choices)	Bayesian learning theory, agent-based approach	The number of friends on social media has an important impact on traveler's departure time choices. Travelers with more connections on their social media tend to get lower travel cost by making better choices.	(Xiao & Lo Hong, 2016)

No.	Scope	Data collection method // Social media platform used (if applic.)	Data analysis	Output / findings	Reference
24	<ul style="list-style-type: none"> <li>- Raise awareness and urge researchers to study the dynamics between bicycle-sharing and social media as they relate to environmental sustainability</li> <li>- Gather related discussions together in one place</li> </ul>	Metanalysis	Theorem and proofs through specific relationships	<p>The existence of sensors in shared-bicycles schemes and the widespread availability of social media help increase the demand for and ease of use of bicycles</p> <ul style="list-style-type: none"> <li>- Increased carbon emission cost savings increases the incentive for usage of bicyclesharing facilities</li> <li>- Harsh environment, negatively impacts shared-bicycle renting firm's performance</li> <li>- Under the service provider's participation constraint and bicycle renter's individual rationality constraints, it is reasonable and possible to reduce the rental cost, even offer free rentals, or provide monetary pay-backs to sharedbicycle users for long distance travels.</li> </ul>	(Piramuthu & Zhou, 2016)
25	Understand the transportation modes and services that have a digital presence in social media as well as the diffusion	Metanalysis, questionnaire	Descriptive, exploratory study of social media	- mobility service apps that have a strong presence in social	(Alrashed, et al., 2016)

No.	Scope	Data collection method // Social media platform used (if applic.)	Data analysis	Output / findings	Reference
	of technology in the context of urban mobility systems			<p>networks are used more than other mobility services</p> <ul style="list-style-type: none"> <li>- active mobility services that interact with their customers through social media seem to attract much more people</li> <li>- transportation services' presence in social networks enables researchers to analyze mobility patterns and model the dynamics between social networks and mobility behavior.</li> </ul>	



#### 4.4.2.3 Interpretation of the results

The descriptive statistics of the 25 eligible records showed that 76.0% were articles published in scientific journals, while 16.0% were book chapters and 8.0% were conference papers. Moreover, all records were published after 2016 – no records captured in 2015 – with 24.0% of them (6 out of 25) being published in 2017 and 4.0% (1 out of 25) in 2019. The distribution presented in Figure 4-5 over the last 6 years indicates that the relationship of social media use with urban mobility has become a well-established part of the relevant literature. Considering also that the reach of social media increases day-by-day, and a higher percentage of the population is using them more frequently, the body of literature in the domain is only expected to increase, and thus, related research will accordingly be enriched.

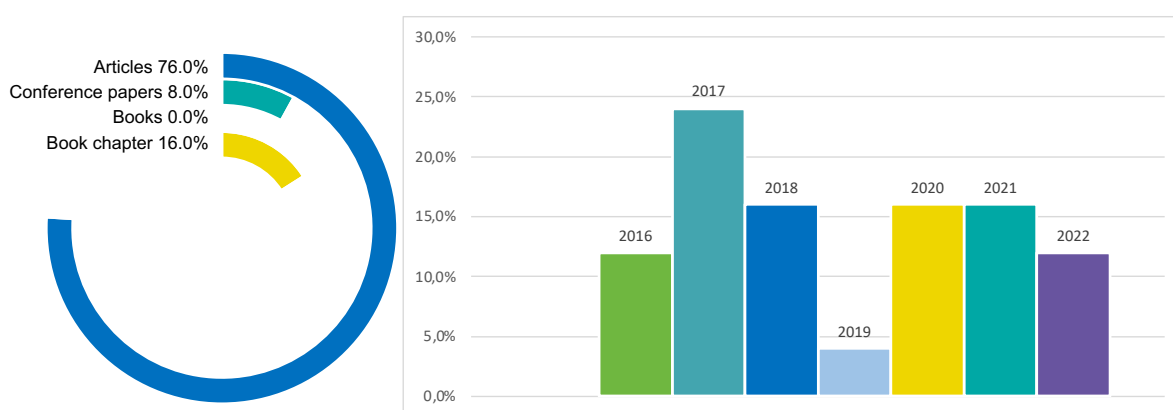


Figure 4-5. Number of records per source type and publication year.

One interesting finding stemming from the analysis of Table 4-6 has to do with the variety of purposes social media records are used for, in the context of urban mobility. Analytically, in an attempt to cluster the identified records per scope and wrap them up as a takeaway of the specific study, the following five categories emerged, see Figure 4-6.

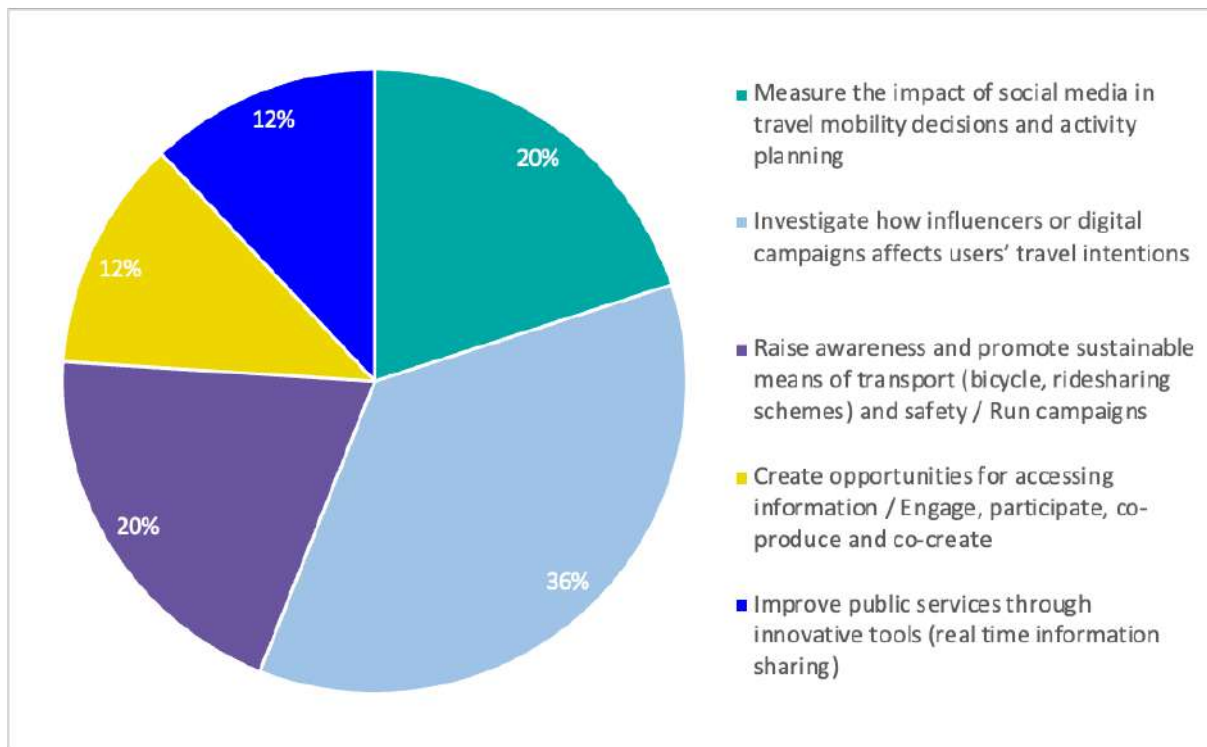


Figure 4-6. Scope of social media records.

Based on Figure 4-6, most of the records (36%, 9 out of 25) serve the scope of investigating how influencers or digital campaigns affects users' travel intentions. This translates to the fact that users' travel intentions are often influenced by a marketing team, indicating the multitude of social media influence on our urban mobility life. "Raise awareness and promote sustainable means of transport and safety / Run campaigns" and "Create opportunities for accessing information / Engage, participate, co-produce and co-create" are often among the scope of transport related social media accounts which will be analyzed in the following section.

#### 4.4.2.4 Transport related social media accounts

A total of 26 social media accounts were identified following the methodological steps of section 4.2. 21 of them were public groups and five were pages. Table 4-7 shows the account names, the scope, the type of shared content and the metrics of the 26 social media accounts. Analytically, the scope of the accounts is either to Raise awareness and promote sustainable means of transport and safety / Run campaigns or to Create opportunities for accessing information / Engage, participate, co-produce and co-create. The shared content is mainly posts with photos and description, events and scheduling of meetings, and shared links of articles. The social media metrics used to measure the interaction with the audience include the average number of reactions, comments, and shares of the last ten posts. Reactions are an extension of the Like button giving people more ways to share their opinion towards a post in a quick and easy way (Like, Love, Care, Haha, Wow, Sad and Angry). Comments allow the users to respond to a post with text format in a publicly visible way. With the 'Share' option, members can publish a post that they're interested in on their own wall, without having to copy and paste the link to their profiles. The average number of 'Seen' of last ten posts for groups with fewer than

250 members is also included. ‘Seen’ appears next to each post only to groups with fewer than 250 people and indicates how many group members have seen/read the posts.

Table 4-7. Transport related social media accounts.

Account name	Scope	Content	Social media metrics
<sup>1</sup> Bicycle commuters of Greece	Promotion and information sharing of bicycle use	Photos of bicycle use in urban context with caption and description	Members: 2,700 Reactions: 36 Comments: 7 Shares: 0 4 posts/day
<sup>1</sup> Με ποδήλατο στη δουλειά	Promotion of bicycle commuting to work through cycling with others	Use of hashtags to share your route, giving the chance to other members to find it and cycle to work together	Members: 2,400 Reactions: 4 Comments:0 Shares:0 4 posts/year
<sup>1</sup> EIT Urban Mobility RIS Hub Greece	Engagement with stakeholders of urban mobility, interaction with start-ups, cities, research and innovative organizations, share of urban mobility- related activities	Trends in urban mobility in Greece and abroad	Members: 121 Reactions: 5 Comments:0 Shares:1 Seen:41 20 posts/year
<sup>1</sup> MOTUM - Urban Mobility App	Promotion of a mobility app that guides members to choose the best transport alternatives tailored to individual preferences that have less environmental impact	Communication of events, news, posts with photos	Members: 1034 Reactions:23 Comments:0 Shares:0 10 posts/year
<sup>1</sup> WR Active Transportation Advisory Team [ATAT]	Promotion of an easy and equitable access to active transportation options	Share of newsletter, events, post with photos	Members: 425 Reactions: 5 Comments: 0 Shares: 0 4 posts/month

Account name	Scope	Content	Social media metrics
<sup>1</sup> Active transportation, Pedestrian friendly, Sustainable transport, Car-free	Build a people-friendly, pedestrian-friendly culture, promotion of active transportation	Posts with stories, thoughts, questions, and resources about active transportation	Members: 128 Reactions:1 Comments: 0 Shares: 0 Seen:17 6 posts/year
<sup>1</sup> Active Transportation Advocates	Promotion of all forms of transportation that get people out their cars, such as walking, biking, transit and emerging micro-mobility technologies	Posts with experiences, exchange ideas, research and public policy options related to active transportation	Members: 39 Reactions: 2 Comments:0 Shares:0 Seen: 13 5 posts/week
<sup>1</sup> Longview Active Transportation	Promotion of active transportation	Posts about projects and successes/challenges of efforts to make active transportation a priority. Events and ways to involve.	Members: 196 Reactions: 3 Comments: 0 Shares: 0 Seen: 68 3 posts/week
<sup>1</sup> Green Transportation	Promotion of green vehicles	Events, posts with green vehicles and their characteristics	Members: 287 Reactions: 0 Comments: 0 Shares: 0 3 posts/year
<sup>1</sup> ClimateActionPlan Transition Strategies for Active Mobility & Land Use	Promotion of active mobility, safe and abundant cycling, scooting, one-wheel rolling and walking in cities	Post with photos about active mobility, shares of posts of active mobility related topics	Members: 1,300 Reactions:2 Comments:0 Shares:0 2 posts/year
<sup>1</sup> BikeandmoreMaroussi	Promotion of bicycle use	Events and meetings for bicycle excursions	Members: 1,500 Reactions: 8 Comments: 1 Shares: 0 3 posts/week

Account name	Scope	Content	Social media metrics
<sup>1</sup> Volos Street Hackers	Promotion of sustainable mobility, improvement of road aesthetics by limiting the vehicle users' misconduct against pedestrians, cyclists	Photos of wrong behaviors and suggestions, events, and actions	Members: 5,000 Reactions: 28 Comments: 13 Shares: 1 10 posts/week
<sup>1</sup> BIKE FUN	Promotion of bicycle use	Events and meetings	Members: 2,400 Reactions: 20 Comments: 5 Shares: 0 5 posts/week
<sup>1</sup> EIT Urban Mobility Malta RIS hub	Engagement with stakeholders of urban mobility, interaction with start-ups, cities, research, and innovative organizations, share of urban mobility- related activities	Share of events, training activities, workshops. Posts about the trends in urban mobility in Malta and abroad	Members: 199 Reactions: 3 Comments: 0 Shares: 0 Seen: 40 8 posts/month
<sup>1</sup> Urban mobility	Share of information about moving people and things through the city (bicycle use, electric vehicles, accessibility as well as information of environmental impact of urban transport	Shared links of news, and articles	Members: 54 Reactions: 2 Comments: 0 Shares: 0 Seen: 15 3 posts/month
<sup>1</sup> Cargo Bike Bloggers, Influencers & Activists - International Group	Promotion of cargo bike lifestyle. Networking of cargo bikers on international level.	Posts with experiences and inspiration	Members: 706 Reactions: 8 Comments: 2 Shares: 0 7 posts/month
<sup>1</sup> GreenTrips - Sustainable Mobility Community	Recognize and reward commuters' positive mobility behavior	Shared links of events, news, and articles	Members: 397 Reactions: 1 Comments: 0 Shares: 0 20 posts/year
<sup>1</sup> Sustainable Transport & Mobility	Promotion of sustainable mobility	Events, shared links of news and articles	Members: 94 Reactions: 2

Account name	Scope	Content	Social media metrics
			Comments: 0 Shares: 0 Seen: 15 2 posts/month
<sup>1</sup> Podilates.gr	Promotion of bicycle use	Events, posts about meetings, shared links of news and articles	Members: 5,400 Reactions:3 Comments: 0 Shares: 0 10 posts/week
<sup>1</sup> ΠοδηλατοΔρώ	Promotion of sustainable ways of transport (bicycle use, walking, public transport)	Post with photos, shared links of articles, events	Members: 1,500 Reactions: 14 Comments: 2 Shares: 0 10 posts/week
<sup>1</sup> Μαμάδες+ στο Δρόμο (Moms+ in the street)	Improvement to conditions for pedestrians in Greece, promotion of accessibility and road safety	Photos of wrong behaviors and suggestions, shared links of articles, polls	Members: 999 Reactions:8 Comments: 1 Shares: 0 3 posts/week
<sup>2</sup> EkoSkola Malta - Promoting Sustainable Mobility Choices	Promotion of sustainable mobility choices	Photos of actions, shared links of articles, events	234 page likes 245 followers Reactions: 1 Comments: 0 Shares: 0
<sup>2</sup> Sustainable Mobility Unit	Investigate, plan, and promote project and policies in the field of sustainable mobility (cycling, walking, public transport)	Post with photos and description, shared links of articles, questionnaires	995 page likes 1,046 followers Reactions: 10 Comments: 0 Shares: 0
<sup>2</sup> Transformative Urban Mobility Initiative	Enable leaders in developing countries and emerging economies to create sustainable urban mobility	Posts with photos and description, videos, shared links of articles	8,493 page likes 9,051 followers Reactions: 18 Comments: 0 Shares: 11

Account name	Scope	Content	Social media metrics
<sup>2</sup> Urban Cycling Institute	Bring cycling knowledge from science to practice and back	Posts with photos, videos, shared links of articles	115,013 page likes 189,750 followers Reactions: 372 Comments: 19 Shares: 111
<sup>2</sup> ΠοδηλαΤΤΙΚΗ Κοινότητα	Promotion of bicycle use as main transportation mode	Posts with photos, shared links of news	3,498 page likes 3,650 followers Reactions: 36 Comments: 2 Shares: 5
Note: <sup>1</sup> Public Groups type, <sup>2</sup> Pages characterized as Educational.			

The analysis showed there is a higher number of public groups that are related to promotion of sustainable mobility compared to pages. The main reason is that a page is for marketing purposes, while a group is for interacting with the audience.

Social media metrics are very important since they determine how much the audience is interested in the shared content. Metrics are a direct measure of the value of the account for the audience. The higher its value, the more influential the shared content. The analysis of Table 4-7 showed that the posting frequency affects the number of reactions. The public group “Bicycle commuters of Greece” with the highest frequency of posting compared to the other groups (4 posts/day) demonstrates the highest average number of reactions per post (36), while the public groups with the scarcest frequency of posting (less than 6 posts/ year) have the lowest average number of reactions (1-4). This finding shows that a more active group with consistency in posting keep its audience engaged. The shared content defines the number of comments and shares. Posts on the analyzed accounts that have content which sparks discussion concentrated high number of comments. Posts with humorous content or with photos of meetings and actions concentrated high numbers of shares. The page “Urban Cycling Institute” with the highest number of followers (189,750) have the highest numbers in reactions (372), comments (19) and shares (111).

Moreover, 40% of the analyzed accounts interact actively with their audience through posts that welcome new members and prompt responses to comments. This interaction makes the members feel part of the community and make them more willing to participate in actions or to give feedback on important initiatives. 80% of the accounts use hashtags related to the sustainable urban mobility such as #greenmobility #sustainablemobility #PublicTransport #cycling #biketouring #cargobikes, etc. The use of hashtags is very important to highlight specific campaigns or posts, start conversations around relevant topics etc. Hashtags can also be used to share coded information. A great example can be seen on the public group “Με ποδήλατο στη δουλειά” (translated as “Cycling to work”). In this group hashtags are used to code and share your route (#City #Origin #Destination #Frequency #Departuretime). An example is given below:

*Hello everyone! I live in #Munich and I cycle to work from #Marienplatz to #Nymphenburg, #everyday, meet me in front of city hall at #8:30 !! ☺*

The analysis showed that only a few accounts keep their audience involved in sustainable urban mobility matters with a proper and well-organized strategy. For this reason, it is very important a set of guidelines to build a social media communication strategy or improve the existed one. The main challenge for the accounts is not only to keep an active and consistent interaction with their audience, but also to reach and engage people who are not interested in sustainable mobility.

This systematic review has limitations. One limitation is related with the keywords' search. The selected keywords were deliberately selected as such to allow the capture of all relevant studies. Nevertheless, there might be some studies with significant contribution that might have been left out due to the imposed filtering criteria. For example, the examined years 2015-2022 may overlook some earlier studies, however, the scope of this review was to provide the most recent body of studies.

Another limitation is related with the review of the social media transport accounts on Facebook. The review was not protocol-driven and thus, it cannot be considered exhaustive. Although this typically yields some concerns as per the existence of bias, most of the accounts aim to promote sustainable aspects of transportation, be that ease from congestion or promotion of ridesharing schemes, and therefore bias context is difficult to determine.

## 4.5 Concluding discussion

In this chapter, the use of social media both as a source of transport-related information and as a mean of information sharing was examined. In the first part, the study focused on Twitter, which has become a major source of publicly shared information. Three cities of different population, language and transport infrastructure were analyzed, and it was found that MSP had the highest Twitter activity compared to Riga and Volos, despite the limited number of geo-referenced tweets in the three cities.

The collected tweets were graded based on a keyword list, and potential transport-related tweets were identified. MSP had the highest percentage of graded tweets with at least one transport-related word, followed by Riga and Volos. The popularity of Twitter in Riga and MSP as well as the language distribution can explain this difference, and the average grade per document for English tweets of the three cities is higher than for tweets in other used languages, supporting the hypothesis about higher potential of tweets in English as a source of transport-related information.

The most frequent domain classes of messages were identified, including general transport-related information, real-time information, complaints, advice/questions, and unrelated tweets. The class of transport-related advice/question was merged with general information due to the limited number of related tweets. A training sample was prepared for classification, including the labeled tweets as related to one of the identified classes. The majority of MSP and Riga's tweets that were manually analyzed were transport-related, while the percentages of transport-related tweets in Volos were low.

In general, the overall intensity of transport-related tweets in the three samples was low, and the most useful transport-related tweets were shared by official bodies and automated volunteered sources. The limited number of transport-related tweets in the city of Volos and the low average grades proved that the utility of retrieved information depends on the intensity of social media use in the study area, as well as on the tweets' language. This observation leads to the conclusion that areas with smaller populations have lower Twitter potential.



Although this research is based on collected qualitative data of social media, it can only be used to enrich datasets of quantitative data sources. In conclusion, the explosive growth of social media use and the amount of publicly shared information have led to huge volumes of available data, but the utility of this information for transportation-related purposes is limited. The results of this study suggest that Twitter can be a valuable source of transport-related information, but its usefulness depends on various factors such as the intensity of social media use, language, and the size of the study area.

The second part examined the use of social media as a promising way to reach many people and spread awareness and transport-related information to them. Social media has emerged as a powerful tool for promoting awareness and engaging citizens in sustainability initiatives. However, the use of social media for the promotion of sustainable urban mobility awareness campaigns and strategies is limited. Some of the reasons of this limited use could be the complexity of the topic, the lack of engagement or the limited resources. Sustainable urban mobility is a complex topic that involves a multitude of factors such as infrastructure, transport modes, land-use planning, and human behavior. Communicating these concepts to the public in a simple and engaging way is challenging, and social media platforms may not be the best medium to do so. The limited attention span of social media users and the need for visually appealing content further exacerbate the problem. Moreover, sustainable urban mobility is not a topic that generates immediate gratification, making it less attractive to the public. Engaging citizens in sustainable urban mobility initiatives is essential for their success. Social media has the potential to reach a large audience and foster engagement through sharing, commenting, and liking content. However, the low engagement rates of sustainable urban mobility campaigns on social media suggest that users are not interested in this topic. This lack of interest may be due to the perception that sustainable urban mobility is not relevant to their daily lives or that it is too complicated to understand. In addition to the challenges of communicating sustainable urban mobility concepts through social media, limited resources can also be a significant hurdle. Initiatives promoting sustainable urban mobility often have limited budgets and staff, which can make it challenging to develop and execute effective social media campaigns. The need for visually appealing and engaging content may require additional resources, such as graphic designers and content creators, which may not be available within the budget. Moreover, limited resources can also impact the ability to monitor and analyze the impact of social media campaigns on promoting sustainable urban mobility. Without adequate resources to track engagement, it may be challenging to determine the effectiveness of social media campaigns and adjust them accordingly.

To influence positively users' attitude towards sustainable mobility, the key is the formulation of an appropriate scheme and form of a transport-related account and content that would be more influential in today's social media landscape. An effective scheme starts from the analysis of pre-existing social media accounts. The current analysis leads to the following scheme that shows how to put a transport-related account and content in practice and how to reach and engage more users.

The first step for a successful scheme is to choose the most appropriate social media platform. This choice should be done after the determination of the account's scope and target group. Facebook is suggested for the creation of a community that ensures the involvement of members and followers. The analysis showed that Facebook groups allow the discussion, opinion sharing and meetings' scheduling among their members. A real time two-way communication with followers can be done through Twitter. This platform is suggested also for the share of real-time information. A visual platform such as Instagram is suggested to collect

images and stories related to the account's scope. Once the appropriate platform/platforms is/are decided, all the accounts should include a detailed description, profile photo and correct links. Then, a proper task distribution and should be done. Descriptions' writing, image processing, content sharing are some of the duties that should be assigned properly.

Consistency is the key to success. Study's findings showed that a more active account with consistency in posting keep its audience engaged. It is important to organize and schedule posts on a regular basis. Sharing of special events, promotion of activities and up to date content will keep audience's interest alive. The current survey, showed that the frequency of posting and the relevant and engaging content affects the number of reactions, comments, and shares. An active interaction with the audience is very important. Posts that welcome new members, prompt responses to comments, question and answer sessions, polls and live chats create opportunities for participation. The use of hashtags relevant to the shared content help posts' categorization, engagement growth and audience reach.

The shared content defines not only the number of reactions but also the number of comments and shares. The more relevant and engaging the content, the more motivated the people are to comment or share it with their "web friends". An informative or a humorous content is more appealing to people, and they enjoy reading it and feel comfortable to share it. In addition, the shared information should be accurate and verified. Lastly, influencers involvement such as mobility activists, associations, bloggers would raise more the awareness on sustainable mobility possibilities.

Social media could be used as the front edge to promote sustainable mobility and spread awareness. This can be succeeded through the development of a proper social media strategy. Social media allow a two-sided communication based on listening and engaging people in a way to build a supportive community to the efforts and plans towards sustainable mobility.

## 5 Use of GPS and self-reported data to evaluate daily trips and the impact of travel information

Daily trips in medium-sized cities are based more on habitual patterns, resulting sometimes in less optimal route choices. In this study, an attempt is made to investigate the travel information seeking and the trips in a medium-sized city and evaluate them to explore the impact of travel information. The research is motivated by the growing importance of sustainable urban mobility and the need to address traffic congestion, environmental concerns, and inefficient transportation choices in the city of Volos, Greece. To achieve that, a survey of two phases was performed. First, self-reported and GPS data of an examined group of 96 participants of the University of Thessaly, Volos, Greece was collected. The data was used to evaluate the daily trips in terms of travel time, cost, and environmental friendliness (Chapter 5). Second, a stated preference survey was designed targeted at motorized vehicle users of the examined group and presented in the Chapter 6. The survey investigated the extent that shared information on social media can be used to recommend a different route than the usual one or convince them to shift to a sustainable way of transportation.

Chapter 5 is an extended and adapted version of the following publications:

Karatsoli Maria, Nathanail Eftihia, 2022. "Use of GPS and self-reported data to evaluate daily trips and the impact of travel information". European Transport Research Review (submitted for publication: under 2nd review).

*Karatsoli Maria, Nathanail Eftihia, 2022. "Use of GPS and self-reported data to evaluate daily trips and the impact of travel information". Transport Research Arena 2022, November 14-17, Lisbon, Portugal.*

*Karatsoli Maria, Nathanail Eftihia, 2021. "Investigating the travel information-seeking behavior for daily trips in a greek medium sized city". In: Nathanail E.G., Adamos G., Karakikes I. (eds) Advances in Mobility-as-a-Service Systems. CSUM 2020. Advances in Intelligent Systems and Computing, vol 1278. Springer, Cham, [https://doi.org/10.1007/978-3-030-61075-3\\_66](https://doi.org/10.1007/978-3-030-61075-3_66)*

### 5.1 Introduction

Unfamiliar destinations, unknown traffic conditions and unreliable public transport timetables could lead to time-consuming and unsafe daily trips. Travel information contributes to a better perception and analysis of a travel situation. This information could change travel behavior and lead to the enhancement of convenience, safety, and efficiency of travel. An optimized travel plan could offer a faster, safer, and more environmentally friendly trip. Travel information systems encompass a wide range of technologies aiming at the provision of up-to-date travel information to travelers. Navigation applications that inform about route alternatives, real-time information about public transport and information-based strategies on social networks encourage commuters to make right travel choices. Although commuters make their own trip choices, these decisions affect the whole network and consequently other commuters at a given time. The potential of travel information to affect travelers' behavior led to an increased interest in its role on travelers' choices (Avineri, 2006; Chorus, et al., 2008).

The selection of optimal routes is crucial in transportation systems, where efficient and timely movement is essential. However, the existence of suboptimal route choices poses a significant problem that hinders the overall effectiveness and performance of transportation networks. The suboptimal route choice refers to instances where individuals select routes that are less efficient compared to available alternatives. Limited information, incomplete knowledge about alternative routes, habitual travel patterns, or suboptimal decision-making processes are some factors that for suboptimal route choice. Consequently, suboptimal route choices can result in several adverse consequences for transportation systems (Papinski & Scott, 2013; Ta, et al., 2016; van Essen, et al., 2020). A primary concern associated with suboptimal route choices is the increased travel time. The selection of routes that are suboptimal in terms of distance, congestion, or road conditions can lead to unnecessary delays. This not only affects individual commuters but also impacts the overall efficiency of a transportation network and leads to decreased productivity, higher fuel consumption, and increased environmental emissions (van Essen, et al., 2020).

The current research took place in the city of Volos, Greece. Volos is a medium-sized city situated in the center of Greece and is the sixth largest city of the country with 139.670 inhabitants (ELSTAT, 2021). The city center is arranged based on the Hippodamian or grid plan and serves high traffic volumes especially during the summer season. In a study conducted by the Volos Development Company SA (ANEVO LTD, 2015), it was found that the central district of Volos is faced with a significant challenge in terms of parking availability. The scarcity of parking areas has resulted in congested roads, as drivers endlessly circle the city center seeking parking spaces for their vehicles. The suboptimal route choice worsens the problem of congestion making imperative the need for more effective solutions in the city (Karakikes, et al., 2021). To this direction, this study aims to investigate the daily trips that are being performed in a medium-sized city and evaluate them to explore the impact of travel information that aims to decongest and reduce environmental pollutants in the overall road network.

## 5.2 Travel information and mobility behavior

The impact of traffic information on travel choices is well stated also in literature (Choocharukul, 2008). The study of Asselin et al. (2016) suggests that the use of new technologies could have immediate results and can assist with trips that necessitate familiarity with roads (Chowdhury & Giacaman, 2015). However, when travel information is available travelers must decide whether to follow it or not. The reliability of information is a key feature on individuals' decision making. A reliable information system is important since inconsistent information may have reverse results and reduce the probability of complying with it (Ramos, et al., 2012). In this study, it was found that travelers are more likely to follow pre-trip information compared to en-route information.

Regarding the factors that affect travel decisions, previous studies found that socioeconomic characteristics (Chorus, et al., 2006), travel-related characteristics, (Tam & Lam, 2005; Al-Deek, et al., 2009) and commuters' attitudes (Choocharukul, 2008; Farag & Lyons, 2008) play an important role on travelers' final decision. The study of van Bladel, et al. (2009), proved that commuters with flexible work schedule are more likely to change their daily activities based on available information. Yeboah et al. (2019) showed that pretravel information seeking behaviors of public transport users are affected by trip frequency, sociodemographic characteristics, trip characteristics and information source. In their study, it

was also mentioned that the understanding of smartphones or other devices usage for information seeking, is important for the development of information provision strategies that serve the needs of public transport passengers.

In medium-sized cities, the familiarity with the road network and knowledge of how to reach destinations make travel information-seeking a less commonly adopted approach. The habitual patterns of daily trips make the road users end up with other than optimal route choices, in terms of cost, time, emissions, etc. Especially for the case of motorized vehicle users, these choices can have significant impacts to the total road network. Strong habitual behaviors in driving tend to neglect alternative ways of travel (Pedersen, et al., 2012; Ramos, et al., 2020). In some cases, travel behavior and route choice are often influenced by the tendency to avoid complex decision-making. Unavailable travel information and presence of constraints shape over time a habitual behavior (Thorhauge, et al., 2020).

The potential of travel information to affect travelers' behavior creates an increased interest in its role on travelers' choices (Karatsoli & Nathanail, 2021). van Essen, et al. (2020) explored how real-time travel information influences the traveler's route switch propensity, concluding that the behavioral inertia to persist in the previous decisions is critical in the actual route choice. Vacca, et al. (2019) related behavioral inertia and route switch propensity, revealing that a higher behavioral inertia corresponds to a lower route switch propensity.

Numerous recent studies have examined travel behavior and route choices in the context of information provision. However, it is recognized that most of these studies have predominantly focused on evaluating the impact of real-time information on individual trip optimization, suggesting the most efficient route for personal journeys. While valuable insights have emerged from these works, there remains a notable gap in research that explores the potential of travel information to address broader goals, such as decongesting road networks in total and reducing environmental pollutants in small and medium-sized cities.

Our research seeks to address this gap by providing novel contributions to the literature by investigating the impact of travel information beyond individual route optimization, specifically exploring its potential in mitigating traffic congestion and environmental issues within the overall road network of medium-sized cities. The main objective of this study is to comprehensively examine the daily travel patterns of motorized vehicle users in medium-sized cities, with a particular focus on the city of Volos, Greece. Through a two-phase survey, self-reported and GPS data from a group of 96 participants were collected, consisting of both students and staff affiliated with the University of Thessaly. Additionally, a stated preference survey was designed to gather insights from motorized vehicle users within this examined group.

By conducting this research, valuable insights can inform policymakers and transportation planners in devising effective strategies for decongesting road networks and promoting sustainable urban mobility. We believe that our findings will shed light on the importance of travel information as a tool for addressing transportation challenges in medium-sized cities and beyond.

### **5.3 Methodological approach**

A survey was conducted to serve the needs of the evaluation of the daily main trips and the impact of travel information in a medium-sized city. Only main trips were analyzed to ensure comparability among all participants. Main trips tend to be more consistent among

participants in terms of purpose, duration, and frequency. This consistency allows for a fairer comparison of results across different individuals. Narrowing the analysis to main trips, reduced inaccuracies from incidental trips and simplified the interpretation of findings. The survey took place in Volos city, Greece, in December 2019. Both self-reported and Global Positioning System (GPS) data of an examined group of 96 participants was collected. The examined group comprised students and staff of the Polytechnic School of the University of Thessaly.

A two-phase approach was adopted to evaluate daily trips and the impact of travel information (see Figure 5-1). Phase 1 included: (i) pre- interview: a digital questionnaire to collect demographic characteristics and investigate participants’ perception of travel times and distances of their main trip, (ii) the collection of participants’ GPS data to record and evaluate their daily trips, and (iii) the creation of a “digital travel file card” for each participant. Phase 2 included: (i) the design of a Stated Preference (SP) survey which was addressed to motorized vehicle users that participated in Phase 1, and (ii) the development of an error component logit model capturing the impact of shared information on social media on participants’ mobility choices. Phase one is presented in this chapter, while the following chapter includes the analysis of Phase 2. The two phases are illustrated below.

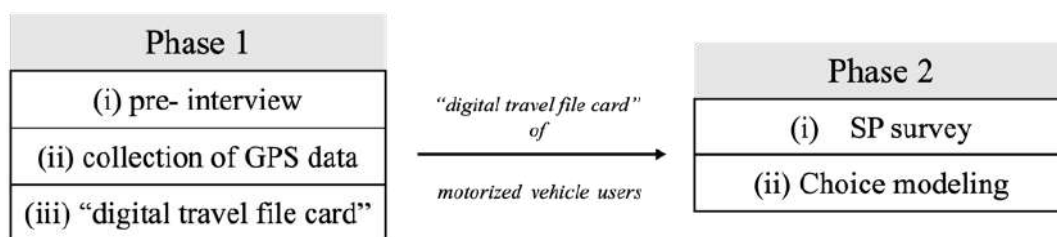


Figure 5-1. Methodological approach.

### 5.3.1 Phase 1: Collection and analysis of GPS data

A total of 130 potential participants, who owned a smartphone, were approached at the Polytechnic School campus of University of Thessaly in Volos, Greece, in December 2019. During the recruitment process, only people from the University community were approached, as they would be easier to be reached and more committed to participate. Hence, all respondents were students and employees of the Polytechnic School. The participation of students was encouraged since they are stronger users of social media and ICT devices. After an analytical description of the survey and its scope they asked about their intention to participate in it. Those who were positive about participating, received an introductory letter about the study which also included (a) the link to the pre-interview (b) a written manual on how the applications work (c) a unique ID. The sample size comprised 108 users, who fully completed the questionnaire and 96 of them proceed to the use of the smartphone application to record their trips.

The three parts of Phase 1: (i) pre- interview (ii) GPS data collection and (iii) participants’ “digital travel file cards” are described below.

#### 5.3.1.1 Pre-interview

A digital questionnaire was formulated to investigate participants’ perception of travel times and distances of their main trip from home to campus and vice versa (Annex F). Additional factors such as transport mode selection and arrival flexibility, that affect the travel

time perception, were also considered. The questionnaire was built on Survey Monkey, and it was written in both Greek and English language, since among the participants were also Erasmus students. The collection period was approximately one month, i.e., December 2019 - January 2020.

The questionnaire consisted of three parts. The first part referred to the daily trips of the participants, in which data regarding the trip distance and duration from and to the University campus, the flexibility at arrival time and the familiarity with traveling in Volos city, were collected. The next part aimed to investigate the intention and the factors that affect the travel information seeking, and its impact on commuters' mobility and travel choices. The last part recorded the socio-economic characteristics of the respondents, by collecting personal information such as gender, age, education level, employment status, etc. The analysis of the data was done through descriptive and inferential statistics. In the first case, sample characteristics, such as age, gender and occupation were addressed by estimating the frequency distribution per characteristic and the median values. In the second case, the statistical analysis of the responses was realized using non-parametric tests. The Mann-Whitney two-sample U-test was performed to assess differences between the samples in characteristics measured on the 5-point scale. Participants responded by rating items ranging from 1 (lower scores) to 5 (higher scores) with 3 as a midpoint. This scale was used as it increases the variance in the measurements and allows a greater differentiation in the results (Krosnick & Presser, 2009). The familiarity with traveling in Volos city, the importance of different factors in travel route choice and the impact of information on daily trip decisions were measured on the 5-point scale (Not at all 1, Slightly 2, Moderately 3, Very 4, Extremely 5). The participants responded on a 5-point scale (Never 1, Seldom 2, Sometimes 3, Often 4, Always 5) if they seek any travel information when traveling in Volos city. The rating of the main daily commute as regards characteristics such as shortest route, environmentally friendly route, economical route, safety, comfort etc. was measured on a 5-point Likert scale (Very dissatisfied 1, Dissatisfied 2, Slightly satisfied 3, Satisfied 4, Very satisfied 5).

### *5.3.1.2 GPS data collection*

Smartphone-based applications -Route Tracker (iPhone Operating System - iOS) and VEZMA (Android)- were used to collect the actual trips and GPS data of the participants in a period of 7 days. A pilot phase took place in November 2019, where the applications were tested by the researchers and ten participants on their own smartphones both on Android-based and iOS-based devices. Reported technical problems, in particular problems with data synchronization were properly addressed.

In our study, respecting the privacy of survey's participants unique IDs randomly assigned to each participant, so there was a limited possibility to connect the respondent identity with his or her daily track and personal data. Furthermore, a detailed privacy policy document with the information how the data will be utilized was prepared. Only one participant resigned from participating in the research to protect his/her privacy. Before downloading, participants could indicate whether they wanted their GPS location to be tracked by the app. Participants could keep private selected trips either by turning off the GPS tracking system at any time or by not recording the trip on the application menu.

Communication and support were provided throughout the duration of the field test. At the beginning of the field test, written instructions and personal guidance were given to each participant about how to download and use the application as well as to register with their

unique ID. Moreover, a Facebook group related to the survey was created to offer support to participants during the field test and send them reminders -three times a day- to activate the application recording. The Facebook chat was also available and used to answer (technical) queries if problems arose while using the application. The account that was created in the context of this research can be found here: <https://www.facebook.com/mobi.mobivolos.9> .

After the installation of the applications, GPS/ Google Mobile Services (GMS) signals were used to record individuals' trips. The applications ran on the participants' smartphones during their travel activities. Participants with Android-based smartphones had to label the trip purpose and specify the transport mode and then press the start button before their trips. Participants could choose among 18 trip purposes (Work (my workplace), Work (other work reason), Education, Go home, Get on/off public transport, Eat/Drink, Entertainment/ Recreation, Social visit, Shopping, Refuel vehicle, Park/ pick up vehicle, Pick up/ deliver a package, Transporting someone, Fitness/ Gym, Health, Accompanying someone, Personal reason, Other). Participants with iOS-based smartphones could press the record button either at the survey beginning and turn it off after seven days or before every trip and turn it off after the trip end. The second way was recommended to avoid battery draining. The iOS application didn't allow to label trip purposes; hence, the ends of the obtained trips were matched manually, with reported frequent places (PoIs). Trip purposes were identified based on the relative location of the GPS trip origin and destination and participant's known home and work location (UTH campus). Subsequently, participants were asked to review and validate the accuracy of the manually labelled trips in a follow-up interview.

The GPS data were used to evaluate the participants' trips and the chosen routes in terms of travel time, cost, and environmental friendliness. To achieve the evaluation of trips in terms of travel time, a comparison of the recorded routes with the suggested routes by route planners was performed. Specifically, the Google Maps Distance Matrix API service was used. This service returns travel distance and travel time between two given points at a specified departure time. The received information is based on the recommended route between these two points (trip start- trip end), as calculated by the Google Maps Distance Matrix API (Google, 2019). The parameters longitude and latitude of start point, longitude and latitude of end point, mode of travel, date and time of departure were used to construct the Uniform Resource Locators (URLs). The URL initiates a Distance Matrix request for distances between the given points. The provided results are JavaScript Object Notation (JSON) objects which contain the destination and origin addresses, the distance and duration in kilometers and minutes respectively. An example of a provided result where the travel mode was driving can be seen in Fig. 2. In this example the value the duration\_in\_traffic was also returned. The parameter traffic\_model (defaults to best\_guess) specifies the assumptions to use when calculating duration in traffic, which contains the predicted time in traffic based on historical averages. It may only be specified for requests where the travel mode is driving, and the request includes a departure\_time. The departure\_time must be set to the current time or sometime in the future and not in the past. Unfortunately, Google Distance Matrix API provides information for present and future travel distances and time. Since the weekday and time determine more travel decisions and traffic, it is decided to request the data based on the weekday that was close to the date that the trip took place. For example, to request data for a recorded trip that took place on Friday 13rd of December 2019 at 09:30 we called future data for Friday 11th of December 2020. Another limitation of the Google Distance Matrix API is the unknown sample size that was used to calculate average travel times for vehicle trips, so the reliability remains unclear and cannot be estimated.



```

{
  "destination_addresses" : [ "Alamanas, Volos 383 34, Greece" ],
  "origin_addresses" : [ "Amaxi, Xenofontos 45, Volos 383 33, Greece" ],
  "rows" : [
    {
      "elements" : [
        {
          "distance" : {
            "text" : "2.4 km",
            "value" : 2368
          },
          "duration" : {
            "text" : "7 mins",
            "value" : 403
          },
          "duration_in_traffic" : {
            "text" : "6 mins",
            "value" : 366
          },
          "status" : "OK"
        }
      ]
    }
  ],
  "status" : "OK"
}
    
```

Figure 5-2. Google Distance Matrix API result.

To evaluate the recorded trips in terms of travel cost, the recorded and Google API distances were multiplied with 0,12 €/km for car trips and 0,06 €/km for motorcycle trips. This stems from the average fuel price back in 2019 of 1,5 €/ℓ, assuming an average consumption of 7,5 ℓ/100km for cars and 3,5 ℓ/100km for motorcycles. Bicycle and walking trips had zero travel cost, trips with public transport had a cost of 0,60 € (student price for single ticket) and 1,10 € (regular price for single ticket). Moreover, to calculate trips’ emissions and determine their environmental impact, COPERT Street Level was used. COPERT Street Level is based on the algorithms of COPERT software allowing the calculation of emissions (CO, CO<sub>2</sub>, NO<sub>x</sub>, PM, VOC) based on traffic flow data i.e. link lengths, traffic volume data and average vehicle speeds per link, of the baselined country and reference year (Emisia, 2018). The calculation of the environmental indicators’ values was based on the recorded GPS data (average speed (km/h), distance (km), fuel type, type of motorized vehicle) of participants.

The self-reported data (pre-interview) and the collected GPS data were compared to investigate the over- and under-estimation of the actual travel times and distances. To avoid confounds only the travel times and distances of participants’ main trip from Home to University campus and vice versa were considered in the analysis. A variable  $d_i$  was defined as the ratio of the stated travel distance and the recorded distance from GPS data. The ratio was calculated for every participant by dividing the average value of the measured distances for these trips. A variable  $t_i$  was defined as the ratio of the stated travel time and the average recorded time from GPS data for these trips. The  $d_i$  and  $t_i$  ratios are defined mathematically as,

$$d_i = \frac{\text{Stated travel distance}}{\text{GPS recorded travel distance}}, \quad t_i = \frac{\text{Stated travel time}}{\text{GPS recorded travel time}} \quad (1, 2)$$

The trips were divided into three groups: overestimated trips, underestimated and accurately estimated trips in terms of travel distance and time. Overestimated trips in terms of travel distance refer to trips with  $d_i > 1$  and in terms of travel time refer to trips with  $t_i > 1$ . Trips with  $d_i < 1$  and  $t_i < 1$  are the underestimated trips and trips with  $d_i = t_i = 1$  are accurately estimated. The intention was not to scrutinize every minute in detail but to understand the general trend of overestimation or underestimation among participants. The calculation of these ratios

enabling us to evaluate and understand better the perception of distance and travel time of drivers in medium-sized cities. By understanding to what extent perceptions deviate from reality, we can tailor information provision to address common misperceptions, provide timely updates on traffic conditions, and offer alternative routes to enhance the overall travel experience.

### 5.3.1.3 “Digital travel file card”

The processed data were used to develop a “digital travel file card” for each participant which included both the analyzed data and suggestions for improving his/ her daily commute. The digital card includes information about participants’ mobility characteristics based on the GPS recorded data. The card consists of three parts. The first part includes the participant’s survey ID, the number of recorded trips, the percentage use of transport modes, and the percentages for the recorded trip purposes. In the second part, the participants can find details about their trips; total travel duration and distance for each selected mode, travel expenses, percentage of recorded routes that are longer compared to the suggested routes by route planners, and the environmental emissions during the days that the trips were recorded. The last part refers to the trip from Home to campus. Analytically, this part includes the participants’ statements about the distance and duration of this trip (Home to campus), as well as the real GPS recorded distance and duration. In addition, a figure shows the recorded route that the participant usually prefers to perform the “Home to campus” trip. The digital cards of the 37 motorized vehicle participants also include a Quick Response (QR) code of second phase’s stated preference online survey. Colors, graphics, and icons were chosen that way to be familiar and attractive to participants without having to spend too much time on card understanding.

The existing literature shows that mobility records such as the “digital travel file cards” with the presented statistics encourage the respondents to think about their overall trip activity and its characteristics and keep them committed to continue with the survey (Matyas & Kamargianni, 2019).

## 5.3.2 Phase 2: Stated preference survey and behavioral modelling

Early results verified that ~35% of the motorized vehicle users have the tendency to use the same route to reach their routine destinations even though this choice is not always the optimal one in terms of travel time and cost. This finding led to the design of a stated preference survey targeted specifically at car and motorcycle users of Phase 1. The analysis can be found in Chapter 6.

## 5.4 Phase 1: Pre-Interview and GPS data analysis

### 5.4.1 Pre-interview data analysis

#### 5.4.1.1 Initial sample that fully completed the pre-interview

The sample size comprised 108 users, who fully completed the pre-interview questionnaire. 52% of them are men and the rest 48% are women. 84% of the respondents belong to the age group of 18–23, 13% of them to 24–40 and 3% to 41–65. In addition, 83% of the participants are students, 8% are students with a part-time job, 4% are students with a full-time job, 3% belong to university staff and the rest 2% are researchers. The place of origin of 23% of participants is Volos and the rest 77% are from other cities. 95% of the respondents live

in Volos. 30% of them live in Volos for less than 4 years, 42% for 4 to 6 years and 28% for more than 7 years. Table 5-1 summarizes the characteristics of respondent’s daily trips. The familiarity with traveling in Volos city, the flexibility in arrival time at workplace/university and the ownership of driver’s license are also included. Most of the participants use car (32%) or walking (31%) for their daily trips. 27% of the participants stated that are extremely familiar with traveling in Volos city and 33% that have not driver’s license (see Table 5-5).

Table 5-1. Pre-interview sample characteristics.

Variables	Level	%
Gender	Female	48
	Male	52
Age	18-23	84
	24-40	13
	41-65	3
Occupation	Student	83
	Student with part-time job	8
	Student with full-time job	4
	University staff	3
	Researcher	2
Education level (completed studies)	High school	87
	Bachelor’s degree	4
	Master’s degree	5
	Phd	4
Place of origin	Volos	23
	Other	77
Place of residence	Volos	95
	Other	5
Years of residence in Volos	<4 years	30
	4-6 years	42
	>7 years	28

Table 5-2. Trip characteristics of the initial pre-interview sample

Variables	Level	%
Transport mode	Car (Diesel/ Gasoline)	32
	Car (Electric, hybrid or other new technology)	1
	Motorcycle	7
	Bicycle	12
	Electric bicycle	1
	Electric scooter	0
	Public Transport	16
	Taxi	0
	On foot	31
	<=2 km	53

Variables	Level	%
Trip distance estimation from residence to workplace/university	>2km	47
Trip duration estimation from residence to workplace/ university	<=10minutes	38
	10<minutes<=15	37
	>15 minutes	25
Trip distance from workplace/university to residence	<=2 km	50
	>2km	50
Trip duration estimation from workplace/university to residence	<=10	40
	10<minutes<=15	31
	>15 minutes	29
Familiarity with traveling in the city of Volos	Not at all	1
	Slightly	6
	Somewhat	32
	Moderately	34
	Very much	27
Is your arrival at work (/Uni) flexible?	Not at all	4
	5-15 minutes	65
	16 - 30 minutes	9
	31 - 60 minutes	3
	I work with a flexible schedule	19
Driver's license	No	33
	Yes, I am an owner less than 1 year	8
	Yes, I am an owner between 1 year and 5 years	44
	Yes, I am an owner more than 5 years	15

5.4.1.2 Importance and rating of trip characteristics

The Importance Performance Analysis (IPA) was used to determine the importance and the quality of participants' daily trips. The respondents were asked to rate the importance and the performance of their commuting characteristics. Ten attributes of a daily route were examined. The participants rated their daily routes in terms of comfort, safety, transport mode, travel time, potential delays, traffic congestion and in terms of shortest, environmentally friendly, economical, and scenic route. The importance was measured on a 5-point scale (Not at all 1, Slightly 2, Moderately 3, Very 4, Extremely 5) as well as the performance (Very dissatisfied 1, Dissatisfied 2, Slightly satisfied 3, Satisfied 4, Very satisfied 5).

The IPA graph consists of four quadrants and each of them suggests a different approach. The Quadrant I includes attributes with the greatest weakness that require actions in order to improve the quality and the performance of the attributes. Attributes that fall in Quadrant II have great quality which should be preserved. The Quadrant III includes attributes where low priority is given by the respondents. Attributes positioned in the Quadrant IV are less important for the respondents but of high performance (Martilla & James, 1977).

The following graph depicts the ten characteristics that were examined in this study. The environmentally friendly route attribute falls in the Quadrant III, showing that the respondents give less priority in such a route, also rating its quality as low. Respondents' trips perform low quality in terms of traffic congestion, potential delays, and scenic features. Even though participants stated that these characteristics are moderately important for them, a slight

change could show that these attributes require actions for improvement. Travel time, safety, and shortest route attributes play an important role for the respondents, so actions should be kept to preserve their high performance. Conclusions about the transport mode, comfort and economical route attributes cannot be safely drawn in this study (Figure 5-3).

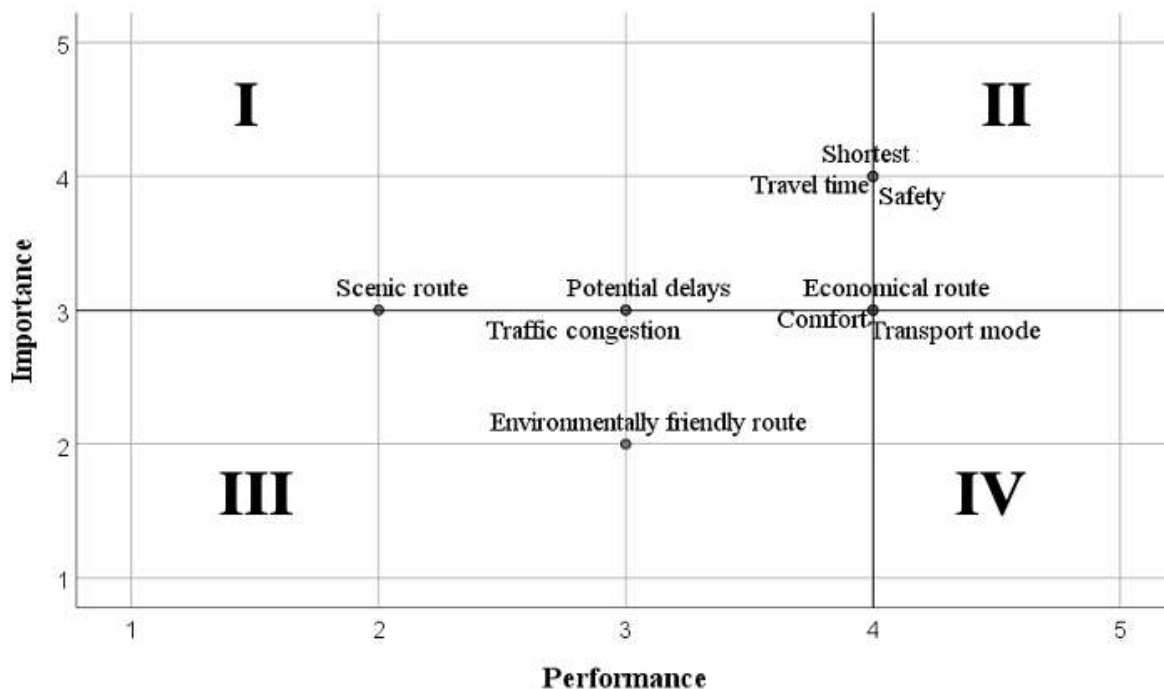


Figure 5-3. Importance of commuting characteristics and rating of current situation.

5.4.1.3 *Travel information seeking parameters' rating*

Parameters related to the frequency of travel information seeking between different origin and destination points (four parameters) and based on different factors (eleven parameters) were further examined. The rating was measured on a 5-point scale (Never 1, Seldom 2, Sometimes 3, Often 4, Always 5). The sample was separated in non-sustainable and sustainable mode users. The separation was done to check to what extent the parameters related to travel information seeking affect the sustainable and non- sustainable mode users. The category of sustainable mode users includes the participants that use sustainable modes for their daily commute. In this survey, public transport, cycling, riding scooter and walking were considered as sustainable modes of transport. The category of non- sustainable mode users includes participants that use non- sustainable mode of transport for their mobility (car, motorbike, or taxi). 60% of the participants use a sustainable mode of transport for their daily trips and the rest use a non-sustainable way of transport. The exact percentages for each mode of transport are included in Table 5-5.

Table 5-3 presents an overview of the median values of the fifteen variables and the test results of the comparisons between non-sustainable and sustainable mode users. Results are described through the U and p-value, indicating the strength of the respective evidence. According to Table 5-3, seven out of the fifteen hypotheses tested were found significant. Results showed that both non-sustainable and sustainable mode users never seek any travel information from their residence to their workplace/university and vice versa. However, this is not the case when it comes to traveling from residence to an activity location. Sustainable mode

users get travel information more often compared to non-sustainable mode users. Non-sustainable mode users would seek more often for information about traffic congestion and dynamic re-routing when traveling in Volos compared to non-sustainable mode users. This can be explained since non-sustainable modes are mainly affected by congestion. Sustainable mode users would search information about public transport itineraries more often compared to non-sustainable mode users. The fact that public transport users belong to this category can explain this frequency between the two groups. Finally, both groups would seldom seek information to identify the ideal transport mode according to their needs when traveling in Volos city.

Table 5-3. Parameters’ rating between non-sustainable and sustainable mode users.

Parameters	Groups					
	Non-Sustainable	Sustainable	N-S vs. S			
	M	SD	M	SD	U	p-value
Do you get travel any information from:						
-your residence to your workplace/ university	1.30	0.74	1.68	0.903	1046.5	<b>0.008</b>
- your workplace/ university to your residence	1.16	0.574	1.42	0.705	1089.0	<b>0.008</b>
- your residence to an activity location	2.33	1.017	2.80	0.971	1048.0	<b>0.022</b>
-your activity location to your residence	1.88	0.981	2.09	0.897	1185.5	0.158
When traveling in the city of Volos, to what extend would you seek information						
-to reach an unknown destination	3.60	1.137	3.74	1.065	1315.0	0.590
-to find the shortest route	2.53	1.077	2.68	1.077	1286.5	0.469
-to find the most environmentally friendly route	1.91	1.130	1.95	1.022	1329.5	0.649
-to find the most economical route	2.58	1.052	2.51	1.214	1331.5	0.680
- to stay informed about the traffic congestion	2.53	1.162	2.05	1.022	1063.5	<b>0.029</b>
-to estimate your travel time	3.21	1.081	3.06	0.998	1264.0	0.381
-to identify the ideal transport mode according to your needs	2.05	0.950	2.58	1.171	1038.5	<b>0.019</b>
-to be informed on public transport itineraries	2.19	0.932	2.92	1.150	892.5	<b>0.001</b>

Parameters	Groups					
-to decide upon your departure time	2.70	1.081	2.95	1.243	1209.5	0.223
-for dynamic re-routing	2.58	1.074	2.15	1.149	1074.0	<b>0.035</b>
-when reliable information is provided	3.12	1.159	2.74	1.108	1149.0	0.108

M: average rating, SD: Standard Deviation, \*statistically significant (p-value< 0.05)

5.4.1.4 Impact of travel information on commuters’ decisions and travel choices

Concerning the possible influence of travel information on commuters’ final decisions, the respondents were asked to rate on a 5-point scale (Not at all 1, Slightly 2, Moderately 3, Very 4, Extremely 5), to what extend their choices may be affected by travel information. Figure 5-4 shows the number of participants per scale point for six different aspects of changes on travel choices. Based on the figure, the availability of travel information, can affect users more often in choosing a particular route. To a smaller extend, the travel information can make users to cancel their plans or change their activities. This may be related to the fact that in both cases radical changes in the initial plans are required.

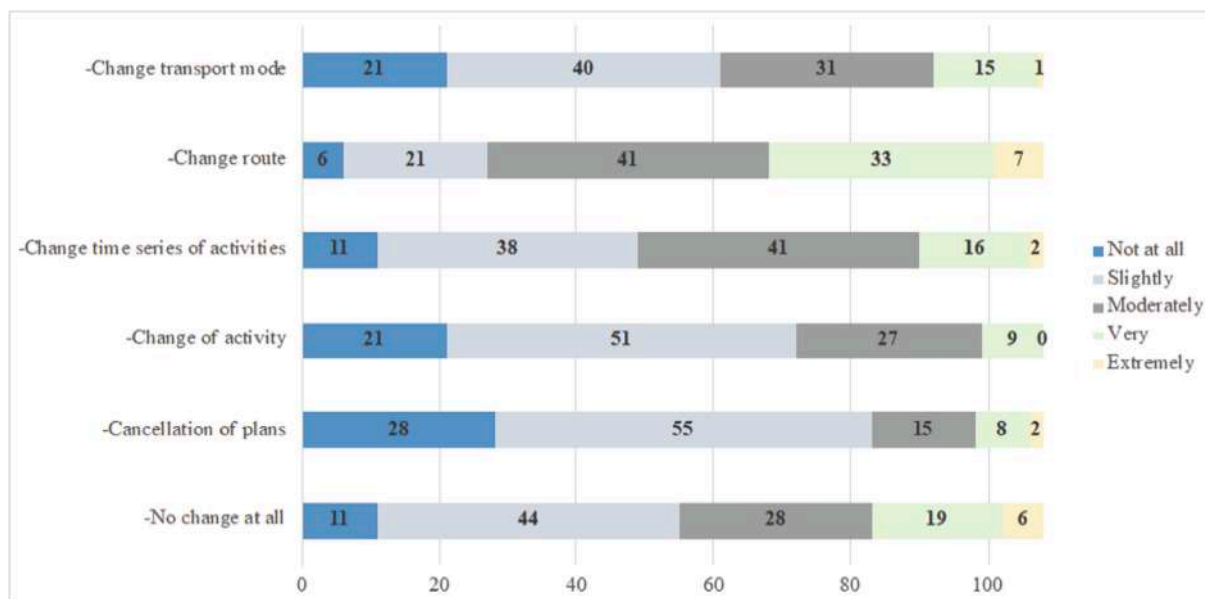


Figure 5-4. Impact of travel information on participants’ travel choices.

5.4.1.5 Sample that proceeded to GPS data collection

The final sample size comprised 96 users, who fully completed the questionnaire and proceeded to the recording of their trips. 50% of them are men and the rest 50% are women. 82% of the respondents belong to the age group of 18-23, 15% of them to 24-40 and 3% to 41-65. In addition, 81% of the participants are students, 9% are students with a part-time job, 4% are students with a full-time job, 3% belong to university staff and the rest 2% are researchers. The highest educational level of 87% of participants is high school, 4% holds a bachelor’s

degree, 5% holds a master’s degree and 2% holds a PhD. The high percentages in the age group of 18-24 years old and in the occupation group of students was expected as the questionnaire survey was carried out at a university campus. Finally, 83% of participants stated that their mobile device is connected to the internet when they are not home.

A summary of the characteristics of respondent’s daily trips can be found in Table 5-4. 33% of the participants use car, 33% travel on foot, 17% use PuT, 12% bicycle, and 5% motorcycle. 47% travel more than 2km from Home to University campus and 53% less, while the respective percentages for the return trip are 50% and 50%. As per the Home to University campus trip duration, 38% spend less than 10 minutes, 37% 10 to 15 minutes, and 25% more than 15 minutes. For the return trip, 40% spend less than 10 minutes, 31% 10 to 15 minutes, and 29% more than 15 minutes. Moreover, 27% of the participants stated that they are extremely familiar with traveling in Volos city and 32% that they do not have a driver’s license. 67% stated that their arrival at university campus is flexible by 5-15 minutes, 8% 16-30 minutes and 2% 31-60 minutes. Further, 20% stated that he/she has a flexible arrival schedule, while 3% has no flexibility, whatsoever. Regarding, the extent to which participants would consider travel information before their commute, 36% and 23% stated they would very much and extremely, respectively, consider travel information. During their commute, 56% of the participants stated that they would moderately consider travel information, while only 14% and 5% would very much and extremely consider it. Concerning the possible influence of travel information on commuters’ final decisions, 37% and 32% respondents stated that their route choice would be affected moderately and very much, respectively. As per the transport mode choice, 38% and 31% stated that they would slightly or moderately affect.

Table 5-4. Trip characteristics of GPS group.

Variables	Level	%
Transport mode	Car (Diesel/ Gasoline)	32
	Car (Electric, hybrid or other new technology)	1
	Motorcycle	5
	Bicycle	11
	Electric bicycle	1
	Electric scooter	0
	Public Transport	17
	Taxi	0
	On foot	33
Trip distance estimation from residence to workplace/university	<=2 km	53
	>2km	47
Trip duration estimation from residence to workplace/university	<=10minutes	38
	10<minutes<=15	37
	>15 minutes	25
Trip distance from workplace/university to residence	<=2 km	50
	>2km	50
	<=10	40



Variables	Level	%
Trip duration estimation from workplace/university to residence	10<minutes<=15	31
	>15 minutes	29
Familiarity with traveling in the city of Volos	Not at all	1
	Slightly	4
	Moderately	31
	Very	37
	Extremely	27
Is your arrival at workplace/university flexible?	Not at all	3
	5-15 minutes	67
	16 - 30 minutes	8
	31 - 60 minutes	2
	I work with a flexible schedule	20
Driver's license	No	32
	Yes, I am an owner less than 1 year	7
	Yes, I am an owner between 1 year and 5 years	44
	Yes, I am an owner more than 5 years	17

### 5.4.2 GPS data analysis

In total 1,164 trips and 1,354 trip legs were recorded. 38.2 % of the participants used car (36.9% conventional car/ 1.3 electric car), 34.4 % travelled on foot, 9.3 % used PT, 8.6% bicycle, and 9.5% motorcycle. The recorded travel time spent per respective transport mode was 32% (4,004 min) for cars, 46.9% (6,054 min) walking, 8.9% (1,147 min) PuT, 7.1% (913 min) bicycle, and 5% (651 min) motorcycle (see Table 5-5).

Table 5-5. Number of trips and travel time (minutes) per transport mode.

Transport mode	Number of trips	%	Minutes	%
Bicycle	97	8.3	898	7
Car	429	36.9	4003	31
Electric bicycle	3	0.3	15	0.1
Electric/ hybrid car	15	1.3	130	1
Motorcycle	111	9.5	651	5
Public transport	109	9.3	1147	8.9
Walking	400	34.4	6054	46.9

The characteristics of trip purposes can be summarized as follows: 35% (403 trips) are Go Home purposed trips, 21% (247 trips) are Education trips, 12% (136 trips) Eat/Drink, 9% (102 trips) Shopping, 7% (76 trips) Social Visit, 5% (54 trips) Entertainment, 4% (52 trips) Fitness/Gym, 3% (36 trips) Work and the rest are ≤ 1% (see Table 5-6).

Table 5-6. Number of trips based on the trip purposes.

<b>Trip purpose</b>	<b>Number of trips</b>	<b>%</b>
Accompanying someone	2	0
Eat/ Drink	136	12
Education (Campus)	233	20
Education (Library)	13	1
Education (Other- i.e. attending a German course in city center)	1	0
Entertainment	54	5
Fitness/ Gym	52	4
Get on/off Public Transport	5	0
Go Home	403	35
Health	2	0
Park-Pick up a vehicle	7	1
Personal reason	6	1
Pickup-deliver something	7	1
Refuel vehicle	6	1
Shopping	102	9
Social Visit	76	7
Transporting someone	12	1
Work	24	2
Work (Campus)	12	1
Other	11	1

It is noted that an analysis of these trips in relation to the weekdays showed that education related trips have a higher percentage on weekdays, while shopping related trips are steeply increased on Saturday. shows the percentage of trips and their purpose based on the weekday (Figure 5-5).

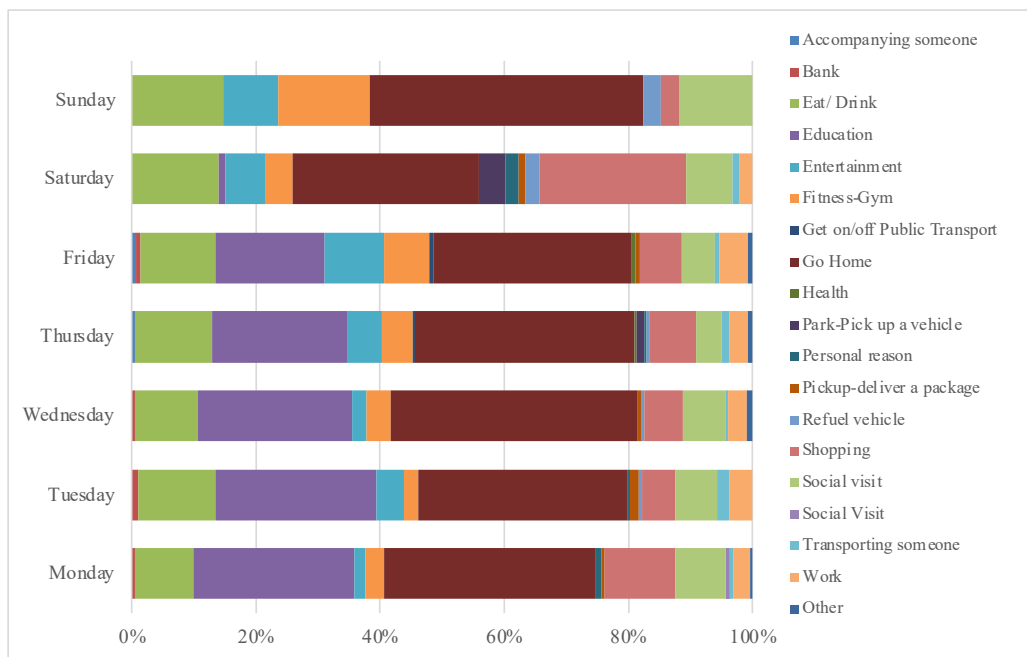


Figure 5-5. Weekdays and trip purposes.

Moreover, 276 missed trips could be identified based on the trip tour. For example, when a trip from home to university was recorded and then the next recorded trip was from Home to Shopping, then it was implied that there was an unrecorded trip from University to Home. 42% of the missed trips were walking trips, 39% car trips, 8% public transport trips, 7% motorcycle trips and 4% were bicycle trips. Table 5-7 shows the purpose of the missed trips.

Table 5-7. Purpose of missed trips.

Trip purpose	Number of trips	%
Eat/ Drink	15	5.4
Education (Campus)	30	10.9
Entertainment	8	2.9
Fitness-Gym	1	0.4
Get on/off Public Transport	4	1.4
Go Home	174	63.0
Health	1	0.4
Park-Pick up a vehicle	2	0.7
Shopping	8	2.9
Social Visit	23	8.3
Work	6	2.2
Work (Campus)	1	0.4
Other	3	1.1

As per the travel time of trips from Home to University campus (and University campus to Home), 50% (and 50%) were overestimated, 43% (and 39%) underestimated and 7% (and 11%) accurately estimated. Respectively, for the travel distance 44% (and 46%) were overestimated, 52% (and 45%) underestimated and 4% (and 9%) accurately estimated (see Table 5-8). Inaccurate travel time and distance estimations can potentially lead to adverse

decisions after information provision, influencing various aspects of commuters' travel behaviors and experiences. Respondents who underestimate their travel times may unintentionally allocate insufficient time for their trips, resulting in time constraints and potential late arrivals to their destinations. This may reduce the overall satisfaction with the travel experience. Conversely, respondents who overestimate travel times might leave earlier than necessary, leading to idle time and missed opportunities for other activities. Additionally, estimations influence route selections, with underestimations leading to the choice of longer or more congested routes, perceived as faster. On the other hand, overestimations may result in opting for shorter but less efficient routes, leading to potential delays. To mitigate the potential negative consequences of inaccurate estimations, providing travelers with more reliable and real-time travel information is essential.

Table 5-8. Frequencies of overestimated and underestimated trips.

Attributes	% of trips
Travel time from Home to University of Thessaly	
Overestimated trips	50
Underestimated trips	43
Accurately estimated	7
Travel time from University of Thessaly to Home	
Overestimated trips	50
Underestimated trips	39
Accurately estimated	11
Travel distance from Home to University of Thessaly	
Overestimated trips	44
Underestimated trips	52
Accurately estimated	4
Travel distance from University of Thessaly to Home	
Overestimated trips	46
Underestimated trips	45
Accurately estimated	9

Additionally, 216 of the 1164 recorded trips were not the same with the suggested routes of the route planners. The total travel cost of the recorded trips was 226.3€. If all the recorded trips would be based on the suggested routes by route planners, the total cost would be 207.2€. The total recorded duration of trips was 215 hours (12898 minutes) and ideally would be 21 hours less (1279 minutes). In terms of environmental emissions, a selection of the suggested routes would lead to 175.1 g less CO, 26.803 kg less CO<sub>2</sub>, 151.1 g less NO<sub>x</sub>, 4.9 g less PM, 28.9 g less VOC.

### 5.4.3 Creation of the “Digital travel file card

The first part of the “Digital travel file card” includes the survey ID, the number of recorded trips, the percentage use of transport modes, and the percentages for the recorded trip purposes. In the second part, further details about the trips can be found, i.e. total distance and total duration per transport mode, expenses, comparisons with the suggested routes of the route

planner (Google maps), total environmental emissions, etc. The last part refers to the trip from home to university campus and vice versa. Analytically, this part includes the respondent's statements about the distance and duration of the trip, the recorded by GPS travel data, cost estimations, and a figure of the recorded route that each respondent usually prefers to perform. The QR code of the stated preference survey was included at the end of the "Digital travel file card" of motorized vehicle participants, urging them to participate right after the reading of their card.

Figure 5-6 is an example of a "Digital travel file card" (the rest cards can be found in Annex I). The card refers to respondent 'mobivolli' who recorded his trips for seven days. The first part of the "Digital travel file card" includes his survey ID mobivolli, the number of recorded trips 31, the percentage use of transport modes 61% car and 39% walking, and the percentages for the recorded trip purposes. The trip purposes were Eat/ Drink, Education, Fitness/ Gym, Go home, Shopping, Pick up/ deliver a package, Work, Transporting someone.

In the second part, details about his trips can be found. The respondent recorded in total 32,3 kilometers and 2 hours and 11 minutes of car trips. He walked in total 10,86 kilometers with total walking time duration of 2 hours and 36 minutes. He spent 3 euros and 88 cents. 23% of his recorded trips are longer compared to the suggested routes of the route planner (Google maps). The total environmental emissions were 61,75g CO, 8727,95g CO<sub>2</sub>, 8,07g NO<sub>x</sub>, 0,13g PM, 6,98 g VOC.

The last part includes the respondent's statements about the distance and duration of the trip from Home to University of the Thessaly and vice versa. The respondent stated that the trip from Home to University of Thessaly is 2 kilometers and lasts 10 minutes and the return trip is 1,5 kilometers and lasts 8 minutes. According to the GPS data the average distance of the "Home to University of Thessaly" trips were 2,2 kilometers and lasted in average 8 minutes. A cost estimation of each trip was 0,26 euros. The trips from University of Thessaly to Home were 1,86 kilometers with an average duration of 10 minutes and an average cost of 0,22 euros. In addition, a figure of the recorded route that the respondent usually prefers to perform the "Home to University of Thessaly" trip is included. The QR code of the stated preference survey was included at the end of card. The rest "Digital travel file cards" can be found in Annex I.

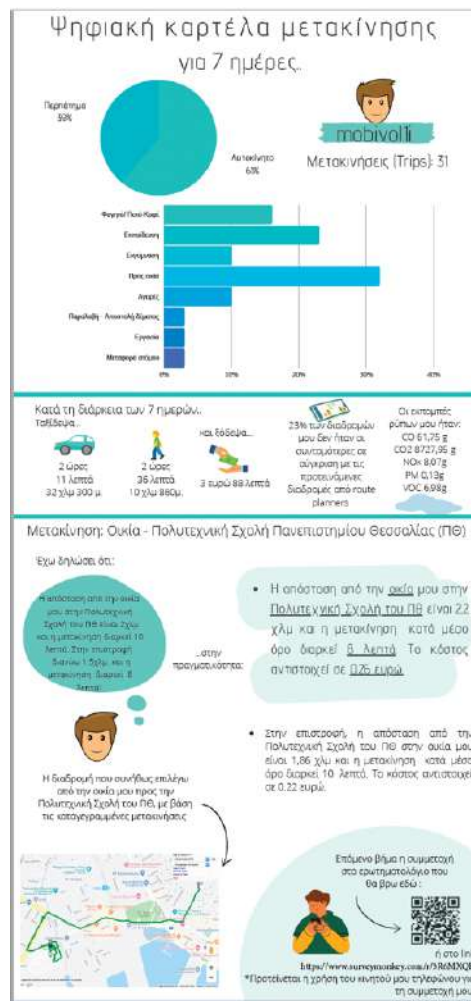


Figure 5-6. Example of “Digital travel file card”.

### 5.5 Conclusions

Understanding daily travel and mobility choices in a medium sized city, provides valuable information about traveler needs and characteristics. This study investigated the daily trips of students and staff from University of Thessaly, in the medium-sized city of Volos, Greece and evaluated them to explore the impact of travel information. The analysis was based on a dataset that combines stated and revealed data. Results verified that ~40% of the participants underestimate the travel time and distance of their main trip from home to campus and vice versa. Familiarity in traveling and less complexity of the road network in a medium sized city make sometimes road users end up with other than optimal route choices without noticing it. While it is possible that participants might have been aware of the optimal route, we acknowledge that travel choices are influenced by a variety of factors beyond mere awareness. Factors such as habitual travel patterns, personal preferences, avoidance of certain areas, and considerations related to traffic conditions or landmarks can all play a role in participants' route selection. Findings of pre-interview indicate that users mostly prefer online sources of travel information such as navigation applications or social networks compared to conventional sources. Most of the respondents stated that they are interested in information about traffic conditions and travel times. A shortest route, safety and travel time were rated as very important by the respondents. However, an environmentally friendly route is slightly important for them.

Results showed that both non-sustainable and sustainable mode users never seek travel information from their residence to their workplace/ university and vice versa. Sustainable mode users get information from residence to an activity location more often compared to non-sustainable mode users. Regarding the impact of information on participants' choices, a route change, or a change of time series of activities is more possible compared to cancellation of plans or change of activity. Information providers should consider commuters' and trip characteristics to develop a reliable information system. Factors that lead to travel information seeking reveal the type and the way how information should be provided in order the commuters to follow it. This study entails limitations. The survey was carried out at a university campus; thus, most of the respondents are students and belong to the young age group. This may bias the results while it is believed that they do not allow sufficient investigation of the behavioral differences among respondents of different occupations and ages.

## 6 A Stated Preference study to explore the impact of travel information on motorized vehicle users

A stated preference survey was designed to examine to what extent shared information on social media can be used to recommend to car and motorcycle users a different route than the usual one or convince them to shift to a sustainable way of transportation, i.e. use of public transport or active transportation. This information aims to decongest and reduce environmental pollutants in the overall road network. It is noted that, the purpose of the content of the shared information was to contribute to decongesting and reducing environmental pollutants in the overall road network, rather than suggesting an optimal route for the personal trip of the motorized vehicle users.

Chapter 6 is an extended and adapted version of the following publication:

Karatsoli Maria, Nathanail Eftihia, 2022. "Use of GPS and self-reported data to evaluate daily trips and the impact of travel information". European Transport Research Review (submitted for publication: under 2nd review).

*Karatsoli Maria, Nathanail Eftihia, 2022. "Use of GPS and self-reported data to evaluate daily trips and the impact of travel information". Transport Research Arena 2022, November 14-17, Lisbon, Portugal.*

### 6.1 Stated preference survey design

The choice experiment included three alternatives: the usual route, the suggested route, and a sustainable way of transport (public transport, active transportation). To facilitate a realistic choice situation, each participant was given access to his/her digital travel file card prior to completing the experiment, while the data collected during the GPS survey was incorporated into the stated choice experiment to allow convenient and clear selections. Once the alternatives of the choice experiment were decided upon, it was necessary to determine which attributes and their corresponding levels should be included to describe them, see Table 6-1. Careful consideration was given to the number of attributes and their respective levels. Awareness of potential cognitive load on participants was critical; an excessive number of variables could potentially compromise response quality due to fatigue or oversight. Statistically, an increase in attributes and levels would require more choice scenarios to ensure the integrity and validity of the results. The study's objectives decisively influenced these choices. A concise set of attributes was maintained, and a diverse range of levels within them was explored to get deeper insights. Realistic attributes and attribute levels were chosen to avoid participants' confusion and assure the results' validity comprehension. Taking into consideration all the above and conducting a pilot testing before finalizing the design, an optimal balance for the study's efficacy and relevance was achieved. The type of personalized information includes real-time traffic updates, alternative route suggestions, and transportation mode recommendations based on individual preferences.



Table 6-1. Alternatives, attributes, and attributes' levels.

Alternative	Attribute	Attribute levels*
Usual route	Travel time	0   +20%
	Travel cost	0   +20%
	Availability of personalized information services about the selected route	Available   Non-available
Suggested route	Travel time	-10%   0   +30%
	Travel cost	-5%   0   +30%
	Availability of personalized information services about the selected route	Available   Non-available
	Availability of navigation and instructions	Available   Non-available
Sustainable way of travel	Transport mode	Walking   Bicycle   PT
	Travel time	-30%   0   +100%   +200%
	Travel cost	0 €   0.60 €

\* The attribute levels were pivoted around the stated values of time and cost, using percentages.

The Minitab software and Microsoft Excel were used to find all the possible combinations of the three alternatives and their attributes and attribute levels. The first alternative gives 8 combinations ( $2^3=8$ ), the second gives 36 combinations ( $3^1*3^1*2^1*2^1=36$ ) and the third one gives 24 combinations ( $3^1*4^1*2^1=24$ ). In total we have  $8*36*24=6912$  combinations. These were eliminated by deleting blocked combinations (i.e combinations were deleted because walking and bicycle cannot have cost, public transport cannot have zero cost, public transport and walking cannot have a reduction in travel time.) The choice situations were built based on the trips that were recorded during phase 1. The collected GPS data was incorporated into the stated choice experimental design to create a realistic choice situation for each survey participant. Hence, the respondents did not have to put a great effort into imagining the described situation. Each respondent was presented with ten choice situations, in which the levels were chosen based on a cleaned random experimental design. As per Walker, et al. (2015), the efficacy of the random design is comparable to other designs, and it can perform even better if the design is sanitized by eliminating the choice tasks where one alternative completely dominates others. Such scenarios have no real tradeoff for the respondents. This approach helps to minimize the occurrence of strictly dominant alternatives that could potentially lead to biased estimates, as suggested by (Bliemer, et al., 2017; Matyas & Kamargianni, 2019). The appearance of choices was differentiated and randomized to avoid selecting biases and to explore the impact of the message appearance on the final choice. The ten presented choice sets can be found in Table 6-2.

Table 6-2. Choice sets

Choice set	Usual route			Suggested route				Sustainable way of travel		
1	+20%	+20%	No	+30%	0	No	Yes	Walking	+200%	0
2	0	+20%	Yes	-10%	+30%	Yes	No	Walking	+100%	0
3	+20%	0	Yes	-10%	0	Yes	Yes	Bicycle	-30%	0
4	+20%	0	Yes	-10%	-5%	No	Yes	Public Transport	+100%	0.60
5	0	0	No	0	0	No	No	Walking	+100%	0
6	0	+20%	No	+30%	-5%	Yes	Yes	Bicycle	0	0
7	+20%	0	Yes	0	-5%	Yes	No	Walking	+200%	0
8	+20%	+20%	No	+30%	-5%	Yes	Yes	Public Transport	+100%	0.60
9	+20%	0	Yes	-10%	+30%	Yes	No	Walking	+100%	0
10	+20%	+20%	Yes	-10%	+30%	Yes	Yes	Walking	+100%	0

The shared content included a post that informed about either congestion or high levels of environmental pollution in the usual route of the respondents, followed by three available travel options. Each respondent had to choose between the three alternatives, thinking of his/her digital travel card. The posts were prepared and shared on a Facebook profile (Mobi MobiVolos) to get screenshots and include them in the presented scenarios of the stated preference survey.

The shared post included text and photos. The text included the message about either congestion or high levels of environmental pollution in the usual route and was followed by a photo of a map showing the usual and the suggested route. A follow-up post included a text about the three available travel options, followed by three pictures representing them. The first picture was related to respondents’ usual travel choice, the second one was related to the suggested travel choice, and the third one was related to the sustainable way of transport. Figure 6-1 illustrates the appearance of the Facebook’s post on a mobile phone of a vehicle user.

The design and the appearance of the shared choice cards on the Facebook account was either plain without any special format or included pictures and colors related to the content of the message and the attribute levels that are presented in Table 6-1. Specifically, the usual route in some choice sets was depicted with a congested road and air pollutants while the suggested route was depicted with a route among trees. For the sustainable way of travel photos related to

the respective suggested way were used i.e., a bus for public transport, a bicycle for cycling or people walking. Figure 6-1 shows an example of the post appearance of the designated account on the Facebook profile *Mobi MobiVolos* that was created in the context of this research. Figure 6-2 shows an example of the of the presented stated preference experiments. The specific example advises to take another route to decongest the usual route. Specifically, the appeared text is in Greek and mentions:

*“G. Lambraki route is congested. Most of drivers choose this route to minimize their travel time. The increased demand has the opposite effect and leads to an increase in travel times. Choose the suggested route or a sustainable way of travel to help decongest the transport network.*

*There are three available travel options to arrive at Polytechnic School of Volos.”*

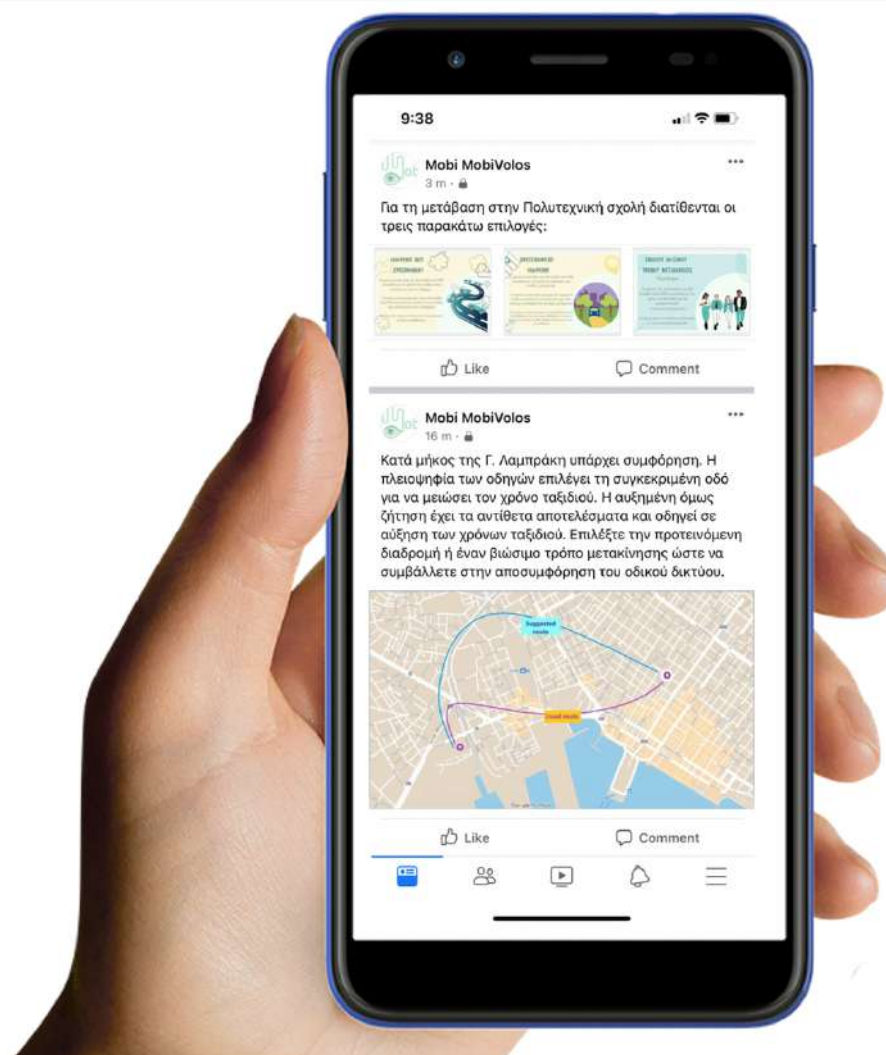


Figure 6-1. Post appearance of the designated account related to sustainable urban transport on a mobile phone of a vehicle user.



Figure 6-2. Example of a Stated Preference experiment addressed to a vehicle user.

## 6.2 Choice model estimation

The collected data were used to develop an error component logit model using Monte-Carlo integration and estimate the probability of an individual choosing one of the three alternatives in the presence of travel information on social media. The error component logit model allows us to account for individual-level heterogeneity and the influence of unobserved factors that may impact travel choices. By incorporating the error component, we can better understand the underlying preferences and decision-making processes of the participants when faced with different travel options. Since in the SP survey the respondents faced several scenarios, the models account for repeated observations from the same individuals in the data set (panel data). The actual choice of variables is determined based on data availability and estimation results of alternative considered models. The utility equations of the three alternatives for the developed model, are presented below:

$$U_{UR} = a_{UR} + \beta_{TT_{UR}} * TT_{UR} + \beta_{GENDER} * GENDER \tag{3}$$

$$U_{SR} = a_{SR} + \beta_{TT_{SR}} * TT_{SR} + \omega_n \tag{4}$$

$$U_{SW} = a_{SW} + \beta_{TC_{SW}} * TC_{SW} + \omega_n \tag{5}$$

$\omega_n$  is an error component normally distributed across individuals  $n$  and is specific to the alternatives suggested route and sustainable way of transport. Specifically,  $\omega_n$  is a random term that captures the individuals' willingness to change. The final model was estimated in Pythonbiogeme software (Bierlaire, 2003) and was determined after testing various specifications and by using 10,000 draws. The description of the coefficients  $a$ ,  $\beta$  is given in Table 6-3 where the model estimation results are presented.

### 6.2.1 Phase 2: Stated preference survey analysis

#### 6.2.1.1 Analysis of stated preference survey data

The final sample size of the stated preference survey comprised 37 motorized vehicle users. 65% of them are men and the rest 35% are women. 70% of the respondents belong to the age group of 18-23, 22% of them to 24-40 and 8% to 41-65. In addition, 62% of the participants are students, 16% are students with a part-time job, 8% are students with a full-time job, 8% belong to university staff and the rest 5% are researchers. 78% of participants stated that their mobile device is connected to the internet when they are not home. Moreover, 89% of the participants uses car and 11% uses a motorcycle for their daily trips.

According to Figure 6-3, 51% of the participants stated that they would moderately consider travel information during their commute. 27% of the stated that are extremely willing to consider travel information before their commute.

Figure 6-4 shows that 57% of the participants would slightly change transport mode if they would get travel information about their main daily trip. 38% of the participants stated that they would be very willing to change their regular route if they got travel information about their main daily trip.

Parameters related to the frequency of travel information seeking when traveling in the city of Volos based on different factors (nine parameters) were examined and can be found on Figure 6-5. The rating was measured on a 5-point scale (Never 1, Seldom 2, Sometimes 3, Often 4, Always 5). According to the findings, 38% of individuals frequently seek information when it is deemed reliable, and the purpose is to estimate their travel time. 11% always seek reliable information for the same purpose. The results suggest that most people prioritize reliability when seeking information about travel time.

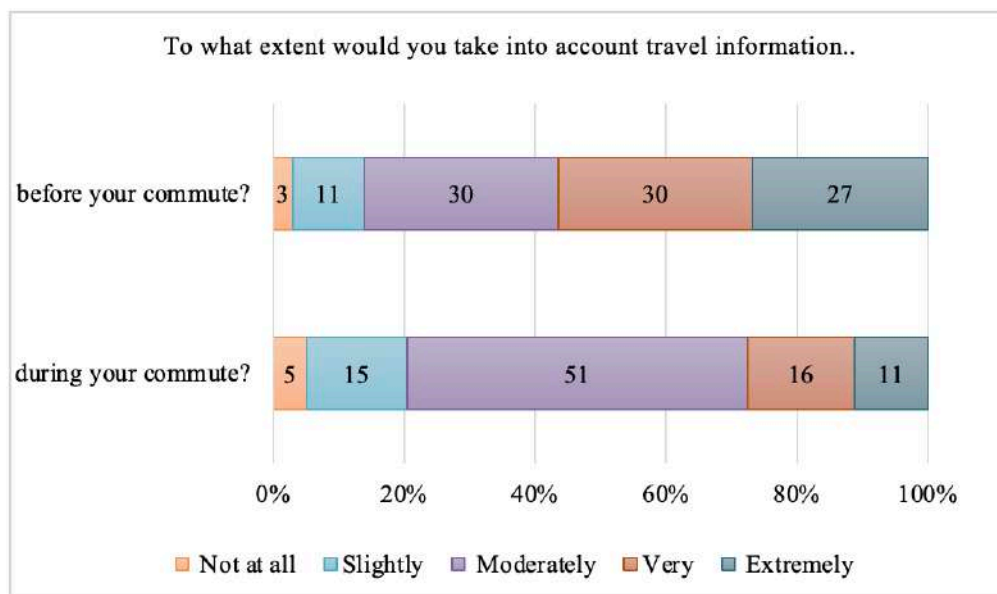


Figure 6-3. Travel information-seeking before/ during commute.

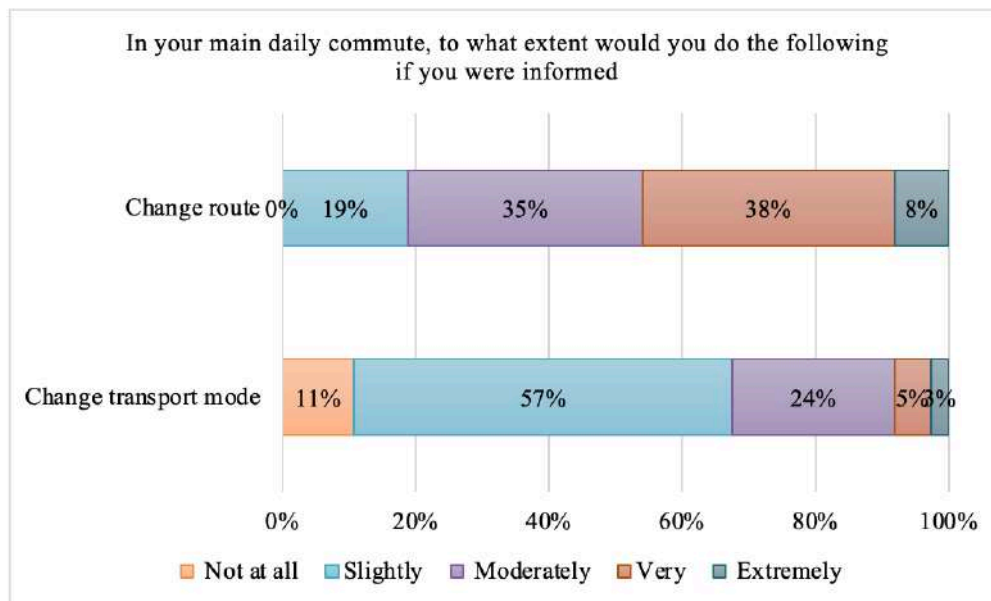


Figure 6-4. Impact of travel information.

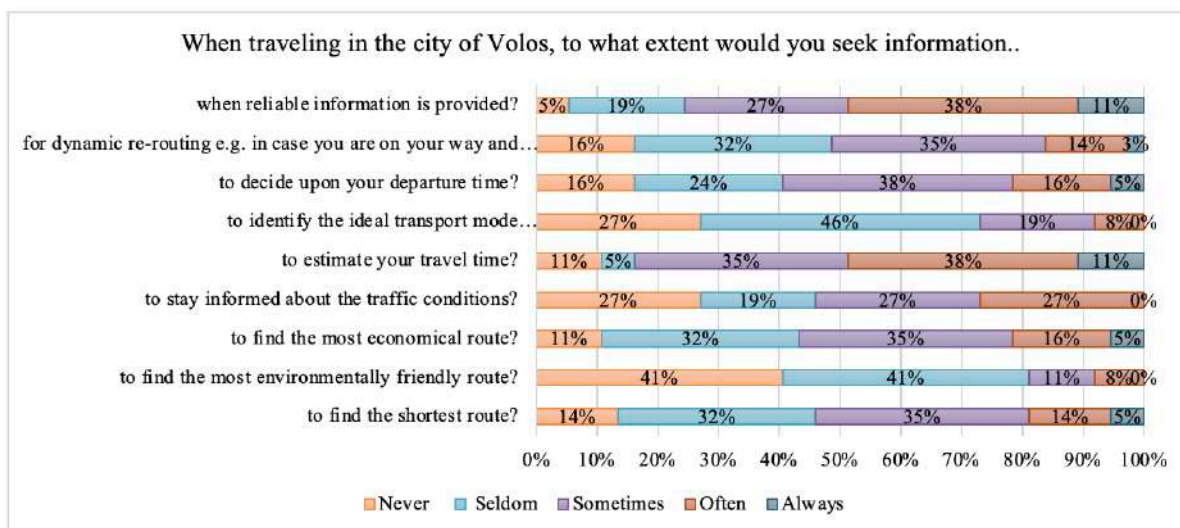


Figure 6-5. Travel information seeking in Volos city.

The analysis of the survey showed that 81% and 78% of the participants are willing to spend up to 0,50 euros more for their trip from home to campus, to contribute to congestion alleviation and reduction of environmental pollutants, respectively. Similarly, 86% and 81% of the participants are willing to prolong up to 5 minutes their total travel time to contribute to the same purposes. Furthermore, the choice experiment showed that the dominant selection of the three given alternatives was the suggested route even though in some cases this scenario added up extra travel time and cost to the participant. The alternative sustainable way of transport was less selected in tasks where the Public Transport level was appeared (Task 4 and 8). In Tasks 1, 5, 7, where the Walking level was appeared, the sustainable way of transport was preferred more compared to the usual route, but still the suggested route was the dominant selection. Two types of messages were appeared at the ten tasks. In the five tasks the message aiming at the decongestion of the road network and in the rest five at the reduction of the environmental

pollution. Nevertheless, the message scope appeared as not that important in the final selection. Finally, 10 participants (27%) agreed and strongly agreed that the appearance (colors and graphics in the option tabs) of the travel information messages affected their final decision. On the opposite side, 10 participants (27%) disagreed and strongly disagreed that the appearance affected their final decision, while 17 participants (46%) remained neutral.

#### 6.2.1.2 *Model estimation results*

Table 6-3 presents the model estimation results. The developed models have been estimated using the software package Biogeme (Bierlaire, 2003) and are considering the panel effect for repeated observations from same individuals in the dataset. After testing various specifications, the final presented models were selected based on statistical goodness-of-fit (likelihood ratio tests, estimated coefficient significance t-tests, the rho-square ( $\rho^2$ ), and adjusted rho-square ( $\bar{\rho}^2$ ) statistics). 10,000 random draws were used for models' estimation. Although model convergence has little direct relation to the number of draws, we are confident that the use of 10,000 draws, which is a relatively high number compared to some modeling practices, was sufficient for our estimation process.

A brief description of the independent variables is also given, and the standard error and statistical significance of each variable are indicated. Initial analysis focused on ensuring that independent variables selected for the model were not excessively correlated. To mitigate this, the correlation matrices for the predictors were developed. These matrices provide the pairwise relationships between variables. Particularly, any correlation coefficient approaching -1 or 1, or exceeding 0.8, was scrutinized, as such values indicate potential multicollinearity. Based on the results, the parameters have the expected signs while most of them are highly significant. With regards to the constant terms of the utility functions, the estimation results indicate that the respondents have some propensity towards the suggested route instead of the usual route. Regarding the sustainable way of transport, respondents prefer the usual route instead of a sustainable way of transport. The preference for the usual route over sustainable transport options highlights the need for further promotion and education on the benefits of sustainable transportation. Concerning the travel time estimate, the negative coefficient indicates that the higher the travel time of the usual and the suggested route, the lower the probability that an individual will choose it. The same applies to travel cost, the negative coefficient indicates that travel cost has a negative effect on the individual's usage of a sustainable way of transport. This applies to the case of public transport as the ticket fee prevents an individual from choosing it. The same applies to travel time; the higher the travel time of the alternative, the lower the probability that an individual will choose it. The negative effect of travel time on the probability of choosing an alternative route aligns with the time-cost tradeoff theory in transportation research. Finally, the respondent's gender is estimated to affect the probability of choosing the usual route. Specifically, the finding that women are more likely to change their usual route suggests a potential gender difference in travel behavior. Overall, the findings provide insights into the factors that influence individuals' travel choices and can inform policy decisions aimed at promoting sustainable and efficient transportation options.

Table 6-3. Model estimation results.

Variable	Description	Estimate	t-test
<b>Alternative specific constants (ASC) (base category: Usual route)</b>			
$\alpha_{UR}$	ASC specific to Usual Route		
$\alpha_{SR}$	ASC specific to Suggested Route	0.696	<b>4.62</b>
$\alpha_{SW}$	ASC specific to Sustainable Way of transport	-0.639	<b>-2.48</b>
<b>Travel time (in minutes)</b>			
$\beta_{TT}$	Travel time specific to Usual and Suggested Route	-0.0357	-1.29
<b>Travel cost (in €)</b>			
$\beta_{TCSW}$	Travel cost specific to Sustainable Way of transport	-1.19	<b>-2.61</b>
<b>Individual's socio-demographic</b>			
$\beta_{GENDER}$	Gender specific to Usual Route	-1.05	<b>-2.15</b>
$\omega_n$	Error component specific to Suggested Route and Sustainable Way of transport	0.472	<b>2.08</b>
$LL_0$	Initial log likelihood	-346.6296	
$LL_\beta$	Final log Likelihood	-290.437	

### 6.3 Conclusions

Model outputs indicate that individuals after travel information provision are more willing to choose the suggested route over their usual route which aligns with the aim of exploring the effectiveness of travel information in decongesting roads by promoting alternative routes. Regarding the sustainable way of transport, the preference for the usual route over a sustainable mode suggests that participants are more inclined to stick to their established travel habits, which may have implications for reducing the environmental impact of daily trips. The negative coefficients for travel time and cost variables highlight that individuals are more likely to avoid longer travel times and higher costs, indicating the potential for travel information to influence route choices that could lead to decongestion and reduced pollution by promoting shorter and more cost-effective routes. Specifically, the travel cost of a sustainable way of transport, reduces the probability that an individual will choose it. In our case public transport



is less preferred compared to walking or biking. A reasonable explanation is that Volos is a flat, bike and walk-friendly city with a long seaside ideal for these ways of mobility.

Another important finding is that women are more likely to change their usual route. This indicates that women may be more willing to change their habits. This gender-related finding could be an important consideration in designing targeted interventions and travel information strategies that can influence route selection and potentially lead to a more efficient and environmentally friendly road network. A similar conclusion has been documented in (Karatsoli & Nathanail, 2020) where the authors concluded that women are affected at a higher degree than men and are more receptive to the information provided by social media.

The model outputs provide valuable insights that are directly relevant to the overall aim of the study. The results suggest that travel information has the potential to influence route choices and contribute to congestion alleviation and reduction of environmental pollutants in a medium-sized city. Understanding the factors that influence travel choices is essential for developing effective interventions, policies, and information campaigns that promote sustainable and eco-friendly travel behaviors. The findings of the study contribute to the broader understanding of travel behavior and have practical implications for urban transportation planning and environmental sustainability efforts. This work highlights the need of understanding more explicitly the role of information dissemination through social media. More specifically, future research should explore how social media are useful for people to access travel information, how they can be used to spread awareness and transport-related information, and how they induce the need to move in more sustainable way.

While this study provides valuable insights into travel behavior, there are limitations to consider. The data collected and the respective analysis is limited to a specific group of people, with specific sociodemographic and mobility characteristics. It is important to note that the choices observed in the study are hypothetical and may not reflect the actual constraints faced by individuals in different societal circumstances. The cost variable and availability of personalized travel information did not show statistical significance in predicting travel preferences among the participants. Therefore, they were not included in the final model. However, we acknowledged this limitation, which may indicate that cost and availability of personalized information might not be a significant factor in the context of this specific study sample or do not affect motorized vehicle users in medium sized cities.

## 7 A Stated Preference study of pedestrians' and public transport users' mobility choices in the era of COVID-19

Social media can be a valuable tool for travel information provision for pedestrians and public transport users (Karatsoli & Nathanail, 2020), including information about crowdedness levels during pandemics such as COVID-19. Public transport agencies and city governments can use social media to share real-time updates on crowdedness levels on buses, trains, and metros, which can help individuals to decide about their trips. Social media can also be used to share information about delays, detours, and other disruptions to public transport services, which can help commuters plan their routes and reduce their risk of exposure to the virus. Similarly, social media can be used to share information about crowdedness levels at popular pedestrian destinations, such as parks and shopping districts. This can help individuals choose routes to avoid areas that may be at higher risk for virus spread. Social media can also be used to share information about social distancing measures and capacity limits at businesses and organizations, which can help individuals plan their activities (Purnomo, et al., 2021). Additionally, social media can be used by individuals to share information about their experiences in real-time, such as how crowded is a certain place, how long they wait for public transport, or even creating chat groups or communities where people can share information about crowdedness levels of certain places, and the best time to visit them. In summary, social media can be a valuable tool for providing real-time travel information for pedestrians and public transport users (Magginas, et al., 2019; Karatsoli & Nathanail, 2020), including information about crowdedness levels during COVID-19, helping people to make informed decisions about where and when to travel, and reducing the risk of exposure to the virus (Ye, et al., 2021).

The COVID-19 pandemic has impacted people's everyday lives, as avoiding being in crowded places became the number one societal rule. Crowdedness has therefore increasingly affected decisions such as a place visit via a specific path, the selection of a public transport stop, itinerary, etc., thereby making related information increasingly relevant. The objective of the following chapter is to examine the route and travel choices of pedestrians and public transport users, with the provisioning of travel information related to crowdedness levels. To that end, a choice experiment was designed to elicit travelers' preferences. Discrete choice models were estimated based on data collected from 465 individuals in Greece. Results showed that crowd avoidance plays a significant role in shaping mobility decisions for both pedestrians and public transport users. Factors such as place of residence, age, the importance of COVID-19 measures and arrival time are found to affect the likelihood of switch routes in response to information about high levels of crowdedness.

This chapter is an extended and adapted version of the following publication:

*Karatsoli Maria, Nathanail Eftihia, Socrates Basbas, Oded Cats, 2023. "A Stated Preference study of pedestrians' and public transport users' choices in the era of COVID-19". Cities (submitted for publication).*

## 7.1 Introduction

The outbreak of the COVID-19 virus in the first months of 2020 forced the European governments to impose measures to stop its rapid spread. These periods of lockdowns and targeted restrictions gradually reinforced people's avoidance of crowded places. The applied measures by governments aimed at mitigating the effects of COVID-19 by controlling human mobility. Being a prominent non-pharmaceutical intervention, mobility faced massive changes and restrictions that significantly changed people's personal travel choices (Rafiq, et al., 2022). The COVID-19 pandemic had a significant impact on walking (Nikiforiadis, et al., 2022; Campisi, et al., 2022) and public transport ridership (Lucchesi, et al., 2022; Shelat, et al., 2022a; Shelat, et al., 2022b). The fear of infection made people hesitant to walk in public spaces, such as busy sidewalks or parks, since the proximity to others increased the risk of exposure to the virus. In this case, using a car instead of walking provided a sense of physical distance and a perceived lower risk of infection. In addition, the reduced services of public transportation systems and the avoidance of crowds in public transport reinforced car use (Zavareh, et al., 2022; Lucchesi, et al., 2022; Shelat, et al., 2022b; Campisi, et al., 2022; Nikiforiadis, et al., 2022). A shift to car use was expected due to the negative perceptions regarding the public transport use and the exposure to crowds and COVID-19 transmission (Zavareh, et al., 2022; Shelat, et al., 2022b). This increasing car use and the diminishing trend of walking and public transport used to minimize exposure to crowds is a serious concern to the development of sustainable cities. These changes in travel behavior may be sustained in the post-pandemic era and have a significant effect on people's confidence in traveling with sustainable modes of transport which are prone to crowdedness, such as public transport (Hörcher, et al., 2022; Hartleb, et al., 2021).

These challenges further intensify the need of new technologies and real-time information systems to promote the public transport use and support switching to active transportation with a lesser risk of COVID-19 transmission (Hörcher, et al., 2022; Hartleb, et al., 2021). Real-time information systems that ensure the respect of social distancing are expected to recover the confidence of people in traveling with others. This demands the need to further understand people's travel decision-making under different crowdedness levels. To this end, we examine the route and travel choices of pedestrians and public transport users, upon travel information provision concerning crowdedness levels. Pedestrians and public transport users are in the focus of this study because they are two of the most common modes of transportation in urban areas.

To evaluate pedestrians' and public transport users' behavior under different crowdedness levels and how they respond to real-time information, we conduct a Stated Preference (SP) experiment (Annex K). In the experiment, 465 participants from Greece responded about their COVID-19 mobility choices after transport information was provided to them by a designated social media account related to sustainable urban mobility. Each respondent had to select between two hypothetical scenarios, thinking of his/her daily main trip. The two alternatives include respondents' usual travel choice and a suggest-ed travel choice with a lower crowdedness level. Scenarios for pedestrians refer to route choice and include three attributes: crowdedness level, walking time, and walking environment. Public transport users' scenarios refer to changes in public transport stop and itinerary and include four attributes: crowdedness level, travel time, walking time and arrival time.

To explain pedestrians and public transport users' choices, discrete choice models are estimated. Personal and trip characteristics, crowdedness levels, and COVID-19 related aspects

(i.e. mandatory use of face masks, social distancing, etc.) are used as independent variables to predict participants' travel choices.

## 7.2 Crowdedness and social distancing in the era of COVID-19

The COVID-19 outbreak has significantly influenced travel choices and has brought changes in crowding perceptions among pedestrians and public transport users. Studies revealed that travelers' psychological and behavioral aspects had a great impact on transport demand during the pandemic (Borkowski, et al., 2021). A reduction in the frequency of public transport use and an increase of walking frequency was observed among young adults in Greek cities (Nikiforiadis, et al., 2022). The practice of social distancing proved to be an effective measure for preventing the transmission of COVID-19 as well as in mitigating feelings like anxiety, fear, and stress (Campisi, et al., 2022). Since 2020, several studies have investigated the potential of social distancing and its implementation on walking and public transport travel choices.

### 7.2.1 Walking and social distancing

The COVID-19 pandemic has highlighted the importance of maintaining social distancing in public spaces, particularly in dense crowds. In recent studies, researchers have conducted controlled experiments to examine the impact of variables such as pedestrian density, walking speed, and prescribed safety distance on social distancing. In the study of Echeverría-Huarte, et al. (2021) controlled laboratory experiments were conducted to examine the impact of variables such as pedestrian density, walking speed and prescribed safety distance, on social distancing within relatively dense crowds. An interesting finding was that to keep a distance of 1 m, the density should not be higher than 0.16 pedestrians per square meter (around 6 m<sup>2</sup> per pedestrian). Seres, et al. (2021) in their experiment, measured distances kept (with or without facemask) before and after mandatory mask use in stores by calculating waiting lines in front of stores. The analyses showed that individuals became less careful in their distancing behavior once relaxation measures became effective. Findings also showed that distancing declined in areas where stores reopened, possibly making it more difficult to keep safe distancing due to crowded sidewalks. Pedestrian physical distancing indicators to quantitatively evaluate different levels of physical distancing were developed by Mohammadi, et al. (2021). In addition, levels of pedestrian physical distancing that can be used for implementation of appropriate mobility interventions were proposed. A mathematical procedure for relative risk estimation of COVID-19 transmission between pedestrians under different walking conditions was also developed. Finally, the application of the proposed approach was demonstrated by the authors by means of a microscopic pedestrian simulation software.

Researchers have explored different approaches to monitor and ensure the respect of social distancing in real-time, combining pedestrian dynamics with infection judgement frameworks to model the probability of transmission. Other studies have used pedestrian microsimulation modelling frameworks to evaluate the effectiveness of different social distancing scenarios in improving pedestrian flow and reducing contact violations. A comprehensive survey was conducted by Himeur, et al. (2022) who reviewed existed contributions related to visual social distancing monitoring, i.e. ensuring the respect of social distancing in public areas by controlling and analyzing the physical distance between pedestrians in real-time. Xiao, et al. (2022) developed a simulation-based approach that combines physical-distancing pedestrian dynamics with an infection judgement framework.

The approach captures the spatial factors influencing the ability of social distancing for COVID-19 prevention and models the probability of transmission in various spatial configurations. In this direction, Alam, et al. (2022) developed a pedestrian microsimulation modelling framework that evaluates different scenarios for a commercial street. The results revealed that the social distancing strategy in the pandemic scenarios significantly improved the pedestrian flow in terms of contact violations reduction. Simulation findings indicated that an increase in sidewalk width can influence contact rates and travel time. In addition, the tested scenario that incorporated wider sidewalks showed a decrease both in total travel time and contact rates. In the work of Möllers, et al. (2022) data from automated pedestrian and bicycle counting stations as well as information data about weather conditions and calendar events were used. The data were used to estimate the isolated impacts of COVID-19 and government interventions on walking and cycling in ten German cities. Results showed that pedestrian levels decrease with more severe government intervention. During all hours of the day, the COVID-19 spread had a negative impact on pedestrian flows, especially on Saturdays. The impact of feelings such as anxiety and stress on walking for either leisure or work in the COVID-19 era was examined by Campisi, et al. (2022). Results showed that there is a strong correlation between age and anxiety and between stress and gender, namely older people and men tend to feel more anxiety while walking during the pandemic period. Most respondents strongly agree that anxiety has an impact on walking during the COVID-19 period.

### 7.2.2 Public transport and crowding

The COVID-19 pandemic has presented significant challenges for public transport systems, including reduced demand and the need to implement new occupancy standards. Based on previous studies, crowding played already a significant role in passengers' route choice in public transport prior to the COVID-19 outbreak (Yap, et al., 2020). Recent studies have investigated the impact of COVID-19 on crowding perception and disutility in public transport systems. The findings of these studies provide insights into how passengers perceive and respond to crowded conditions, as well as the impact of social distancing measures on perceived comfort levels. The great challenges for public transport systems induced by the pandemic, including the sharp reduction of public transport demand, the occupancy levels and their new standards were thoroughly discussed in the work of Tirachini & Cats (2020). A year later, Aghabayk, et al., (2021) investigated the impact of COVID-19 on crowding perception and crowding disutility in metro rail system of Tehran, revealing that the value of crowding increased during the pandemic. Stated preference data before and during COVID-19 were used to develop mixed logit models. Results showed that an increase in density of standees and of occupied seats leads to a decrease in the perceived comfort level. The difficulty of maintaining social distance reinforces a feeling of insecurity resulting in low comfort scores.

A public transport traveler behavior related to COVID-19 risks was also analyzed by Shelat, et al. (2022b) and Shelat, et al. (2022a). The authors conducted a stated choice experiment with train travelers in the Netherlands at the end of the first pandemic wave. The data were analyzed using a latent class choice model with two classes 'COVID Conscious' and 'Infection Indifferent'. Older and female travelers are more likely to belong to the first class of 'COVID Conscious' while more frequent users of trains during the pandemic tend to be 'Infection Indifferent'. Results showed that the first class has a significantly higher valuation of crowding, prefers to sit alone and are quite sensitive to the infection rate. By contrast, the second class has a slightly higher value of crowding than pre-pandemic estimates and is relatively unaffected by infection rates. Chen, et al. (2022) examined the impact of COVID-19

policies on travel decisions influenced by the latent aspects. Stated preference data were used to develop a hybrid choice model to investigate the impact of COVID-19 related policies on individuals' transportation mode choices during pandemic. Findings showed that attributes like travel time and cost become less relevant during pandemic compared to normal situations. Moreover, the travel preferences during the pandemic are significantly associated with latent factors of social responsibility, infection fear, risk perception, and travel anxiety. In general, public transport is identified as an insecure alternative compared with private modes of transport.

Real-time information systems are used to improve passengers' on-board experience and the performance of the system by influencing passengers' route choices (Fonzone, et al., 2016; Karatsoli & Nathanail, 2020; Karatsoli & Nathanail, 2021). A comprehensive literature review about the impact of real time information on the travel behavior of public transport passengers was conducted by Brakewood & Watkins (2019). Later, in the work of Drabicki, et al. (2021) the authors investigated the instantaneous real-time crowding information systems in public transport networks. A passenger path choice model was developed accounting for the impact of real time information on passengers' travel experience and crowding. After the spread of COVID-19, studies focused on real time crowding information systems (Krusche, et al., 2022; Peftitsi, et al., 2022) or other methods such as dynamic pricing (Hörcher, et al., 2022; Saharan, et al., 2020) that bring benefits to the public transport system while make safer its use. A discrete model was developed by Hadas, et al. (2022), to assess the factors that affect the choice of whether to board an overcrowded vehicle or not. The model examined to what extend attributes such as age, income level, extra waiting time, crowdedness level, and discount and penalty levels affect the willingness of passengers to wait for the next vehicle. The findings of the research indicated that the longer the waiting time, the lower the willingness to board the next vehicle. It was revealed that participants older than 50 were less willing to wait for the next bus. Moreover, the willingness to wait was higher when a penalty was introduced as opposed to a discount.

### 7.2.3 Study contributions

The study aims to fill a research gap by investigating the potential and impact of information provision on travel choices under pandemic circumstances, specifically focusing on the travel behavior of pedestrians and public transport users. While previous studies have examined travel behavior during the COVID-19 era, there is limited knowledge regarding the influence of real-time information about crowdedness levels on individuals' travel decisions.

The contributions of this study to the existing literature are twofold. Firstly, the study examines the travel choices of both pedestrians and public transport users when provided with travel information specifically related to crowdedness levels during the COVID-19 pandemic. By exploring how individuals respond to this information, the study sheds light on the role of real-time information in shaping travel decisions. Secondly, the study integrates personal and travel characteristics, crowdedness levels, and COVID-related aspects (such as the mandatory use of face masks and social distancing) within participants' final travel choices. By considering these factors, the study provides a comprehensive understanding of the multiple influences on individuals' decision-making processes when it comes to crowdedness and COVID-19 concerns.

By examining the interplay between various factors and individuals' travel decisions, the study contributes to the development of strategies and policies that can effectively promote sustainable and safe travel behavior in urban areas.

### 7.3 Survey timeline

Our study takes place in Greece, where the first measures and restrictions against the spread of COVID-19 were implemented at the end of February 2020. The first lockdown period started in the last week of March 2020 until the beginning of May 2020. During this period, only trips for specific purposes were permitted (shopping of necessities, bank transactions, assistance to elderly people, attendance of ceremonies such as funeral with a limited number of people, outdoor physical exercise, and pet/dog walking). Traveling between Greek prefectures was not permitted, with exceptions (work, health), and public transport schedules were modified. In early May 2020, the first lockdown period was over, but social distancing restrictions were mandatory in all types of activities to prevent the spread of COVID-19. The use of face mask was mandatory in public transport and taxis, elevators, and health-related buildings. The second lockdown period started in November 2020 until May 2021. During this period, schools reopened in January and February 2021 but closed again in March 2021. The data collection period began on March 29th, 2021 and ended on April 30th, 2021. Beginning of April 2021, witnessed the reopening of retail stores under certain restrictions (e.g., SMS permission with specific duration, limited number of costumers). In May 2021, restaurants and cafes reopened after a six-month period (HellenicRepublic, 2022). Figure 7-1 shows the timeline of the experiment and the restrictions that took place in Greece.



Figure 7-1. COVID-19 restrictions in Greece and experiment timeline

### 7.4 Methodological approach

The response of pedestrians' and public transport users to available information about crowdedness levels consists of a series of actions and decisions that occur over time. Figure 7-2 illustrates the methodological framework for switching from a habitual travel pattern to a safer - less crowded alternative in the presence of information. Travelers' decision-making is

influenced by both personal and trip characteristics (Polydoropoulou & Ben-Akiva, 1999; Polydoropoulou, et al., 1994; Polydoropoulou, et al., 1996; Tsirimpa, et al., 2007). An additional category with COVID-related context characteristics (such as mandatory use of facemasks, social distancing, cleanliness, sense of security) that strongly affect travel decisions under the influence of information about crowdedness levels, is included. Personal characteristics include socioeconomic information such as gender, age, educational level, city of residence, income. Trip characteristics refer to general travel pattern that travelers are likely to encounter during daily main trip.

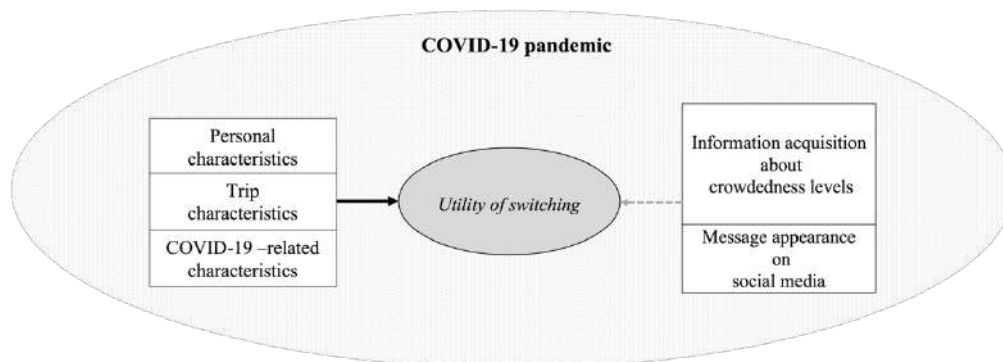


Figure 7-2. Methodological approach

### 7.4.1 Survey design

The questionnaire was developed (in Greek) using Survey Monkey (Annex K), targeting individuals who reside in Greece. The questionnaire consists of six parts (Part A - Part F), as shown in Figure 7-3. The first part (Part A) referred to the general trip characteristics, i.e. trip purpose, departure/arrival time flexibility, mode used in daily main trip. Part B collected the mode specific trip characteristics – trip duration, trip distance, route selection, use of travel applications, perceptions about the quality of the trip – based on respondents’ responses concerning the daily main trip mode in Part A. Only pedestrians’ and public users’ choices with respect to crowdedness in the COVID-19 era were considered in this study (Figure 7-3) and were directed to third part (Part C1 and Part C2, respectively). The third part includes the stated preference scenarios and constitutes the core of the survey. This part examined whether travel information that is related to crowdedness level affects route and travel choices of pedestrians and public transport users. Furthermore, the fourth part (Part D) examined the impact of information and message appearance on the final decision. Similar to Part C, this part was answered only by pedestrians and public transport users. The last two parts (Part E and F) were addressed to all respondents. The fifth part (Part E) collected information about the impact of COVID-19 on the daily main trip, while the last part (Part F) recorded the socio-economic characteristics of the respondents, by collecting personal information such as gender, age, employment status, place of residence and income.

Descriptive statistics of the general trip characteristics, the impact of COVID-19 on daily main trip and the socio-demographic characteristics of car/motorbike and bicycle users can be found in Annex L and Annex M since the following analysis focuses on pedestrians and public transport users.



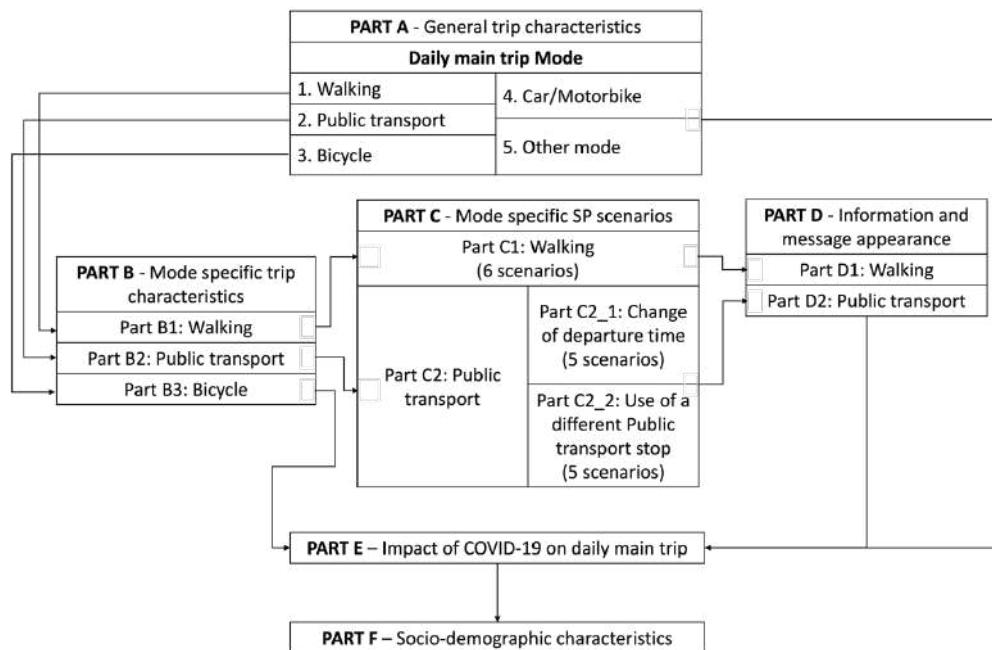


Figure 7-3. Flowchart based on survey’s logic sequence.

7.4.1.1 Stated preference survey design

A stated preference survey was designed to elicit the route and travel choice preferences of pedestrians (Part C1) and public transport users (Part C2\_1 and Part C2\_2) when provisioning transport information related to crowdedness levels.

7.4.1.1.1 Shared information on social media

The information was provided to respondents by a designated social media account related to sustainable urban mobility and referred to their daily main trip. For this study an account related to sustainable mobility was created on Facebook. The shared content included a post that informed about the high crowdedness levels in the usual route of the respondents, followed by two available travel options. Each respondent had to choose between the two alternatives, thinking of his/her daily main trip. In the context of this survey, the term daily main trip is used to describe a planned and repetitive daily commute that has a specific purpose and destination before the outbreak of the pandemic in March 2020. The posts were prepared and shared on Facebook to get screenshots and include them in the presented scenarios of the stated preference survey.

The shared post included text and photos. The text included the message about high crowdedness levels of the usual route and was followed by a photo showing a crowded route or a public transport mode. A follow-up post included a text about the two available travel options, followed by two pictures representing them. The first picture was related to respondents’ usual travel choice with depicted high/moderate crowds and the second one was related to the suggested travel choice with depicted moderate/low crowds. Figure 7-4 illustrates the appearance of the Facebook’s post on a mobile phone of a pedestrian and a public transport user.

The design and the appearance of the shared photos on the Facebook account was related to the content of the message and the attribute levels that are presented in the following section.

Specifically, the different crowdedness levels were depicted with the corresponding density of illustrated people. For the pedestrians’ scenarios real photos were used as a background to represent the different walking scenarios that were used as attribute levels.

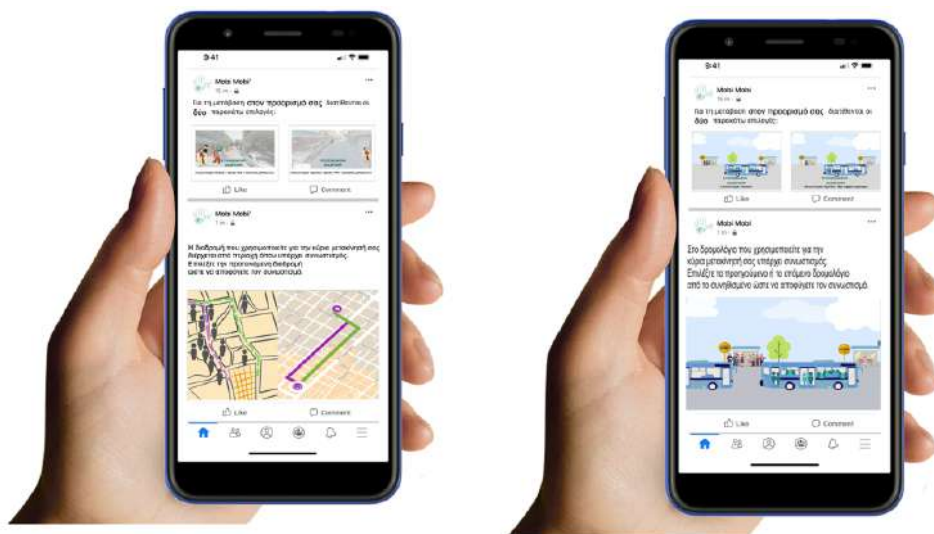


Figure 7-4. Post appearance of the designated account related to sustainable urban transport on a mobile phone of (a) a pedestrian; (b) a public transport user.

It is concluded that the use of colors and graphics in the option tabs influenced significantly the final choice of both pedestrians and public transport users by making the information more visually appealing and easy to understand. Colors can be used to draw attention to important information and make it stand out, which can help make the message more memorable and increase the chances that people will take notice of it. Certain colors are used to indicate more important information, making it easier for people to identify the most relevant information quickly. Graphics make information more understandable, by providing visual cues that help people to understand the meaning of the message. Overall, the use of colors and graphics can help to make the message more engaging and accessible, increasing the chances that people will choose the presented option (Magginas, et al., 2019).

**7.4.1.1.2 Attributes and attribute levels**

Once the two alternatives of the choice experiment were devised, it was necessary to determine which attributes and their corresponding levels should be included to describe them. The final choice of attributes and their respective levels was done carefully to avoid any fatigue or oversight of participants due to excessive number of variables. Based on the study’s objectives and the pilot testing a concise set of attributes and a realistic range of levels was achieved. The type of personalized information includes real-time traffic updates, alternative route suggestions, and transportation mode recommendations based on individual preferences. Details about the walking and public transport scenarios can be found in the following sections.

Due to the large number of attributes and attribute levels involved, it was not feasible to create a complete factorial design. Instead, the levels of the presented scenarios were chosen based on a cleaned random experimental design (Walker, et al., 2015; Matyas & Kamargianni, 2019). Walker, et al. (2015) suggest that a random design performs equally well compared to other designs, and its performance improves further when irrelevant scenarios, where one alternative clearly dominates the others, are removed. Therefore, a condition was applied to ensure that the scenarios in this study were internally consistent and aligned with the research

topic. This approach maintains the validity of the findings and helps to minimize the occurrence of strictly dominating alternatives, which could introduce significant bias into the estimates (Bliemer, et al., 2017).

Pedestrians’ scenarios refer to route choice, as shown in Table 7-1. The first alternative - Usual route - includes two attributes: crowdedness level and walking environment. The levels of crowdedness could be moderate or high and the walking environment could be commercial, residential or with sightseeing/ natural beauty. The second alternative - Suggested route - includes three attributes: crowdedness level, travel time and walking environment. Crowdedness level could be low or moderate and the walking environment could be the same as the three levels mentioned above. The walking travel time includes three levels. The one level is the stated time as it was reported by the respondent in a previous question in Part B (trip characteristics). The other two levels were the stated values of travel time increased by +10% and +30%. These percentages were decided based on the values of the stated travel times and the literature findings about usual walking times for main activities (Panter, et al., 2011). Six SP scenarios were presented to each participant. The appearance of the alternatives was differentiated and was related to the appeared attribute’s levels to make a more realistic choice environment.

Table 7-1. Alternatives, attributes, and attributes’ levels for pedestrians.

Alternative	Attribute	Attribute levels
Usual route	Crowdedness level	Moderate High
	Travel time	Same as reported <sup>1</sup>
	Walking environment	Commercial Residential Sightseeing/ natural beauty
Suggested route	Crowdedness level	Low Moderate
	Travel time	Same as reported <sup>1</sup> +10% <sup>2</sup> +30% <sup>2</sup>
	Walking environment	Commercial Residential Sightseeing/ natural beauty
<sup>1</sup> Respondents were asked about the estimated travel time for their main daily trip.		
<sup>2</sup> The attribute levels were pivoted around the stated values of travel time.		

The public transport users’ scenarios refer to the itinerary (five SP scenarios) and public transport stop choice (five SP scenarios). The five scenarios that were referring to the change of departure time (itinerary choice), see Table 7-2 include two alternatives. The first alternative - Usual itinerary - includes the attribute of crowdedness with moderate and high levels. The second alternative - Suggested itinerary - refers to a departure time change and suggests an earlier or later departure to avoid the peak hour crowdedness. The alternative includes three attributes: the crowdedness level, the travel time on the public transport mode and the arrival

time. The crowdedness level could be low or moderate and the arrival time could be earlier or later. The travel time includes three levels. One level is the stated time as was reported by the respondent in a previous question in Part B (trip characteristics). The other two levels were the stated values of travel time decreased by -10% and -20%. The percentages were decided based on the values of the stated travel times. A reduction of travel time was assumed since a choice of an off-peak hour itinerary reflects a less crowded road network and/or a lower number of boarding/alighting than an overcrowded itinerary during peak hours. Five SP scenarios were presented to each participant. The appearance of the alternatives was differentiated and was related to the appeared attribute’s levels, to improve the realism of the choice experiment.

Table 7-2. Alternatives, attributes, and attributes’ levels for public transport users- change of departure time.

Alternative	Attribute	Attribute levels
Usual itinerary	Crowdedness level	Moderate High
Suggested itinerary	Crowdedness level	Low Moderate
	Travel time (on the public transport mode)	-10% <sup>2</sup> -20% <sup>2</sup> Same as reported <sup>1</sup>
	Arrival time	Earlier Later
<sup>1</sup> Respondents were asked about the estimated travel time (on the public transport mode) of their main daily trip.		
<sup>2</sup> The attribute levels were pivoted around the stated values of travel time.		

The last five scenarios refer to the use of a different public transport stop, see Table 7-3 and include two alternatives. The first alternative - Usual public transport stop - includes the attribute of crowdedness with moderate and high levels. The second alternative - Suggested public transport stop - refers to the use of a different stop with a reduction of 10% in time on the mode. This percentage was decided based on the stated time on the mode and the average travel distance between stops. The decrease in time that someone remains in the mode was mentioned for each scenario. The second alternative includes two attribute levels: the crowdedness with low and moderate levels and the walking time with two levels. One level was the stated values of walking time to the stop increased by 50% and the other one by 100%. The percentages were decided considering an average walking speed of 4.5 km/hour (Alves, et al., 2020) and assuming a distance range between stops 200m-400m (bus stops), 400m-600m (tram stops) and 500m-1000m (metro stops) (van Soest, et al., 2020; Tennøy, et al., 2022). The appearance of the alternatives was differentiated and randomized to mitigate potential biases.

Table 7-3. Alternatives, attributes, and attributes’ levels for public transport users- use of different public transport stop.

Alternative	Attribute	Attribute levels
Usual public transport stop	Crowdedness level	Moderate
		High
Suggested public transport stop	Crowdedness level	Low
	Walking time	Moderate
		+50% <sup>1,2</sup>
		+100% <sup>1,2</sup>
<sup>1</sup> Respondents were asked about the estimated walking time (to the public transport stop) on their main daily trip.		
<sup>2</sup> The attribute levels were pivoted around the stated values of travel time.		

The following figure shows an example of the presented stated preference experiments.

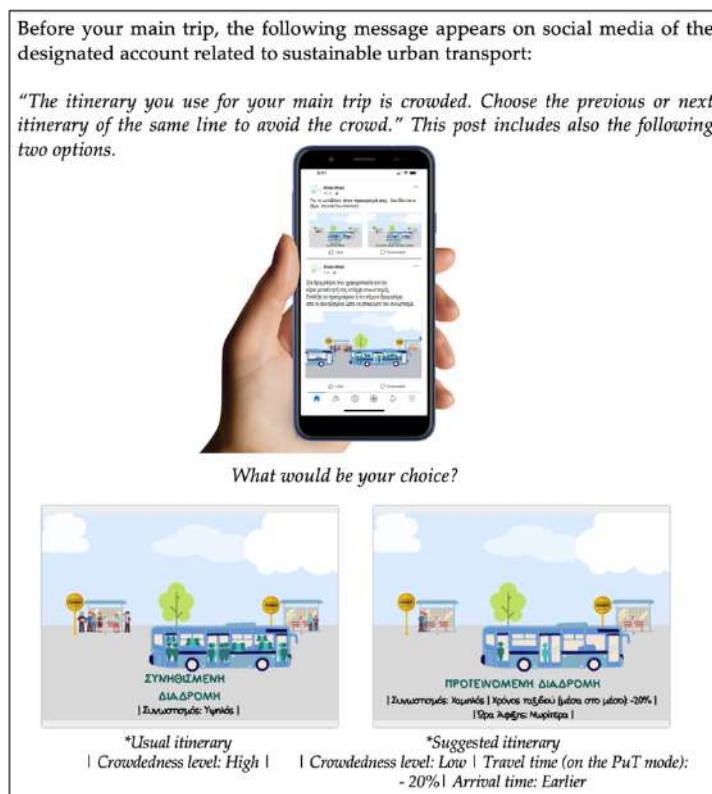


Figure 7-5. Example of a Stated Preference experiment addressed to public transport users (the specific example advises to take the previous itinerary). The original text of the experiment was in Greek.

## 7.4.2 Data collection - Sample recruitment

### 7.4.2.1 Pilot study

A small sample of 20 respondents was used for piloting the survey. This step is an important stage of the research and aims at getting an assessment of the survey design by identifying potential problematic areas, deficiencies, or ambiguities in the research instruments. No attempt was made to recruit a representative sample of respondents because the intention of the pilot survey was not to collect usable data, but rather to test the survey design and methodology. The pilot study revealed that some questions were unclear or confusing to participants, making it difficult for them to provide accurate or meaningful responses. These issues were identified and addressed before the questionnaire was shared with a larger group. Respondents provided valuable feedback about the content and design of the questionnaire by pointing out which questions are most engaging, or which parts of the survey are confusing. This feedback was used to improve the questionnaire and ensure that it is effective in achieving the research goals.

### 7.4.2.2 Survey distribution

The online survey was targeted to respondents who use social media. As a first step, emails were sent to 3436 contacts of the Traffic, Transportation and Logistics (TTLog) laboratory of University of Thessaly contact list comprised of research institutions, ministries, municipalities, associations, groups, companies, actions, projects, and postgraduate students. The emails were sent from the email account of TTLog laboratory. As a second step, the questionnaire link was shared on first author's personal social media accounts. The link to the questionnaire was active for one month, April 2021. Along with the invitation to participate, information about the purpose and the design of the survey was sent. An initial sample of 1349 responses were collected with a completion rate of 69%. The final sample size comprised 925 users, who fully completed the questionnaire. However, as the aim of the study dictates, the main analysis in this paper was made based on 465 respondents, who use walking or public transport for their daily main trip. The collection period was approximately one month, i.e., 29th March 2021 – 30th April 2021.

### 7.4.2.3 Sample characteristics

The initial sample comprised 925 participants, who fully completed the questionnaire. The sample is representative of the overall population of social media users in Greece in terms of gender, which is roughly evenly split between males and females and age level, with the largest age group of 24-40 years old and the expected lowest age group of over 66 years old (ELSTAT, 2021). 38.2% choose walking for their daily main trip, 12.1% use public transport, 43.7% use car/motorbike, 5.4% use bicycle and the rest 0.6% responded Other. Table 7-6 summarizes the socio-demographic characteristics of the respondents.

Table 7-4. Sample characteristics

Variable	Level	%
Gender	Female	55.4
	Male	44.6
Age	18-23	35
	24-40	52.1
	41-65	12
	>66	0.9
Monthly income	0-500	46.1
	501-1000	30.2
	1001-1500	16.3
	>1501	7.5
Occupation	Students	39.9
	Part-time job	28.6
	Full-time job	15.2
	Freelancer	9.4
	Household	0.9
	Unemployed	4.3
	Retired	1.2
	Other	0.5
Place of residence	Large-sized (Athens)	25.5
	Medium-sized (Thessaloniki, Patra, Heraklion, Larisa, Volos)	44.6
	Small-sized	29.8
Transport mode	Walking	38.2
	Public transport	12.1
	Car/Motorbike	43.7
	Bicycle	5.4
	Other	0.6

As it is already mentioned above, the main analysis in this chapter was made based on the 465 respondents. The analysis is focused on the two groups of pedestrians and public transport users, since the crowdedness levels affect to a great extent these modes of transport. Descriptive statistics of the rest participants can be found in Annex L and Annex M.

### 7.4.3 Data analysis

The analysis of socio-demographic and general characteristics was done through descriptive and inferential statistics. Sample characteristics, such as age, gender, occupation, flexibility at arrival time are analyzed in terms of the frequency distribution per characteristic. Furthermore, the mean values and standard deviations, and medians were calculated. The statistical analysis of the responses was carried out using non-parametric tests which are regarded as particularly powerful for analyzing data collected through questionnaire surveys (Park, 2009; Siegel & Castellan, 1988). Specifically, the Mann-Whitney two-sample U-test is performed to assess differences between the two groups of ordinal variables measured on the 5-point scale. Participants responded by rating items ranging from 1 (lower scores) to 5 (higher scores) with 3 as a midpoint. This scale was used as it increases the variance in the measurements and allows a greater differentiation in the results (Krosnick & Presser, 2009). The 5-point scale: 1: Not at all, 2: A little, 3: Moderate, 4: Much, 5: Very much was used to

measure (i) the willingness to be informed via applications such as Google maps or social media about the crowdedness levels of the main trip (ii) the willingness to change the usual travel choice after receiving information about high levels of crowdedness on the main trip, and (iii) the importance and performance of measures against the COVID-19 spread. The evaluation of the daily main trip in terms of crowdedness levels, travel time and walking environment was also done using the 5-point scale: 1: Not at all satisfactory, 2: Slightly satisfactory, 3: Somewhat satisfactory, 4: Satisfactory, 5: Very satisfactory. The opinion on statements about information and appearance of the message on social media was measured on the scale: 1: Strongly Disagree, 2: Disagree, 3: Neutral, 4: Agree, 5: Strongly Agree. Table 7-5 includes the list of the tested variables.

Table 7-5. List of tested variables.

Variable	Type	Description
-Willingness to be informed via applications such as Google maps or social media about the crowdedness levels of the main trip)	Ordinal	1: Not at all, 2: A little, 3: Moderate, 4: Much, 5: Very much
-Willingness to change the usual travel choice after receiving information about high levels of crowdedness on the main trip	Ordinal	1: Not at all, 2: A little, 3: Moderate, 4: Much, 5: Very much
-Importance and performance of measures against the COVID-19 spread <ul style="list-style-type: none"> <li>• Mandatory use of face mask in outdoor spaces</li> <li>• Mandatory use of face mask in indoor spaces</li> <li>• Social distancing</li> <li>• Levels of cleanliness and disinfection in public spaces</li> <li>• Public Health</li> <li>• A sense of security (absence of worry of infection/ illness)</li> <li>• A sense of individual responsibility of people around you</li> <li>• Personal hygiene measures</li> </ul>	Ordinal	1: Not at all, 2: A little, 3: Moderate, 4: Much, 5: Very much
-Evaluation of daily main trip <ul style="list-style-type: none"> <li>• Crowdedness level</li> <li>• Travel time</li> <li>• Walking area of the surrounding route</li> </ul>	Ordinal	1: Not at all satisfactory, 2: Slightly satisfactory, 3: Somewhat satisfactory, 4: Satisfactory, 5: Very satisfactory
-Information and message appearance <ul style="list-style-type: none"> <li>• The use of colors and graphics in the option tabs made their content more understandable</li> <li>• The use of colors and graphics in the option tabs made their content more visually appealing and enjoyable.</li> </ul>	Ordinal	1: Strongly Disagree, 2: Disagree, 3: Neutral, 4: Agree, 5: Strongly Agree



Variable	Type	Description
<ul style="list-style-type: none"> <li>The use of colors and graphics in the option tabs influenced my final choice</li> <li>Using the same colors and graphics in the option tabs enhances the objectivity of my final choices</li> </ul>		

7.4.3.1 Choice model estimation

The collected data (socio-demographic characteristics, trip characteristics, revealed and stated preference data) is used to estimate Mixed Multinomial Logit Models (MMNL) and estimate the probability of an individual choosing a less crowded alternative based on the random utility theory (Ben-Akiva & Bierlaire, 2013; Train, 2003). MMNL is a highly flexible model that can approximate any random utility model (McFadden & Train, 2000). MMNL is very close to the concept of MNL models, which are widely used for modeling traveler behavior, allowing the comparison and evaluation of coefficients across models. Furthermore, the advent of simulation and of tools to specify and estimate MMNL models make them widely accessible to researchers and practitioners (Train, 2003; Walker, 2001). Since in the SP survey the respondents faced several scenarios, the MMNL models account for repeated observations from the same individuals in the data set (panel data).

This research focused on enhancing the discrete choice models to better predict how people make choices in the COVID-19 era. Thus, these improvements are part of the hybrid choice models. In the developed models, latent psychological factors such as attitudes and perceptions (latent variables) towards COVID-19 measures were included. In total, three models are developed for both pedestrians and public transport users. Specifically, the first model (Model I) refers to the SP of pedestrians’ group and the other two models (Model IIa and Model IIb) to the two SPs of public transport users: a) change of departure time and b) use of a different public transport stop. The utility equations of the two alternatives for the three developed models are presented below. All the variables are specific to the suggested alternative and not to the usual choice. This decision is made to emphasize the impact of different aspects on the switching behavior and to interpret the results based on the willingness to change. The presented model specification is a standard linear-in-the-parameters specification, used in most of such models. The actual choice of variables is determined based on data availability and estimation results of alternative considered models. The utilities of Model I specific to individual  $n$ ,  $n = 1 \dots N$  are:

$$U_{UR,n} = ASC_{UR}$$

$$\begin{aligned}
 U_{SR,n} = & ASC_{SR} + \beta_{RESID_A} \times RESID_A + \beta_{RESID_B} \times RESID_B + \beta_{TT_{DIFF}} \times TT_{DIFF} + \beta_{CROWD_A} \times CROWD_A \\
 & + \beta_{CROWD_B} \times CROWD_B + \beta_{COVIDIMP} \times COVIDIMP + \beta_{COVIDPERP} \times COVIDPERP \\
 & + \beta_{ACTIVCHANGE} \times ACTIVCHANGE + \beta_{ROUTECHANGE} \times ROUTECHANGE \\
 & + \beta_{WILLMIN} \times WILLMIN + \sigma_{PEDES} \times \varepsilon_{PEDES,n}
 \end{aligned}$$

The utilities of Model IIa specific to individual  $n$ ,  $n = 1 \dots N$  are:

$$U_{UR,n} = ASC_{UR}$$

$$U_{SR,n} = ASC_{SR} + \beta_{AGE\_B} \times AGE\_B + \beta_{AGE\_C} \times AGE\_C + \beta_{AT\_SR} \times AT\_SR + \beta_{CROWD\_A} \times CROWD\_A + \beta_{CROWD\_B} \times CROWD\_B + \beta_{STTDI} \times STTDI + \beta_{STTDU} \times STTDU + \beta_{STWDU} \times STWDU + \beta_{TRIPPER} \times TRIPPER + \beta_{COVIDIM} \times COVIDIM + \beta_{STOPCHANGE} \times STOPCHANGE + \sigma_{PuT} \times \varepsilon_{PuT,n}$$

The utilities of Model Iib specific to individual n, n = 1...N are:

$$U_{UR,n} = ASC_{UR}$$

$$U_{SR,n} = ASC_{SR} + \beta_{GENDER} \times GENDER + \beta_{WT\_DIFF} \times WT\_DIFF + \beta_{CROWD\_A} \times CROWD\_A + \beta_{CROWD\_B} \times CROWD\_B + \beta_{STWDU} \times STWDU + \beta_{INFTYPE\_A} \times INFTYPE\_A + \beta_{INFTYPE\_B} \times INFTYPE\_B + \beta_{INFTYPE\_C} \times INFTYPE\_C + \beta_{STOPCHANGE} \times STOPCHANGE + \sigma_{PuT} \times \varepsilon_{PuT,n}$$

The  $U_{UR}$  and  $U_{SR}$  denotes the utility derived from the alternatives: usual route and suggested route, respectively. The coefficient  $ASC_{UR}$  represents the alternative-specific constant of the usual choice alternative, while the remaining alternative serves as the base case. A description of the tested variables and their abbreviations for pedestrians and public transport users are given in Table 7-6 and Table 7-7, respectively. Random effects for the alternative associated with the suggested option has been introduced into the MMNL model specification, while the usual choice is used as the reference. The random terms  $\sigma$  are normally distributed, and  $\varepsilon$  are zero-mean, standard, normal error terms.

Table 7-6. List of tested variables for pedestrians.

Variable Name	Type	Abbreviation
<i>Socio-demographic characteristics</i>		
Place of residence: Large-sized (Athens)	Dummy	RESID_A
Place of residence: Medium-sized (Thessaloniki, Patra, Heraklion, Larisa, Volos)	Dummy	RESID_B
Place of residence: Small-sized (Reference)	Reference	RESID_C
<i>Stated preference attributes</i>		
Travel time difference between suggested and usual route	Continuous	TT_DIFF
Crowdedness level from High to Moderate	Dummy	CROWD_A
Crowdedness level from High to Low	Dummy	CROWD_B
Crowdedness level from Medium to Low (Reference)	Reference	CROWD_C
<i>Crowdedness and Covid-related characteristics</i>		
Importance of measures against COVID-19 spread (Factor analysis see section 4.3.2)	Factor	COVIDIMP

Variable Name	Type	Abbreviation
Performance of measures against COVID-19 spread (Factor analysis see section 4.3.2)	Factor	COVIDPERP
Impact of stops for activities at intermediate destinations on final decision regarding changes on main trip after getting information about crowdedness levels (1: Not at all, A little; 0: Moderate, Much, Very much)	Dummy	ACTIVCHANGE
Willingness to change the usual route after receiving information about high levels of crowdedness on main trip (1: Not at all, A little; 0: Moderate, Much, Very much)	Dummy	ROUTECHANGE
Additional minutes that someone is willing to travel more on a less crowded route, after receiving information about high levels of crowdedness on their main trip	Continuous	WILLMIN

Table 7-7. List of tested variables for public transport users.

Variable Name	Type	Abbreviation
<b><i>Socio-demographic characteristics</i></b>		
18-23 (Reference)	Reference	AGE A
24-40	Dummy	AGE B
41-65	Dummy	AGE C
Female:1 Male:0	Dummy	GENDER
<b><i>Stated preference attributes</i></b>		
Arrival time at suggested option (1: Later 0: Earlier)	Dummy	AT_SR
Difference of walking time to the public transport stop between usual and suggested option	Continuous	WT_DIFF
Crowdedness level from High to Moderate	Dummy	CROWD A
Crowdedness level from High to Low	Dummy	CROWD B
Crowdedness level from Medium to Low	Reference	CROWD C
<b><i>Travel information</i></b>		
Applications such as Google maps	Dummy	INFTYPE A
Public transport applications	Dummy	INFTYPE B
Social media	Dummy	INFTYPE C
None (Reference)	Reference	INFTYPE D
<b><i>Trip characteristics</i></b>		
Stated travel distance (on transport mode)	Continuous	STTDI
Stated travel duration (on transport mode)	Continuous	STTDU
Stated walking duration to the public transport stop	Continuous	STWDU
Performance of the main daily trip	Factor	TRIPPER
<b><i>Crowdedness and Covid-related characteristics</i></b>		
Importance of COVID-19 measures	Factor	COVIDIM

Variable Name	Type	Abbreviation
Willingness to use a different public transport stop than usual after receiving information about high levels of crowdedness on your main trip? (1: Not at all, A little; 0: Moderate, Much, Very much)	Dummy	STOPCHANGE

7.4.3.2 Factor analysis

Four variables (COVIDIMP and COVIDPERP for pedestrians, TRIPPER and COVIDIM for public transport users) are specified based on a factor analysis. The exploratory factor analysis was used to reduce many variables to a smaller set of summary variables. Principal Component Analysis (PCA) was applied to transform the set of variables into a smaller representation while retaining most of the information from the initial dataset. The Kaiser-Meyer-Olkin measures confirmed the sample adequacy, with the Bartlett’s Test of Sphericity being significant ( $p < 0.05$ ).

The first latent variable is labelled “COVIDIMP- Importance of measures after COVID-19 spread” and includes the recorded importance of eight measures against the spread of COVID-19 based on the pedestrians’ responses (see Table 7-8). The second one is labelled “COVIDPERP- Performance of the measures after COVID-19 spread” and includes the recorded performance of the eight measures against the COVID-19 spread, based on pedestrians’ responses (see Table 7-8). The Cronbach’s alpha values were greater than 0.8 indicating a very good level of reliability.

Table 7-8. Factor analysis for pedestrians (COVIDIMP and COVIDPERP variables).

Statement	Component
<b>COVIDIMP: Importance of the following measures after COVID-19 spread</b>	
Mandatory use of face mask in outdoor spaces	0.387
Mandatory use of face mask in indoor spaces	0.422
Social distancing	0.437
Levels of cleanliness and disinfection in public spaces	0.502
Public Health	0.466
A sense of security (absence of worry of infection/ illness)	0.528
A sense of individual responsibility of people around you	0.606
Personal hygiene measures	0.441
<i>Kaiser-Meyer-Olkin Measure of Sampling Adequacy.</i>	0.836
<i>Bartlett’s Test of Sphericity</i>	<0.001
<i>Cronbach’s alpha</i>	0.827
<b>COVIDPERP: Performance of the following measures after COVID-19 spread</b>	
Mandatory use of face mask in outdoor spaces	0.253

Statement	Component
Mandatory use of face mask in indoor spaces	0.391
Social distancing	0.428
Levels of cleanliness and disinfection in public spaces	0.676
Public Health	0.676
A sense of security (absence of worry of infection/ illness)	0.666
A sense of individual responsibility of people around you	0.528
Personal hygiene measures	0.373
<i>Kaiser-Meyer-Olkin Measure of Sampling Adequacy.</i>	0.850
<i>Bartlett's Test of Sphericity</i>	<0.001
<i>Cronbach's alpha</i>	0.853

The collected data of public transport users' responses regarding the COVID-19 measures and the trip performance are used to determine the two factors COVIDIM and TRIPPER, respectively. The first latent variable is labelled "COVIDIM-Importance of the measures after COVID-19 spread" and includes the recorded importance of eight measures against the spread of COVID-19 with Cronbach's alpha= 0.838 (see Table 7-9).The second one is labelled "TRIPPER- Trip performance with a public transport mode" and includes the recorded performance of a trip in terms of crowdedness, duration, walking time to the public transport stop, arrival time and surrounding area of the walking route (see Table 7-9).

Table 7-9. Factor analysis for public transport users (COVIDIM and TRIPPER variables).

Statement	Component
<b>COVIDIM: Importance of the following measures after COVID-19 spread</b>	
Mandatory use of face mask in outdoor spaces	0.326
Mandatory use of face mask in indoor spaces	0.555
Social distancing	0.467
Levels of cleanliness and disinfection in public spaces	0.463
Public Health	0.470
A sense of security (absence of worry of infection/ illness)	0.603
A sense of individual responsibility of people around you	0.574
Personal hygiene measures	0.568
<i>Kaiser-Meyer-Olkin Measure of Sampling Adequacy.</i>	0.860
<i>Bartlett's Test of Sphericity</i>	<0.001
<i>Cronbach's alpha</i>	0.838
<b>TRIPPER: Trip performance with a public transport mode</b>	
Crowdedness level (on public transport vehicle or/and at the station)	0.545

Statement	Component
Trip duration (on public transport vehicles)	0.732
Walking time	0.078
Arrival time at the final destination	0.710
The surrounding area of the walking route	0.287
<i>Kaiser-Meyer-Olkin Measure of Sampling Adequacy.</i>	
	0.728
<i>Bartlett's Test of Sphericity</i>	
	<0.001
<i>Cronbach's alpha</i>	
	0.678

The four factors are measured by using the COVIDIMP, COVIDPERP, COVIDIM and TRIPPER latent variables.

### 7.5 Descriptive and inferential statistics

Table 7-10 presents the descriptive statistics of the pedestrians' and public transport users' characteristics. Respondents of both groups were approximately evenly distributed between gender categories (pedestrians: 56% female and 44% male; public transport users: 49% female and 51% male), the average age of the respondents was also evenly distributed between the age categories 18-23 and 24-40 years old. The analyzed samples are mostly composed of participants with monthly income 0-500Euros which can be explained since most of them belong to the category of students (58% of pedestrians and 46% of public transport users are students). In addition, half of the pedestrians (about 50%) live in a medium-sized city while half of the public transport users (about 49%) live in Athens. The percentages of the variable "place of residence" are in line with the existence and availability of public transport in these places. Athens, the capital city of Greece, offers a wide variety of routes, combining the metro, railway, buses, trolleybuses, and trams. The availability of different public transport means, and the long distances can explain the high percentages of public transport use (and low percentages of pedestrians 27%) in Athens. The low score of 6% of public transport users in the small sized cities is due to the short distances and the absence of an integrated transportation system.

Table 7-10. Descriptive statistics of pedestrians and public transport users.

Variables	Pedestrians (n=353)	Pedestrians (%)	Public transport users (n=112)	Public transport users (%)
<i>Gender</i>				
Female	198	56	55	49
Male	155	44	57	51
<i>Age</i>				
18-23	183	52	45	40
24-40	144	41	65	58
41-65	24	7	2	2

<b>Variables</b>	<b>Pedestrians (n=353)</b>	<b>Pedestrians (%)</b>	<b>Public transport users (n=112)</b>	<b>Public transport users (%)</b>
>66	2	-	-	-
<i>Monthly income</i>				
0-500	234	66	59	53
501-1000	73	21	33	29
1001-1500	30	8.5	12	11
>1501	16	4.5	8	7
<i>Occupation</i>				
Students	205	58	52	46
Part-time job	19	6	14	13
Full-time job	71	20	39	35
Freelancer	24	7	7	6
Household	5	1	-	-
Unemployed	22	6	-	-
Retired	4	1	-	-
Other	3	1	-	-
<i>Place of residence</i>				
Large-sized (Athens)	82	23	55	49
Medium-sized (Thessaloniki, Patra, Heraklion, Larisa, Volos)	177	50	50	45
Small-sized	94	27	7	6

With regards to the respondents’ commuting habits and the impact of COVID-19 on their daily main trip, Table 7-11 presents the percentages of both groups. Most of the public transport users (about 57%) chose the trip to work as daily main trip, while the option Other was indicated as daily trip by 36% of pedestrians. Walking is typically chosen for more flexible in terms of arrival time activities compared to work/education. A social visit, entertainment, outdoor physical exercise or going to the gym are some activities that the 36% of the pedestrians in the “Other” category could have as a purpose of their daily main trip. As indicated, for half of the pedestrians (about 46%) there is no limit on the arrival time, while most of the public transport users have a flexibility of 5-15 minutes on their arrival time. During a lockdown period 46% of the public transport users did not perform the trip at all, while 66% of the pedestrians performed the trip with less frequency compared to a non-lockdown period. The spread of COVID-19 had also an impact on the frequency of the daily main trip on a period without a

lockdown. Specifically, 37% of pedestrians and 38% of public transport users perform the trip with less frequency, while 19% of public transport users don't perform the trip at all. Due to the spread of COVID-19, a change in the transport mode of the daily main trip was recorded in both groups. 51% of pedestrians and 58% of public transport users changed their transport mode.

Table 7-11. Trip characteristics of pedestrians and public transport users.

Variables	Pedestrians (%)	Public transport users (%)
<i>Scope of daily main trip</i>		
Work	25	57
Education	14	35
Shopping	25	4
Other	36	4
<i>Flexibility</i>		
Not at all	5	10.7
5-15 minutes	34	63.4
16-30 minutes	10	12.5
31-60 minutes	5	2.7
There is no time limit on arrival	46	10.7
<i>Frequency of the daily main trip after the spread of COVID-19 during a lockdown period:</i>		
with the same frequency	20	19
with less frequency	66	35
not at all	14	46
<i>Frequency of the daily main trip after the spread of COVID-19 without a lockdown</i>		
with the same frequency	55	44
with less frequency	38	37
not at all	7	19
<i>Change of the transport mode of the main trip due to the spread of COVID-19?</i>		
Yes	51	58
No	49	42

The following table includes the tested variables that were presented on Table 7-5. The participants were asked to rate on a 1–5 scale: (i) the willingness to be informed via applications such as Google maps or social media about the crowdedness levels of the main trip; (ii) the willingness to change the usual travel choice after receiving information about high levels of crowdedness on the main trip, (iii) the importance and (iv) performance of measures against the COVID-19 spread. Participants were also asked to (v) evaluate the daily main trip and to (vi) express their agreement on statements about the information and message appearance. Table 7-12 presents an overview of the average values (m), medians (mdn) and standard deviations (sd) of the tested variables and the test results of the mode choice effect on the attributed ratings. Results are described through Mann-Whitney U statistic and p-value, indicating the strength of the respective evidence. Statistically significant differences between the two groups were reported in the variables: (i) willingness to be informed via applications such as Google maps



or social media about the crowdedness levels of the main trip; (ii) willingness to change the usual travel choice after receiving information about high levels of crowdedness on the main trip, (iii-iv.e) Public Health in terms of importance and performance (iv.a) mandatory use of face mask in outdoor spaces in terms of performance(v.a and v.b) crowdedness level and travel time, in terms of existed trip evaluation and (vi.c) the use of colors and graphics in the option tabs influenced my final choice in terms of Information and message appearance. Table 7-12 shows that public transport users are more willing than pedestrians to be informed via applications such as Google maps or social media about the crowdedness levels of the main trip (p-value< 0.05). Pedestrians are more willing than public transport users to change the usual travel choice after receiving information about high levels of crowdedness on the main trip. Public Health was rated more in terms of importance and less in terms of performance by public transport users compared to pedestrians. The mandatory use of face mask in outdoor spaces was rated higher by pedestrians (m=2.93) than public transport users (m=2.63). In terms of crowdedness level and travel time, pedestrians evaluate higher their daily main trip (m=3.71 and m=3.89, respectively) compared to public transport users (m=2.54 and m=3.11, respectively).

Table 7-12. Tested ordinal variables: pedestrians vs public transport users

Variables	Groups						Test parameter relation	Pedes. vs. PuT users	
	Pedestrians			PuT users				U	p-value
	m	mdn	sd	m	mdn	sd			
<b>(i)</b> Willingness to be informed via applications such as Google maps or social media about the crowdedness levels of the main trip	2.94	3	1.255	3.65	4	1.113	$r_{Ped} < r_{PuT}$	13,513	<0.001
<b>(ii)</b> Willingness to change the usual travel choice after receiving information about high levels of crowdedness on the main trip	3.18	3	1.046	2.85	3	1.024	$r_{Ped} > r_{PuT}$	16,273	0.003
<b>(iii)</b> Importance measures against the COVID-19 spread									
- Mandatory use of face mask in outdoor spaces	3	4	1.300	3.19	3	1.319	$r_{Ped} < r_{PuT}$	17,964	0.136
- Mandatory use of face mask in indoor spaces	4.39	5	0.942	4.44	5	0.908	$r_{Ped} < r_{PuT}$	19,329	0.680
- Social distancing	3.62	4	1.130	3.65	4	1.080	$r_{Ped} < r_{PuT}$	19,490	0.816

Variables	Groups						Test parameter relation	Pedes. vs. PuT users	
	Pedestrians			PuT users				U	p-value
	m	mdn	sd	m	mdn	sd			
- Levels of cleanliness and disinfection in public spaces	4.51	5	0.773	4.65	5	0.654	$\Gamma_{Ped} < \Gamma_{PuT}$	17,945.5	0.075
- Public Health	4.63	5	0.661	4.79	5	0.560	$\Gamma_{Ped} < \Gamma_{PuT}$	<b>17,350</b>	<b>0.010</b>
- A sense of security (absense of worry of infection/ illness)	4.14	4	1.044	4.30	5	0.919	$\Gamma_{Ped} < \Gamma_{PuT}$	18,215.5	0.173
- A sense of individual responsibility of people around you	4.38	5	0.855	4.43	5	0.877	$\Gamma_{Ped} < \Gamma_{PuT}$	18,951	0.454
- Personal hygiene measures	4.57	5	0.716	4.63	5	0.659	$\Gamma_{Ped} < \Gamma_{PuT}$	18,996.5	0.446
<b>(iv) Performance of measures against the COVID-19 spread</b>									
- Mandatory use of face mask in outdoor spaces	2.93	3	1.154	2.63	3	1.148	$\Gamma_{Ped} > \Gamma_{PuT}$	<b>16,800.5</b>	<b>0.013</b>
- Mandatory use of face mask in indoor spaces	3.62	4	1.092	3.65	4	1.071	$\Gamma_{Ped} < \Gamma_{PuT}$	19,565.5	0.865
- Social distancing	2.89	3	1.128	2.71	3	1.104	$\Gamma_{Ped} > \Gamma_{PuT}$	17,953.5	0.128
- Levels of cleanliness and disinfection in public spaces	3.12	3	1.141	2.90	3	1.162	$\Gamma_{Ped} > \Gamma_{PuT}$	17,683.5	0.082
- Public Health	3	3	1.224	2.64	3	1.154	$\Gamma_{Ped} > \Gamma_{PuT}$	<b>16,418.5</b>	<b>0.005</b>
- A sense of security (absense of worry of infection/ illness)	2.86	3	1.236	2.65	3	1.071	$\Gamma_{Ped} > \Gamma_{PuT}$	17,983	0.138
- A sense of individual responsibility of people around you	3.08	3	1.181	2.87	3	1.044	$\Gamma_{Ped} > \Gamma_{PuT}$	17,960	0.131
- Personal hygiene measures	3.96	4	0.972	3.83	4	0.967	$\Gamma_{Ped} > \Gamma_{PuT}$	18,201	0.183
<b>(v) Evaluation of daily main trip</b>									
- Crowdedness level	3.71	4	0.948	2.54	3	1.122	$\Gamma_{Ped} > \Gamma_{PuT}$	<b>8,624</b>	<b>&lt;0.001</b>
- Travel time	3.89	4	0.870	3.11	3	1.110	$\Gamma_{Ped} > \Gamma_{PuT}$	<b>11,702</b>	<b>&lt;0.001</b>
- Walking area of the surrounding route	3.68	4	0.943	3.46	4	1.146	$\Gamma_{Ped} > \Gamma_{PuT}$	18,175.5	0.178
<b>(vi) Information and message appearance</b>									
- The use of colors and graphics in the option tabs made their content more understandable	4.17	4	0.765	4.03	4	0.776	$\Gamma_{Ped} > \Gamma_{PuT}$	17,707	0.071

Variables	Groups						Test parameter relation	Pedes. vs. PuT users	
	Pedestrians			PuT users				U	p-value
	m	mdn	sd	m	mdn	sd			
- The use of colors and graphics in the option tabs made their content more visually appealing and enjoyable.	4.20	4	0.798	4.27	4	0.723	$\Gamma_{Ped} < \Gamma_{PuT}$	19,087.5	0.550
- The use of colors and graphics in the option tabs influenced my final choice	3.01	3	1.119	2.68	3	1.109	$\Gamma_{Ped} > \Gamma_{PuT}$	<b>16,519.5</b>	<b>0.006</b>
- Using the same colors and graphics in the option tabs enhances the objectivity of my final choices	3.46	3	0.932	3.47	3	0.958	$\Gamma_{Ped} < \Gamma_{PuT}$	19,698	0.952

## 7.6 Model estimation results

This section presents the model estimation results. The developed MMNL models have been estimated using the software package Biogeme (Bierlaire, 2003) and consider the panel effect for repeated observations from the same individuals in the dataset. It was ensured that the chosen independent variables were not interrelated to a problematic extent. Multicollinearity, which arises when two or more predictors in a model demonstrate strong linear interdependencies, can complicate model interpretation. To address this concern, correlation matrices of the predictors were reviewed. Specific note of any correlation coefficients nearing -1 or 1 was taken, as such number show high multicollinearity.

After testing various specifications, the final presented models are selected based on statistical goodness-of-fit (likelihood ratio tests, estimated coefficient significance t-tests, the rho-square ( $\rho^2$ ), and adjusted rho-square ( $\bar{\rho}^2$ ) statistics). 10,000 random draws are used for models' estimation. It was verified that the coefficient estimates and the model statistics, had converged before reaching that number, therefore, it was confirmed that 10,000 draws are sufficient. All the estimated coefficients are specific to the suggested option.

### 7.6.1 Pedestrians

A total of 2118 SP observations were collected from 353 individuals, who use walking for their daily main trip. The model estimation results for pedestrians are presented in Table 7-13.

The negative sign of the estimated alternative-specific constant value (ASC\_UR: corresponding to the usual route) shows that there is tendency towards the suggested route with the lower crowdedness levels, all else being equal. The negative signs of the place of residence show that pedestrians who live in Athens or in other medium sized cities are less likely to change their usual route compared to residents of small sized Greek cities.

The stated preference data that are used to estimate the choice probability in the presented model concern difference in travel time and crowdedness levels. The travel time difference seems to increase slightly the possibility a pedestrian to shift away from the crowded

usual route. The positive values of the estimated coefficients associated with the crowdedness levels (CROWD\_A and CROWD\_B) indicate that pedestrians have a high tendency towards changing the usual route when the crowdedness level is high. The results show that, as expected, travelers are more likely to change their route to experience moderate crowdedness level rather than high (CROWD\_A) and, respectively, to experience low crowdedness level rather than high (CROWD\_B) as compared to moderate to low (CROWD\_C, reference variable).

The positive value of the estimated coefficient associated with the importance and performance of measures against the spread of COVID-19 indicates that pedestrians that rated highly the importance and performance of measures are more likely to change their usual route due to high levels of crowdedness in their trip. Pedestrians that stated intermediate stops for activities do not affect at all or affect very little their daily main trip after getting information, are more likely to change their usual route in response to information about crowdedness levels. This is captured by the positive sign of the related dummy variable ACTIVCHANGE (1: Not at all, A little; 0: Moderate, Much, Very much).

Pedestrians that are not willing at all or exercise a low willingness to change the usual route after receiving information about high levels of crowdedness on their main trip, are less likely to use the less crowded suggested route in response to this information. This is captured by the negative sign of the related dummy variable ROUTECHANGE (1: Not at all, A little; 0: Moderate, Much, Very much) associated with the willingness to change the usual route. The additional minutes that someone is willing to travel longer on a less crowded route, after receiving information about high levels of crowdedness on their main trip, seem to slightly increase the probability of change their route.

Table 7-13. Model estimation results- pedestrians

Variable Name	Coef. Est.	t-test
<i>Alternative- specific constant (ASC) (base case: Suggested route)</i>		
ASC UR	-0.996	-4.58
<i>Socio-demographic characteristics</i>		
B_RESID_A	-0.464	-2.02
B_RESID_B	-0.39	-2.02
<i>Stated preference attributes</i>		
B_TT_DIFF	0.0322	0.0129
B_CROWD_A	1.88	10.7
B_CROWD_B	0.779	5.52
<i>Covid-related characteristics</i>		
B_COVIDIMP	0.445	5.58
B_COVIDPERP	0.135	1.63
B_ACTIVCHANGE	0.247	1.54
B_ROUTECHANGE	-0.853	-4.57
B_WILLMIN	0.0217	1.88
$\sigma$ Put (specific to suggested route)	0.856	7.62
<i>Summary statistics</i>		

Variable Name	Coef. Est.	t-test
N	Number of observations	2118
LL <sub>0</sub>	Initial log likelihood	-2917.274
LL <sub>b</sub>	Final log likelihood	-910.9256
$\rho^2$	Rho-square	0.693
$\bar{\rho}^2$	Adjusted Rho-square	0.689

### 7.6.2 Public transport users

In the estimated models of public transport users (change of departure time and use of a different public transport stop) a total of 560 observations were collected from 112 individuals.

#### 7.6.2.1 Change of departure time

Table 7-14 shows the model estimation results for change of departure time. The negative sign of the estimated alternative-specific constant value (ASC\_UR: corresponding to the usual route) shows that there is tendency towards the suggested option of less crowdedness levels which involves changing the departure time.

Amongst the socioeconomic characteristics only the independent variable of 41-65 aged group is found significant. The positive and high value of the estimated coefficient indicates that people aged 41-65 are more likely to change their departure time than younger people, aged 18-23 years.

The presented model uses also stated preference data to estimate the choice probability. We find that public transport users are less likely to change their departure time if they will arrive later at their destination compared to an earlier arrival. This is captured by the negative sign of the related dummy variable associated with the arrival time (1: Later, 0: Earlier). The positive values of the estimated coefficients associated with the crowdedness levels (CROWD\_A and CROWD\_B) indicate that public transport users have a high tendency towards changing their departure time when the crowdedness level of their usual choice is high. The results show that travelers are more likely to change their trips' departure time to experience moderate crowdedness level rather than high (CROWD\_A) and, respectively, to experience low crowdedness level rather than high (CROWD\_B) as compared to moderate to low (CROWD\_C, reference variable).

The stated travel distance (in transport mode) and the stated walking duration to the public transport stop seem to increase slightly the possibility to change the departure time, while the stated travel duration (on-board time) seems to decrease slightly this possibility. An explanation could be a specific arrival time in mind, a good preparation for the challenges of crowded trips (packed with necessary supplies, such as masks or hand sanitizer) or even an on-board activity (e.g., reading, listening to music/watching videos, working). The negative sign of the estimated coefficient associated with the trip performance factor (TRIPPER) with a public transport mode (in terms of Crowdedness level (on-board the public transport mode or/and at the public transport station); Trip duration (on-board the public transport mode); Walking time; Arrival time at the final destination; Surrounding area of the walking route) indicates that travelers who rated higher their usual public transport trip are less likely to change their departure time when they receive information about high crowdedness levels.

The positive value of the estimated coefficient associated with the importance of measures against the spread of COVID-19 indicates that public transport users that rated the importance of measures as high are more likely to change their departure time due to high levels of crowdedness along their usual trip. Public transport users that are not willing at all or show low willingness to use a different public transport stop than usual after receiving information about high levels of crowdedness on their main trip, are less prone to change their departure time in response to this information. This is captured by the negative sign of the related dummy variable 1: Not at all, A little; 0: Moderate, Much, Very much) associated with the willingness to change of public transport stop.

Based on the estimation results the coefficient  $\sigma_{Put}$ , (corresponding to the standard deviation of the random error terms for the alternative suggested route) is highly significant, suggesting that the model allows for capturing intrinsic correlations among the observations of the same individual.

Table 7-14. Model estimation results: public transport users- change of departure time

Variable Name	Coef. Est.	t-test
<i>Alternative- specific constant (ASC) (base case: Suggested route)</i>		
ASC UR	-2.16	-2.86
<i>Socio-demographic characteristics</i>		
B AGE B	0.676	1.56
B AGE C	6.27	2.6
<i>Stated preference attributes</i>		
B AT SR	-2.86	-5.26
B CROWD A	2.86	3.53
B CROWD B	2.72	6.07
<i>Daily main trip characteristics</i>		
B STTDI	0.0692	1.92
B STTDU	-0.0487	-3.15
B STWDU	0.027	1.57
B TRIPPER	-0.454	-1.9
<i>Covid-related characteristics</i>		
B COVIDIM	1.19	4.88
B STOPCHANGE	-1.17	-2.53
$\sigma_{Put}$ (specific to suggested route)	-1.35	-4
<i>Summary statistics</i>		
N	Number of observations	560
LL <sub>0</sub>	Initial log likelihood	-952.8573
LL <sub>b</sub>	Final log likelihood	-157.0244
$\rho^2$	Rho-square	0.835
$\bar{\rho}^2$	Adjusted Rho-square	0.822

7.6.2.2 *Change of public transport stop*

Table 7-15 shows the model estimation results referring to the willingness to use a different public transport stop than the usual one after receiving information about high levels of crowdedness on your main trip. The positive sign of the estimated alternative specific constant value (ASC\_UR: corresponding to the usual route) shows that there is a tendency to stick to the usual public transport stop despite the lower crowdedness levels experienced if switching. None of the coefficients associated with the socioeconomic characteristics are found significant.

Public transport users are less likely to change the public transport stop if they will walk more to the public transport stop compared to their usual trip. This is captured by the negative sign of the related continuous variable associated with the difference of the walking time. The positive values of the estimated coefficients associated with the crowdedness levels (CROWD\_A and CROWD\_B) indicate that public transport users have a high tendency towards changing the stop when the crowdedness level of their usual choice is high. The results show that travelers are more likely to change their trips' departure time to experience moderate crowdedness level rather than high (CROWD\_A) and, respectively, to experience low crowdedness level rather than high (CROWD\_B) as compared to moderate to low (CROWD\_C, reference variable). The stated travel walking duration seems to increase slightly the possibility to use a different public transport stop.

The three variables (INFTYPE A, INFTYPE B, INFTYPE C) capture the effect of the three means for travel information provision: Applications such as Google maps; Public transport applications; social media respectively. The category None was used as a reference variable. In all cases, the provision of information by the three means increases the propensity of the public transport users to switch from their usual public transport stop, as expected. The travelers' propensity towards a stop change is increased when there is information on crowdedness levels is shared on social media compared to no sharing at all.

Public transport users that are not willing at all or have a low willingness to use a different public transport stop than usual after receiving information about high levels of crowdedness on their main trip, are less prone to use a different public transport mode in response to this information. This is captured by the negative sign of the related dummy variable 1: Not at all, A little; 0: Moderate, Much, Very much) associated with the willingness to change of public transport stop.

Table 7-15. Model estimation results: public transport users- change of public transport stop

Variable Name	Coef. Est.	t-test
<i>Alternative- specific constant (ASC) (base case: Suggested route)</i>		
ASC_UR	3.04	1.57
<i>Socio-demographic characteristics</i>		
B_GENDER	-1	-1.52
<i>Stated preference attributes</i>		
B_WT_DIFF	-0.16	-3.47
B_CROWD_A	2.03	4.87

Variable Name	Coef. Est.	t-test
B_CROWD_B	2.14	5.05
<i>Daily main trip characteristics</i>		
B_STWDU	0.0798	1.86
<i>Travel information</i>		
B_INFTYPE_A	5.21	2.67
B_INFTYPE_B	4.8	2.54
B_INFTYPE_C	6.02	2.56
<i>Covid-related characteristics</i>		
B_STOPCHANGE	-1.64	-2.35
$\sigma_{\text{Put}}$ (specific to suggested route)	2.73	6.29
<i>Summary statistics</i>		
N	Number of observations	560
LL <sub>0</sub>	Initial log likelihood	-654.1905
LL <sub>b</sub>	Final log likelihood	-233.0567
$\rho^2$	Rho-square	0.644
$\hat{\rho}^2$	Adjusted Rho-square	0.627

## 7.7 Discussion

The COVID-19 pandemic has led to changes in people's lifestyles and mobility habits. It has also affected travel choices and had a significant impact on both pedestrians and public transport users. Due to social distancing measures and lockdowns, many people have been encouraged or even required to avoid crowded places and shift to alternative ways of transport. This has resulted in a decrease in walking and public transport usage in many cities around the world (Nikiforiadis, et al., 2022). Additionally, many public transport systems have implemented measures such as increased cleaning and capacity limitations to reduce the spread of the virus. As a result, waiting times for public transport trips became longer, and some commuters chose to avoid it. Overall, the pandemic has led to significant changes in the way people use public spaces and transport (Downey et al. 2021; de Palma et al. 2022).

The use of real-time information about crowdedness levels during COVID-19 can help individuals decide where to go and when to avoid areas that may be at higher risk for spreading the virus. It can also help businesses and organizations to implement social distancing measures and adjust their operations to reduce the risk of transmission. Additionally, it can assist public health officials in identifying and addressing hotspots of transmission, which can help slow the spread of the virus and reduce the overall impact of the pandemic (Stroom, et al., 2021).

Based on research findings, it can be concluded that crowd avoidance plays a significant role in shaping mobility decisions for pedestrians and public transport users during pandemics. Results showed that pedestrians in Athens as well as in other medium-sized Greek cities are less likely to change their usual route compared to those in smaller Greek cities which is consistent with a previous study (Karakikes & Nathanail, 2022). The level of familiarity with



the city and the high crowdedness levels of larger cities in general are factors that could explain this finding. Residents of smaller cities may have a more intimate knowledge of their city and be more familiar with alternative routes to take. In addition, Athens and other medium-sized cities may face high crowdedness levels in general, so residents may be more accustomed to dealing with crowdedness and less likely to change their usual route. Consistent with previous studies, pedestrians who rated high the importance and performance of measures against COVID-19 are more likely to change their usual route due to high levels of crowdedness in their trip. This group of people is more likely to prioritize its own health and safety (Shelat, et al., 2022b). These individuals may believe that measures such as social distancing and mandatory mask use are effective in reducing the spread of COVID-19 and are more likely to take action to avoid crowded areas. Additionally, they may also be more proactive in obtaining information about the measures and crowdedness level and have access to reliable sources that they are willing to follow. Pedestrians who stated that stops for activities at intermediate destinations do not affect or affect little their daily main trip after getting information, are more likely to change their usual route in response to information about crowdedness levels. These individuals may have more flexibility in their travel plans and be more willing to adjust their routes to avoid crowded areas. They may not have strict time constraints or a specific schedule that they need to adhere to. Additionally, the intermediate stops could be non-essential parts of their trip and therefore be more willing to make changes. Another possible reason is that they may be more likely to be in a leisure mode making them more adaptable to changes and more responsive to information about crowdedness levels.

Another useful conclusion stemming from this research, is that the 41-65 age group is more likely to change their departure time to avoid high crowdedness levels on public transportation. This finding is in line with previous studies (Shelat, et al., 2022b; Campisi, et al., 2022) revealing that older adults may have a greater sense of personal safety and be more sensitive to issues related to personal space and comfort thus, they are more likely to avoid crowds to reduce the exposure to COVID-19 or other illnesses. Compared to the 18-23 age group, 41-65 age group may have access to a private vehicle which leads to use alternatives to public transportation when it is too crowded.

The decision to change departure time is affected by factors such as arrival time at destination and the perceived quality of the usual public transport trip. Public transport users are less likely to change their departure time to avoid the crowd if they will arrive later at their destination compared to an earlier arrival which is in line with the study of (Hadas, et al., 2022). In addition, travelers who rated higher their usual public transport trip are less likely to change their departure time when they receive information about high crowdedness levels. People prioritize different factors depending on their personal circumstances before every trip which can lead to different decisions about their departure time to avoid crowds. The importance of arriving on time to work or other commitments, the level of inconvenience or discomfort associated with a crowded public transport trip, and the perceived importance of measures to prevent the spread of COVID-19 are some factors that play an important role on the final decision.

While this study provides valuable insights into travel behavior, there are limitations to consider. Firstly, the collected data and the respective analysis is limited one country, with specific sociodemographic and mobility characteristics. Secondly, the information about the crowdedness levels can only be estimated and may not be accurate or available in all areas. This type of information is not widely available, and the way it is presented can impact how respondents value it. It is important to note that the choices observed in the study are

hypothetical and may not reflect the actual constraints faced by individuals in different societal circumstances. Finally, we acknowledge that our observations and participants' behavior may change as the pandemic continues to evolve and people adapt to a new reality. However, research's findings are still valuable because they provide an insight into traveler preferences at crucial phases of the pandemic which can assist in making proactive decisions in the future. In addition, the results can be useful for governments in developing policies that effectively control the spread of a pandemic and improve public transport services. Additionally, our findings suggest that targeted communication and information-sharing campaigns, tailored to specific groups and trip types, could be an effective strategy for promoting crowd avoidance behaviors.

## 8 Conclusions and future research

### 8.1 Main findings and conclusions

This dissertation aimed at investigating the potential applications of big data and social media in transportation, and their impact on travel behavior, decision-making, and promotion of sustainable urban mobility. This was accomplished through four specific objectives: RO1, RO2, RO3, and RO4 (see Section 1.2). Analytically, the related research questions and the respective provided answers are:

**RQ1: What are the most frequent big data sources used in transport studies, in which application field have these sources contributed the most, and how can they be utilized to minimize congestion, improve traveler information and assistance, fulfill commuters' needs, and increase road safety?**

**Data used:** Self-collected

**Method:** Literature review and descriptive statistical analysis

**Answer:** The most frequent application fields where big data sources have contributed in transport studies during the last years are transportation planning, traffic management, public transport management, and incident management and safety.

Most of the extracted big data is oriented towards supporting traffic management. Traffic management involves the real-time monitoring and control of traffic flows to reduce congestion, improve safety, and enhance the efficiency of transport networks. Big data sources such as GPS devices, Bluetooth detectors, and ANPRs are used to analyze traffic conditions and develop predictive models for traffic flow optimization. In traffic management studies, GPS data is the most frequent big data source. Bluetooth detectors and ANPRs are used to collect data on traffic flows, vehicle speed, and travel time on specific routes or sections of road.

Transportation planning involves the analysis of travel patterns and behavior to develop sustainable transport policies, infrastructure plans, and land use strategies. Mobile phone data and user-generated content on social media are primarily used in transportation planning studies. Mobile phones generate data on the location and movement of individuals, which can be used for trip and activity pattern analysis. Social media platforms and community-driven applications allow individuals to share their travel experiences, opinions, and preferences, providing valuable qualitative data for transport studies.

Public transport management involves the analysis of public transport operations to improve service quality, reliability, and accessibility. Big data sources such as smart card systems and mobile applications are used to collect data on passenger behavior, service performance, and customer satisfaction. Smart card systems are widely used in public transport systems to collect data on passenger boarding and alighting times, trip duration, and fare payment, which is primarily used in public transport operation studies.

Incident management and safety involve the identification and mitigation of risks associated with transportation, such as accidents, road hazards, and security threats. Big data sources such as social media and community-driven applications are used to collect data on incidents and disseminate real-time information to travelers, which can improve safety and reduce travel disruptions.

Furthermore, the use of big data has allowed for the integration of various data sources, resulting in a more comprehensive understanding of transportation systems and their complex interactions. This has been evident in the 13% of analyzed transport studies that used data from more than one big data source, with 11% using data from two sources and 2% using data from three. Big data applications have contributed significantly to the advancement of transportation studies, particularly in the context of sustainable urban mobility, with the most frequent application fields being transportation planning, traffic management, public transport management, and incident management and safety. The most common sources of big data used in transportation studies over the last decade are GPS devices, smart card systems, Bluetooth detectors, ANPRs, mobile phones, smart vehicles, social media, and community-driven applications.

**RQ2: How does social media use affect the travel choices and mobility decisions of commuters, and what specific types of social media content are most influential in this process? How is it associated with gender and social media usage aspects?**

**Data used:** Questionnaire data

**Method:** Descriptive statistics, Inferential statistics, Ordinal regression analysis

**Answer:** Based on the findings, it is evident that social media platforms are widely used as a source of information for travel planning. The study found that 82% of participants use social media platforms before embarking on a trip or activity. The most common activities for which social media is used include entertainment and travel arrangements. However, it is worth noting that participants also reported using complementary sources of information such as friends and relatives, tourism-related social websites, and blogs/forums, highlighting the importance of personal recommendations and word-of-mouth for planning.

Reviews and ratings, photos and videos, and negative reviews were found to have a significant impact on decision-making, with positive reviews being the most important factor in activity choice. In terms of transport mode, the study found that it has a moderate impact on decision-making. Additionally, most respondents reported that they sometimes make changes to their plans after using social media. Designated transport accounts were found to be the most effective way to raise awareness of travel possibilities, while sponsored messages were perceived as the least effective. This finding emphasizes the importance of authenticity and trust in social media marketing. Organizations must strive to create genuine connections with their target audience to be successful in their social media campaigns. The informative approach was found to be the most appealing message approach, followed by the humorous approach. This finding implies the need of informative and engaging content that resonates with the target audience to increase engagement and interaction.

The study investigated the most important criteria for commuters' final decision regarding their activity choice. The results showed that both sustainable and non-sustainable mode users prioritize accessibility to public transport, distance from home/work, and parking availability. However, sustainable mode users (i.e., those who use only sustainable modes of transport for their daily commute) place more importance on accessibility to public transport and distance from home/work, while non-sustainable mode users (i.e., those who use at least one non-sustainable mode of transport) prioritize parking availability.

Based on the findings, participants who are younger than 18 years old are less likely to change their mobility plans based on social media information than older participants. Students

and full-time employees are more likely to change their plans after social media use compared to others.

The study also found that the rare use of public transport and the minimum time spent on social media have a negative impact on changing mobility plans after using social media as a source of information. Participants who stated that social media do not help them with the mobility-planning phase have a decreased probability to change their mobility plans upon social media use. Furthermore, participants who hold a driver's license are less likely to change their mobility plans based on social media information about a proposed transport mode. Respondents who use public transport rarely or sometimes are also less likely to change their mobility plans compared to those who use public transport always.

As expected, the proposed transport mode has a significantly high negative impact on participants who stated that social media never help them with the mobility-planning phase compared to those who stated that social media always help them.

Regarding the gender aspect, it was found that women are more likely to use social media compared to men, and they are keener than men on reaching out for information provided by social media, with the difference being statistically significant. In addition, both men and women indicated interest in receiving information from social media, particularly when planning an activity. However, women are more likely to use social media for activity planning and travel arrangements than men, and the differences are statistically significant. It is also found that the influence of social media content on activity planning is associated with gender, with women being more receptive to visual information and feedback based on experience (such as photos and videos) than men.

**RQ3: What is the potential of social media platforms, such as Twitter, as a source of transport-related information across different regions with varying demographics, languages, and infrastructure?**

**Data used:** Twitter data

**Method:** Preliminary Grading Results, Classification

**Answer:** Twitter activity in three cities of different population, language, and transport infrastructure: Volos, Riga, and Minneapolis-St. Paul (MSP), was analyzed. The initial selection of transport-related tweets using keyword-based grading provided an early indication of social media's potential as a source of transport-related data. The keyword lists used were designed to be similar across all the examined languages, allowing for comparable grading results.

The findings showed significant differences in the percentage of graded tweets with at least one transport-related word for different research areas, with 15% for Volos, 22% for Riga, and 27% for MSP. Two area-specific characteristics that could explain these differences were identified: Twitter popularity, which is higher in Riga and MSP, and language distribution. The results supported the hypothesis that tweets in English have higher potential as a source of transport-related information.

The collected tweets of each city were manually classified into four classes: general transport-related information, real-time transport-related information, transport-related complaints, and unrelated tweets. The class of transport-related advice/question was merged with general information due to the limited number of related tweets. It was found that more than half of the manually analyzed tweets in MSP and Riga were related to transportation, which

is consistent with the higher average grades reported. Conversely, the low percentage of analyzed tweets related to transportation in Volos and Riga are also reflected in the lower average grades reported above.

It is concluded that the potential of Twitter data is higher in areas with larger populations, such as MSP. The limited number of collected tweets in Volos, along with the low average grades, contribute to the high number of tweets unrelated to transportation. The utility of retrieved information depends on the intensity of social media use in the study area, as well as on the tweets' language. In general, the overall intensity of transport-related tweets in the three samples was low, and the most useful transport-related tweets were shared by official bodies and automated volunteered sources.

**RQ4 What are the challenges of using social media for promoting awareness and engagement in sustainable urban mobility initiatives, and what is an effective scheme for putting a transport-related account and content into practice?**

**Data used:** Self-collected

**Method:** Literature review and review of transport-related social media accounts and content

**Answer:** Social media can be a powerful tool for promoting sustainable urban mobility initiatives. However, there are several challenges that need to be overcome for effective implementation. Based on the findings of the study, one of the major challenges is the variety of purposes for which social media is used in the context of urban mobility. Five categories of social media use emerged, including investigating how influencers or digital campaigns affect users' travel intentions, raising awareness and promoting sustainable means of transport and safety, creating opportunities for accessing information, engaging, participating, co-producing, and co-creating. These diverse purposes require different strategies and approaches for effective engagement.

Another challenge is the posting frequency and content shared on social media accounts. Posting frequently with consistent and engaging content can keep the audience interested and engaged. The analysis showed that a more active group with consistency in posting keeps its audience engaged, and humorous or discussion-stimulating content generates more shares and comments. Social media metrics, such as the number of reactions, comments, and shares, determine the value of the account for the audience. The higher the value, the more influential the shared content.

Interacting actively with the audience, welcoming new members, and using hashtags related to sustainable urban mobility can make members feel part of the community and willing to participate in actions or provide feedback. Pages are useful for marketing purposes, while groups are more suitable for interacting with the audience.

Based on these findings, an effective scheme for putting a transport-related account and content into practice includes identifying the specific purpose of the account, posting frequently and consistently with engaging content, actively interacting with the audience, and using hashtags related to sustainable urban mobility.

**RQ5: What are the key characteristics that affect the mobility choices of motorized vehicle users, pedestrians, and public transport users? How does the provision of transport-related information influence the mobility choices of different types of**

**travelers, and how do these effects vary across different transport modes and demographic groups?**

**Data used:** Questionnaire data, Stated preference data

**Method:** Descriptive statistics, IPA analysis, discrete choice modeling

**Answer:** Based on the findings, the key characteristics that affect the mobility choices of motorized vehicle users, pedestrians, and public transport users in a medium-sized city are travel time, safety, shortest route, potential delays, traffic congestion, scenic features, and environmentally friendly route. Among these characteristics, travel time, safety, and shortest route play an important role for the respondents. Meanwhile, attributes such as potential delays, traffic congestion, and scenic features performed poorly in terms of quality. The respondents gave less priority to the environmentally friendly route attribute, also rating its quality as low. Furthermore, the study found that 60% of the participants use sustainable modes of transport for their daily trips, and the rest use non-sustainable ways of transport. The importance of different parameters related to travel information seeking was also examined, but no safe conclusions about the transport mode, comfort, and economical route attributes can be drawn from the study. In terms of travel information seeking, sustainable mode users get travel information more often than non-sustainable mode users. Non-sustainable mode users would seek more often for information about traffic congestion and dynamic re-routing when traveling. Overall, the findings suggest that efforts should be made to improve the quality and performance of attributes that are rated as important and to increase the priority given to environmentally friendly routes.

It can be concluded that the provision of transport-related information can influence individuals' mobility choices. More specifically, a majority of participants in the survey indicated that they would consider travel information during their commute and that they would be willing to change their transport mode or route if they received reliable information about their main daily trip. Additionally, the study found that individuals prioritize reliability when seeking information about travel time. The results also suggest that individuals' preference for sustainable transportation options is not significantly influenced by the provision of travel information. The study found that the cost of sustainable transportation options, such as public transport, reduces the probability that individuals will choose them. Furthermore, the preference for walking or biking over public transport may be due to the fact that Volos is a flat, bike and walk-friendly city with a long seaside, making these options more attractive and feasible for individuals. Finally, a potential gender difference in travel behavior was found, with women being more likely to change their usual route.

The provision of transport-related information influences also the mobility choices of pedestrians and public transport users. Pedestrians are more willing than public transport users to change their usual travel choice after receiving information about high levels of crowdedness on their main trip, while public transport users are more willing than pedestrians to be informed via applications such as Google maps or social media about the crowdedness levels of the main trip. Based on the conducted survey, there are variations in how different demographic groups respond to the provision of transport-related information. For example, pedestrians who live in Athens or in other medium-sized cities are less likely to change their usual route compared to residents of small-sized Greek cities. People aged 41-65 are more likely to change their departure time than younger people aged 18-23 years. The results also showed that travelers are more likely to change their trips' departure time or route to experience moderate crowdedness level rather than high and, respectively, to experience low crowdedness level rather than high

as compared to moderate to low. Public transport users have a high tendency towards changing their departure time or stop when the crowdedness level of their usual choice is high. The study also found that the provision of information through various means such as applications like Google maps or social media increases the propensity of public transport users to switch from their usual public transport stop, as expected. The travelers' propensity towards a stop change is increased when information on crowdedness levels is shared on social media compared to no sharing at all.

## 8.2 Practical implications of main findings

The field of transport and mobility has significantly benefited from the availability of big data, as the increasing usage of smart devices, IoT technologies, and social media platforms has led to the growth of big data sources in transport field over the last years. The most common sources of big data used in transport studies include GPS devices, smart card systems, Bluetooth detectors, ANPRs, mobile phones, smart vehicles, social media, and community-driven applications. Big data has played a crucial role in achieving key transportation objectives such as increasing travel security and comfort, reducing travel time and costs, and improving traveler information and assistance. Big data applications have significantly contributed to the advancement of transport studies, particularly in the context of sustainable urban mobility. GPS devices have become an essential source of data in transport studies due to their ability to provide accurate location data and travel trajectories of individuals or vehicles. Big data sources have been effective in providing insights into travel demand, mode choice, trip purposes, and activity patterns, which are essential for transportation planning. By combining data from multiple sources, transportation researchers can gain a more complete picture of travel demand, mode choice, trip purposes, and activity patterns, which are essential for developing sustainable transport policies, infrastructure plans, and land use strategies. The availability and analysis of big data have provided valuable insights into travel patterns, behavior, and preferences in transport studies. Big data applications have been effective in optimizing transport operations, reducing emissions, improving the travel experience for passengers, and enhancing the overall efficiency of transport networks. The development of new technologies and the increasing availability of big data sources will continue to provide new opportunities for transportation studies, enabling further optimization of transport systems, reduction of congestion, improvement of traveler information and assistance, fulfillment of commuters' needs, and increase of road safety.

Beyond conventional data, the impact of social media on mobility behavior emerges as a practical focal point. The study underscores the influential role of attributes like travel time, safety, and environmentally friendly routes on mobility choices. By addressing these factors, transportation planners can cater more effectively to commuters' preferences. However, it's apparent that individual characteristics like age and occupation shape the impact of social media on mobility choices. Younger participants, for instance, may be less affected by social media information due to their dependence on other household members for their travel needs. Full-time employees and students, on the other hand, are more likely to adjust their plans based on social media information, reflecting their need for efficient schedule management. Crucially, the perceived utility of social media in planning mobility plays a pivotal role. When social media is deemed a helpful source of information, individuals are more likely to change their mobility plans upon social media use. Dissertation's findings suggest that personal preferences and habits play a role in determining the impact of social media on mobility behavior.



The study highlights several factors that influence the impact of social media on mobility behavior, including gender, age, occupation, frequency of public transport use, perceived usefulness of social media in planning mobility, and shared content. In summary, the study's depth of exploration and its findings hold substantial practical implications. It underscores the need for transportation planners and policymakers to harness the power of big data and social media effectively. This entails not only capitalizing on diverse data sources to inform policies and strategies but also leveraging social media to promote sustainable travel choices across various demographics. The selection of the appropriate social media platform is crucial. Facebook, for instance, is effective for fostering communities and discussions, while Twitter excels at disseminating real-time updates. Instagram, being image-centric, can be employed to visualize transportation stories and scenarios. Regular and relevant posting, paired with validated information, can gain more engagement from the public. Using appropriate hashtags can amplify the reach of posts. Additionally, endorsements from notable personalities or entities in the mobility sector can further boost awareness. In essence, a well-organized social media strategy can be instrumental in promoting sustainable mobility principles and practices. Such insights equip decision-makers with actionable knowledge, empowering them to create more efficient, sustainable, and equitable urban transportation systems that cater to the diverse needs of commuters.

### **8.3 Research limitations and recommendations for future research**

The potential applications of big data and social media in the field of transportation and mobility are vast and promising. Through the exploration of these technologies and their impact on travel behavior, decision-making, and promotion of sustainable urban mobility, this research has uncovered numerous opportunities for future research. By addressing the identified research gaps, researchers and practitioners can maximize the potential benefits of big data and social media in transportation and mobility, ultimately leading to more efficient, sustainable, and equitable urban transportation systems. While this research has contributed valuable insights into the applications of big data and social media in transportation and mobility, it is important to acknowledge its limitations. These limitations provide fertile ground for future research endeavors, enabling a more comprehensive understanding of the intricate interplay between technology, behavior, and urban mobility.

One limitation pertains to the exclusivity of our focus on big data and social media, potentially neglecting the transformative impact of emerging technologies. Future research could expand its scope to encompass technologies such as the Internet of Things (IoT), blockchain, and artificial intelligence (AI) within the transportation domain. Investigating these technologies alongside big data and social media could provide a more holistic understanding of their synergistic potential.

The research's focus on applications may have understated the ethical implications inherent in utilizing personal data from social media and other sources for transportation and mobility insights. As more personal data is collected and used in transportation, it is crucial to consider the ethical implications of such use. Future research could focus on investigating the ethical implications of collecting, analyzing, and using large amounts of personal data from social media and other sources in the context of transportation and mobility. Researchers could explore issues such as data privacy, security, and transparency to ensure that the use of big data and social media in transportation is conducted in an ethical and responsible manner.

While the research has highlighted the potential of social media for promoting sustainable transportation practices, it has not comprehensively examined effective strategies for achieving this. To promote sustainable transportation practices, future research could delve into the design and evaluation of strategies that leverage social media and similar technologies to incentivize sustainable modes of transportation, such as carpooling, biking, and walking.

While urban transportation has been the focus of this dissertation, the potential impact of big data and social media on transportation and mobility in rural regions remains underexplored. Future research could delve into how these technologies can be tailored to address unique challenges in rural mobility and improve access to transportation services. For instance, the use of big data in transportation could be used to identify transportation deserts and improve access to public transportation services in rural areas.

Although our research has offered a snapshot of big data and social media's impact on travel behavior, the lack of longitudinal studies hinders a complete understanding of their enduring effects. Conducting longitudinal studies that track changes over time could provide valuable insights into how these technologies influence travel behavior and decision-making and inform the development of more effective transportation policies and strategies.

These limitations underscore the dynamic nature of research in the realms of transportation, mobility, and digital communication. By acknowledging these constraints and embracing future research recommendations, the way for a more comprehensive and impactful exploration of the potential, challenges, and ethical considerations surrounding big data, social media, and emerging technologies in the urban mobility landscape is paved.

## References

- Abbasi, A., Rashidi, T., Maghrebi, M. & Waller, S., 2015. Utilising Location Based Social Media in Travel Survey Methods: bringing Twitter data into the play. Seattle, Washington, USA, 8th ACM SIGSPATIAL International Workshop on Location-Based Social Networks.
- Abdulhai, B. & Katann, L., 2003. Reinforcement learning: Introduction to theory and potential for transportation applications. *Canadian Journal of Civil Engineering*, Volume 30, pp. 981-991.
- Abedi, N., Bhaskar, A., Chung, E. & Miska, M., 2015. Assessment of antenna characteristic effects on pedestrian and cyclists travel-time estimation based on Bluetooth and WiFi MAC addresses. *Transportation Research Part C: Emerging Technologies*, Volume 60, pp. 124-141.
- Aghabayk, K., Esmailpour, J. & Shiwakoti, N., 2021. Effects of COVID-19 on rail passengers' crowding perceptions. *Transportation Research Part A: Policy and Practice*, Volume 154, pp. 186-202.
- Al-Deek, H., Chilakamarri Venkata, S. & Flick, J., 2009. Impact of dynamic message signs on satisfaction and diversion of toll road travelers. *Transportation Research Record*, 2099(1), pp. 1-13.
- Alam, M., Habib, N., Holmes, D. & Habib, A. M., 2022. Pedestrian movement modelling for a commercial street considering COVID-19 social distancing strategies. *Procedia Computer Science*, Volume 201, pp. 64-71.
- Alexander, L., Jiang, S., Murga, M. & González, M. C., 2015. Origin- destination trips by purpose and time of day inferred from mobile phone data. *Transportation Research Part C: Emerging Technologies*, Volume 58, pp. 240-250.
- Alrashed, T. et al., 2016. *Social Communities in Urban Mobility Systems*. Toronto, Canada, Springer, Cham, pp. 177-187.
- Alves, F. et al., 2020. Walkability Index for Elderly Health: A Proposal. *Sustainability*, Volume 12.
- Amirjamshidi, G. & Roorda, M., 2019. Multi-objective calibration of traffic microsimulation models. *Transportation Letters*, 11(6), pp. 311-319.
- An, S. et al., 2016. Mining urban recurrent congestion evolution patterns from GPS-equipped vehicle mobility data. *Information Sciences*, Volume 373, pp. 515-526.
- Anda, C., Erath, A. & Fourie, P., 2017. Transport Modelling in the Age of Big Data. *International Journal of Urban Sciences*, Volume 21, pp. 19-42.
- Andrienko, N., Andrienko, G., Fuchs, G. & Janko, P., 2016. Scalable and privacy-respectful interactive discovery of place semantics from human mobility traces. *Information Visualization*, 15(2), pp. 117-153.
- Andy Lee, H., Law, R. & Murphy, J., 2011. Helpful Reviewers in TripAdvisor, an Online Travel Community. *Journal of Travel & Tourism Marketing*, 28(7), pp. 675-688.
- ANEVO LTD, 2015. [Online] Available at: [http://www.anevo.gr/active\\_article.php?id=43&cat=4](http://www.anevo.gr/active_article.php?id=43&cat=4). [Accessed 18 January 2023].

- Aparicio-Martínez, P. et al., 2020. Gender differences in the addiction to social networks in the southern Spanish university students. *Telematics and Informatics*, Volume 46.
- Arun, K. & Jabasheela, L., 2014. Big Data: Review, Classification and Analysis Survey. *International Journal of Innovative Research in Information Security (IJIRIS)*, 1(3), pp. 17-23.
- Asdecker, B., 2022. Travel-Related Influencer Content on Instagram: How Social Media Fuels Wanderlust and How to Mitigate the Effect. *Sustainability*, 14(855).
- Asselin-Miller, N. et al., 2016. Study on the deployment of C-ITS in Europe: final report framework contract on impact assessment and evaluation studies in the field of transport study on the deployment of cooperative intelligent transport systems , London, United Kingdom: TRT.
- ASTUTE consortium, 2009. ASTUTE Final Evaluation Report, London: London European Partnership for Transport.
- Avineri, E., 2006. The effect of reference point on stochastic equilibrium. *Transportation Science*, 40(4), pp. 409-420.
- Axer, S., Rohde, J. & Friedric, B., 2012. Level of service estimation at traffic signals based on innovative traffic data services and collection techniques. *Procedia-Social and Behavioral Sciences*, Volume 54, pp. 159-168.
- Ayeh, J. K., Au, N. & Law, R., 2013. Predicting the intention to use consumer-generated media for travel planning. *Tourism Management*, 35(4), pp. 132-143.
- Bekhor, S., Cohen, Y. & Solomon, S., 2013. Evaluating long-distance travel patterns in Israel by tracking cellular phone positions. *Journal of Advanced Transportation*, Volume 47, pp. 435-446.
- Belgiawan, P. F. et al., 2014. Car ownership motivations among undergraduate students in China, Indonesia, Japan, Lebanon, Netherlands, Taiwan, and USA. *Transportation*, 41(6), pp. 1227-1244.
- Ben-Akiva, M. & Bierlaire, M., 2013. Discrete choice models with applications to departure time and route choice. In: R. Hall, ed. *Handbook of transportation science*. 2nd Edition ed. s.l.:Kluwer, pp. 7-38.
- Berlingerio, M. et al., 2013. AllAboard: A system for exploring urban mobility and optimizing public transport using cellphone data. Prague, Czech Republic, Joint European Conference on Machine Learning and Knowledge Discovery in Databases, pp. 663-666.
- Bierlaire, M., 2003. BIOGEME: A free package for the estimation of discrete choice models. Ascona, Switzerland, 3rd Swiss Transportation 947 Research Conference.
- Bingham, C. et al., 2016. Peer passenger norms and pressure: experimental effects on simulated driving among teenage males. *Transportation Research F: Traffic Psychology and Behaviour*, Volume 41, pp. 124-137.
- Bliemer, C. M., Rose, M. J. & Chorus, G. C., 2017. Detecting dominance in stated choice data and accounting for dominance-based scale differences in logit models. *Transportation Research Part B: Methodological*, Volume 102, pp. 83-104.
- Booth, L., Norman, R. & Pettigrew, S., 2019. The potential implications of autonomous vehicles for active transport. *Journal of Transport & Health*, Volume 15.

Borkowski, P., Jażdżewska-Gutta, M. & Szmelter-Jarosz, A., 2021. Lockdowned: Everyday mobility changes in response to COVID-19. *Journal of Transport Geography*, Volume 90.

Borowski, E., Chen, Y. & Mahmassani, H., 2020. Social media effects on sustainable mobility opinion diffusion: Model framework and implications for behavior change. *Travel Behaviour and Society*, Volume 19, pp. 170-183.

Bou Mjahed, L. et al., 2017. Exploring the Role of Social Media Platforms in Informing Trip Planning: Case of Yelp.com. *Transportation Research Record*, 2666(1), pp. 1-9.

Brakewood, C. & Watkins, K., 2019. A literature review of the passenger benefits of real-time transit information. *Transport Reviews*, 39(3), pp. 327-356.

Bregman, S., 2012. *Uses of social media in public transportation*. Washington, D. C., s.n.

Brennan, L. & Binney, W., 2010. Fear guilt, and shame appeals in social marketing. *Journal of Business Research*, 63(2), pp. 140-146.

Briand, A. S., Côme, E., Trépanier, M. & Oukhellou, L., 2017. Analyzing year-to-year changes in public transport passenger behaviour using smart card data. *Transportation Research Part C: Emerging Technologies*, Volume 79, pp. 274-289.

Buningh, S., Venema, A. & Martijnse-Hartikka, R., 2016. *MOBI Final Report*, Breda: DTV Consultants.

Bureau, U. C., 2017. *National Population Projections Datasets*. [Online] Available at: <https://www.census.gov/data/datasets/2017/demo/popproj/2017-popproj.html> [Accessed February 2018].

Byon, Y. —, Abdulhai, B. & Shalaby, A., 2009. Real-time transportation mode detection via tracking global positioning system mobile devices. *Intelligent Transportation Systems*, 13(4), pp. 161-170.

Caceres, N., Romero, L.-M. & Benitez, F.-G., 2020. Exploring strengths and weaknesses of mobility inference from mobile phone data vs. travel surveys. *Transportmetrica A Transport Science*, 16(3), pp. 574-601.

Calabrese, F., Lorenzo, G. D., Liu, L. & Ratti, C., 2011. Estimating Origin-Destination Flows Using Mobile Phone Location Data. *IEEE Pervasive Computing*, 10(4), pp. 36-44.

Campisi, T. et al., 2022. Anxiety, fear and stress feelings of road users during daily walking in COVID-19 pandemic: Sicilian cities. *Transportation Research Procedia*, Volume 62, pp. 107-114.

Can Diker, A. & Nasibov, E., 2012. Estimation of Traffic Congestion Level via FN-DBSCAN Algorithm by Using GPS Data. *Baku, Azerbaijan, IV International Conference "Problems of Cybernetics and Informatics" (PCI)*.

Carpenter, C., Fowler, M. & Jay Adler, T., 2012. Generating Route-Specific Origin-Destination Tables Using Bluetooth Technology. *Transportation Research Record: Journal of the Transportation Research Board*, Volume 2308, pp. 96-102.

Casas, I. & Delmelle, E. C., 2017. Tweeting about public transit — Gleaning public perceptions from a social media microblog. *Case Studies on Transport Policy*, 5(4), pp. 634-642.

Castro, P. S., Zhang, D. & Li, S., 2012. Urban Traffic Modelling and Prediction Using Large Scale Taxi GPS Traces. Newcastle, UK, 10th International Conference on Pervasive Computing, pp. 57-72.

Chandrasekar, P., 2015. Big data and transport modeling: Opportunities and challenges. *International Journal of Applied Engineering Research*, ISSN 0973-4562, 10(17), pp. 38038-38044.

Chapman, C., Chua, W. F. & Fiedler, T., 2021. Seduction as control: Gamification at Foursquare. *Management Accounting Research*, Volume 53.

Chawla, S., Zheng, Y. & Hu, J., 2012. Inferring the root cause in road traffic anomalies. Washington, DC, USA, ICDM '12 Proceedings of the 2012 IEEE 12th International Conference on Data Mining, pp. 141-150.

Chen, C. et al., 2013. B-Planner: Night Bus Route Planning using Large-scale Taxi GPS Traces. San Diego, USA, Pervasive Computing and Communications (PerCom), 2013 IEEE International Conference.

Chen, C., Bian, L. & Ma, J., 2014. From traces to trajectories: How well can we guess activity locations from mobile phone traces?. *Transportation Research Part C: Emerging Technologies*, Volume 46, pp. 326-337.

Chen, C., Feng, T. & Gu, X., 2022. Role of latent factors and public policies in travel decisions under COVID-19 pandemic: Findings of a hybrid choice model. *Sustainable Cities and Society*, Volume 78.

Chen, S., Bekhor, S., Yuval & Broday, D. M., 2016. Aggregated GPS tracking of vehicles and its use as a proxy of traffic-related air pollution emissions. *Atmospheric Environment*, Volume 142, pp. 351-359.

Chen, X. & Deng, H., 2019. A correlation analysis of information use, social networks and cooperation consciousness in travel behaviors. *Transportation Research Part F: Traffic Psychology and Behaviour*, Volume 62, pp. 819-832.

Cheng, Z., Caverlee, J., Lee, K. & Sui, D., 2011. Exploring Millions of Footprints in Location Sharing Services. Barcelona, Spain, Fifth International Association for the Advancement of Artificial Intelligence Conference on Weblogs and Social Media.

Cho, E., Myers, S. & Leskovec, J., 2011. Friendship and mobility: User movement in location-based social networks. San Diego, United States, proceedings of the 17th ACM SIGKDD International conference on knowledge discovery and data mining.

Choe, Y., Kim, J. & Fesenmaier, D., 2017. Use of social media across the trip experience: An application of latent transition analysis. *Journal of Travel & Tourism Marketing*, 34(4), pp. 431-443.

Choocharukul, K., 2008. Effects of attitudes and socioeconomic and travel characteristics on stated route diversion: structural equation modeling approach of road users in Bangkok. *Transportation Research Record*, Volume 2048, pp. 35-42.

Chorus, C., Arentze, T. A. & Timmermans, H., 2008. A comparison of regret-minimization and utility maximization in the context of travel mode-choices. Washington, DC, 87th Annual Meeting of the Transportation Research Board.

Chorus, G., Molin, J. & Van Wee, B., 2006. Use and effects of advanced traveller information services: a review of the literature. *Transport Reviews*, 26(2), pp. 127-149.

Chowdhury, S. & Giacaman, N., 2015. En-route planning of multi-destination public-transport trips using smartphones. *Public Transportation*, 18(4), pp. 31-45.

Chung, N. & Koo, C., 2015. The use of social media in travel information search. *Telematics and Informatics*, 32(2), pp. 215-229.

Chung, Y. & Won, M., 2018. A Novel Framework for Sustainable Traffic Safety Programs Using the Public as Sensors of Hazardous Road Information. *Sustainability*, 10(3892).

Cici, B., Markopoulou, A., Frias-Martinez, E. & Laoutaris, N., 2014. Assessing the potential of ride-sharing using mobile and social data: A tale of four cities. Seattle, Washington, Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing.

Cipriani, E. et al., 2021. Traffic demand estimation using path information from Bluetooth data. *Transportation Research Part C: Emerging Technologies*, 133(103443).

City of Vancouver, 2016. Active Transportation Promotion & Enabling Plan, Vancouver: City of Vancouver.

CIVITAS, 2020. The use of social media to involve citizens in urban mobility projects and city planning, POLICY NOTE. [Online] Available at: [https://civitas.eu/sites/default/files/civ\\_pol-an3\\_m\\_web.pdf](https://civitas.eu/sites/default/files/civ_pol-an3_m_web.pdf) [Accessed 21 March 2022].

Cohen-Blankshtain, G. & Rotem-Mindali, O., 2016. Key research themes on ICT and sustainable urban mobility. *International Journal of Sustainable Transportation*, 10(1), pp. 9-17.

Collins, C., Hasan, S. & V.S, U., 2013. A Novel Transit Rider Satisfaction Metric: Rider Sentiments Measured from Online Social Media Data. *Journal of Public Transportation*, 16(2), pp. 21-45.

Cottrill, C. & Derrible, S., 2015. Leveraging Big Data for the Development of Transport Sustainability Indicators. *Journal of Urban Technology*, Volume 22, pp. 45-64.

Cottrill, C. et al., 2017. Tweeting Transit: An examination of social media strategies for transport information management during a large event. *Transportation Research Part C: Emerging Technologies*, Volume 77, pp. 421-432.

Cox, D. & Snell, E. J., 1989. Analysis of Binary Data. 2nd Edition ed. London: Chapman and Hall/CRC.

Cui, J. X. et al., 2016. Identifying mismatch between urban travel demand and transport network services using GPS data: A case study in the fast growing Chinese city of Harbin. *Neurocomputing*, Volume 181, pp. 4-18.

D'Ambra, L. et al., 2021. Evaluation of the social and economic impact of carbon dioxide (CO<sub>2</sub>) emissions on sustainable mobility using cumulative ordinal models: trend odds model. *Socio-Economic Planning Sciences*, Volume 75.

D'Andrea, E., Ducange, P., Lazzarini, B. & Marcelloni, F., 2015. Real-Time Detection of Traffic From Twitter Stream Analysis. *IEEE Transactions on Intelligent Transportation Systems*, 16(4), pp. 1-15.

de Abreu e Silva, J., de Oña, J. & Gasparovic, S., 2017. The relation between travel behaviour, ICT usage and social networks. The design of a web based survey. *Transportation Research Procedia*, Volume 24, pp. 515-522.

De Mauro, A., Greco, M. & Grimaldi, M., 2016. A formal definition of Big Data based on its essential features. *Library Review*, 65(3), pp. 122-135.

de Palma, A. V. S. L. F., 2022. An overview of effects of COVID-19 on mobility and lifestyle: 18 months since the outbreak. *Transportation Research Part A: Policy and Practice*, Volume 159, pp. 372-397.

Delbosc, A. & Currie, G., 2014. Changing demographics and young adult driver license decline in Melbourne, Australia. *Transportation*, 41(3), pp. 529-542.

Dewulf, B. et al., 2015. Examining commuting patterns using Floating Car Data and circular statistics: Exploring the use of new methods and visualizations to study travel times. *Journal of Transport Geography*, Volume 48, pp. 41-51.

di Nunzio, A., Montesi, G., Pattara, C. & Pasquini, E., 2010. *Students Today Citizens Tomorrow- Making University Life More Sustainable*, Italy: Intelligent Energy.

Dormanesh, A., Majmundar, A. & Allem, J., 2020. Follow-Up Investigation on the Promotional Practices of Electric Scooter Companies: Content Analysis of Posts on Instagram and Twitter. *JMIR Public Health Surveill*, 6(1).

dos Reis, R. A., Grant-Muller, S., Lovelace, R. & Hodgson, F., 2022. Different people, different incentives? Examining the public acceptance of smartphone-based persuasive strategies for sustainable travel using psychographic segmentation. *International Journal of Sustainable Transportation*, 16(1), pp. 1-21.

Douglass, J. et al., 2018. Measuring the Effectiveness of a Transit Agency's Social Media Engagement with Travelers. *Transportation Research Record*, 2672(50), pp. 46-55.

Dowling, R. et al., 2004. Guidelines for Calibration of Microsimulation Models: Framework and Applications. *Transportation Research Record*, 1876(1), pp. 1-9.

Downey, L., Fonzone, A., Fountas, G. & Semple, T., 2021. Impact of COVID-19 on travel behaviour, transport, lifestyles and 949 location choices in Scotland. arXiv:2104.10440.

Drabicki, A., Kucharski, R., Cats, O. & Szarata, A., 2021. Modelling the effects of real-time crowding information in urban public transport systems. *Transportmetrica A: Transport Science*, 17(4), pp. 675-713.

Dwityas, N. & Briandana, R., 2017. Social media in travel decision making process. *International Journal of Humanities and Social Science*, 7(7), pp. 193-201.

Echeverría-Huarte, I. et al., 2021. Estimating density limits for walking pedestrians keeping a safe interpersonal distancing. *Scientific Reports*, 11(1534).

Eggermond, M., Chen, H., Erath, A. & Cebrian, M., 2017. Investigating the potential of social network data for transport demand models. Washington DC, Transportation Research Board (TRB) 94th Annual Meeting.

ELSTAT, 2021. Hellenic Statistical Authority. [Online] Available at: [www.statistics.gr](http://www.statistics.gr) [Accessed 15 June 2021].



Emani, C., Cullot, N. & Nicolle, C., 2015. Understandable big data. *Computer science review*, 17(C), pp. 70-81.

Emisia, 2018. COPERT Street Level. [Online] Available at: <https://www.emisia.com/utilities/copert-street-level/> [Accessed 12 December 2021].

Eom, J. K., Song, J. Y. & Moon, D. S., 2015. Analysis of public transit service performance using transit smart card data in Seoul. *KSCE Journal of Civil Engineering*, 19(5), pp. 1530-1537.

Esztergár-Kiss, D. & Tettamanti, T., 2019. Stakeholder engagement in mobility planning. In: P. Coppola & D. Esztergár-Kiss, eds. *Autonomous vehicles and future mobility*. s.l.:Elsevier, pp. 113-123.

European Commission, 2013. Together Towards Competitive and Resource-Efficient Urban Mobility, Brussels: /COM/2013/913 final/.

Farag, S. & Lyons, G., 2008. What affects pre-trip public transport information use? empirical results of a qualitative study. Washington DC, Proceedings of the Transportation Research Board Annual Meeting.

FDOT, 2014. Project Traffic Forecasting Handbook. [Online] Available at: <https://www.fdot.gov/docs/default-source/statistics/trafficdata/PTF.pdf> [Accessed 2 February 2022].

Ferrer, R., 2018. Who are the millennials?. *Strategic planning and research.*, Volume 4.

FHWA, 2018. Traffic Data Computation Method, Washington, DC: U.S. Department of Transportation.

Fiedler, M. & Fenton, B., 2011. *Staying Mobile-A Guide to Mobility Management in Ageing Societies*, Budapest: The Regional Environmental Center for Central and Eastern Europe.

Fonzone, A., Jan-Di Schmöcker, J. D. & Viti, F., 2016. New services, new travelers, old models? Directions to pioneer public transport models in the era of big data. *Journal of Intelligent Transportation Systems*, 20(4), pp. 311-315.

Fu, K., Nune, R. & Jason, X. T., 2015. *Social Media Data Analysis for Traffic Incident Detection and Management*. Washington, DC USA, Transportation Research Board 94th Annual Meeting.

Furletti, B., Gabrielli, L., Renso, C. & Rinzivillo, S., 2013. Analysis of GSM calls data for understanding user mobility behavior. Silicon Valley, CA, USA, IEEE International Conference on Big Data.

Fusco, G., Colombaroni, C. & Isaenko, N., 2016. Short-term speed predictions exploiting big data on large urban road networks. *Transportation Research Part C: Emerging Technologies*, Volume 73, pp. 183-201.

Gal- Tzur, A., Rechavi, A., Beimel, D. & Freund, S., 2018. An improved methodology for extracting information required for transport-related decisions from Q & A forums: A case study of TripAdvisor. *Travel Behaviour and Society*, Volume 10, pp. 1-9.

Gal-Tzur, A., Grant-Muller, M., Minkov, E. & Nocera, S., 2014. The Impact of Social Media Usage on Transport Policy: Issues, Challenges and Recommendations. *Procedia - Social and Behavioral Sciences*, Volume 111, pp. 937-946.

- Gao, H., Tang, J. & Liu, H., 2012. Exploring social-historical ties on location- based social networks. Dublin, 6th International AAAI conference on weblogs and social media.
- Gately, C. K., Hutyra, L. R., Peterson, S. & Sue Wing, I., 2017. Urban emissions hotspots: Quantifying vehicle congestion and air pollution using mobile phone GPS data. *Environmental pollution*, Volume 229, pp. 496-504.
- Gennaro, M., de Paffumi, E. & Martini, G., 2016. Big Data for Supporting Low-Carbon Road Transport Policies in Europe: Applications, Challenges and Opportunities. *Big Data Research*, Volume 6, pp. 11-25.
- Germann Molz, J., 2012. *Travel Connections: Tourism, Technology and Togetherness in a Mobile World*. 1st edition ed. London: Routledge..
- Goetzke, F. & Weinberger, R., 2012. contextual from endogenous effects in automobile ownership models. *Environment and Planning A: Economy and Space*, 44(5), pp. 1032-1046.
- Gokasar, I., Simsek, K. & Ozbay, K., 2014. Using Big Data of Automated Fare Collection System for Analysis and Improvement of BRT-Bus Rapid Transit Line in Istanbul. Washington, DC, United States, Transportation Research Board 94th Annual Meeting.
- Gong, L., Liu, X., Wu, L. & Liu, Y., 2016. Inferring trip purposes and uncovering travel patterns from taxi trajectory data. *Cartography and Geographic Information Science*, 43(2), pp. 103-114.
- Gonzalez, M., Hidalgo, C. & Barabasi, A., 2008. Understanding individual human mobility patterns. *Nature*, 453(7196), pp. 779-782.
- Google, 2019. Google Maps Distance Matrix API. Developer's Guide. [Online] Available at: <https://developers.google.com/maps/documentation/distance-matrix/intro#Introduction> [Accessed 20 October 2020].
- Gore, N., Arkatkar, S., Joshi, G. & Bhaskar, A., 2019. A Novel Methodology to Derive Vehicle Occupancy Using Wi-Fi Sensors Under Heterogenous Traffic Conditions. Washington DC, United States, TRB 2019 Annual Meeting.
- Gossling, S. & Stavrinidi, I., 2015. Social Networking, Mobilities, and the Rise of Liquid Identities. *Mobilities*, 11(5), pp. 723-743.
- Gossling, S., 2017. ICT and transport behaviour: A conceptual review. *International Journal of Sustainable Transportation*, 12(3), pp. 153-164.
- Gschwender, A., Munizaga, M. & Simonetti, C., 2016. Using smart card and GPS data for policy and planning: The case of Transantiago. *Research in Transportation Economics*, Volume 59, pp. 242-249.
- Gu, Y., Qian, Z. & Chen, F., 2016. From Twitter to detector: Real-time traffic incident detection using social media data. *Transportation Research Part C Emerging Technologies*, Volume 67, pp. 321-342.
- Gunnarsson, S. O., 2000. Studies in travel behaviour and mobility management need a special scientific discipline: "Mobilistics".. *IATSS Research*, Volume 24, pp. 69-75.
- Gutiérrez, C. et al., 2015. Twitter mining for traffic events detection. London, UK, Proceedings of the 2015 Science and Information Conference (SAI).

Gutiérrez, P. A. et al., 2016. Ordinal regression methods: Survey and experimental study. *IEEE Transactions on Knowledge and Data Engineering*, Volume 28, pp. 127-146.

Hadas, Y., Tillman, A., Tsadikovich, D. & Ozalvo, A., 2022. Assessing public transport passenger attitudes towards a dynamic fare model based on in-vehicle crowdedness levels and additional waiting time. *International Journal of Transportation Science and Technology*.

Haghani, A. et al., 2010. Data Collection of Freeway Travel Time Ground Truth with Bluetooth Sensors. *Transportation Research Record: Journal of the Transportation Research Board*, 2160(1), pp. 60-68.

Hainen, A. et al., 2011. Estimating Route Choice and Travel Time Reliability with Field Observations of Bluetooth Probe Vehicles. *Transportation Research Record Journal of the Transportation Research Board*, Volume 2256, pp. 43-50.

Hartleb, J., Friedrich, M. & Richter, E., 2021. Vehicle scheduling for on-demand vehicle fleets in macroscopic travel demand models. *Transportation*, Volume 49, pp. 1133-1155.

Hasan, S. & Ukkusuri, S. V., 2014. Urban activity pattern classification using topic models from online geo-location data. *Transportation Research Part C: Emerging Technologies*, Volume 44, pp. 363-381.

Hasan, S. & Ukkusuri, S., 2015. Location contexts of user check-ins to model urban geo life-style patterns. *PLoS ONE*, 10(5).

Hasan, S., Zhan, X. & Ukkusuri, S., 2013. Understanding urban human activity and mobility patterns using large-scale location-based data from online social media. s.l., s.n.

Hastings, G., Stead, M. & Webb, J., 2004. Fear appeals in social marketing: Strategic and ethical reasons for concern. *Psychology and Marketing*, 21(11), p. 961–986.

Hawelka, B. et al., 2014. Geo-located Twitter as proxy for global mobility patterns. *Cartography and Geographic Information Science*, 41(3), pp. 260-271.

He, C. et al., 2016. Congestion Avoidance Routing Based on Large-Scale Social Signals. *IEEE Transactions on Intelligent Transportation Systems*, 17(9), pp. 2613-2626.

He, K., Wang, J., Deng, L. & Wang, P., 2014. Congestion avoidance routing in urban rail transit networks. Qingdao, China, 2014 IEEE 17th International Conference on Intelligent Transportation Systems (ITSC), pp. 200-205.

HellenicRepublic, 2022. Public Health. [Online] Available at: <https://covid19.gov.gr/ygeia-covid19/> [Accessed 18 December 2022].

Himeur, Y. et al., 2022. Deep visual social distancing monitoring to combat COVID-19: A comprehensive survey. *Sustainable Cities and Society*, Volume 85.

Hood, J., Sall, E. & Charlton, B., 2011. A GPS-based bicycle route choice model for San Francisco, California. *Transportation Letters: The International Journal of Transportation Research*, 3(1), pp. 63-75.

Hoque, M. A., Kamrani, M., Davis, C. & Khattak, A., 2019. Real-Time Alerting of Hazardous Driving Behavior Using Internet of Things (IOT) and Connected Vehicles. Washington DC, United States, TRB 2019 Annual Meeting.

Hörcher, D., Singh, R. & Graham, D., 2022. Social distancing in public transport: mobilising new technologies for demand management under the Covid-19 crisis. *Transportation*, Volume 49, pp. 735-764.

Horn, C., Gursch, H., Kern, R. & Cik, M., 2016. QZTool—Automatically Generated Origin-Destination Matrices from Cell Phone Trajectories. In: S. A.N, S. Landry, G. Di Bucchianico & A. Vallicelli, eds. *Advances in Human Aspects of Transportation*. Florida, USA: Springer, pp. 823-833.

Hosmer, J. D. W., Lemeshow, S. & Sturdivant, R., 2013. *Applied Logistic Regression*. 3rd Edition ed. s.l.:John Wiley & Sons.

Hourdakis, J., Michalopoulos, G. P. & Kottommannil, J., 2003. Practical Procedure for Calibrating Microscopic Traffic Simulation Models. Washington, DC, TRB Annual Meeting, pp. 12-16.

Hu, Y. et al., 2015. Extracting and understanding urban areas of interest using geotagged photos. *Computers, Environment and Urban Systems*, Volume 54, pp. 240-254.

Hurk, E. V. D., Kroon, L., MarÅ, sti, G. & Vervest, P., 2015. Deduction of passengers' route choices from smart card data. *IEEE Transactions on Intelligent Transportation Systems*, 16(1), pp. 430-440.

Idemudia, C. E., Raisinghani, S. M., Adeola, O. & Achebo, N., 2017. *The effects of gender on the adoption of social media: An empirical investigation*. Boston, s.n.

Iqbal, M. S., Choudhury, C. F., Wang, P. & González, M., 2014. Development of origin–destination matrices using mobile phone call data. *Transportation Research Part C: Emerging Technologies*, Volume 40, pp. 63-74.

J.H, L., Davis, A., McBride, E. & Goulias, K., n.d. s.l., s.n.

Jaffray, P., 2019. *Taking stock with teens*, s.l.: eMarketer.

Jagadish, H. V. et al., 2014. Big Data and Its Technical Challenges. *Communications of the ACM*, 57(7), pp. 86-94.

Jalali, S., Afshari, H. H., Ghods, A. H. & Raahemi, B., 2019. Estimation of Bus Passengers' Origin-Destination Using Clustering Method on Wi-Fi and Bluetooth Data. Washington DC, United States, TRB 2019 Annual Meeting.

Jamal, S. & Habib, M., 2020. Smartphone and daily travel: How the use of smartphone applications affect travel decisions. *Sustainable Cities and Society*, 53(1).

Jiang, S. et al., 2015. Mining point-of-interest data from social networks for urban land use classification and disaggregation. *Computers, Environment and Urban Systems*, Volume 53, pp. 36-46.

Ju, G. et al., 2015. Smart transportation between three phases through a stimulus-responsive functionally cooperating device. *Advanced Materials*, 25(21), p. 2915–2919.

Julio, N., Giesen, R. & Lizana, P., 2016. Real-time prediction of bus travel speeds using traffic shockwaves and machine learning algorithms. *Research in Transportation Economics*, Volume 59, pp. 250-257.

Jurdak, R. et al., 2015. Understanding Human Mobility from Twitter. *PLoS ONE*, 10(7).

Kan, Z. et al., 2022. Assessing individual activity-related exposures to traffic congestion using GPS trajectory data. *Journal of Transport Geography*, 98(103240).

Karakikes, I. & Nathanail, E., 2022. Assessing the Impacts of Crowdshipping Using Public Transport: A Case Study in a Middle-Sized 962 Greek City. *Future Transportation*, 2(<https://doi.org/10.3390/futuretransp2010004>), pp. 55-83.

Karakikes, I., Nathanail, E. & Karatsoli, M., 2021. Validating urban freight deliveries through traffic microsimulation: An experimental study. In: E. Nathanail, G. Adamos & I. Karakikes, eds. *Advances in Intelligent Systems and Computing*. s.l.:Springer, Cham.

Karakikes, I., Spangler, M. & Margreiter, M., 2016. Motorway simulation using bluetooth data. *Transport and Telecommunication Journal*, 17(3), p. 242–251.

Karatsoli, M. & Nathanail, E., 2018. Thorough Review of Big Data Sources and Sets Used in Transportation Research. In: I. Kabashkin, I. Yatskiv & O. Prentkovskis, eds. *Reliability and Statistics in Transportation and Communication. RelStat 2017. Lecture Notes in Networks and Systems*. Riga, Latvia: Springer, Cham, pp. 540-550.

Karatsoli, M. & Nathanail, E., 2019. Investigating the Role and Potential Impact of Social Media on Mobility Behavior. *Skiathos Island, Greece, Springer, Cham*.

Karatsoli, M. & Nathanail, E., 2020. Examining gender differences of social media use for activity planning and travel choices. *European Transport Research Review*, 12(44).

Karatsoli, M. & Nathanail, E., 2021. Social influence and impact of social media on users' mobility decisions. *Journal of Sustainable Development of Transport and Logistics*, 6(1), pp. 32-48.

Karatsoli, M., Margreiter, M. & Spangler, M., 2016. Simulation based Performance Test of Incident Detection Algorithms Using Bluetooth Measurements. *Transport and Telecommunication Journal*, 17(4), pp. 167-273.

Karatsoli, M., Margreiter, M. & Spangler, M., 2017. Bluetooth-based travel times for automatic incident detection – A systematic description of the characteristics for traffic management purposes. *Transportation Research Procedia*, Volume 24, pp. 204-211.

Keith, D., Sterman, J. & Struben, J., 2012. Understanding spatiotemporal patterns of hybrid-electric vehicle adoption in the United States. *Washington, USA, s.n*.

Kemp, G. et al., 2015. Aggregating and Managing Big Real-time Data in the Cloud: application to intelligent transport for Smart Cities. *Lisbon, Portugal, 1st International Conference on Vehicle Technology and Intelligent Transport Systems*, pp. 107-112.

Khan, S. et al., 2017. Social media data in transportation. In: M. Chowdhury & A. Apon, eds. *Data analytics for intelligent transportation systems*. Amsterdam: Elsevier, p. 265–282.

Kitali, A., Alluri, P., Sando, T. & Lentz, R., 2019. Impact of Primary Incident Spatiotemporal Influence Thresholds on the Detection of Secondary Crashes. *Washington DC, United States, TRB 2019 Annual Meeting*.

Kokkinogenis, Z. et al., 2015. Mobility Network Evaluation in the User Perspective: Real-Time Sensing of Traffic Information in Twitter Messages. In: J. Rossetti & L. R, eds. *Advances in Artificial Transportation Systems and Simulation*. Zhejiang, China: Academic Press, pp. 219-234.

Kokkinos, K., Nathanail, E. & Papageorgiou, E., 2019. Applying unsupervised and supervised machine learning methodologies in social media textual traffic data. In: E. Nathanail & I. Karakikes, eds. *Data Analytics: Paving the Way to Sustainable Urban Mobility*. Skiathos Island, Greece: Springer, Cham, pp. 665-672.

Kong, X. et al., 2018. Lotad: long-term traffic anomaly detection based on crowdsourced bus trajectory data. *World Wide Web*, 21(3), pp. 825-847.

Kopsidas, A., Milioti, C., Kepaptsoglou, K. & Vlachogianni, E., 2021. How did the COVID-19 pandemic impact traveler behavior toward public transport? The case of Athens, Greece. *Transportation Letters*, 13(5), pp. 344-352.

Król, K. & Zdonek, D., 2021. Most Often Motivated by Social Media: The Who, the What, and the How Much—Experience from Poland. *Sustainability*, 13(20).

Krosnick, J. A. & Presser, S., 2009. Question and questionnaire design. In: *Handbook of survey research*. San Diego: Elsevier.

Krumm, J., Caruana, R. & Count, S., 2013. *Learning Likely Locations*. Rome, Italy, International Conference on User Modeling, Adaptation, and Personalization.

Krusche, A. et al., 2022. Developing public transport messaging to provide crowding information during COVID-19: Application of the COM-B model and behaviour change wheel. *Transportation Research Interdisciplinary Perspectives*, Volume 13.

Kuflik, T. et al., 2017. Automating a framework to extract and analyse transport related social media content: the potential and the challenges. *Transportation Research Part C: Emerging Technologies*, Volume 77, pp. 275-291.

Lee, J., Davis, A., McBride, E. & Goulias, K., 2017. *Exploring Social Media Data for Travel Demand Analysis: A comparison of Twitter, household travel survey and synthetic population data in California*. Washington, D.C., s.n.

Lee, J., Davis, A., Yoon, S. & G, G. K., 2016. *Activity Space Estimation with Longitudinal Observations of Social Media Data*. Washington, D.C., s.n.

Lee, S. G. & Hickman, M., 2014. Trip purpose inference using automated fare collection data. *Public Transport*, 6(1-2), pp. 1-20.

Lee, Y. & Circella, G., 2019. ICT, millennials' lifestyles and travel choices. In: E. Ben-Elia, ed. *Advances in transport policy and planning*. s.l.:Elsevier, pp. 107-141.

Leleux, C. & Webster, W., 2018. Delivering Smart Governance in a Future City: The Case of Glasgow. *Media and Communication*, 6(4), pp. 163-174.

Lenormand, M., Tugores, A., Colet, P. & Ramasco, J., 2014. Tweets on the road. *PLoS ONE*, 9(8).

Li, H., Remias, S. M., Taylor, A. & Bullock, D. M., 2016. *Scalable Methods for Monitoring Limited Access Roadways using Crowd-Sourced Probe Data*. Washington DC, United States, Transportation Research Board 95th Annual Meeting.

Li, R. M., Chen, X. Y. & Zhang, R. B., 2015. OD estimation based on turning movement. *Journal of Transportation Systems Engineering and Information Technology*, 15(6), pp. 170-176.

Li, X. et al., 2017. Revealing spatial variation and correlation of urban travels from big trajectory data. *ISPRS - International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, Volume XLII-2/W7, pp. 53-57.

Liao, Y. & Yeh, S., 2018. Predictability in Human Mobility based on Geographical-boundary-free and Long-time Social Media Data. Maui, HI, USA, 21st International Conference on Intelligent Transportation Systems (ITSC).

Liberati, A. et al., 2009. The PRISMA statement for reporting systematic reviews and meta-analyses of studies that evaluate healthcare interventions: explanation and elaboration. *BMJ*, 339(21).

Lima, A. et al., 2016. Understanding individual routing behaviour. *Royal Society Interface*, 13(116).

Lin, K. Y. & Lu, H. P., 2011. Why people use social networking sites: An empirical study integrating network externalities and motivation theory. *Computers in Human Behavior*, 27(3), p. 1152–1161.

Lin, X. & Wang, X., 2020. Examining gender differences in people's information-sharing decisions on social networking sites. *International Journal of Information Management*, Volume 50, pp. 45-56.

Lin, X. & Wang, X., 2020. Examining gender differences in people's information-sharing decisions on social networking sites. *International Journal of Information Management*, Volume 50, pp. 45-56.

Line, T., Jain, J. & Lyons, G., 2011. The role of ICTs in everyday mobile lives. *Journal of Transport Geography*, 19(6), pp. 1490-1499.

Liu, S., Yamamoto, T., Yao, E. & Nakamuta, T., 2021. Examining public transport usage by older adults with smart card data: A longitudinal study in Japan. *Journal of Transport Geography*, 93(103406).

Long, Y., Han, H., Tu, Y. & Shu, X., 2015. Evaluating the effectiveness of urban growth boundaries using human mobility and activity records. *Cities*, Volume 46, pp. 76-84.

Long, Y., Zhang, Y. & Cui, C., 2012. Identifying Commuting Pattern of Beijing Using Bus Smart Card Data. *Journal of Geographical Sciences*, 67(10), pp. 1339-1352.

Lou, Y., Zhang, C. & Zheng, Y., 2009. Map-Matching for Low-Sampling-Rate GPS Trajectories. Seattle, Washington, 17th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems, pp. 352-361.

Lucchesi, S., Tavares, V., Rocha, M. & Larranaga, A., 2022. Public Transport COVID-19-Safe: New Barriers and Policies to Implement Effective Countermeasures under User's Safety Perspective. *Sustainability*, 14(5), pp. 1525-1558.

Luo, X. et al., 2017. Analysis on spatial-temporal features of taxis' emissions from big data informed travel patterns: a case of Shanghai, China. *Journal of Cleaner Production*, 142(2), pp. 926-935.

Ma, X. et al., 2013. Mining smart card data for transit riders' travel patterns. *Transportation Research Part C: Emerging Technologies*, Volume 36, pp. 1-12.

Ma, X. et al., 2017. Understanding commuting patterns using transit smart card data. *Journal of Transport Geography*, Volume 58, pp. 135-145.

Magginas, V., Karatsoli, M., Adamos, G. & Nathanail, E., 2019. Campaigns and Awareness-Raising Strategies on Sustainable Urban Mobility. Skiathos Island, Greece, Springer, Cham.

Maheshwary, P., Bhattacharyya, K., Maitra, B. & Boltze, M., 2019. A methodology for calibration of traffic micro-simulator for urban heterogeneous traffic operations. *Journal of Traffic and Transportation Engineering*, 7(4), pp. 507-519.

Mai, E. & Hranac, R., 2013. Twitter interactions as a data source for transportation incidents. Washington, United States, Transportation Research Board 92nd Annual Meeting.

Manca, M. B. L., Roman, V. M., Martori i Gallissà, O. & Kaltenbrunner, A., 2017. Using social media to characterize urban mobility patterns: State-of-the-art survey and case-study. *Online Social Networks and Media*, Volume 1, pp. 56-69.

Martilla, J. & James, J., 1977. Importance–performance analysis. *Journal of Marketing*, 41(1), pp. 77-79.

Martin, J. A. et al., 2019. National Vital Statistics Reports. Final data for 2018, 68(13).

Mathieson, A. & Wall, D., 1982. *Tourism: economic, physical and social impacts*. London: Longman Pub Group.

Matsushashi, N., Hyodo, T. & Takahashi, Y., 2005. Image processing analysis of motorcycle oriented mixed traffic flow in Vietnam. s.l., *Proceedings of the Eastern Asia Society for Transportation Studies*, pp. 929-944.

Matyas, M. & Kamargianni, M., 2019. Survey design for exploring demand for Mobility as a Service plans. *Transportation*, Volume 46, p. 1525– 1558.

McFadden, D. & Train, K., 2000. Mixed MNL models of discrete response. *Journal of Applied Econometrics*, Volume 15, p. 447–470.

McFadden, D., 1973. Conditional Logit Analysis of Qualitative Choice Behaviour. In: P. Zarembka, ed. *Frontiers in Econometrics*. New York: Academic Press , pp. 105-142.

Meloni, I., Sanjust, B. & Spissu, E., 2012. Soft transport policy measures: implementing personalized travel planning.. Glasgow, European Transport Conference 2012.

Mercader, P. & Haddad, J., 2020. Automatic incident detection on freeways based on Bluetooth traffic monitoring. *Accident Analysis & Prevention*, 146(105703).

Michau, G. et al., 2014. Retrieving Dynamic Origin-Destination Matrices from Bluetooth Data. Washington DC, United States, Transportation Research Board 93rd Annual Meeting.

Milioti, C., Katopodis, V., Kepaptsoglou, K. & Tyrinopoulos, Y., 2019. Assessing the influence of social media in tourist mobility of young travelers. Washington, D.C., s.n.

Milne, D. & Watling, D., 2019. Big data and understanding change in the context of planning transport systems. *Journal of Transport Geography*, Volume 76, pp. 235-244.

Mohammadi, A., Chowdhury, M. U., Yang, S. & Park, Y. P., 2021. Developing levels of pedestrian physical distancing during a pandemic. *Safety Science*, Volume 134.

Mohammadreza, M., 2012. A study on effects of demographic variables on success of social media. *Management Science Letters*, Volume 2, pp. 2557-2564.



- Møller-Jensen, L., Kofie, R. Y. & Allotey, A. N., 2012. Measuring accessibility and congestion in Accra. *Norsk Geografisk Tidsskrift-Norwegian Journal of Geography*, 66(1), pp. 52-60.
- Möllers, A., Specht, S. & Wessel, J., 2022. The impact of the Covid-19 pandemic and government intervention on active mobility. *Transportation Research Part A: Policy and Practice*, Volume 165, pp. 356-375.
- MoMa.BIZ Consortium, 2013. MoMa.BIZ Final Publishable Report, Italy: MoMa.BIZ Consortium.
- Morstatter, F., Pfeffer, J., Liu, H. & Carley, K., 2013. Is the Sample Good Enough? Comparing Data from Twitter's Streaming API with Twitter's Firehose. Boston, USA, ICWSM 2013.
- Moscholidou, I. & Colclough, J., 2017. The Traffic Snake Game Network: Final Results Report, Leeds: WYG Group.
- Munizaga, M. & Palma, C., 2012. Estimation of a Disaggregate Multimodal Public Transport Origin–Destination Matrix from Passive Smart Card Data from Santiago, Chile. *Transportation Research Part C: Emerging Technologies*, Volume 24, pp. 9-18.
- Muresan, M., Fu, L. & Zhong, M., 2019. Continuous Updating of Traffic Signal Timing Plans Using Bluetooth and Wifi Data. Washington DC, United States, TRB 2019 Annual Meeting.
- Nagelkerke, N. J. D., 1991. A Note on a General Definition of the Coefficient of Determination. *Biometrika*, Volume 78, pp. 691-692.
- Nakamura, T. et al., 2016. Urban Public Transport Mileage Cards: Analysis of Their Potential with Smart Card Data and an SP Survey. Washington DC, United States, Transportation Research Board 95th Annual Meeting.
- Neilson, A., Indratmo, Daniel, B. & Tjandra, S., 2019. Systematic Review of the Literature on Big Data in the Transportation Domain: Concepts and Applications. *Big Data Research*, Volume 17, pp. 35-44.
- Nikiforiadis, A. et al., 2022. Exploring mobility pattern changes between before, during and after COVID-19 lockdown periods for young adults. *Cities*, Volume 125.
- Nikolaidou, A. & Papaioannou, P., 2017. Social media and transport choices: how social media can affect tripmakers' choices. *Sustainable development and planning*, Volume 226, pp. 605-616.
- Noboa, L., Lemmerich, F., Singer, P. & Strohmaier, M., 2016. Discovering and Characterizing Mobility Patterns in Urban Spaces: A Study of Manhattan Taxi Dat. Montreal, Canada, 6th International Workshop on Location and the Web at WWW2016.
- Noulas, A., Mascolo, C. & Frias-Martinez, E., 2013. Exploiting foursquare and cellular data to infer user activity in urban environments, paper presented at the Mobile Data Management. Milan, Italy, 2013 IEEE 14th International Conference on Mobile Data Management, pp. 167-176.
- Nurdayat, I. et al., 2018. Understanding Irregular Traffic Patterns from Traffic Condition Reports. Jakarta, Pulse Lab Research Dive.

Osborne, J. W., 2015. *Best Practices in Logistic Regression*. 1st Edition ed. London:: SAGE Publications.

Osorio-Arjona, J. & García-Palomares, J. C., 2019. Social media and urban mobility: Using twitter to calculate home-work travel matrices. *Cities*, Volume 89, pp. 268-280.

Paiano, A., Passiante, G., Valente, L. & Mancarella, M., 2017. A Hashtag Campaign: A Critical Tool to Transmedia Storytelling Within a Digital Strategy and Its Legal Informatics Issues. s.l., Springer , pp. 49-71.

Pan, B., Zheng, Y., Wilkie, D. & Shahabi, C., 2013. Crowd Sensing of Traffic Anomalies based on Human. New York, United States, 21st ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems, pp. 344-353.

Pang, L. X., Chawla, S., Liu, W. & Zheng, Y., 2013. On detection of emerging anomalous traffic patterns using GPS data. *Data & Knowledge Engineering*, Volume 87, pp. 357-373.

Panter, J. et al., 2011. Correlates of time spent walking and cycling to and from work: baseline results from the commuting and health in Cambridge study. *International Journal of Behavioral Nutrition and Physical Activity*, 8(1).

Papinski, D. & Scott, D. M., 2013. Route Choice Efficiency: An Investigation of Home-To-Work Trips Using GPS Data. *Environment and Planning A: Economy and Space*, 45(2), p. 263–275.

Park, B. & Schneeberger, J., 2003. Microscopic Simulation Model Calibration and Validation: case study of Vissim simulation model for a coordinated actuated Signal system. *Transportation Research Record: Journal of the Transportation Research Board*, Volume 1856, pp. 185-192.

Park, H., 2009. *Comparing Group Means: T-test and One-Way ANOVA Using STATAM, SAS, R, and SPSS*. Indiana University, The University Information Technology Services (UITS) Center for Statistical and Mathematical Computing.

Park, N. & Lee, H., 2014. Gender differences in social networking on smartphones: A case study of Korean college student smartphone users. *International Telecommunications Policy Review*, 21(2), pp. 1-18.

Pathak, A., Patra, B., Chakraborty, A. & Agarwal, A., 2015. A City Traffic Dashboard using Social Network Data. Bangalore, India, 2nd IKDD Conference on Data Sciences.

Paz, A. et al., 2015. alibration of traffic flow models using a memetic algorithm,. *Transportation Research Part C: Emerging Technologies*, Volume 55, pp. 432-443.

Pearanalytics, 2010. Pearanalytics Twitter study. [Online] Available at: <https://pearanalytics.com/wp-content/uploads/2012/12/Twitter-Study-August-2009.pdf> [Accessed 11 January 2018].

Pedersen, T., Kristensson, P. & Friman, M., 2012. Counteracting the focusing illusion: Effects of defocusing on car users' predicted satisfaction with public transport. *Journal of Environmental Psychology*, 32(1), pp. 30-36.

Peftitsi, S., Jenelius, E. & Cats, O., 2022. Modeling the effect of real-time crowding information (RTCI) on passenger distribution in trains. *Transportation Research Part A: Policy and Practice*, Volume 166, pp. 354-368.

Pineda, C., Schwarz, D. & Godoy, E., 2016. Comparison of passengers' behavior and aggregate demand levels on a subway system using origin-destination surveys and smartcard data. *Research in Transportation Economics*, Volume 59, pp. 258-267.

Pinelli, F. et al., 2016. Data-Driven Transit Network Design From Mobile Phone Trajectories. *IEEE Transactions on Intelligent Transportation Systems*, 17(6), pp. 1724-1733.

Piramuthu, O. B. & Zhou, W., 2016. Bicycle Sharing, Social Media, and Environmental Sustainability. Koloa, HI, USA, IEEE, pp. 2078-2083.

Polydoropoulou, A. & Ben-Akiva, M., 1999. The effect of advanced traveler information systems (ATIS) on travelers behaviour.. *Behavioural and Network Impacts of Driver Information Systems*, p. 317–352.

Polydoropoulou, A., Ben-Akiva, M. & Kaysi, I., 1994. Revealed preference models of the influence of traffic information on drivers route choice behavior. *Transportation Research Record*, Issue 1453, pp. 56-65.

Polydoropoulou, A., Ben-Akiva, M., Khattak, A. & Lauprete, G., 1996. Modeling revealed and stated en-route travel response to ATIS. *Transportation Research Record*, Issue 1537, p. 38–45.

Pressl, R. & Kollinger, C., 2012. *Transport Learning-Empowerment of Practitioners to Achieve Energy Savings in Urban Transport*, Graz: Austrian Mobility Research FGM-AMOR.

Purnomo, E. et al., 2021. How Public Transportation Use 958 Social Media Platform during Covid-19: Study on Jakarta Public Transportations' Twitter Accounts?. *Webology*, Volume 18, pp. 1-19.

Rafiq, R., Ahmed, T. & Yusuf Sarwar Uddin, M., 2022. Structural modeling of COVID-19 spread in relation to human mobility. *Transp Res Interdiscip Perspect*, Volume 13.

Ramos, E. M. S., Bergstad, J. & Nässén, J., 2020. Understanding daily car use: Driving habits, motives, attitudes, and norms across trip purposes. *Transportation Research Part F: Traffic Psychology and Behaviour*, Volume 68, pp. 306-315.

Ramos, G. D. O., Bazzan, A. L. C. & da Silva, B. C., 2018. Analysing the impact of travel information for minimising the regret of route choice. *Transportation Research Part C: Emerging Technologies*, Volume 88, pp. 257-271.

Ramos, G., Frejinger, M. E., Daamen, W. & Hoogendoorn, S., 2012. A revealed preference study on route choices in a congested network with real-time information. Toronto, *Proceedings of the 13th International Conference on Travel Behaviour Research*, pp. 15-20.

Ribeiro, A., Vieira, A. & Silva, L., 2013. FUN 4.1-Awareness Raising Campaign for Sustainable Mobility, Measure Evaluation Results Template, Funchal: CIVITAS.

Rodríguez, L., Palanca, J., del Val, E. & Rebollo, M., 2020. Analyzing urban mobility paths based on users' activity in social networks. *Future Generation Computer Systems*, Volume 102, pp. 333-346.

Romancyshyn, T., Lesani, A. & Miranda-Moreno, L., 2017. Monitoring Travel Delay at Signalized Intersections with Bluetooth and Wifi Duration Data. Washington DC, United States, *TRB 2017 Annual Meeting*.

Roth, C., Kang, S. M., Batty, M. & Barthelemy, M., 2011. Structure of urban movements: polycentric activity and entangled hierarchical flows. *PloS one*, 6(1), pp. 1-8.

Rusitschka, S. & Curry, E., 2016. Big data in the energy and transport sectors. In: J. Cavanillas, E. Curry & W. Wahlster, eds. *New Horizons for a Data-Driven Economy*. s.l.:Springer International Publishing, Cham, p. 225–244.

S, G. & Stavrini, I., 2015. Social Networking, Mobilities, and the Rise of Liquid Identities. *Mobilities*, 11(5), pp. 723-743.

Saeedi, A., Park, S., Kim, D. & Porter, J., 2013. Improving accuracy and precision of travel time samples collected at signalized arterial roads with Bluetooth sensors. *Transportation Research Record*, Volume 2380, pp. 90-98.

Saharan, S., Bawa, S. & Kumar, N., 2020. Dynamic pricing techniques for Intelligent Transportation System in smart cities: A systematic review. *Computer Communications*, Volume 150, pp. 603-625.

Sakaki, T., Okazaki, M. & Matsuo, Y., 2010. Earthquake shakes Twitter users: real-time event detection by social sensors. Raleigh, North Carolina, USA, Proceedings of the 19th International Conference on World Wide Web.

Salas, A., Georgakis, P. & Petalas, Y., 2017. Incident detection using data from social media. Yokohama, Japan, IEEE 20th International Conference on Intelligent Transportation Systems (ITSC).

Sanaullah, I., Quddus, M. & Enoch, M., 2016. Developing Travel Time Estimation Methods Using Sparse GPS Data. *Journal of Intelligent Transportation Systems*, 20(6), pp. 532-544.

Santi, P. et al., 2014. Quantifying the benefits of vehicle pooling with shareability networks. *Proceedings of the National Academy of Sciences*, 111(37), pp. 13290-13294.

Sarker, R. I., Mailer, M. & Sikder, S. K., 2019. Walking to a public transport station: Empirical evidence on willingness and acceptance in Munich, Germany. *Smart and Sustainable Built Environment*, 9(1), pp. 38-53.

Schmöcker, J. D., Shimamoto, H. & Kurauchi, F., 2013. Generation and Calibration of Transit Hyperpaths. *Transportation Research Part C: Emerging Technologies*, Volume 36, pp. 406-418.

Schneider, M. C. et al., 2013. Unraveling Daily Human Mobility Motifs. *Journal of the Royal Society Interface*, 10(84).

Schoner-Schatz, L., Hofmann, V. & Stokburger-Sauer, N. E., 2021. Destination's social media communication and emotions: An investigation of visit intentions, word-of-mouth and travelers' facially expressed emotions. *Journal of Destination Marketing & Management*, Volume 22.

Schrank, D., Eisele, B. & Lomax, T., 2015. *Urban Mobility Report*, s.l.: Southwest Region University Transportation Center (SWUTC).

Schroeder, A. & Pennington-Gray, L., 2015. The role of social media in international tourist's decision making. *Journal of Travel Research*, 54(5), pp. 584-595.

Schulz, A., Ristoski, P. & Paulheim, H., 2013. I see a car crash: Real-time detection of small scale incidents in microblogs, in *The Semantic Web*. In: P. Cimiano, et al. eds. *I see a car crash: Real-time detection of small scale incidents in microblogs, in The Semantic Web*. Montpellier, France: Springer, pp. 22-33.

Seres, G. et al., 2021. Face mask use and physical distancing before and after mandatory masking: No evidence on risk compensation in public waiting lines. *Journal of Economic Behavior & Organization*, Volume 192, pp. 765-781.

Sharma, S., 2016. Expanded Cloud Plumes Hiding Big Data Ecosystem. *Future Generation Computer Systems*, Volume 59, pp. 63-92.

Shelat, S. et al., 2022a. Analysing the impact of COVID-19 risk perceptions on route choice behaviour in train networks. *PLoS One*, 17(3).

Shelat, S., Cats, O. & van Cranenburgh, S., 2022b. Traveller behaviour in public transport in the early stages of the COVID-19 pandemic in the Netherlands. *Transportation Research Part A: Policy and Practice*, Volume 159, pp. 357-371.

Shen, L. & Stopher, R. P., 2013. A process for trip purpose imputation from Global Positioning System data. *Transportation Research Part C: Emerging Technologies*, Volume 36, pp. 261-267.

Siegel, S. & Castellan, J., 1988. *Non parametric statistics for the behavioral sciences*. 2nd Edition ed. New York: McGraw-Hill.

Simms, A., 2012. Online user- generated content for travel planning- different for different kinds of trips?. *e- Review of Tourism Research*, 10(3), pp. 76-85.

So, J., Ostojic, M., Jolovic, D. & Stevanovic, A., 2016. Building, Calibrating, and Validating A Large-Scale High-Fidelity Microscopic Traffic Simulation Model – A Manual Approach.. Washington, DC, 95th Annual Meeting of the Transportation Research Board.

Spais, S. G. & Vasileiou, K., 2006. An ordinal regression analysis for the explanation of consumer overall satisfaction in the food-marketing context: The managerial implications to consumer strategy management at a store level. *Database Marketing & Customer Strategy Management*, Volume 14, pp. 51-73.

Statcounter, 2020. Market share held by the leading social networks in Greece from 2010 to 2019. [Online] Available at: <https://www.statista.com/statistics/621193/leading-social-networks-ranked-by-market-share-in-greece/> [Accessed April 2020].

Statista, 2022. Number of monthly active Facebook users worldwide as of 1st quarter 2022. [Online] Available at: [https://www.statista.com/statistics/264810/number-of-monthly-active-facebook-usersworldwide/#:~: text=How%20many%20users%20does%20Facebook, years%20to%20reach%20this%20milestone](https://www.statista.com/statistics/264810/number-of-monthly-active-facebook-usersworldwide/#:~:text=How%20many%20users%20does%20Facebook,years%20to%20reach%20this%20milestone) [Accessed 29 April 2022].

Staus, A., 2008. An ordinal regression model using dealer satisfaction data. *Journal of Economics*, Volume 112, pp. 168-172.

Stebbins, F. L., 2015. *Finding reliable information online: Adventures of an information sleuth*. 1st Edition ed. USA: Rowman & Littlefield.

Steiger, E., Resch, B., de Albuquerque, J. & Zipf, A., 2016. Mining and correlating traffic events from human sensor observations with official transport data using self-organizing-maps. *Transportation Research Part C*, Volume 73, pp. 91-104.

Stewart, G. et al., 2019. Predicting mental health help seeking orientations among diverse Undergraduates: An ordinal logistic regression analysis. *Journal of Affective Disorders*, pp. 2271-2280.

- Strauss, J., Miranda-Moreno, L. F. & Morency, P., 2015. Mapping cyclist activity and injury risk in a network combining smartphone GPS data and bicycle counts. *Accident Analysis & Prevention*, Volume 83, pp. 132-142.
- Stroom, M., Eichholtz, P. & Kok, N., 2021. Avoiding Crowded Places During COVID-19: Common Sense or a Complex Strategic 954 Decision?. *Frontiers in Psychology*, Volume 12, p. doi: 10.3389/fpsyg.2021.700640.
- SurveyMonkey, 1999. Survey Monkey. [Online] Available at: <https://www.surveymonkey.com> [Accessed 10 2 2018].
- Swennen, B. et al., 2016. SWITCH Project Final Report, Vienna: SWITCH Consortium.
- Ta, N., Zhao, Y. & Chai, Y., 2016. Built environment, peak hours and route choice efficiency: An investigation of commuting efficiency using GPS data. *Journal of Transport Geography*, Volume 57, pp. 161-170.
- Tam, M. & Lam, W. K., 2005. Modeling the market penetration of personal public transport information system in Hong Kong. *Intelligent Transportation Systems*, 9(2), pp. 81-89.
- Tang, L., Duan, Z. & Zhao, Y., 2019. Toward using social media to support ridesharing services: challenges and opportunities. *Transportation Planning and Technology*, 42(4), pp. 355-379.
- Tasse, D. & Hong, J. I., 2018. Using social media data to understand cities. *Journal contribution*, p. <https://doi.org/10.1184/R1/6470645.v1>.
- Tennøy, A., Knapskog, M. & Wolday, F., 2022. Walking distances to public transport in smaller and larger Norwegian cities. *Transportation Research Part D: Transport and Environment*, Volume 103.
- Thorhauge, M., Swait, J. & Cherchi, E., 2020. The habit-driven life: Accounting for inertia in departure time choices for commuting trips. *Transportation Research Part A: Policy and Practice*, Volume 133, pp. 272-289.
- Thormann, A. & Dotter, F., 2010. Creating livable neighbourhoods while lowering transport energy consumption, Austria: PRO.MOTION.
- Tian, Y. et al., 2016. Quality assessment of social media traffic reports – a field study in Austin, Texas. Washington D.C., s.n.
- Tian, Z. Z., Urbanik, T., Engelbrecht, R. & Balke, K., 2002. Variations in Capacity and Delay Estimates from Microscopic Traffic Simulation Models. *Transportation Research Record*, 1802(1), pp. 23-31.
- Tirachini, A. & Cats, O., 2020. COVID-19 and Public Transportation: Current Assessment, Prospects, and Research Needs. *Journal of Public Transportation*, 22(1).
- Toledo, T. & Koutsopoulos, H., 2004. Statistical Validation of Traffic Simulation Models. *Transportation Research Record*, 1876(1), pp. 142-150.
- Tønnesen, A., Hagen, O. & Tennøy, A., 2021. Use of public information for road-capacity reductions: a study of mediating strategies during tunnel rehabilitations in Oslo. *Transportation*, Volume 48, p. 2263–2286.

Toole, J. L. et al., 2015. The path most traveled: Travel demand estimation using big data resources. *Transportation Research Part C: Emerging Technologies*, 58(B), pp. 162-177.

Toole, J., Ulm, M., Gonz, M. & Bauer, D., 2012. Inferring land use from mobile phone activity. Beijing, China, UrbComp '12: Proceedings of the ACM SIGKDD International Workshop on Urban Computing, pp. 1-8.

Train, K. E., 2003. *Discrete choice methods with simulation*. 1st Edition ed. Cambridge, UK: Cambridge University Press.

Transport for London, 2016. *Traffic Modeling Guidelines Version 3.0*. [Online] Available at: <http://content.tfl.gov.uk/traffic-modelling-guidelines.pdf> [Accessed 2 March 2022].

Treiber, M. & Kesting, A., 2013. *Microscopic Calibration and Validation of Car-Following Models – A Systematic Approach*. *Social and Behavioral Sciences*, Volume 80, pp. 922-939.

Tsirimpa, A., Polydoropoulou, A. & Antoniou, C., 2007. Development of a Mixed Multi-Nomial Logit Model to Capture the Impact of Information Systems on Travelers' Switching Behavior. *Journal of Intelligent Transportation Systems*, 11(2), pp. 79-89.

Tsitsogiannis, L., 2017. *Storing traffic volumes of Volos road network using GIS*. Volos: University of Thessaly - Department of Civil Engineering.

Tsouros, I., Polydoropoulou, A. & Tsirimpa, A., 2017. Multimodal alternaties: How do users perceive the different combination of modes?. Naples, Italy, 5th IEEE International Conference on Models and Technologies for Intelligent Transportation Systems (MT-ITS).

Twenge, J. M. & Martin, G., 2020. Gender differences in associations between digital media use and psychological well-being: Evidence from three large datasets. *Journal of Adolescence*, Volume 79.

U.S. Department of Transportation, 2016. *Beyond Traffic: the Smart City Challenge*, Minneapolis, USA: s.n.

U.S. Department of Transportation, 2019. *Traffic Analysis Toolbox Volume III: Guidelines for Applying Traffic Microsimulation Modeling Software 2019 Update to the 2004 Version*, Washington, DC 20590: Federal Highway Administration.

U.S. Department of Transportation, 2019. *Traffic Analysis Toolbox Volume III: Guidelines for Applying Traffic Microsimulation Modeling Software 2019 Update to the 2004 Version*, Washington, DC 20590: Federal Highway Administration.

UK Highways Agency, 2005. *Design Manual for Roads and Bridges, Volume 12*. [Online] Available at: <https://web.archive.org/web/20051026234844/http://www.archive2.officialdocuments.co.uk/document/deps/ha/dmrb/index.htm> [Accessed 17 February 2022].

Vacca, A., Prato, C. & Meloni, I., 2019. Should I stay or should I go? Investigating route switching behavior from revealed preferences data. *Transportation*, 46(9), pp. 1-19.

van Bladel, K., Bellemans, T., Janssens, D. & Wets, G., 2009. Activity travel planning and rescheduling behavior: empirical analysis of influencing factors. *Transportation Research Record*, 2134(1), pp. 135-142.

van den Berg, P., Sharmeen, F. & Weijs-Perrée, M., 2017. On the subjective quality of social Interactions: Influence of neighborhood walkability, social cohesion and mobility choices. *Transportation Research Part A: Policy and Practice*, Volume 106, pp. 309-319.

van Essen, M., Thomas, T., van Berkum, E. & Chorus, C., 2020. Travelers' compliance with social routing advice: evidence from SP and RP experiments. *Transportation*, Volume 47, pp. 1047-1070.

van Oort, N. & Cats, O., 2015. Improving public transport decision making, planning and operations by using Big Data Cases from Sweden and the Netherlands. Canary Islands (Spain), 18th International Conference on Intelligent Transportation Systems - (ITSC 2015).

van Oort, N., Brands, T. & de Romph, E., 2015. Short-Term Prediction of Ridership on Public Transport with Smart Card Data. *Transportation Research Record Journal of the Transportation Research Board*, 2535(1), pp. 105-111.

van Soest, D., Tight, M. & Rogers, C. D., 2020. Exploring the distances people walk to access public transport. *Transport Reviews*, 40(2), pp. 160-182.

van Wee, B., 2015. Peak car: the first signs of a shift towards ICT-based activities replacing travel? A discussion paper. *Transport Policy*, Volume 42, pp. 1-3.

Varghese, V. & Jana, A., 2019. Interrelationships between ICT, social disadvantage, and activity participation behaviour: A case of Mumbai, India. *Transportation Research Part A: Policy and Practice*, Volume 125, pp. 248-267.

Vegni, A. M., Biagi, M. & Cusani, R., 2013. Smart Vehicles, Technologies and Main Applications in Vehicular Ad hoc Networks. In: G. Giordano & L. Reggiani, eds. *Vehicular Technologies - Deployment and Applications*. Rijeka, Croatia: IntechOpen, pp. 3-20.

Viens, A., 2019. Visualizing social media by generation. *World economic forum articles*.

VISSIM, 2015. *PTV VISSIM 7 - USER MANUAL*, Karlsruhe, Germany: PTV AG.

Walker, J. L., 2001. *Extended Discrete Choice Models: Integrated Framework, Flexible Error Structures, and Latent Variables*, Massachusetts: Ph.D. Dissertation, Department of Civil and Environmental Engineering, Massachusetts Institute of Technology.

Walker, J., Wang, Y., Thorhauge, M. & Ben-Akiva, M., 2015. D-efficient or deficient? A robustness analysis of experimental design in a VOT estimation. Washington D.C., USA, *Transportation Research Board 94th Annual Meeting*.

Walker, R., 2015. *From Big Data to Big Profits: Success with Data and Analytics*. New York, United States of America: Oxford University Press.

Walsh, R. P. & Dodds, R., 2022. The impact of intermediaries and social marketing on promoting sustainable behaviour in leisure travellers. *Journal of Cleaner Production*, Volume 338.

Wang, P., Hunter, T., Bayen, A. M. & Schechtner, K., 2012. *Understanding Road Usage Patterns in Urban Areas*. Scientific reports, 2(1001).

Wang, S. et al., 2017. Computing Urban Traffic Congestions by Incorporating Sparse GPS Probe Data and Social Media Data. *ACM Transactions on Information Systems*, Volume 35, pp. 1-30.



- Wang, X. et al., 2015. What is the level of volatility in instantaneous driving decisions?. *Transportation Research Part C: Emerging Technologies*, 58(B), pp. 413-427.
- Wang, Z. et al., 2013. Visual Traffic Jam Analysis Based on Trajectory Data. *IEEE Transactions on Visualization and Computer Graphics*, 19(12), pp. 2159-2168.
- Wanichayapong, N., Pruthipunyaskul, W., Pattara-Atikom, W. & Chaovalit, P., 2011. Social-based traffic information extraction and classification. St. Petersburg, 11th International Conference on ITS Telecommunications, pp. 107-112.
- Warner-Søderholm, G. et al., 2018. Who trusts social media?. *Computers in Human Behavior*, Volume 81, p. 303–315.
- Watson, H. J., 2014. *Big Data Analytics: Concepts, Technology, and Applications*. Association for Information Systems, Volume 34, pp. 5-16.
- WBCSD, 2015. *Methodology and indicator calculation method for sustainable urban mobility*., Geneva, Switzerland: World Business Council for Sustainable Development.
- Widhalm, P. et al., 2015. Discovering urban activity patterns in cell phone data. *Transportation*, Volume 42, p. 597–623.
- Wilcox, R., 2012. *Estimating Measures of Location and Scale*. 3rd Edition ed. s.l.:Academic Press.
- Wood, S. A., Guerry, A. D., Silver, J. M. & Lacayo, M., 2013. Using social media to quantify nature-based tourism and recreation. *Scientific Reports*, 3(2976).
- Work, D.-B. et al., 2008. An ensemble Kalman filtering approach to highway traffic estimation using GPS enabled mobile devices. Cancun, Mexico, 47th IEEE Conference on Decision and Control, pp. 5062-5068.
- Xiang, Z. & Gretzel, U., 2010. Role of social media in online travel information search. *Tourism Management*, 31(2), pp. 179-188.
- Xiao, G., Juan, Z. & Zhang, C., 2016. Detecting trip purposes from smartphone-based travel surveys with artificial neural networks and particle swarm optimization. *Transportation Research Part C: Emerging Technologies*, 30(4), pp. 447-463.
- Xiao, T. et al., 2022. A dynamic physical-distancing model to evaluate spatial measures for prevention of Covid-19 spread. *Physica A: Statistical Mechanics and its Applications*, Volume 592.
- Xiao, Y. & Lo Hong, K., 2016. Day-to-day departure time modeling under social network influence. *Transportation Research Part B: Methodological*, Volume 92, pp. 54-72.
- Xiong, C. & al, e., 2015. Developing a 24-Hour Large-Scale Microscopic Traffic Simulation Model for the Before-and-After Study of a New Tolloed Freeway in the Washington, DC– Baltimore Region. *Journal of Transportation Engineering*, 141(6), p. 501.
- Xu, Y. & González, M. C., 2017. Collective benefits in traffic during mega events via the use of information technologies. *Royal Society Interface*, 14(129).
- Yamagishi, Y., Saito, K. & Ikeda, T., 2016. Modeling of Travel Behavior Processes from Social Media. Phuket, Thailand, PRICAI'16: Proceedings of the 14th Pacific Rim International Conference on Trends in Artificial Intelligence.

Yang, W., Wang, X., Rahimi, S. M. & Luo, J., 2015. Recommending Profitable Taxi Travel Routes Based on Big Taxi Trajectories Data. Ho Chi Minh, Vietnam, Pacific-Asia Conference on Knowledge Discovery and Data Mining, pp. 370-382.

Yap, M., Cats, O. & van Arem, B., 2020. Crowding valuation in urban tram and bus transportation based on smart card data. *Transportmetrica A: Transport Science*, 16(1), pp. 23-42.

Ye, Q., Ozbay, K., Zuo, F. & Chen, X., 2021. Impact of Social Media on Travel Behaviors during the COVID-19 Pandemic: 960 Evidence from New York City.. *Transportation Research Record*.

Yeboah, G. et al., 2019. Understanding factors influencing public transport passengers' pre-travel information seeking behavior. *Public Transport*, 11(1).

Yildirimoglu, M., 2019. Joint estimation of paths and travel times with Bluetooth traffic monitoring. Washington DC, United States, TRB 2019 Annual Meeting.

Ying, G. et al., 2018. Anomalous Trajectory Detection Between Regions of Interest Based on ANPR System. Wuxi, China, 18th International Conference on Computational Science.

Yoo, H. & Gretzel, U., 2011. Influence of personality on travel-related consumer-generated media creation. *Computers in Human Behavior*, 27(2), pp. 609-621.

Yoo, K.-H. & Gretzel, U., 2012. Use and Creation of Social Media by Travellers. *Social Media in Travel, Tourism and Hospitality: Theory, Practice and Cases*, pp. 189-206.

Yu, H. et al., 2016. Headway-based bus bunching prediction using transit smart card data. *Transportation Research Part C*, Volume 72, pp. 45-59.

Yu, M. & Fan, W., 2017. Calibration of microscopic traffic simulation models using metaheuristic algorithms. *International Journal of Transportation Science and Technology*, 6(1), pp. 63-77.

Yu, W., Mao, M., Wang, B. & Liu, X., 2014. Implementation evaluation of Beijing urban master plan based on subway transit smart card data. Kaohsiung, Taiwan, 22nd International Conference on Geoinformatics.

Yuan, J. & Abdel-Aty, M., 2019. Real-Time Crash Risk Analysis for Signalized Intersections. Washington DC, United States, TRB 2019 Annual Meeting.

Yuan, J. et al., 2010. T-Drive: Driving Directions Based on Taxi Trajectories. San Jose California, Proceedings of the 18th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems, pp. 99-108.

Yuan, J. et al., 2018. Utilizing bluetooth and adaptive signal control data for real-time safety analysis on urban arterials. *Transportation Research Part C: Emerging Technologies*, Volume 97, pp. 114-127.

Zavareh, M., Mehdizadeh, M. & Nordfjærn, T., 2022. Demand for mitigating the risk of COVID-19 infection in public transport: The role of social trust and fatalistic beliefs. *Transportation Research Part F: Traffic Psychology and Behaviour*, Volume 84, pp. 348-362.

Zhan, X., Hasan, S., Ukkusuri, S. V. & Kanga, C., 2013. Urban link travel time estimation using large-scale taxi data with partial information. *Transportation Research Part C: Emerging Technologies*, Volume 33, pp. 37-49.

Zhang, W. et al., 2015. City-Scale Social Event Detection and Evaluation with Taxi Traces. *ACM Transactions on Intelligent Systems and Technology*, 6(3), pp. 1-20.

Zhang, Z., He, Q., Gao, J. & Ni, M., 2018. A deep learning approach for detecting traffic accidents from social media data. *Transportation Research Part C: Emerging Technologies*, Volume 86, pp. 580-596.

Zhang, Z., Tang, Z. T. Q. & Huang, H.-J., 2019. Modeling the social-influence-based route choice behavior in a two-route network. *Physica A: Statistical Mechanics and its Applications*, Volume 531.

Zheng, X. et al., 2016. Big data for social transportation. *IEEE Transactions on Intelligent Transportation Systems*, Volume 17, p. 620–630.

Zhou, J., Murphy, E. & Long, Y., 2014. Commuting efficiency in the Beijing metropolitan area: An exploration combining smartcard and travel survey data. *Journal of Transport Geography*, Volume 41, pp. 175-183.

Zhu, L., Guo, F., Polak, J. W. & Krishnan, R., 2018. Urban link travel time estimation using traffic states-based data fusion. *IET Intelligent Transport Systems*, 12(7), pp. 651-663.

Ziolkowski, R., 2018. Sectional speed control system as system to evaluate driver's behaviour on rural roads. *Engineering for Rural Development*, Volume 17, pp. 2092-2097.

Zou, L., Xu, J.-M. & Zhu, L.-X., 2005. Arterial speed studies with taxi equipped with global positioning receivers as probe vehicle. Wuhan, China, *Proceedings of the 2005 International Conference on Wireless Communications, Networking and Mobile, Computing*, pp. 1343-1347.

## Annexes

**Annex A:** Questionnaire- “Social media use before, during and after an activity/trip”.

**Annex B:** Survey charts about social media use of men and women.

**Annex C:** Descriptive statistics of social media use before, during and after and activity/trip.

**Annex D:** Indicative example of the keyword list, assigned a grade from 0 (not related to transport) to 5 (highly related to transport).

**Annex E:** Indicative example of the analyzed tweets.

**Annex F:** Pre-interview questionnaire.

**Annex G:** Pre-interview survey charts.

**Annex H:** Inferential statistics- Travel information seeking between genders.

**Annex I:** Digital travel file cards.



**Annex J:** Questionnaire- “A Stated Preference survey- GPS group of motorized users”.

**Annex K:** Questionnaire- “COVID-19: A Stated Preference survey about the daily main trip”.

**Annex L:** Mobility in the COVID-19 era- tables and charts.

**Annex M:** Bicycle use in the COVID-19 era.

**Annex A: Questionnaire- “Social media use before, during and after an activity”.**



**Investigating the role and potential impact of social media on mobility behavior**

**Part 1 - Personal Information**

**This survey is part of a PhD research entitled “Intelligent transport systems with usage of “big data” for management of sustainable mobility”, conducted at the University of Thessaly in Greece. It has been formulated to investigate the degree of social media usage in terms of the type of information searched, reached and shared, time of information and purpose for which the information was created. By answering what, when and why and by combining these answers to the actual travel choices and preferences, this research builds causal relations to facilitate, explain and predict travel behavior based on social media influence.**

**The estimated time to complete the questionnaire is 10 minutes.  
This survey contains a PollLink ([www.poll-pool.com](http://www.poll-pool.com)) on the last page.**

**\* 1. Age**

<input type="radio"/> <18	<input type="radio"/> 36-45
<input type="radio"/> 18-25	<input type="radio"/> >45
<input type="radio"/> 26-35	

**\* 2. Gender**

Female  
 Male

**\* 3. Occupation**

<input type="radio"/> Student	<input type="radio"/> Full-time job
<input type="radio"/> Part-time job	<input type="radio"/> Unemployed
<input type="radio"/> Other (please specify)	

**\* 4. Where do you currently live**

Country

City

**\* 5. Do you own a drivers' license?**

Yes  
 No

**1**

**\* 6. Which transport mode do you use mainly during an activity?**

(you can select more than one answer)

- Car
- Motorbike
- Bike
- Other (please specify)
- Public transport
- Walking

**\* 7. How often do you use public transport?**

- Always
- Often
- Sometimes
- Seldom
- Never

**\* 8. Which electronic devices do you use?**

(you can select more than one answer)

- Desktop
- Laptop
- Tablet
- Other (please specify)
- Smartphone
- Smartwatch
- Cell phone

**\* 9. Do you use social media?**

- Yes
- No



Investigating the role and potential impact of social media on mobility behavior

Part 2 - Social Media

**\* 10. Which social media do you use?**

(you can select more than one answers)

- |   |                                      |
|---|--------------------------------------|
| <input type="checkbox"/> Facebook               | <input type="checkbox"/> Google plus |
| <input type="checkbox"/> Instagram              | <input type="checkbox"/> Pinterest   |
| <input type="checkbox"/> Twitter                | <input type="checkbox"/> LinkedIn    |
| <input type="checkbox"/> Other (please specify) |                                      |

**\* 11. How many days per week do you use social media?**

- |                                |                                   |
|--------------------------------|-----------------------------------|
| <input type="radio"/> Everyday | <input type="radio"/> 2 - 1       |
| <input type="radio"/> 5 - 6    | <input type="radio"/> More rarely |
| <input type="radio"/> 4 - 3    |                                   |

**\* 12. When using social media how many minutes do you spend on average per time?**

- |                               |                               |
|-------------------------------|-------------------------------|
| <input type="radio"/> 0 - 5   | <input type="radio"/> 31 - 60 |
| <input type="radio"/> 6 - 15  | <input type="radio"/> >60     |
| <input type="radio"/> 16 - 30 |                               |

**\* 13. Have you used social media (or other tourism-related social websites i.e TripAdvisor) to arrange an activity within the last month?**

- Yes  
 No

**\* 14. Which time of the day do you use most frequently social media?**

- |                                     |                                     |
|-------------------------------------|-------------------------------------|
| <input type="radio"/> 07:00 - 12:00 | <input type="radio"/> 17:00 - 00:00 |
| <input type="radio"/> 12:00 - 14:00 | <input type="radio"/> 00:00 - 07:00 |
| <input type="radio"/> 14:00 - 17:00 |                                     |

**\* 15. Where are you while you are using social media?**

(you can select more than one answer)

- |   |   |
|---|---|
| <input type="checkbox"/> Home                   | <input type="checkbox"/> Restaurant, cafe (during a leisure activity) |
| <input type="checkbox"/> Workplace              | <input type="checkbox"/> On the way                                   |
| <input type="checkbox"/> Public area            | <input type="checkbox"/> Anywhere                                     |
| <input type="checkbox"/> Other (please specify) |   |

**\* 16. Which is/are the main reason(s) you are using social media?**

(you can select more than one answer)

- Travel arrangements (get directions, view maps, find local businesses)
- Entertainment (communicate with friends/relatives, Share experiences, photos, videos with other)
- Health (join health discussion forums, follow accounts about health and medicine )
- Business/Job (search for job opportunities)
- Fitness (watch fitness videos, find tips for a higher life quality, follow fitness brands)
- Shopping activities (search for products to buy)
- Other (please specify)

**\* 17. Do you share fake information on social media?**

- Always
- Often
- Sometimes
- Seldom
- Never



Investigating the role and potential impact of social media on mobility behavior

Part 3a - Use of social media before an activity

**In the context of this survey, the term "activity" is used to describe the preparational (planning, trip, etc) and realizational (execution) actions in order to perform an activity. For example: going to a restaurant, visiting a museum, participating in an outdoor yoga class, visiting a doctor, going to a shopping mall etc.**

**\* 18. Do you use social media when planning an activity?**

- Always
- Often
- Sometimes
- Seldom
- Never



Investigating the role and potential impact of social media on mobility behavior

Part 3b - Use of social media before an activity



**\* 19. What type of activity do you plan by using social media?**

(you can select more than one answer)

- Travel arrangements
- Entertainment
- Health
- Business / Job
- Fitness
- Shopping activities
- Other (please specify)

**\* 20. While planning for an activity, except for social media, do you use any other sources of information?**

- Yes
- No

**21. If the answer is yes, which other sources of information do you use?**

(you can select more than one answer)

- Friends and/or relatives
- Blogs and forums
- Newspapers/ magazines, leaflets
- Television, radio
- Tourism related social websites (such as TripAdvisor)
- Other (please specify)

**\* 22. How do you use social media when planning an activity?**

(you can select more than one answer)

- Search for specific offers and discounts
- Search for parks/ outdoor activities
- Get an inspiration for your next activity/trip through photos/videos
- Search the location of an activity and how to reach the destination
- Search for reviews of restaurants, bars, cafes, hotels
- Search the appropriate transport mode and timetable of transport
- Search for an upcoming event/concert/party
- Check opening hours/ crowdedness of a place

**\* 23. Do you follow any pages regarding activities and upcoming events on social media?**

- Yes
- No

24. If yes, on which social network?

(you can select more than one answer)

- |   |                                      |
|---|--------------------------------------|
| <input type="checkbox"/> Facebook               | <input type="checkbox"/> Google plus |
| <input type="checkbox"/> Instagram              | <input type="checkbox"/> LinkedIn    |
| <input type="checkbox"/> Twitter                | <input type="checkbox"/> Pinterest   |
| <input type="checkbox"/> Other (please specify) |                                      |

25. Have you ever attended an activity/event that you saw on these pages?

- Yes  
 No

\* 26. How often do you buy products that you see on social media?

- |                                 |                              |
|---------------------------------|------------------------------|
| <input type="radio"/> Always    | <input type="radio"/> Seldom |
| <input type="radio"/> Often     | <input type="radio"/> Never  |
| <input type="radio"/> Sometimes |                              |

\* 27. How would you prefer to buy these products?

(you can select more than one answer)

- Online  
 Visit the physical store

\* 28. Do reviews and ratings affect your buying decisions?

- |                                 |                              |
|---------------------------------|------------------------------|
| <input type="radio"/> Always    | <input type="radio"/> Seldom |
| <input type="radio"/> Often     | <input type="radio"/> Never  |
| <input type="radio"/> Sometimes |                              |

\* 29. What kind of review affects more your buying decisions?

- |                                       |                                       |
|---------------------------------------|---------------------------------------|
| <input type="radio"/> Negative review | <input type="radio"/> Positive review |
| <input type="radio"/> Neutral review  | <input type="radio"/> None            |

\* 30. How often do you visit a place/perform an activity shared on social media?

- |                                 |                              |
|---------------------------------|------------------------------|
| <input type="radio"/> Always    | <input type="radio"/> Seldom |
| <input type="radio"/> Often     | <input type="radio"/> Never  |
| <input type="radio"/> Sometimes |                              |

\* 31. Do reviews and ratings affect your decisions regarding a place visit (restaurant, bar etc)/an activity?

- Always
- Often
- Sometimes
- Seldom
- Never

\* 32. Do pictures/videos affect your decisions regarding a place visit (restaurant, bar etc)/an activity?

- Always
- Often
- Sometimes
- Seldom
- Never

\* 33. What kind of review affects more your final decision on place visit/activity planning?

- Negative review
- Neutral review
- Positive review
- None

\* 34. Does the proposed transport mode on social media affect your final decision?

- Always
- Often
- Sometimes
- Seldom
- Never

\* 35. Do you make changes to all or parts of your activity plans after using social media?

- Always
- Often
- Sometimes
- Seldom
- Never

\* 36. To what extent social media influence your activity planning?

(you can select more than one answer)

- Change destination
- Change purpose/ activity
- Change time or date of activity
- Other (please specify)
- Change of transport mode
- Cancel your activity

\* 37. What would raise mostly your awareness on traveling possibilities?

- A message post by a famous person/account that you follow
- A sponsored message
- Other (please specify)
- A message by a designated account related to transport

\* 38. Select up to three approaches of the message that would appeal more to you.

	Select
hard socking, fear	<input type="checkbox"/>
confronting	<input type="checkbox"/>
informative	<input type="checkbox"/>
encouraging	<input type="checkbox"/>
emotional	<input type="checkbox"/>
humorous	<input type="checkbox"/>

\* 39. Do you post any information on social media about your activity before its occurrence?

<input type="radio"/> Always	<input type="radio"/> Seldom
<input type="radio"/> Often	<input type="radio"/> Never
<input type="radio"/> Sometimes	

40. In continuation to the above question, which social media platform do you use for this posting?

(you can select more than one answer)

<input type="checkbox"/> Facebook	<input type="checkbox"/> Google plus
<input type="checkbox"/> Instagram	<input type="checkbox"/> LinkedIn
<input type="checkbox"/> Twitter	<input type="checkbox"/> Pinterest
<input type="checkbox"/> Other (please specify)	

41. What kind of information do you post?

(you can select more than one answer)

<input type="checkbox"/> Photos/ videos	<input type="checkbox"/> Polls
<input type="checkbox"/> Comments on events, posts of others	<input type="checkbox"/> Share posts
<input type="checkbox"/> Posts with comments	<input type="checkbox"/> Like posts
<input type="checkbox"/> Stories	<input type="checkbox"/> Interested/Going on Facebook events
<input type="checkbox"/> Other (please specify)	

\* 42. Which are for you the most important criteria for the activity choice?

<input type="checkbox"/> Positive reviews	<input type="checkbox"/> Accessibility to public transport
<input type="checkbox"/> Low cost	<input type="checkbox"/> Available parking
<input type="checkbox"/> Close to your home/workplace	<input type="checkbox"/> It is a trend on social media
<input type="checkbox"/> Other (please specify)	

\* 43. Do you consider that social media help you in planning your activity?

- Always
- Often
- Sometimes
- Seldom
- Never



Investigating the role and potential impact of social media on mobility behavior

Part 4a - Use of social media during an activity

\* 44. Do you use social media platforms during your activity to get any sort of information for it?

- Always
- Often
- Sometimes
- Seldom
- Never



Investigating the role and potential impact of social media on mobility behavior

Part 4b - Use of social media during an activity

\* 45. Do you make changes to all or part of your activity after using the content provided on social media?

- Always
- Often
- Sometimes
- Seldom
- Never

46. In continuation to the above question, what is the type of the activity?

(you can select more than one answer)

- Travel arrangements
- Health
- Fitness
- Other (please specify)
- Entertainment
- Business/ Job
- Shopping activities

\* 47. How do you use social media during an activity planning?

(you can select more than one answer)

- Search for specific offers and discounts
- Search uploaded photos/videos from web friends
- Search for reviews of the restaurant, bar, cafe you are visiting
- Plan for your next activity
- Other (please specify)
- Search the location of the next activity you are going to visit after and how to reach there
- Search the appropriate transport mode to get to the new location and the timetable in case you choose public transport
- Check distance covered, calories, heart beats

\* 48. Do you post any information on social media during your activity?

- Always
- Often
- Sometimes
- Seldom
- Never

49. If yes, which social media platform do you use for this posting?

(you can select more than one answer)

- Facebook
- Instagram
- Twitter
- Other (please specify)
- Google plus
- LinkedIn
- Pinterest

50. In continuation to the above question, what kind of information do you post?

(you can select more than one answer)

- Photos/ videos
- Posts with comments
- Stories
- Polls
- Other (please specify)
- Share posts
- Check-ins
- Walking/ running route maps

\* 51. Do you consider that social media help you during your trip?

- Always
- Often
- Sometimes
- Seldom
- Never



Investigating the role and potential impact of social media on mobility behavior

Part 5a - Use of social media after an activity

\* 52. Once your activity is over, do you provide feedback (i.e photos, posts etc) and/or write a review of your experiences?

- Always
- Often
- Sometimes
- Seldom
- Never



Investigating the role and potential impact of social media on mobility behavior

Part 5b - Use of social media after an activity

\* 53. Do you provide feedback (i.e photos, posts)/review upon a:

(you can select more than one answer)

- Negative experience
- Positive experience
- Neutral experience

\* 54. Which social media platform do you use for this feedback (i.e photos, posts)/review?

(you can select more than one answer)

- Facebook
- Google plus
- Instagram
- LinkedIn
- Twitter
- Pinterest
- Other (please specify)

\* 55. What kind of information do you post?

(you can select more than one answer)

- Photos/ videos
- Rating
- Posts with comments
- Stories
- Polls
- Walking/running route maps
- Share posts
- Travel itinerary
- Reviews
- Other (please specify)



Investigating the role and potential impact of social media on mobility behavior

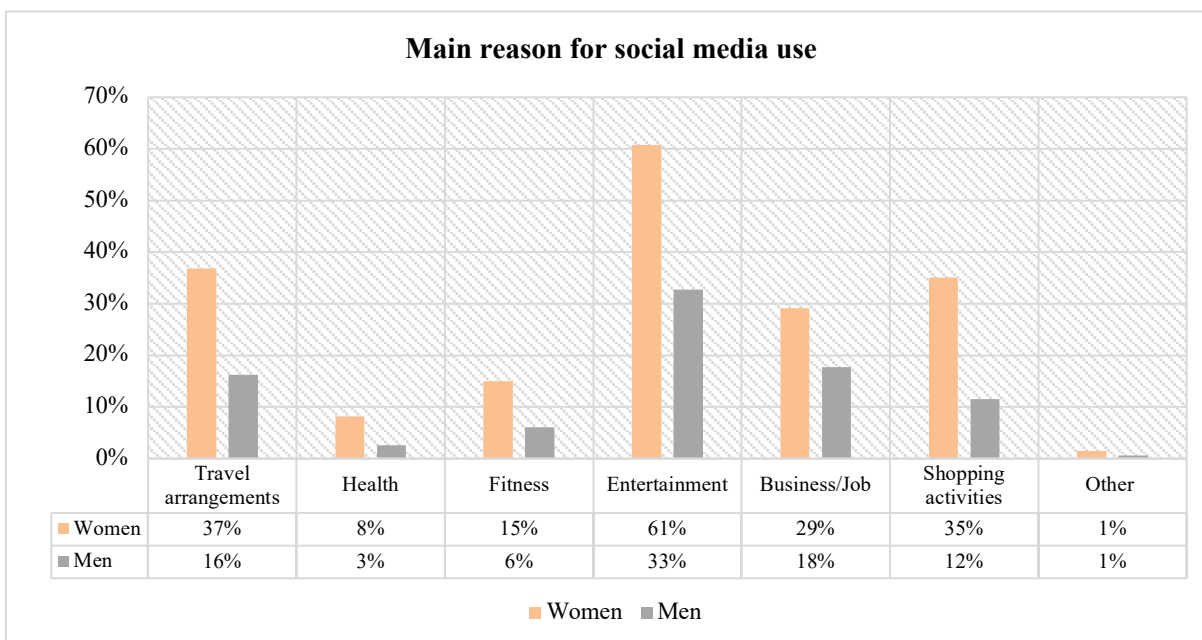
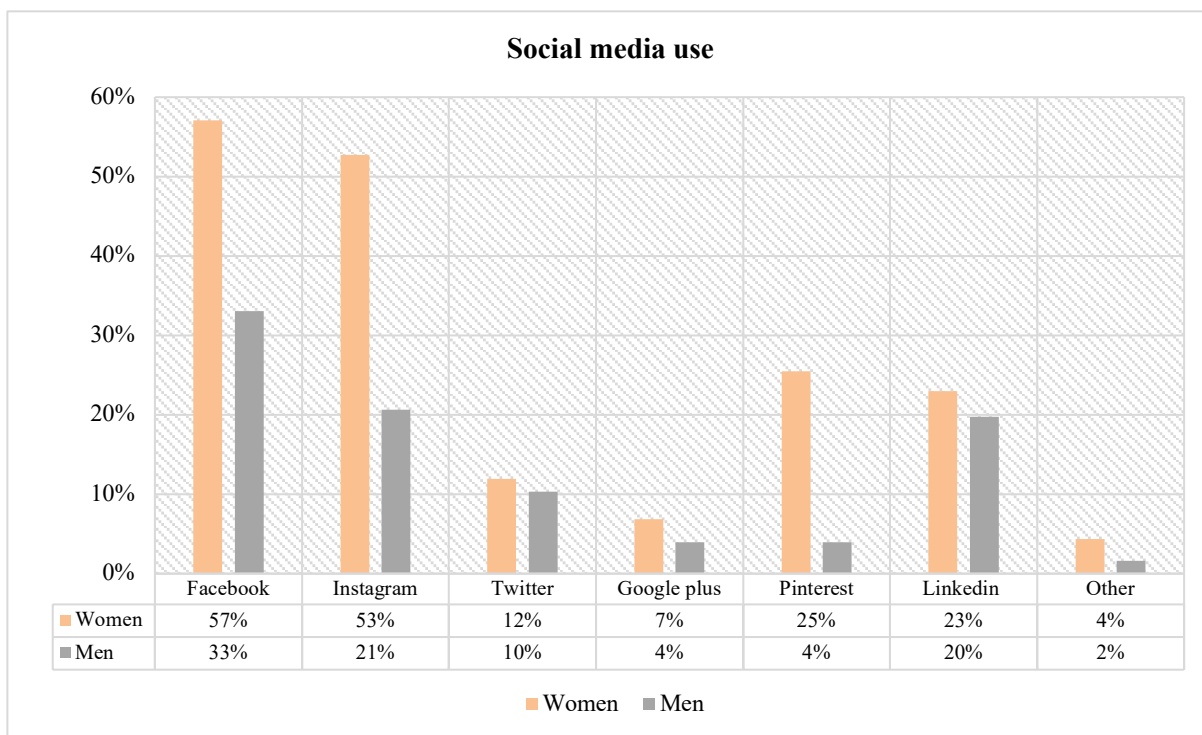
End of questionnaire

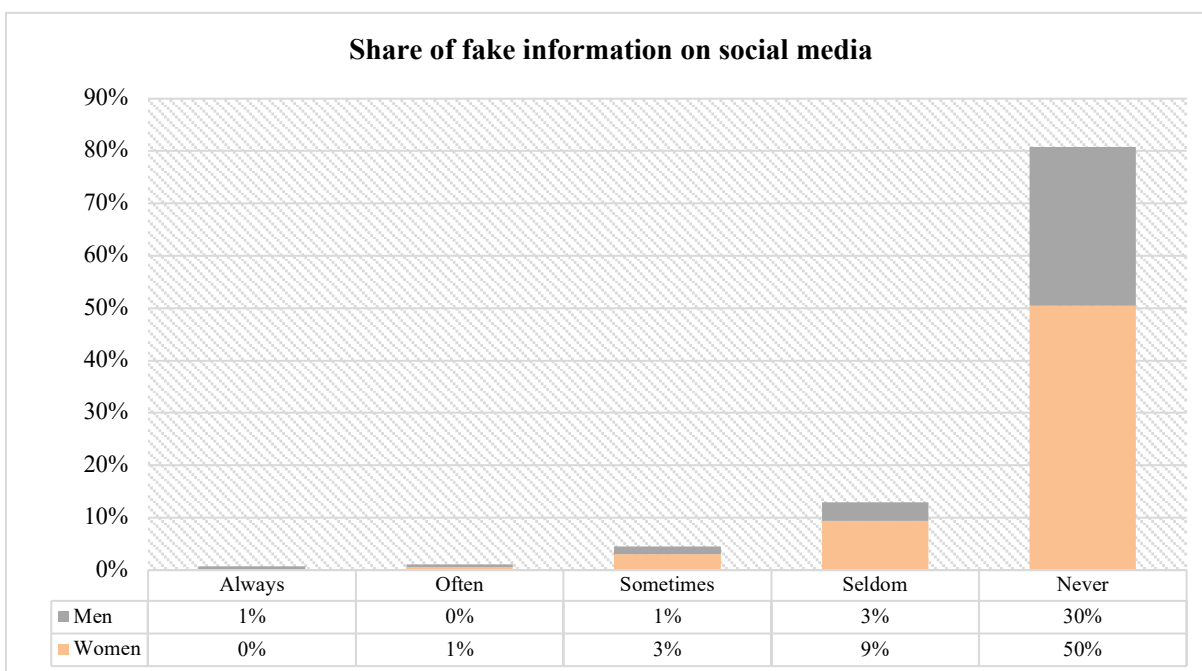
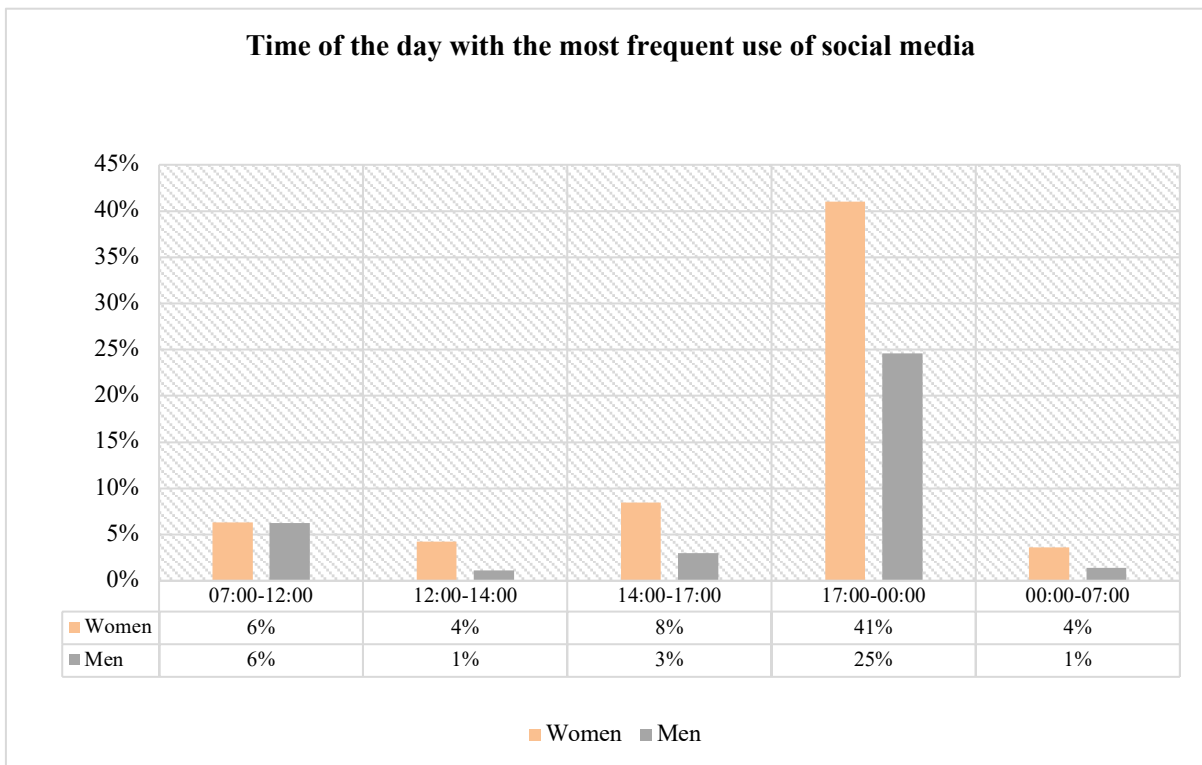
Thank you very much for your participation!

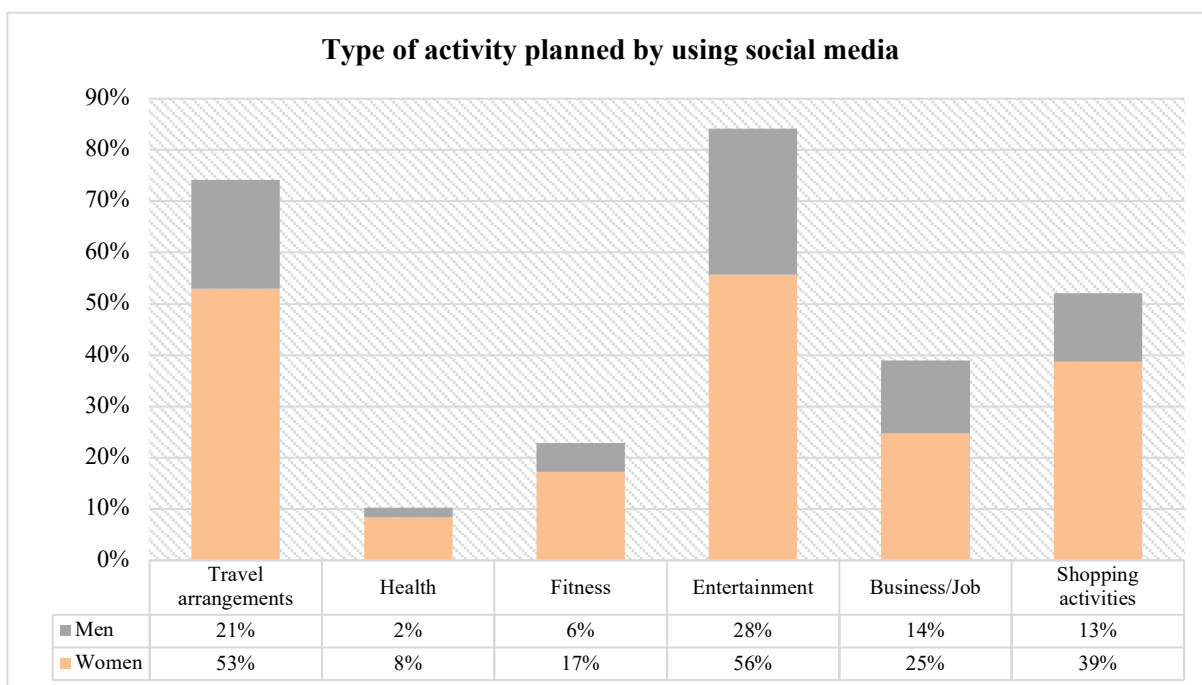
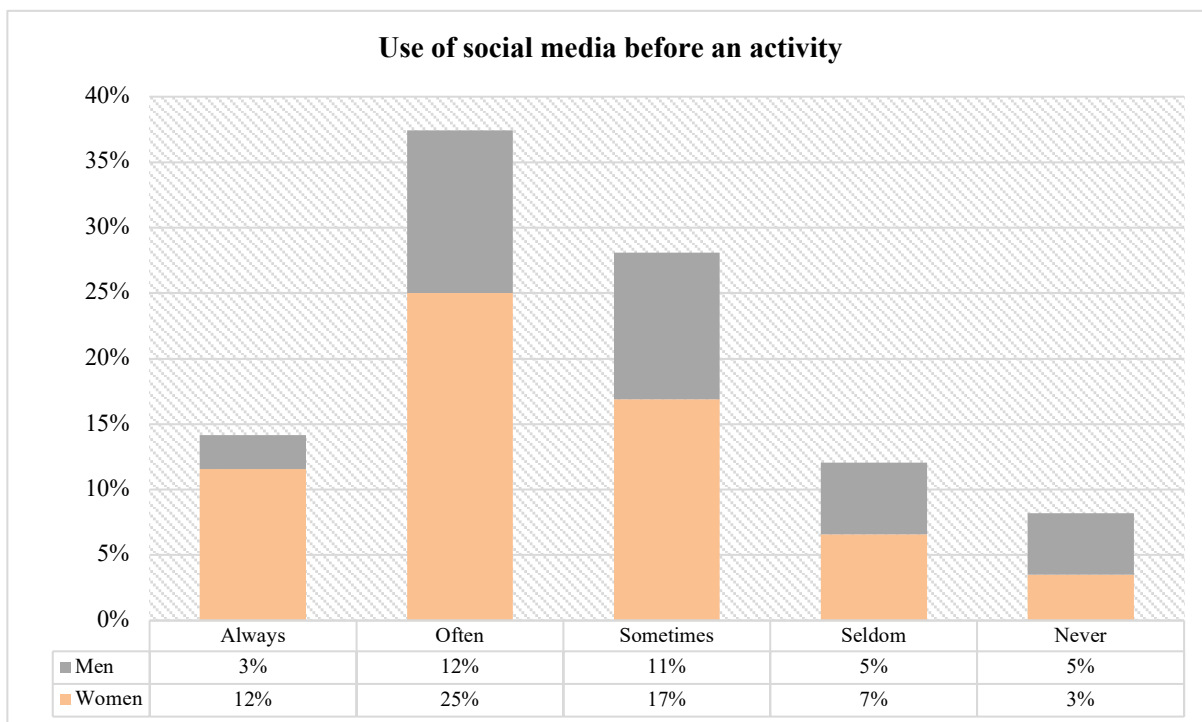
PollPool Link: <https://www.poll-pool.com/r/authorise?id=y6ue594tmktcemzuhuls&vc=buqo29lw>

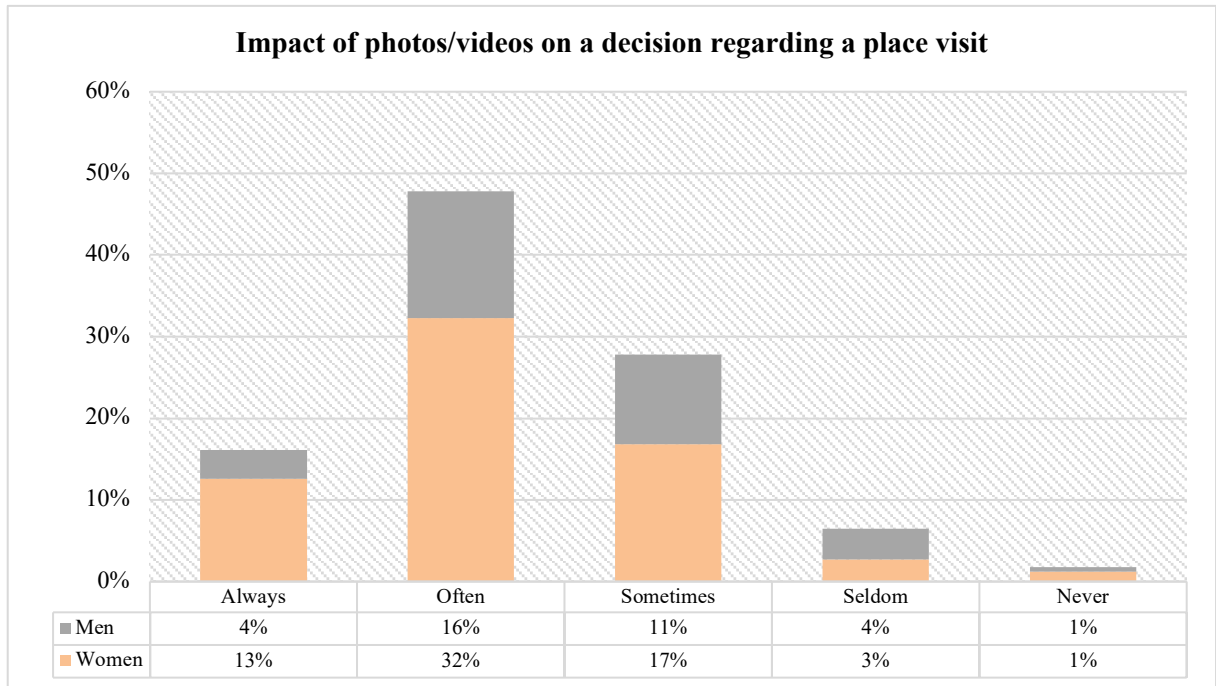


**Annex B:** Survey charts about social media use of men and women.









**Annex C:** Descriptive statistics of social media use before, during and after an activity.

Table C1. Use of social media before an activity/ trip

Variables	Level	%
What type of activity do you plan by using social media		
Health	Yes	10
	No	90
Fitness	Yes	23
	No	77
Which other sources of information except social media do you use?		
Newspapers/ magazines, leaflets	Yes	28
	No	72
Television, radio	Yes	22
	No	78
How do you use social media when planning an activity		
Search for specific offers and discounts	Yes	60
	No	40
Search for an upcoming event/concert/party	Yes	57
	No	43
Do you follow any pages regarding activities and upcoming events on social media?	Yes	78
	No	22
If yes, on which social network?		
Facebook	Yes	69
	No	31
Instagram	Yes	36
	No	64
Twitter	Yes	4
	No	96
Google plus	Yes	
	No	
LinkedIn	Yes	

Variables	Level	%
	No	
Pinterest	Yes	
	No	
Have you ever attended an activity/event that you saw on these pages?	Yes	72
	No	28
How often do you buy products that you see on social media?	Never	15.7
	Seldom	40.4
	Sometimes	32.8
	Often	10.0
	Always	1.1
	Mean=3.6, SD=0.907	
How would you prefer to buy these products? (you can select more than one answer)	Online	33.2
	Visit the physical store	35.6
	Both	15.4
	I never buy products I saw on social media	15.7
Do reviews and ratings affect your buying decisions?	Never	2.3
	Seldom	8.1
	Sometimes	34.6
	Often	39.3
	Always	15.7
	Mean=2.42, SD=0.927	
What kind of review affects more your buying decisions?	Negative review	58.1
	Neutral review	9.3
	Positive review	26.6
	None	6

Variables	Level	%
Once your activity is over, do you provide feedback (i.e photos, posts etc.) and/or write a review of your experience	Never	5.8
	Seldom	18.7
	Sometimes	33.8
	Often	25.1
	Always	16.5
	Mean=3.28, SD=1.121	
Do you provide feedback (i.e photos, posts)/ review upon a:		
Negative experience	Yes	49
	No	51
Neutral experience	Yes	78
	No	22
Positive experience	Yes	81
	No	19
Which social media platform do you use for this feedback (i.e photos, posts)/review?		
Facebook	Yes	67
	No	33
Instagram	Yes	49
	No	51
Twitter	Yes	5
	No	95
What kind of information do you post		
Photos/videos	Yes	73
	No	27
Posts with comments	Yes	43
	No	57
Reviews	Yes	39

Variables	Level	%
	No	61
Ratings	Yes	36
	No	64
Stories	Yes	34
	No	66
Share posts	Yes	10
	No	90

Table C2. Social media content shared before an activity/ trip

Variables	Level	%
Which social media platform do you use for posting on social media about your activity before its occurrence?		
Google plus	Yes	1
	No	99
LinkedIn	Yes	3
	No	97
Pinterest	Yes	1
	No	99
What kind of information do you post? (you can select more than one answer)		
Comments on events	Yes	24
	No	76
Polls	Yes	5
	No	95
Interested/Going on Facebook events	Yes	27
	No	73



Table C3. Use of social media during an activity/ trip

Variables	Level	%
What is the type of the activity that you make changes to all or part of it after using the content provided on social media?		
Health	Yes	7
	No	93
Fitness	Yes	15
	No	85
Shopping activities	Yes	41
	No	59
How do you use social media during your activity/trip?		
Search for specific offers and discounts	Yes	55
	No	45
Search uploaded photos/videos from web friends	Yes	48
	No	52
Search for reviews of the restaurant, bar, café you are visiting	Yes	75
	No	25
Check distance covered, calories, heart beats	Yes	13
	No	87

Table C4. Social media content shared during an activity/ trip

Variables	Level	%
Which social media platform do you use for this posting?		
Google plus <small>was shut down for business and personal use on April 2, 2019.)</small>	Yes	1
	No	99
LinkedIn	Yes	3
	No	97
Pinterest	Yes	1
	No	99
What kind of information do you post		

Variables	Level	%
Polls	Yes	5
	No	95
Share posts	Yes	9
	No	91

Table C5. Use of social media after an activity/ trip


Variables	Level	%
Which social media platform do you use for this feedback (i.e photos, posts)/review?		
GooglePlus (was shut down for business and personal use on April 2, 2019.)	Yes	6
	No	94
LinkedIn	Yes	6
	No	94
Pinterest	Yes	1
	No	99
What kind of information do you post		
Polls	Yes	5
	No	95
Share posts	Yes	10
	No	90
Walking/running route maps	Yes	4
	No	96
Travel itinerary	Yes	6
	No	94




Annex E: Indicative example of the analyzed tweets.

Table with columns: TweetID, Language, Lon, Lat, CreatedAt, Author, Text, Retweets, Fav, Grade, Grade#Word, Column 1. Contains a list of tweets with their metadata and content.

**Annex F: Pre-interview questionnaire.**



**TTLog**  
Traffic,  
Transportation  
and Logistics  
Laboratory



UNIVERSITY OF THESSALY  
1974

Investigating the impact of information on commuters' behavior

Welcome to the survey!

The survey is part of a PhD research entitled "Intelligent Transport Systems for Sustainable Mobility Management", conducted at the Department of Civil Engineering of University of Thessaly. The answers to the questionnaire, along with the GPS data collected from the application installed on your mobile phone, form the database of your revealed travel preferences. The purpose of this database is to investigate the impact of information on commuters' behavior.

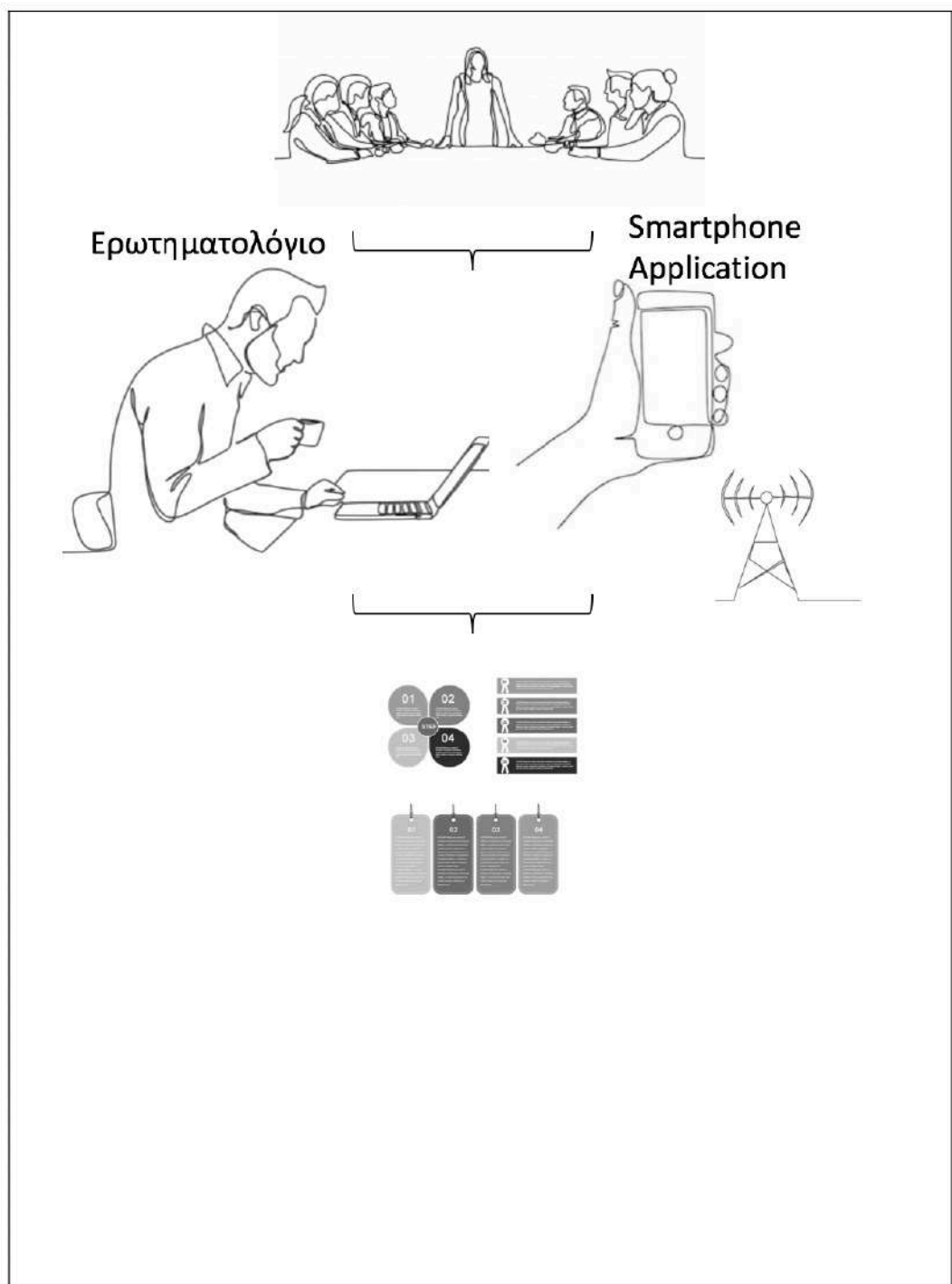
Upon completion of the survey, each participant will receive his/her own "digital travel file card" containing the processed data as well as suggestions for improving his / her daily commute.


The questionnaire consists of three parts and its estimated completion time is 10 minutes.


In the context of the intensification of the protection of personal data and the transposition into national law of Directive (EU) 2016/680 of the European Parliament and of the Council on 27 April 2016, it is noted that TTLog laboratory will keep all data anonymous and confidential in its research team. Data will be used exclusively for research purposes. Your personal data will NOT be forwarded to third parties or other groups.

For any further clarifications please contact TTLog laboratory (ttlog@uth.gr) or the coordinator of the research Ms. Maria Karatsoli (mobivoloss@gmail.com).

1







Investigating the impact of information on commuters' behavior

Questionnaire – Part A

**\* 1. Which transport mode do you mainly use for your daily commute?**

<input type="radio"/> Car (Diesel / Gasoline)	<input type="radio"/> Electric scooter
<input type="radio"/> Car (Electric, Hybrid or other new technology)	<input type="radio"/> Public transportation
<input type="radio"/> Motorcycle	<input type="radio"/> Taxi
<input type="radio"/> Bicycle	<input type="radio"/> On foot
<input type="radio"/> Electric bicycle	

**\* 2. Estimate the trip distance when traveling from your residence to your work place (or University if you are a student).**  
(fill in "3.5" if the distance is 3.5 km)

**\* 3. Estimate the trip distance when traveling from your work place (or University if you are a student) to your residence.**  
(fill in "4" if the distance is 4 km)

**\* 4. Estimate the trip duration when traveling from your residence to your work place (or University if you are a student).**  
(fill in "13" if the duration is 13 minutes)

**\* 5. Estimate the trip duration when traveling from your work place (or University if you are a student) to your residence.**  
(fill in "11" if the duration is 11 minutes)


\* 6. Is your arrival at work (or University if you are a student) flexible?

- Not at all
- 5 - 15 minutes
- 16 - 30 minutes
- 31 - 60 minutes
- I work with a flexible schedule


\* 7. How familiar are you with traveling in the city of Volos?

- 1 - Not at all
- 2 - Slightly
- 3 - Somewhat
- 4 - Moderately
- 5 - Very much





Traffic,  
Transportation  
and Logistics  
Laboratory



**Investigating the impact of information on commuters' behavior**

**Questionnaire – Part B**

\* 8. Do you get informed by navigation applications (i.e. Google maps), radio or social media about the route you will take, when travelling ...

	1 - Never	2 - Seldom	3 - Sometimes	4 - Often	5 - Always
from your residence to your work place (or University if you are a student)?	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
from your work place (or University if you are a student) to your residence?	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
from your residence to an activity location (e.g. restaurant, fitness center, etc.)?	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
from your activity location to your residence?	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

\* 9. What information source do you prefer for receiving information when traveling to your work place (or University if you are a student)?

<input type="radio"/> Navigation applications (i.e. Google maps)	<input type="radio"/> Variable Message Signs (VMS)
<input type="radio"/> Radio	<input type="radio"/> In-vehicle GPS navigator
<input type="radio"/> Social media	<input type="radio"/> None

\* 10. What information source do you prefer for receiving information when traveling to an activity location?

<input type="radio"/> Navigation applications (i.e. Google maps)	<input type="radio"/> Variable Message Signs (VMS)
<input type="radio"/> Radio	<input type="radio"/> In-vehicle GPS navigator
<input type="radio"/> Social media	<input type="radio"/> None

\* 11. What information source do you prefer for receiving information when traveling to your residence?

Navigation applications (i.e. Google maps)       Variable Message Signs (VMS)  
 Radio       In-vehicle GPS navigator  
 Social media       None

\* 12. When traveling in the city of Volos, to what extent would you seek information..

	1 - Never	2 - Seldom	3 - Sometimes	4 - Often	5 - Always
to reach an unknown destination?	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
to find the shortest route?	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
to find the most environmentally friendly route?	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
to find the most economical route?	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
to stay informed about the traffic conditions?	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
to estimate your travel time?	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
to identify the ideal transport mode according to your needs?	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
to be informed on public transport itineraries?	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
to decide upon your departure time?	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
for dynamic re-routing e.g. in case you are on your way and encounter traffic congestion?	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
when reliable information is provided?	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

\* 13. How important are the following when choosing your travel route?

	1 - Not at all	2 - Slightly	3 - Moderately	4 - Very	5 - Extremely
Shortest route	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Environmentally friendly route	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Economical route	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Traffic congestion	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Potential delays	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Travel time	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Transport mode	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Safety	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Graphic route	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Comfort	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

\* 14. How would you rate your main daily commute e.g. residence – work place – residence as regards the following?

	1 – Very dissatisfied	2 – Dissatisfied	3 – Slightly satisfied	4 – Satisfied	5 – Very satisfied
Shortest route	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Environmentally friendly route	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Economical route	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Traffic congestion	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Potential delays	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Travel time	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Transport mode	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Safety	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Scenic route	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Comfort	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

\* 15. What type of information would you like to receive on your mobile device before and / or during your commute?

You can select more than one answers.


- Incidents
- Travel times
- Traffic conditions
- Alternative routes
- Economical ways of travel
- Environmentally friendly routes
- None


\* 16. To what extent would you take into account travel information..

	1 - Not at all	2 - Slightly	3 - Moderately	4 - Very	5 - Extremely
during your commute?	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
before your commute?	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

\* 17. In your main daily commute, to what extent would you do the following if you were informed accordingly?

	1 - Not at all	2 - Slightly	3 - Moderately	4 - Very	5 - Extremely
Change transport mode	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Change route	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Change time series of activities	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Change of activity	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Cancellation of plans	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
No change at all	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>





Investigating the impact of information on commuters' behavior

Questionnaire - Part C

\* 18. Fill in the survey number assigned to you.

Examples

If you were assigned the username `mobivol5` fill in "5".

If you were assigned the email `user6mobivolos@gmail.com` fill in "6".

If you were assigned the email `mobivoloss+91@gmail.com` fill in "91".

\* 19. Operation system of your mobile device

iOS

Android

Other (BlackBerry OS, webOS, Windows Phone 7)

I don't use smartphone

\* 20. Gender

Woman

Man

I do not wish to respond

\* 21. Age

18-23

24-40

41-65

> 66

I do not wish to respond

\* 22. Occupation

Student

Student with part time job

Student with full part time job

University Staff

Researcher

9

\* 23. Education level (completed studies)

High school

Bachelor's Degree

Master's Degree

PhD

\* 24. Select the sentence that you agree with more.

My mobile device is connected to the internet when I am not home.

My mobile device is NOT connected to the internet when I am not home.

\* 25. Place of origin  
(e.g. Volos, Magnesia)

\* 26. Place of residence  
(e.g. Volos, Magnesia)

\* 27. Number of years that you reside in Volos  
(Fill in "2", if you reside in Volos 2 years)  
(Fill in "0", if you do not reside in Volos)

\* 28. Please fill in the roads' names that delimit your residence.  
(e.g. Dimitriadou with K. Kartali)

\* 29. Do you own a drivers' license?

No

Yes, I am an owner less than 1 year

Yes, I am an owner between 1 year and 5 years

Yes, I am an owner more than 5 years

Annex G: Pre-interview survey charts.

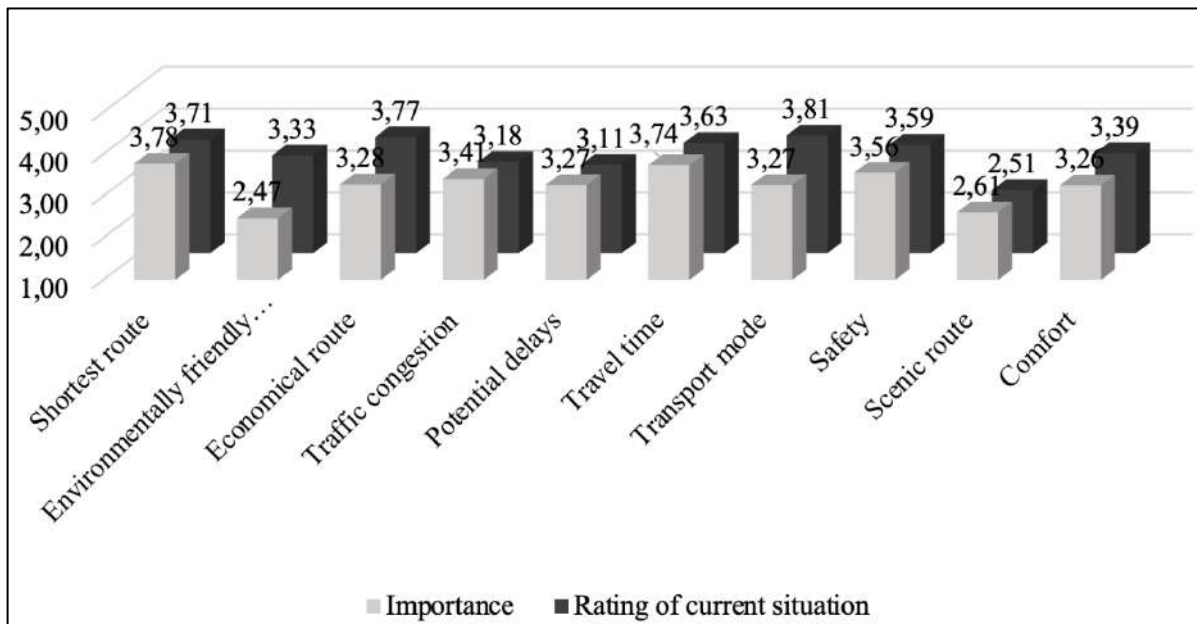


Figure G1. Importance and performance of current situation- column graph

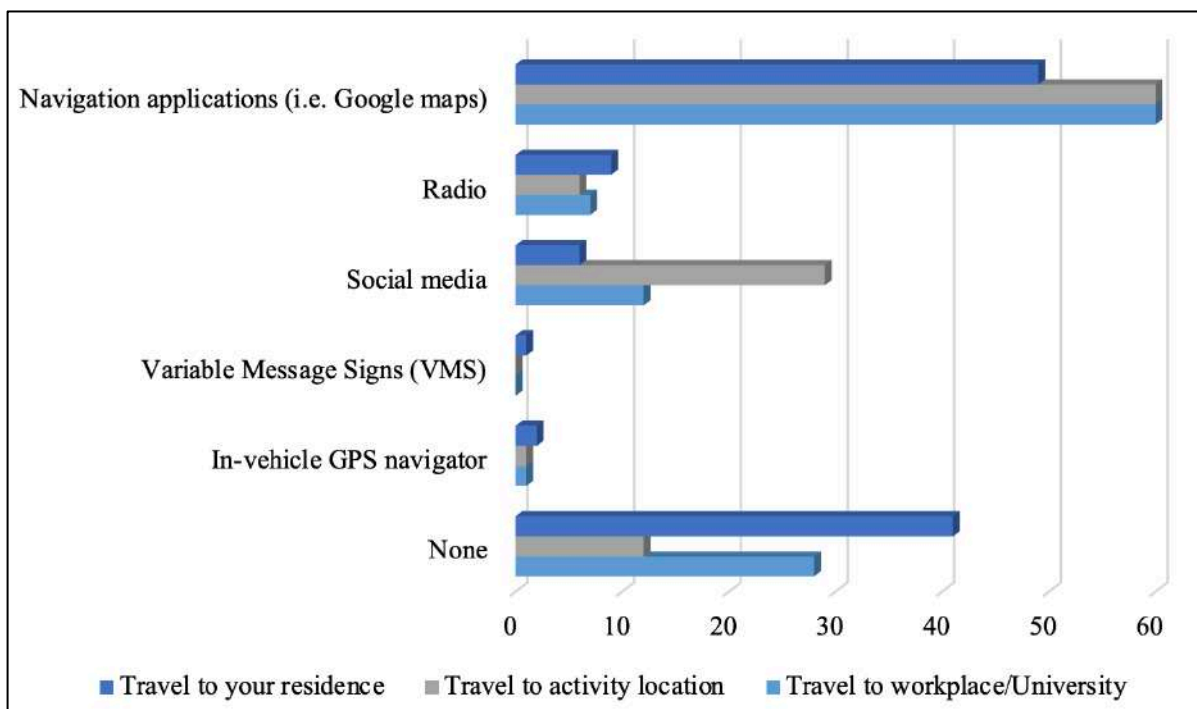


Figure G2. Preferable source of information

**Annex H:** Inferential statistics- Travel information seeking between genders.

Women consider travel information before their commute more often (Mean=3.90) compared to male participants (Mean=3.45), the differences between the two groups were statistically significant (U=1062.5, p-value=0.01).

Table H1. Impact of travel information on commuters’ mobility and travel choices, female vs male.

Parameters	Groups					
	Women		Men		W vs. M	
	M	SD	M	SD	U	p-value
To what extend would you take into account travel information:						
-during your commute	2.90	0.77	2.88	0.99	1414.0	0.77
- before your commute	3.90	0.96	3.45	0.99	1062.5	<b>0.01</b>
In your main daily commute, to what extend would you do the following if you were informed accordingly						
-change transport mode	2.52	0.96	2.29	1.00	1263.5	0.21
-change route	3.10	1.03	3.16	0.95	1430.0	0.86
-change time series of activities	2.65	0.95	2.61	0.91	1400.5	0.71
-change of activity	2.23	0.76	2.21	0.95	1420.0	0.81
-cancellation of plans	2.06	0.94	2.11	0.93	1400.5	0.71
-no change at all	2.67	0.96	2.68	1.15	1445.5	0.95
M: average rating, SD: Standard Deviation, *statistically significant (p-value< 0.05)						

When traveling in the city of Volos, women seek travel information-to reach an unknown destination and -to find the most environmentally friendly route more often compared to men, with the differences between the two groups being statistically significant.

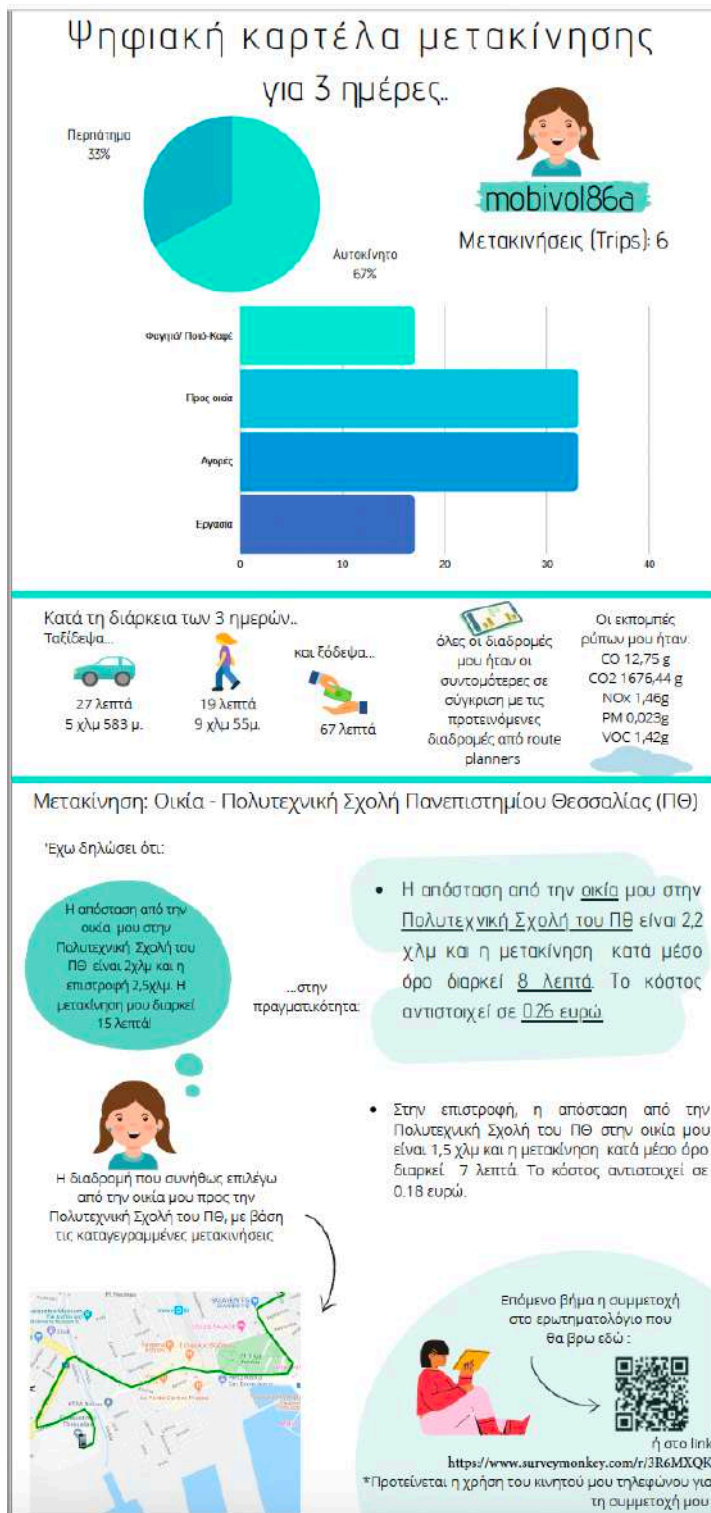
Table H2. Travel information seeking parameters’ rating between female and male users.

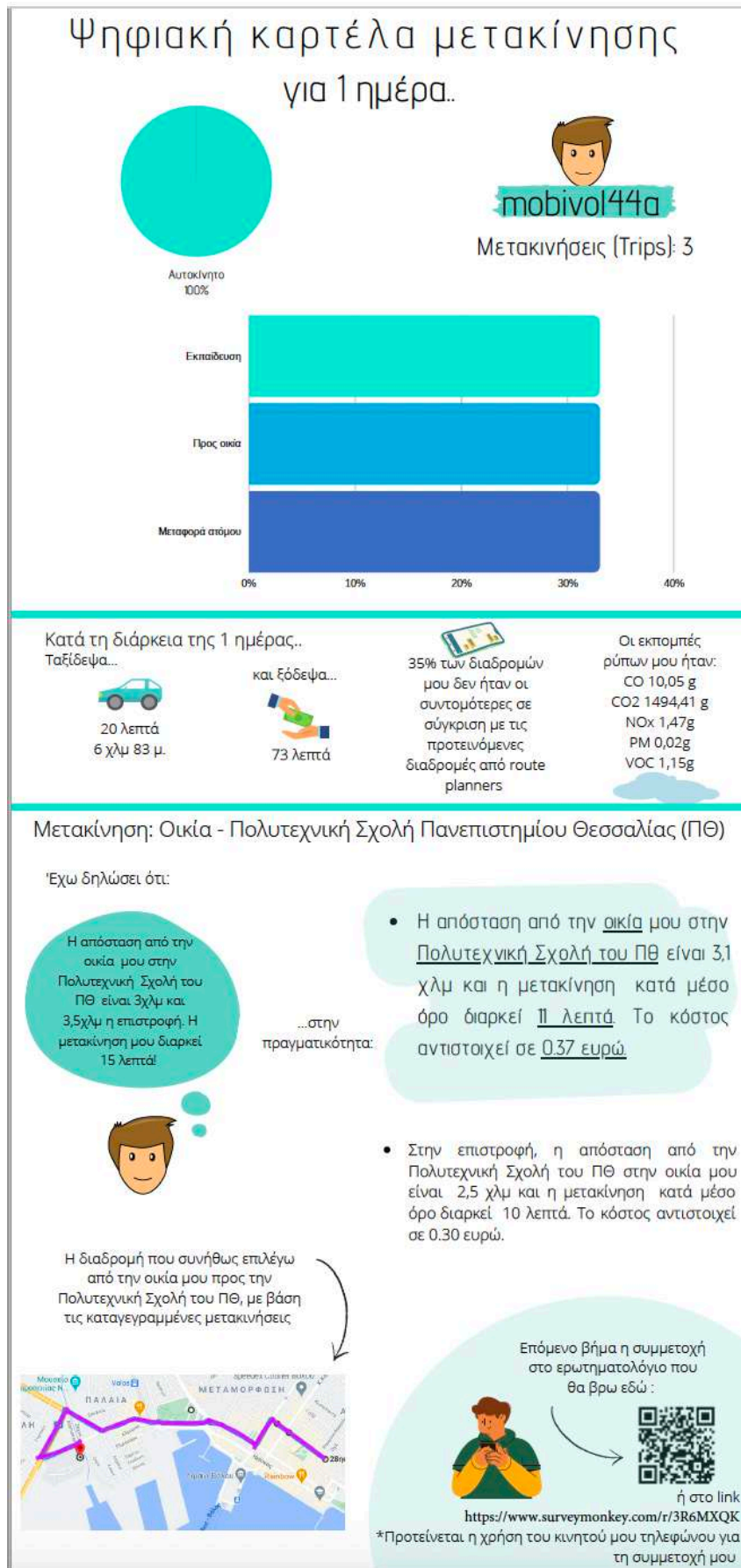
Parameters	Groups					
	Women		Men		W vs. M	
	M	SD	M	SD	U	p-value
Do you get travel any information from:						

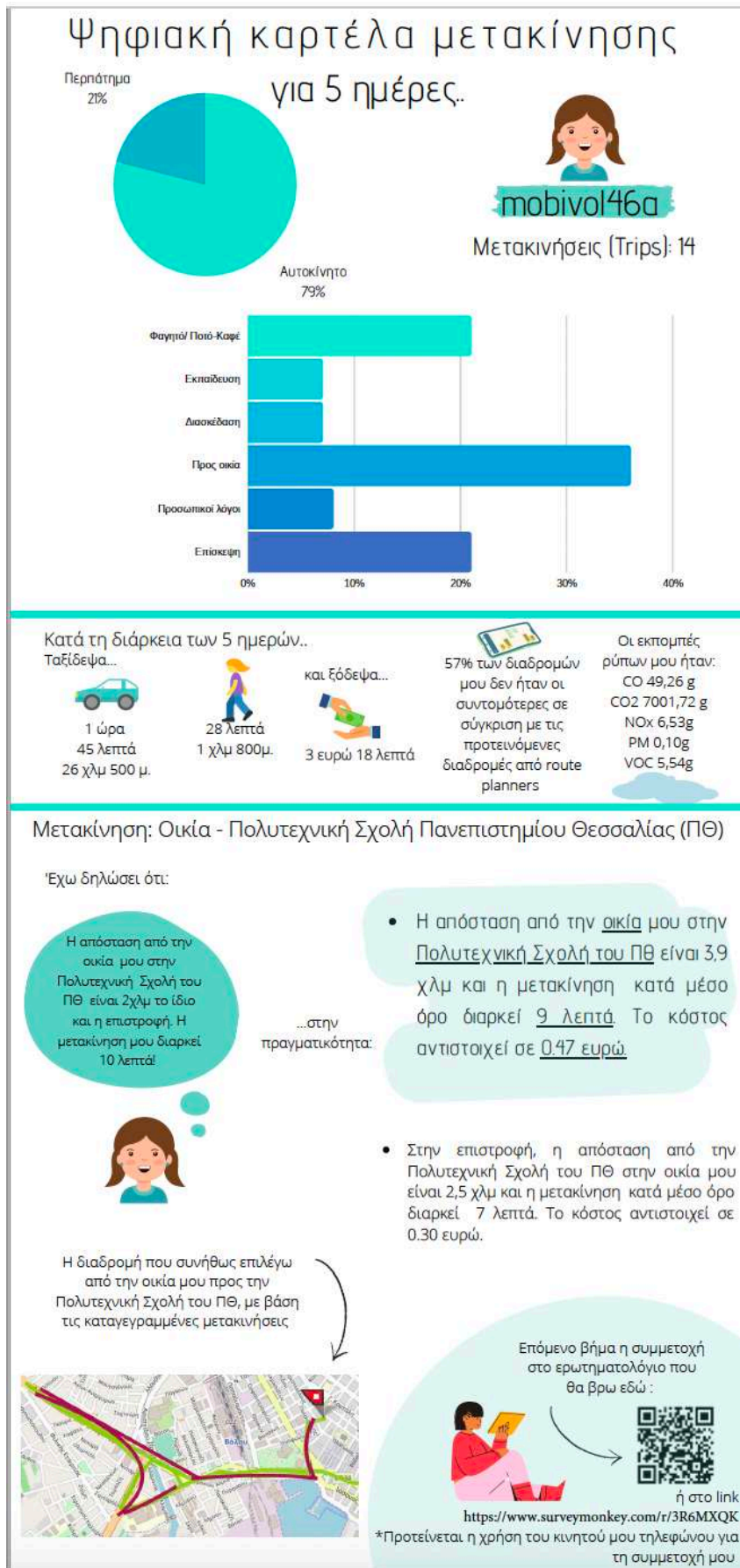


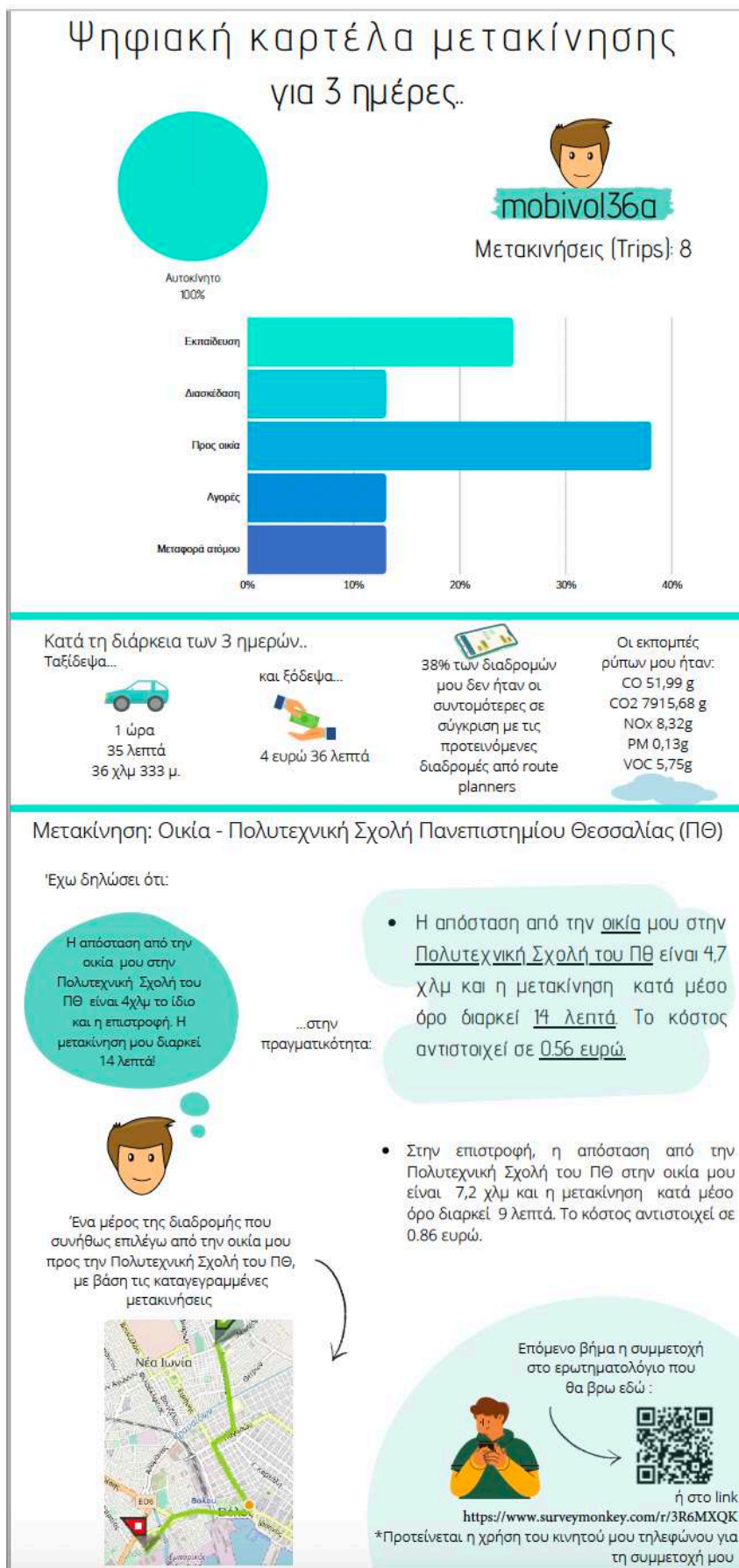
Parameters	Groups					
	Women		Men		W vs. M	
	M	SD	M	SD	U	p-value
-your residence to your workplace/ university	1.50	0.78	1.55	0.93	1438.5	0.89
- your workplace/ university to your residence	1.23	0.47	1.39	0.8	1378	0.51
- your residence to an activity location	2.77	0.92	2.46	1.08	1220.5	0.13
-your activity location to your residence	2.15	0.89	1.88	0.96	1175.5	0.07
When traveling in the city of Volos, to what extend would you seek information						
-to reach an unknown destination	3.90	1.02	3.48	1.13	1156	<b>*0.05</b>
-to find the shortest route	2.65	1.10	2.59	1.06	1405.5	0.75
-to find the most environmentally friendly route	2.17	1.12	1.71	0.97	1111	<b>*0.02</b>
-to find the most economical route	2.65	1.24	2.43	1.06	1316	0.38
- to stay informed about the traffic congestion	2.21	1.11	2.27	1.10	1413.5	0.79
-to estimate your travel time	3.17	1.06	3.07	1.01	1355	0.52
-to identify the ideal transport mode according to your needs	2.52	1.09	2.23	1.13	1224.5	0.14
-to be informed on public transport itineraries	2.83	1.17	2.45	1.06	1193	0.09
-to decide upon your departure time	2.92	1.14	2.79	1.23	1333.5	0.44
-for dynamic re-routing	2.21	1.14	2.43	1.13	1290	0.29
-when reliable information is provided	2.81	1.14	2.96	1.14	1338.5	0.45
M: average rating, SD: Standard Deviation, *statistically significant (p-value< 0.05)						

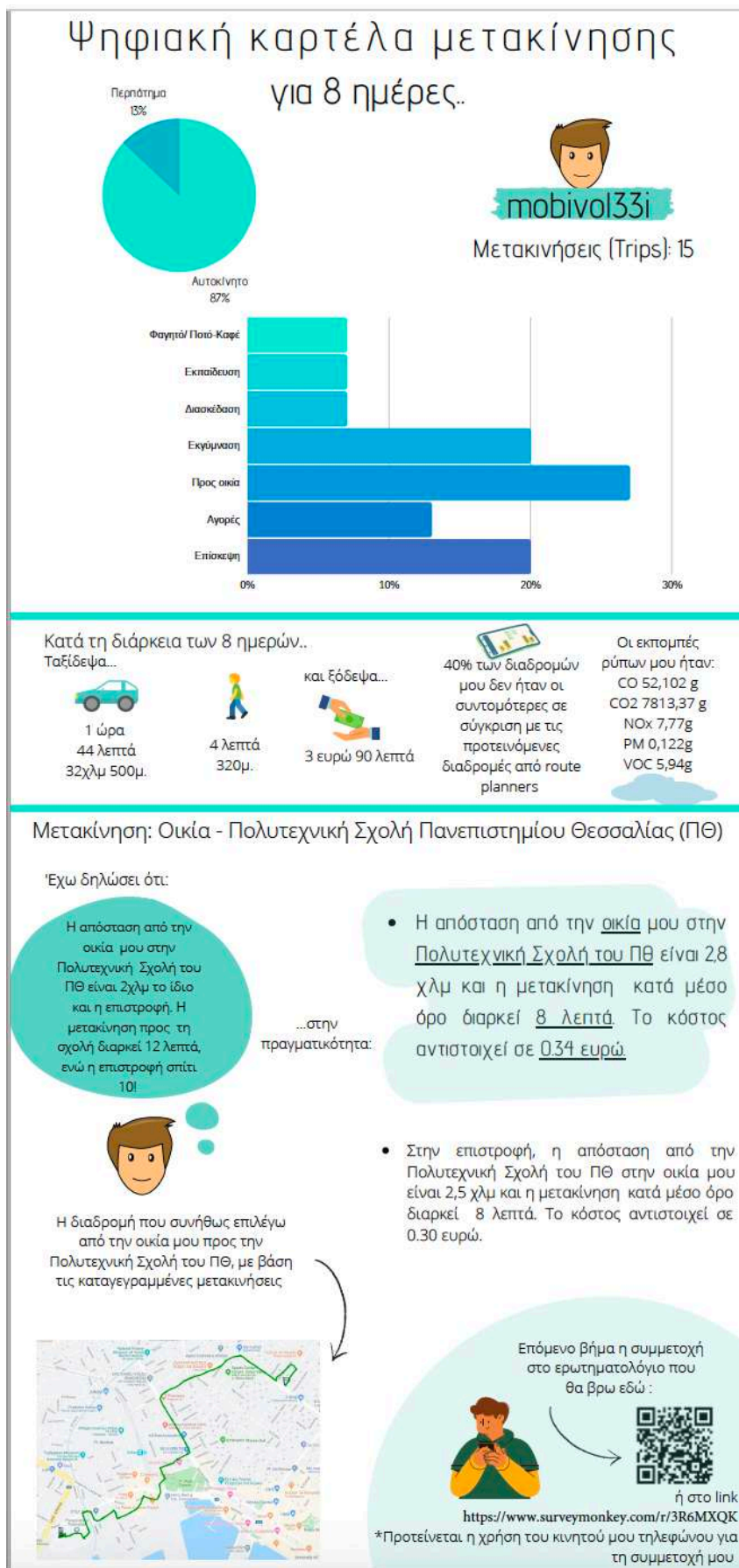
Annex I: Digital travel file cards.

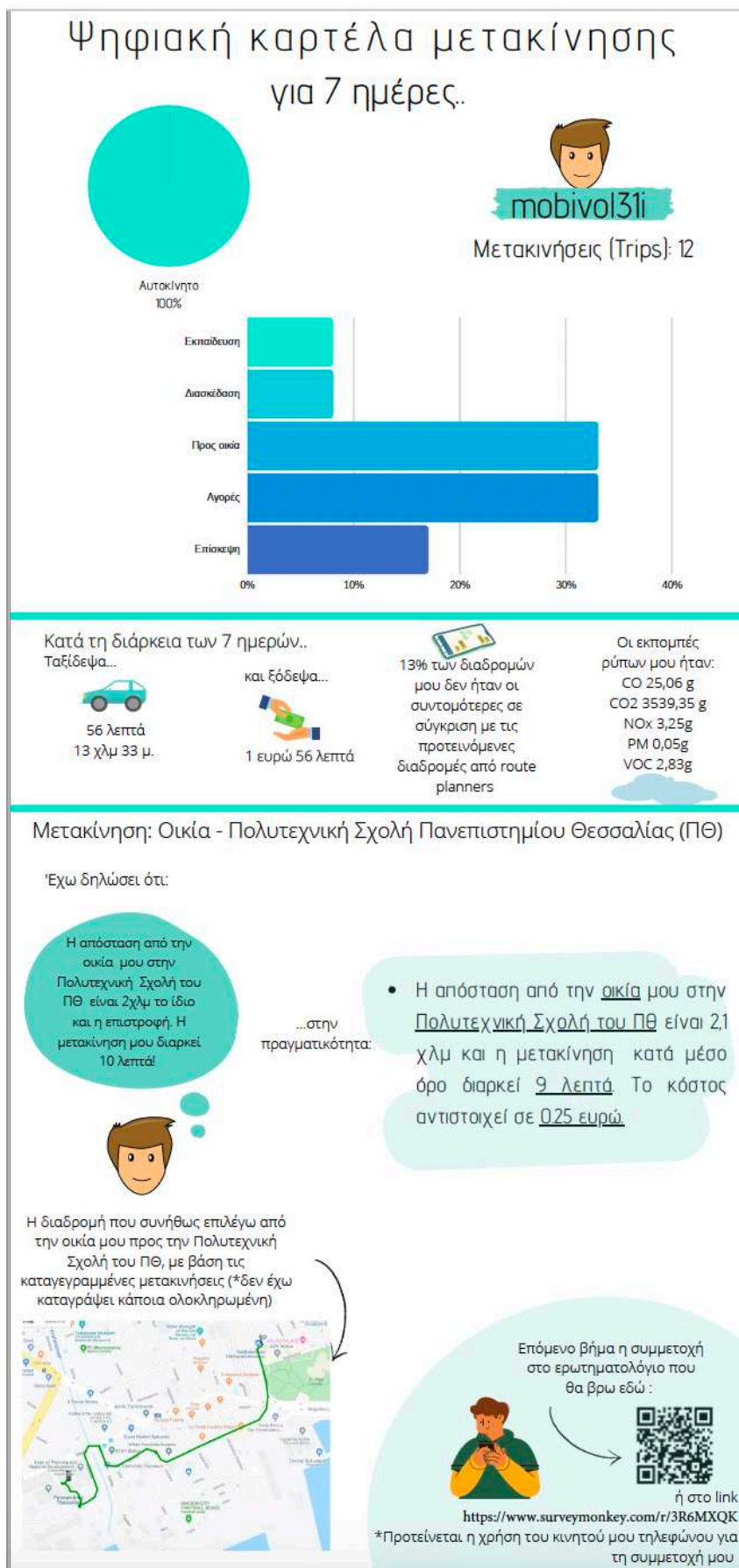


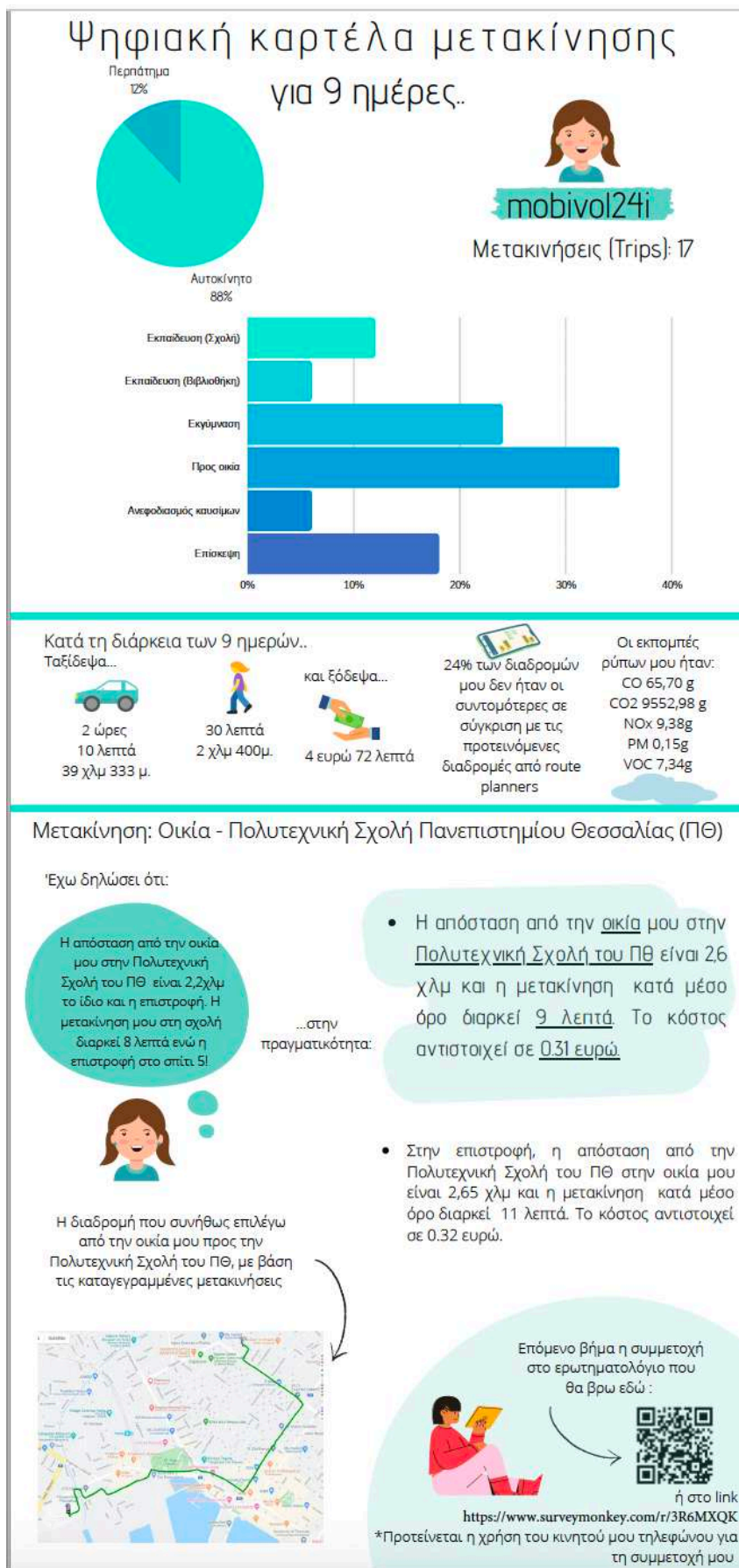




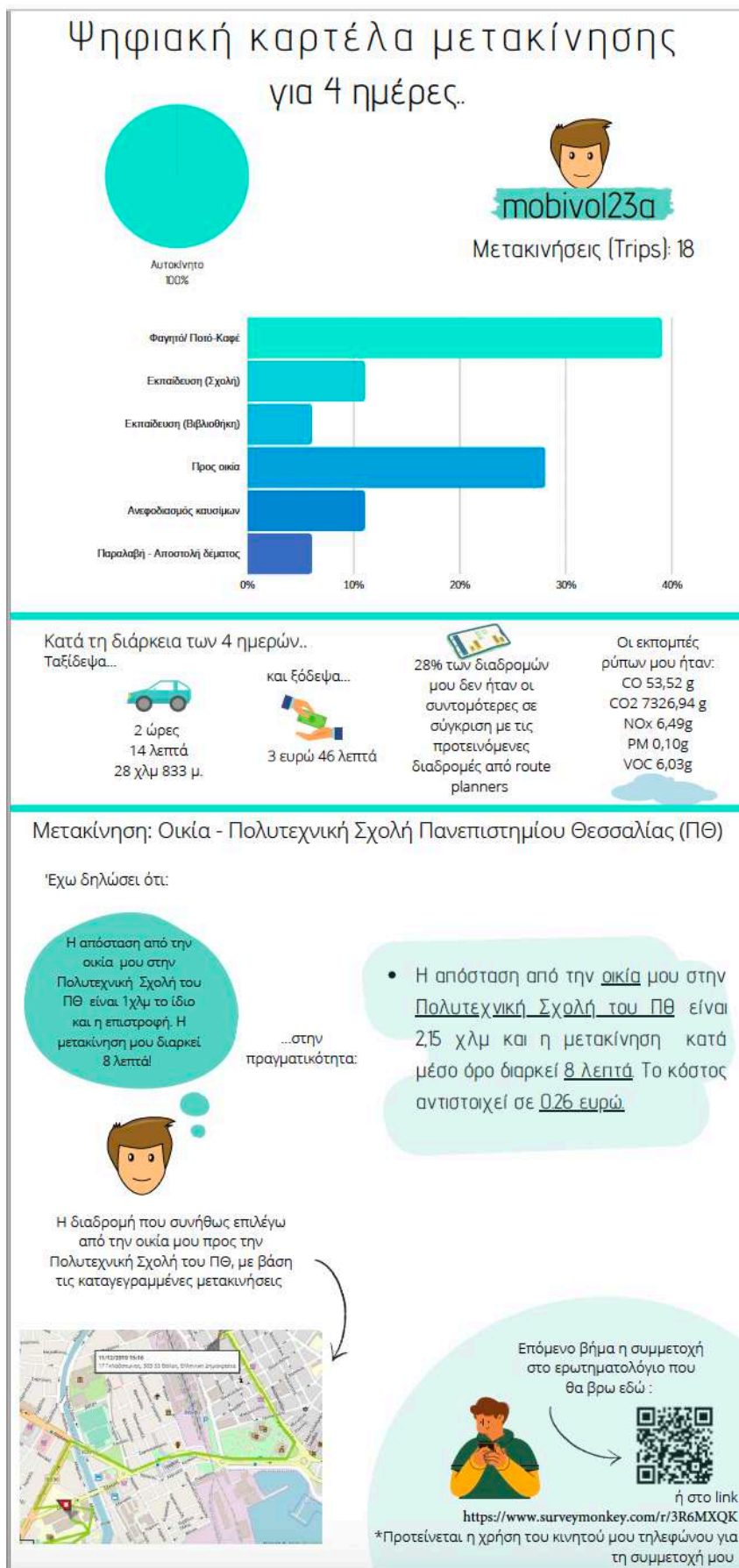


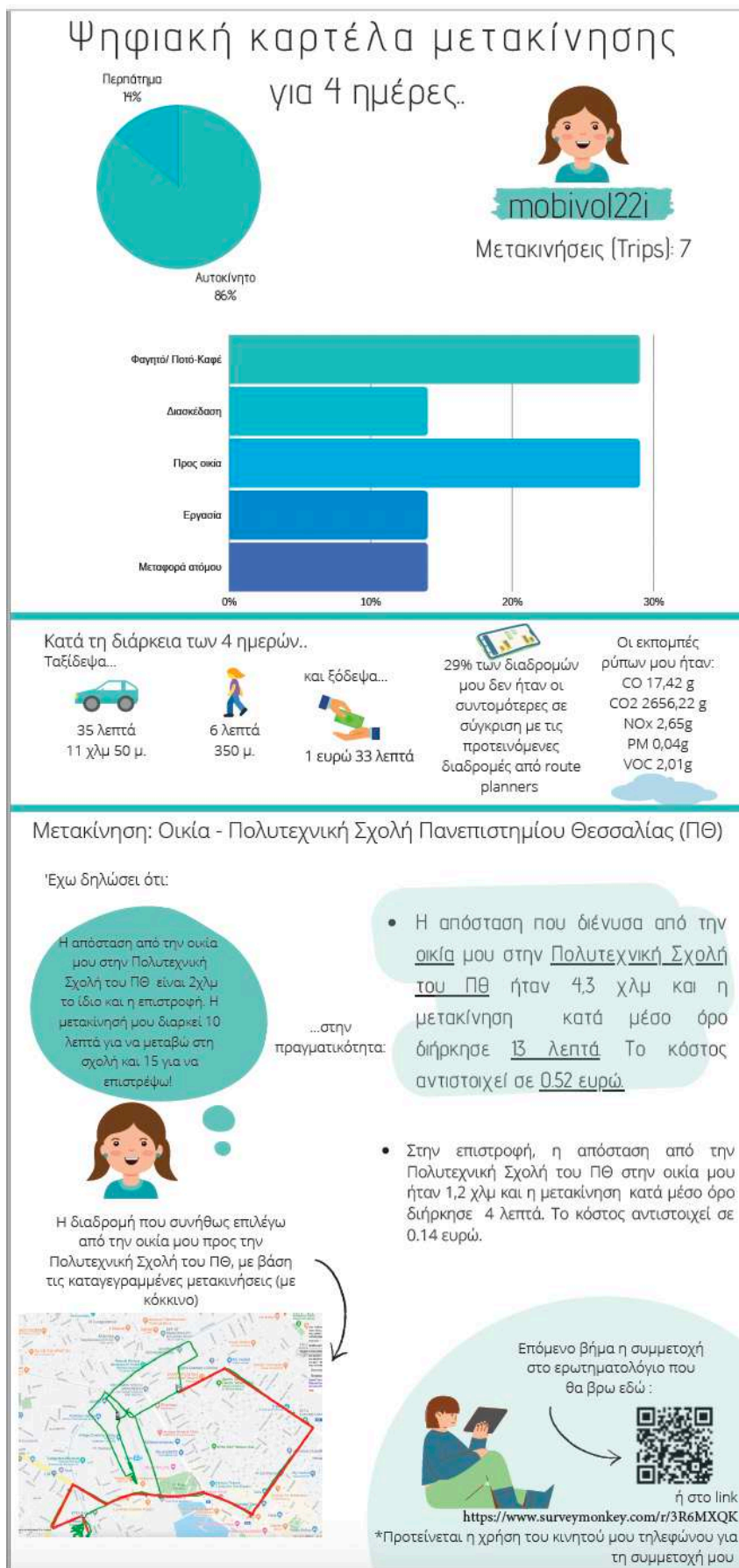


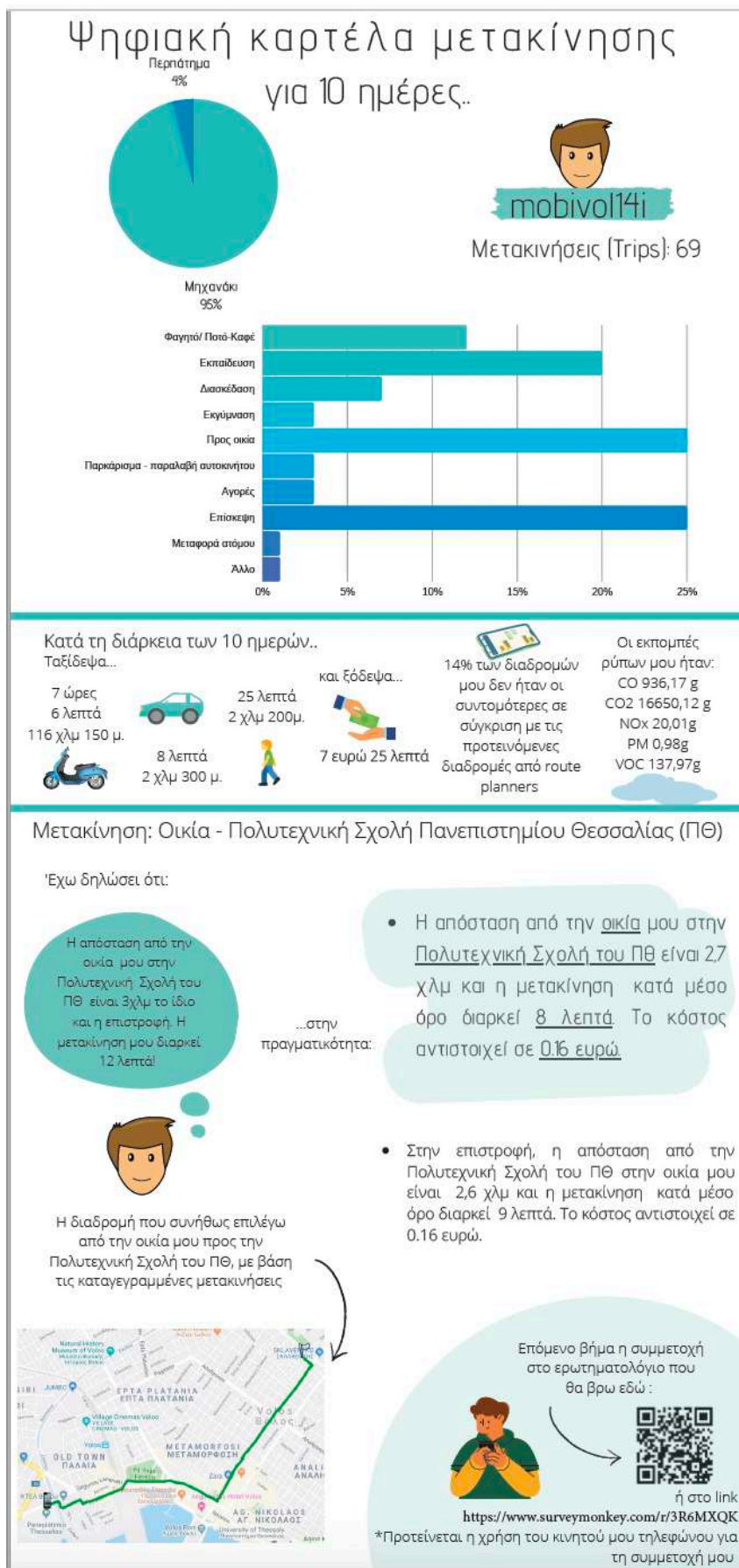


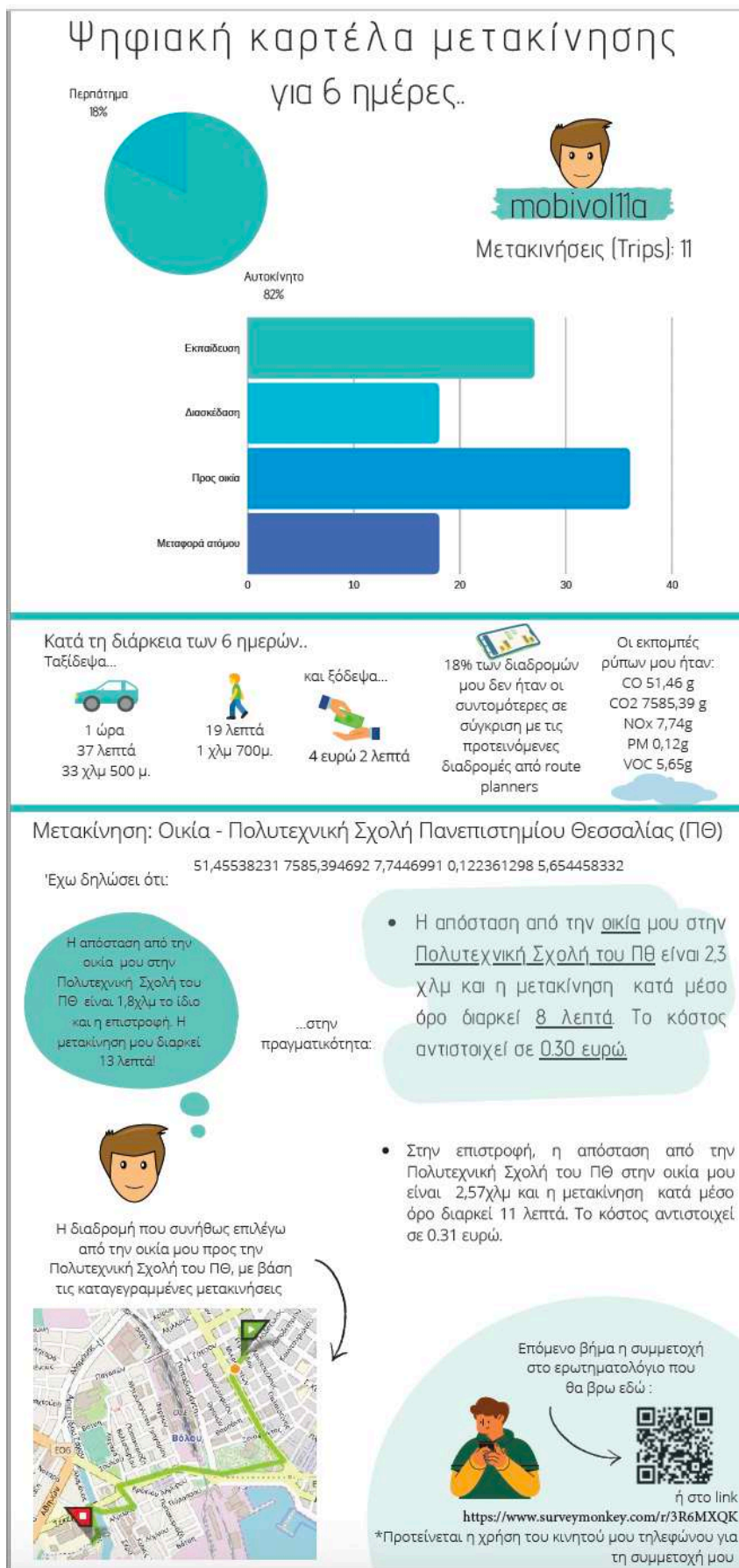


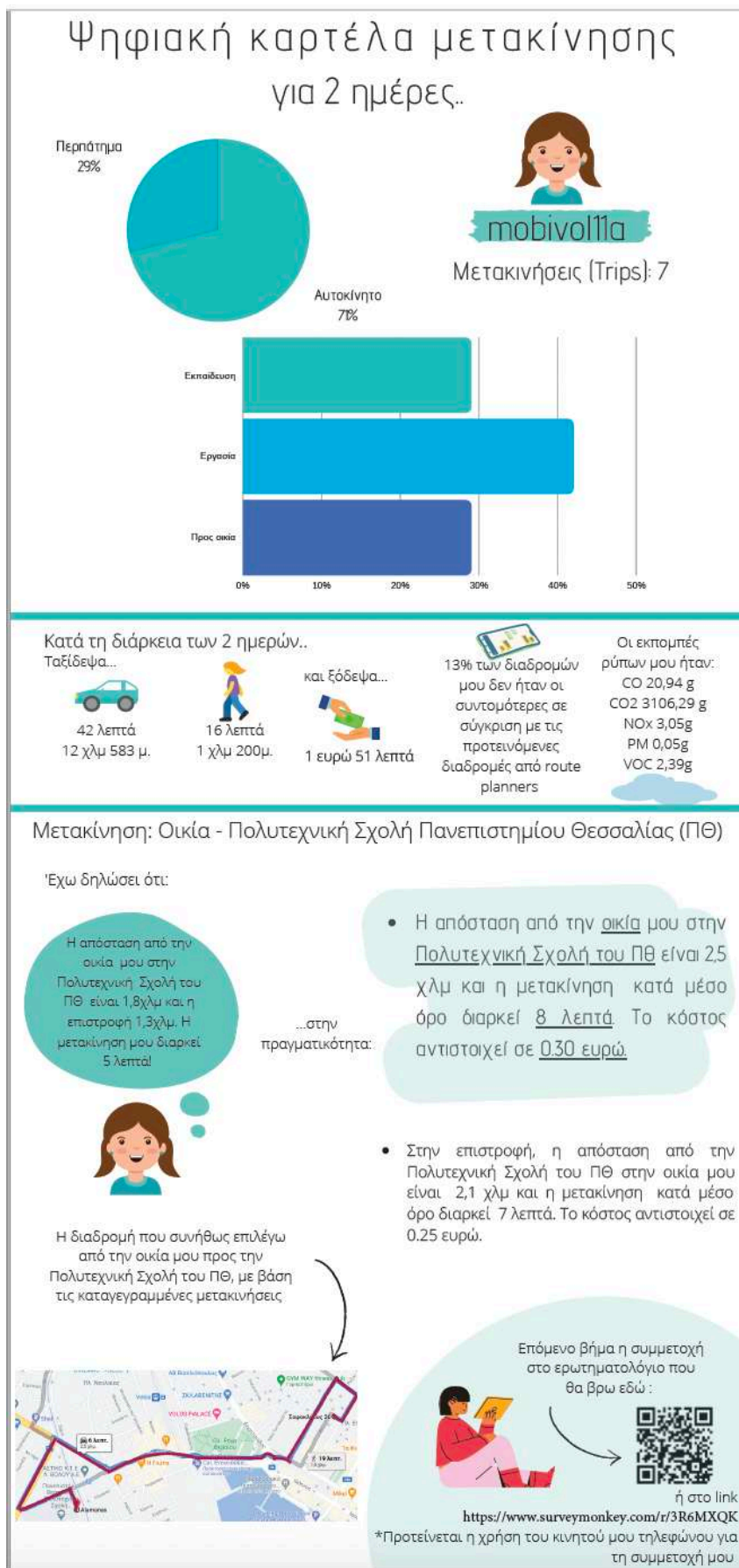


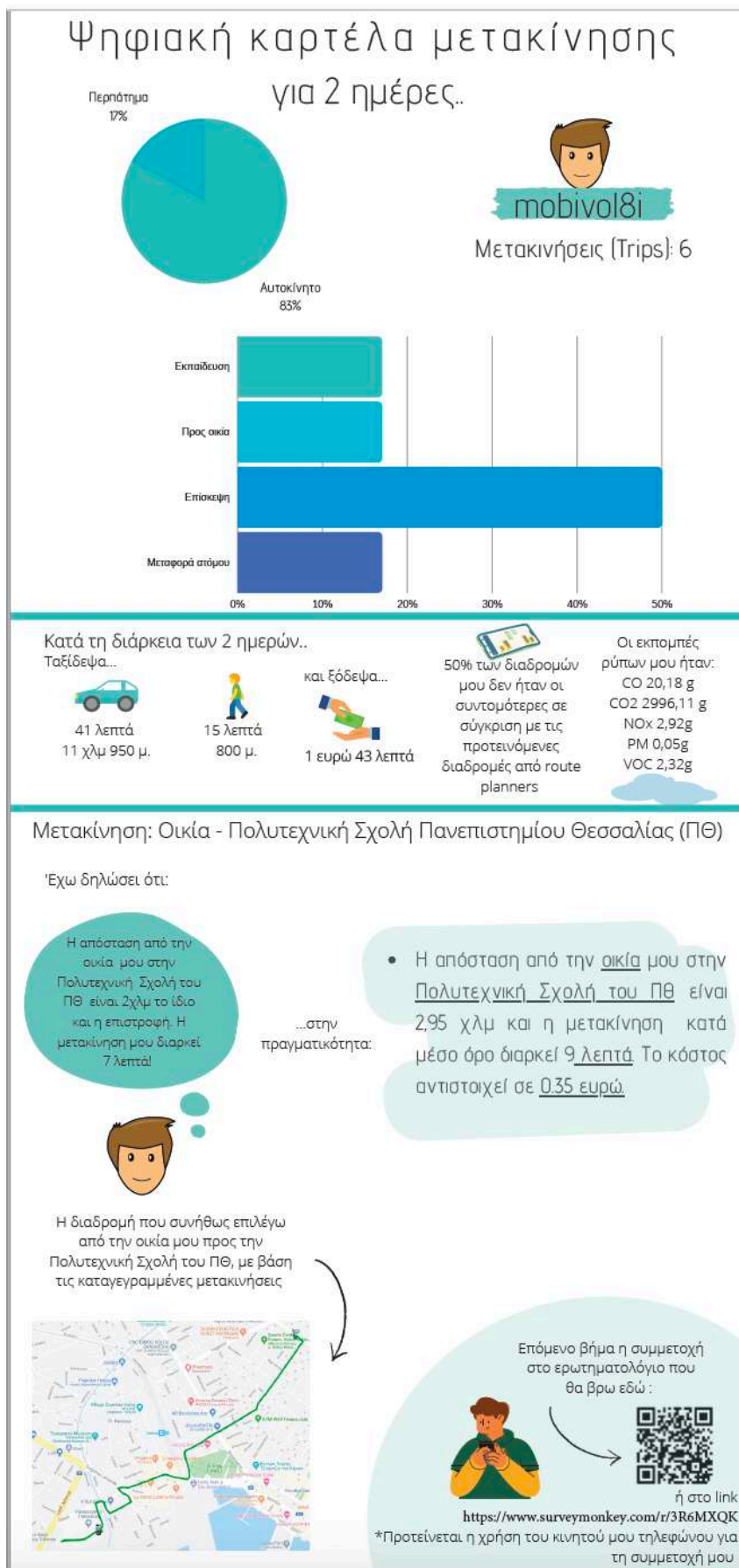


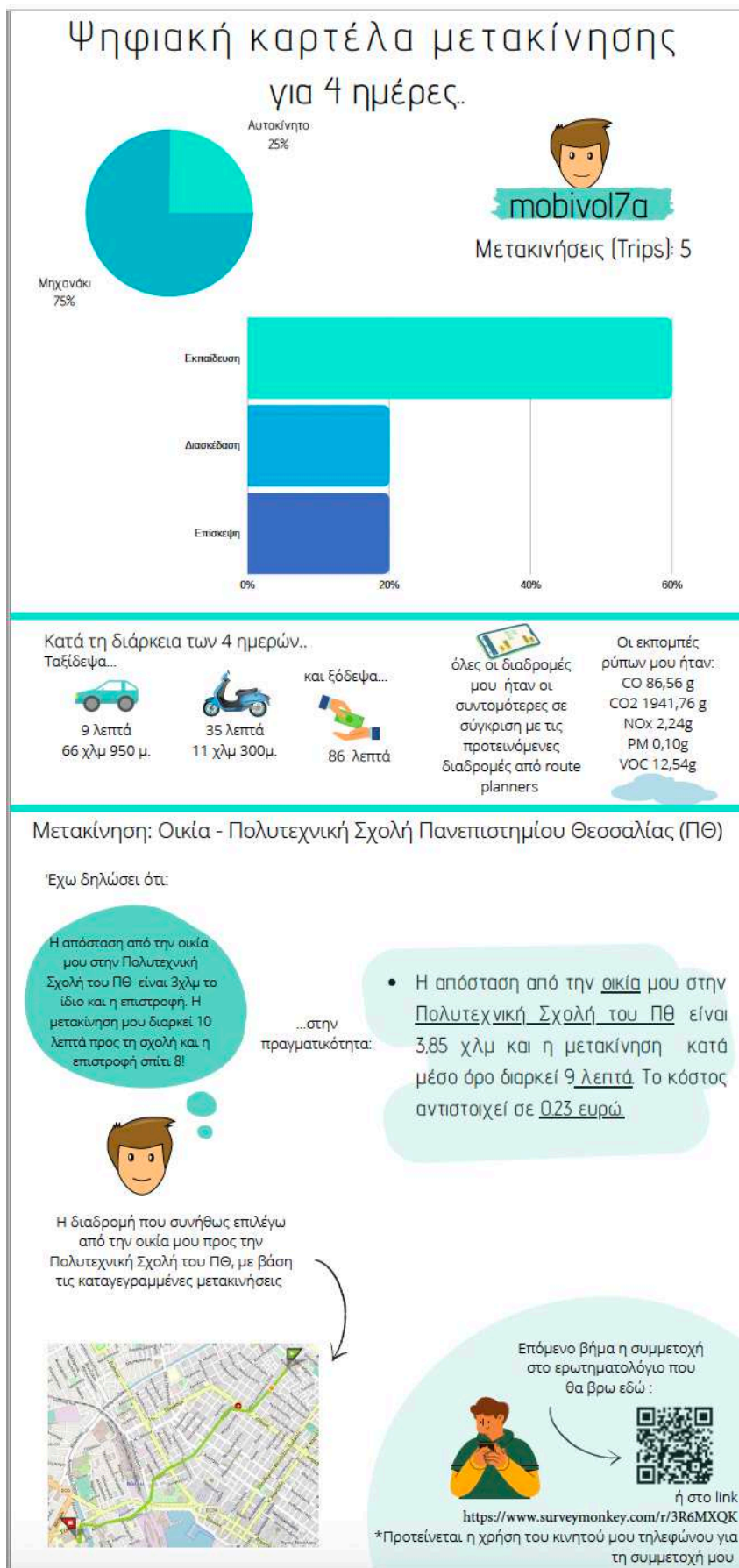


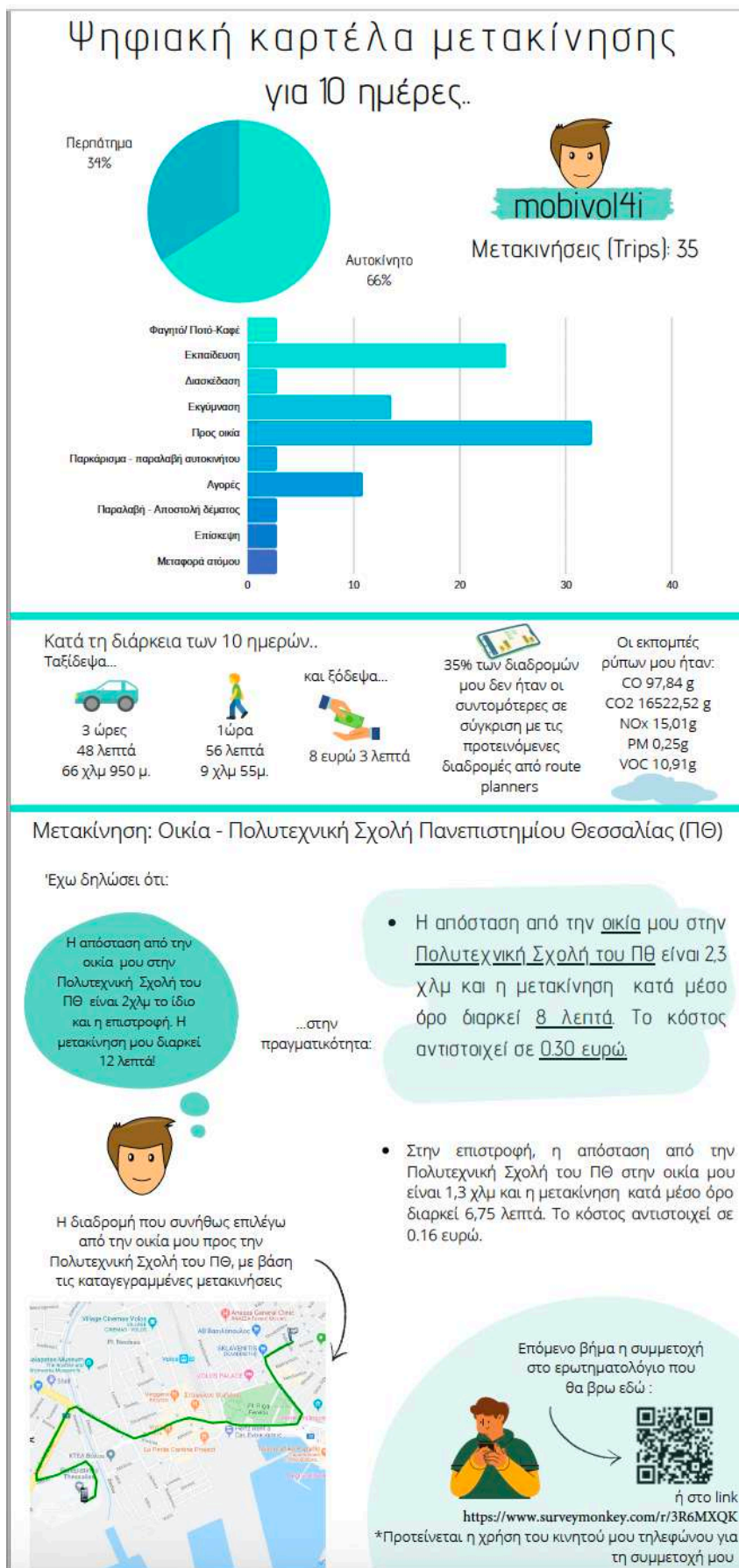




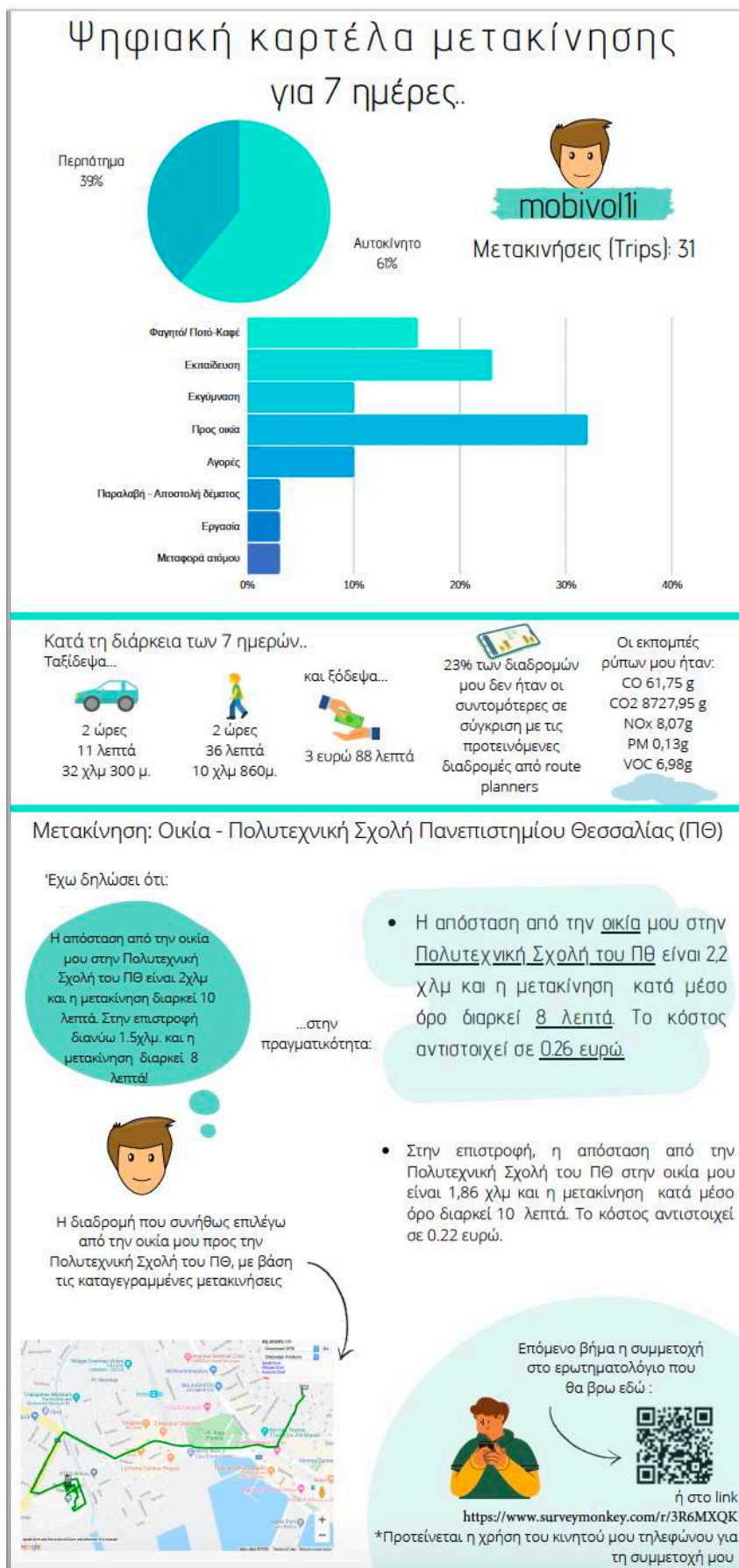


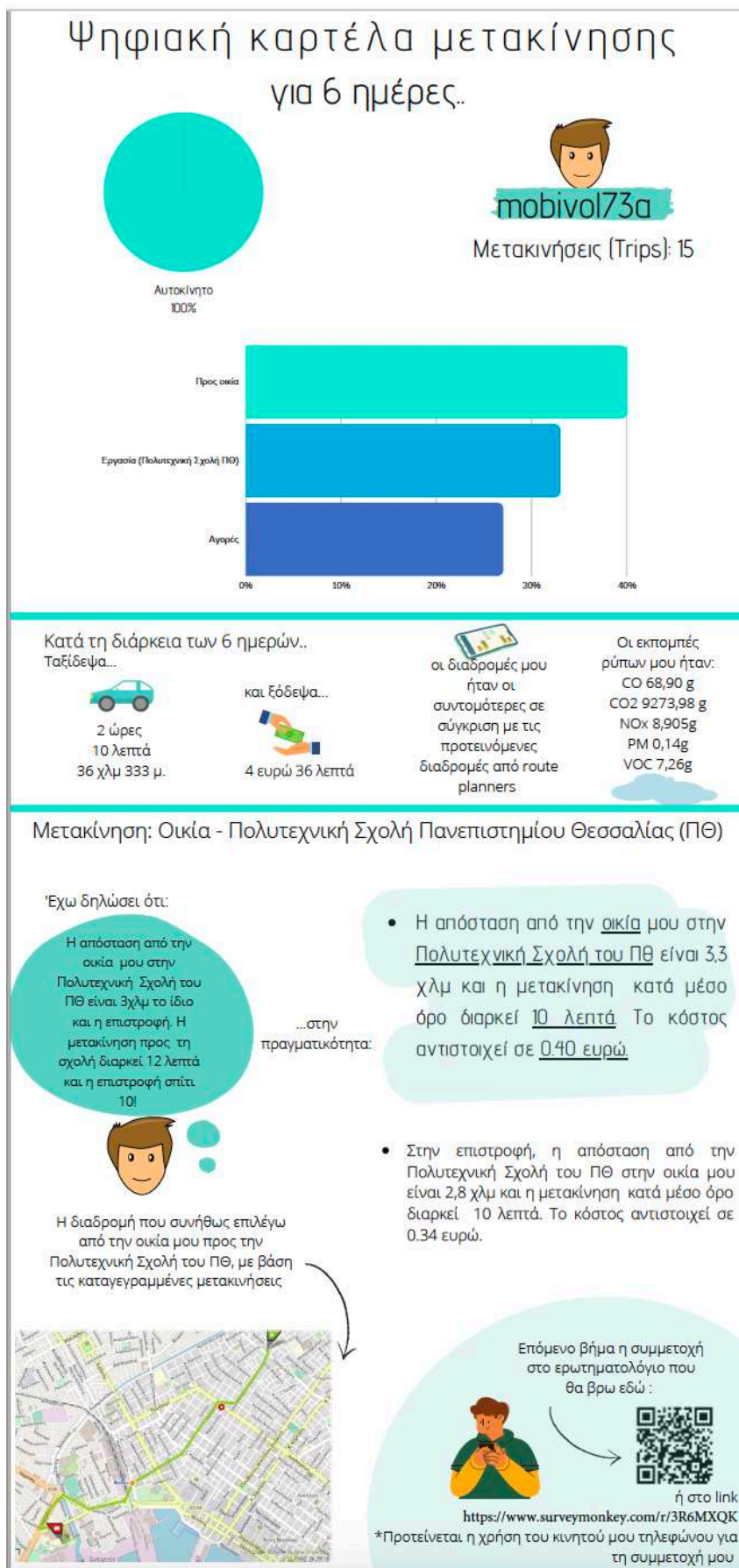


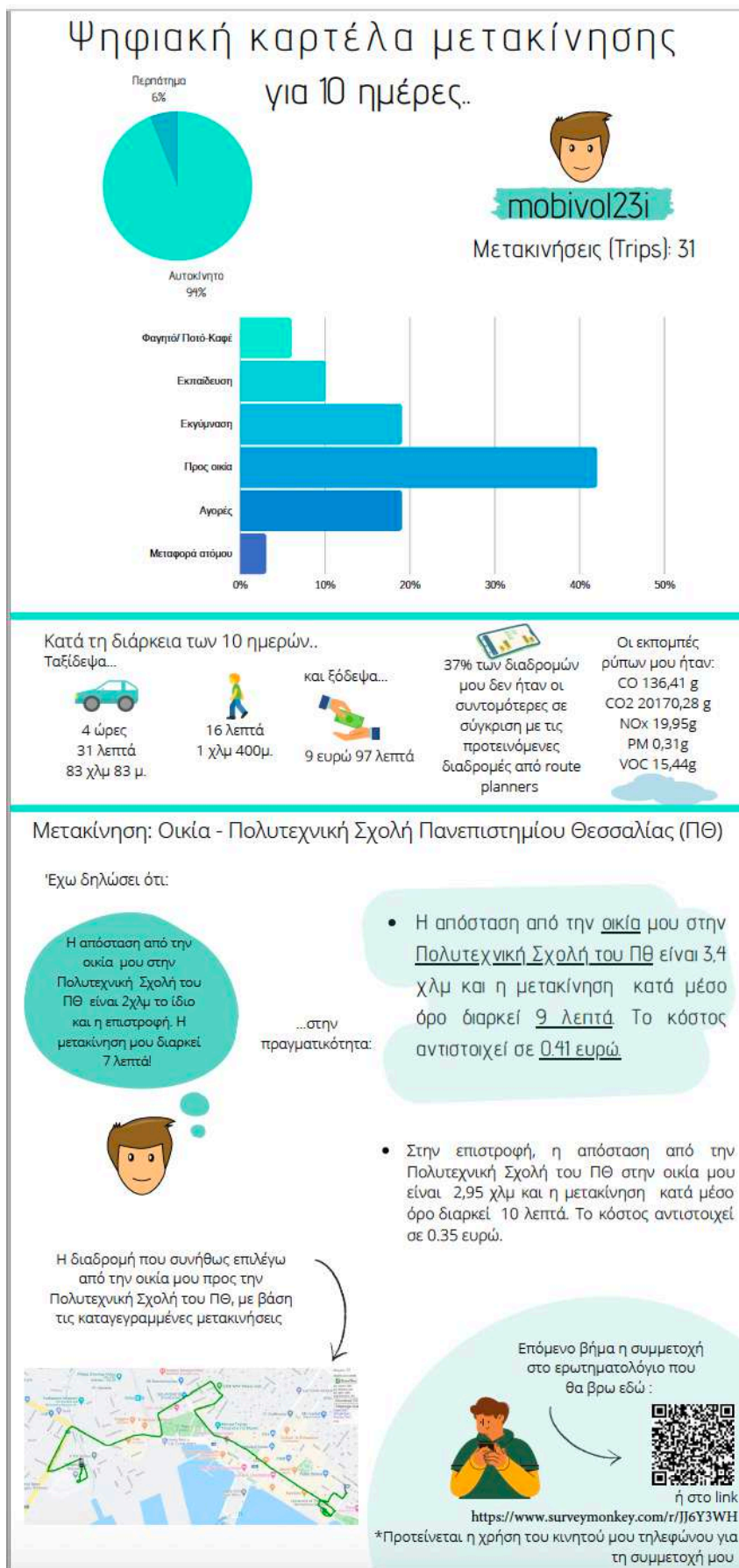


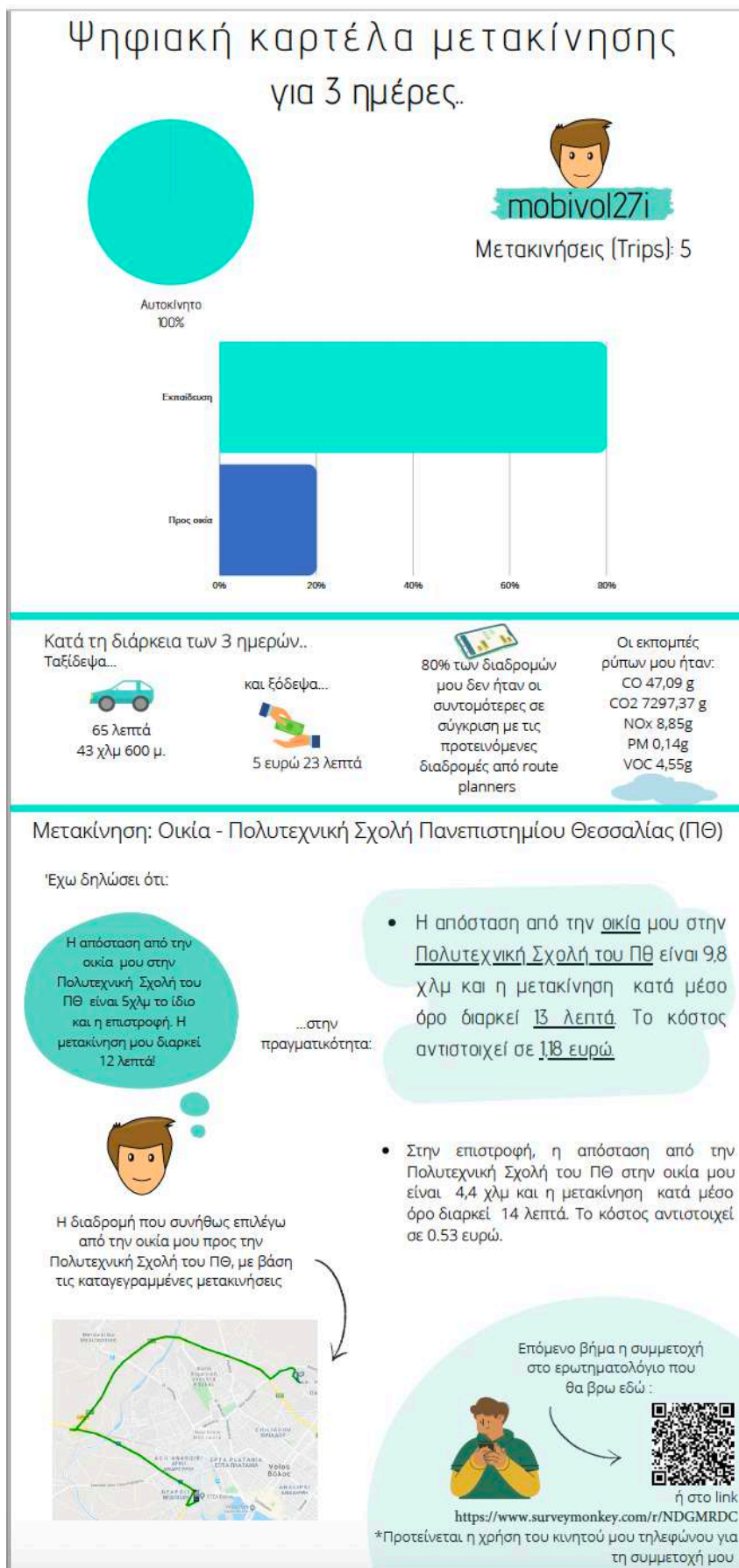


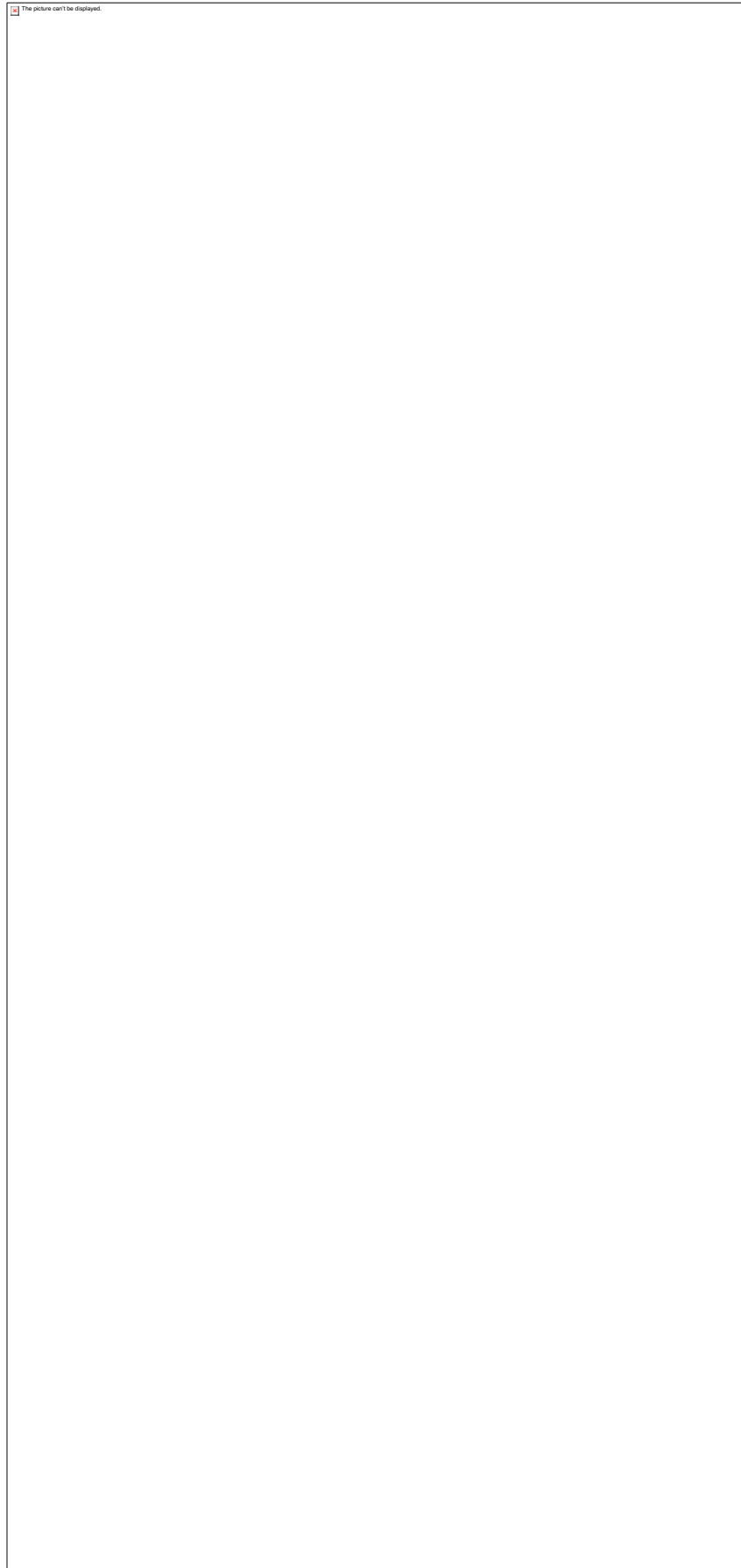


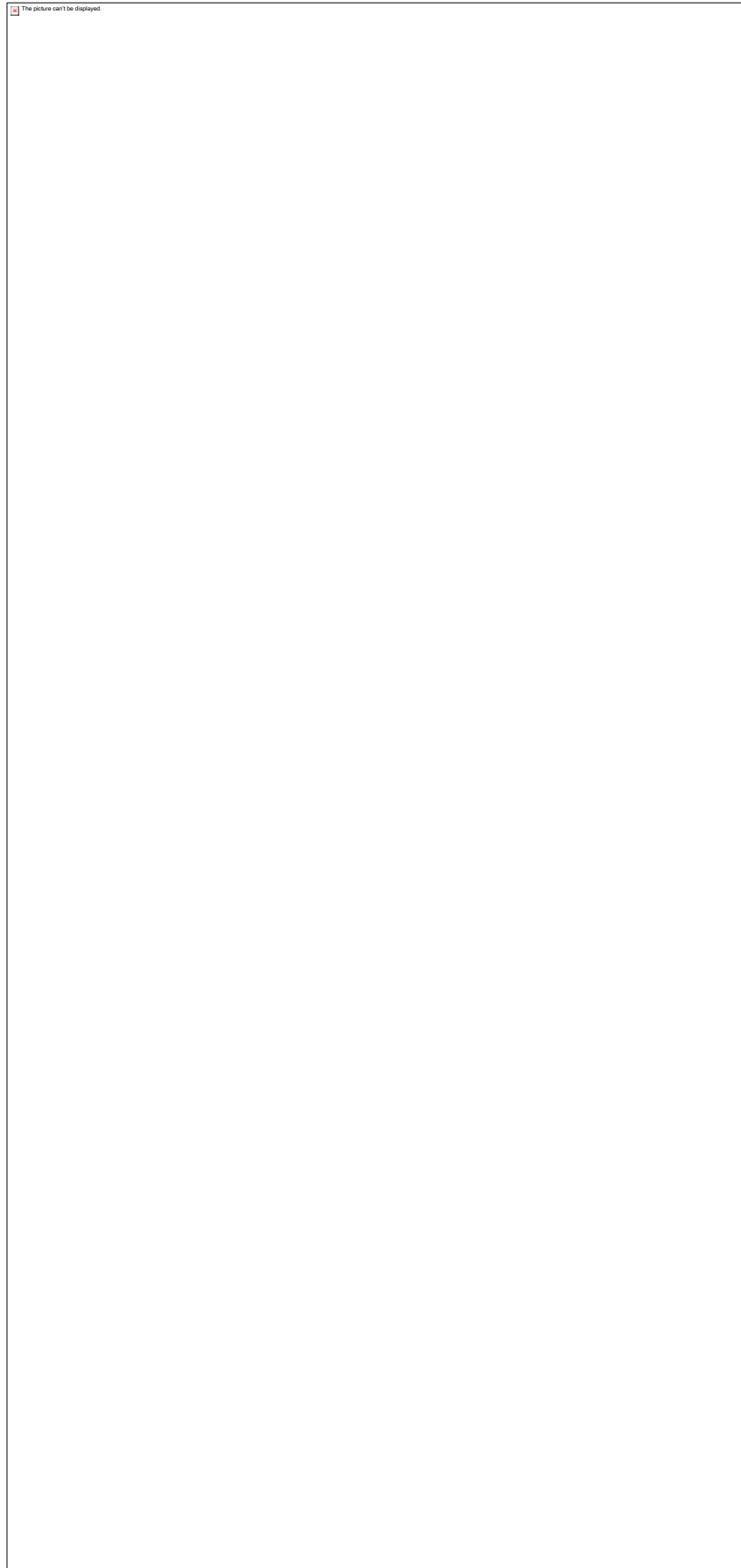


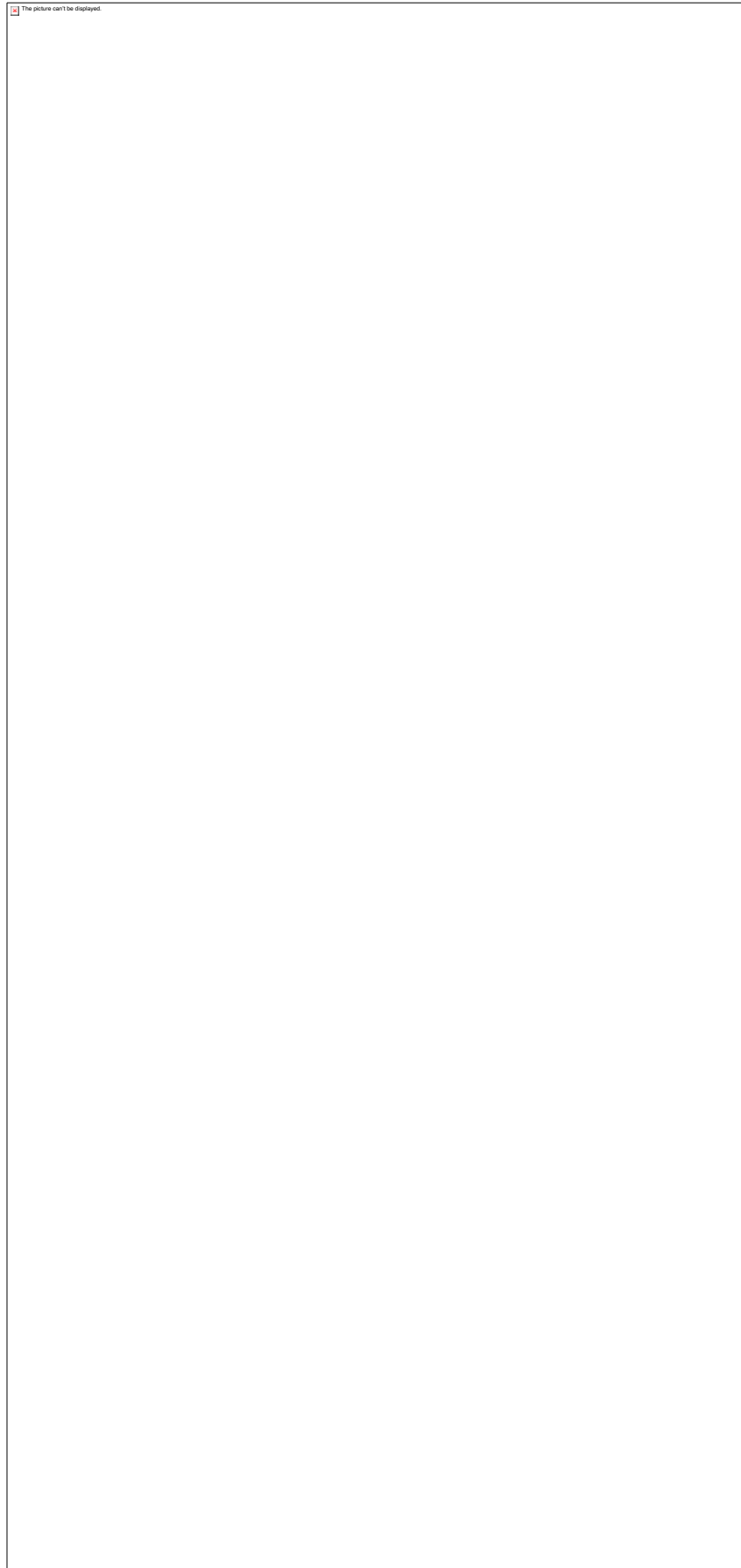


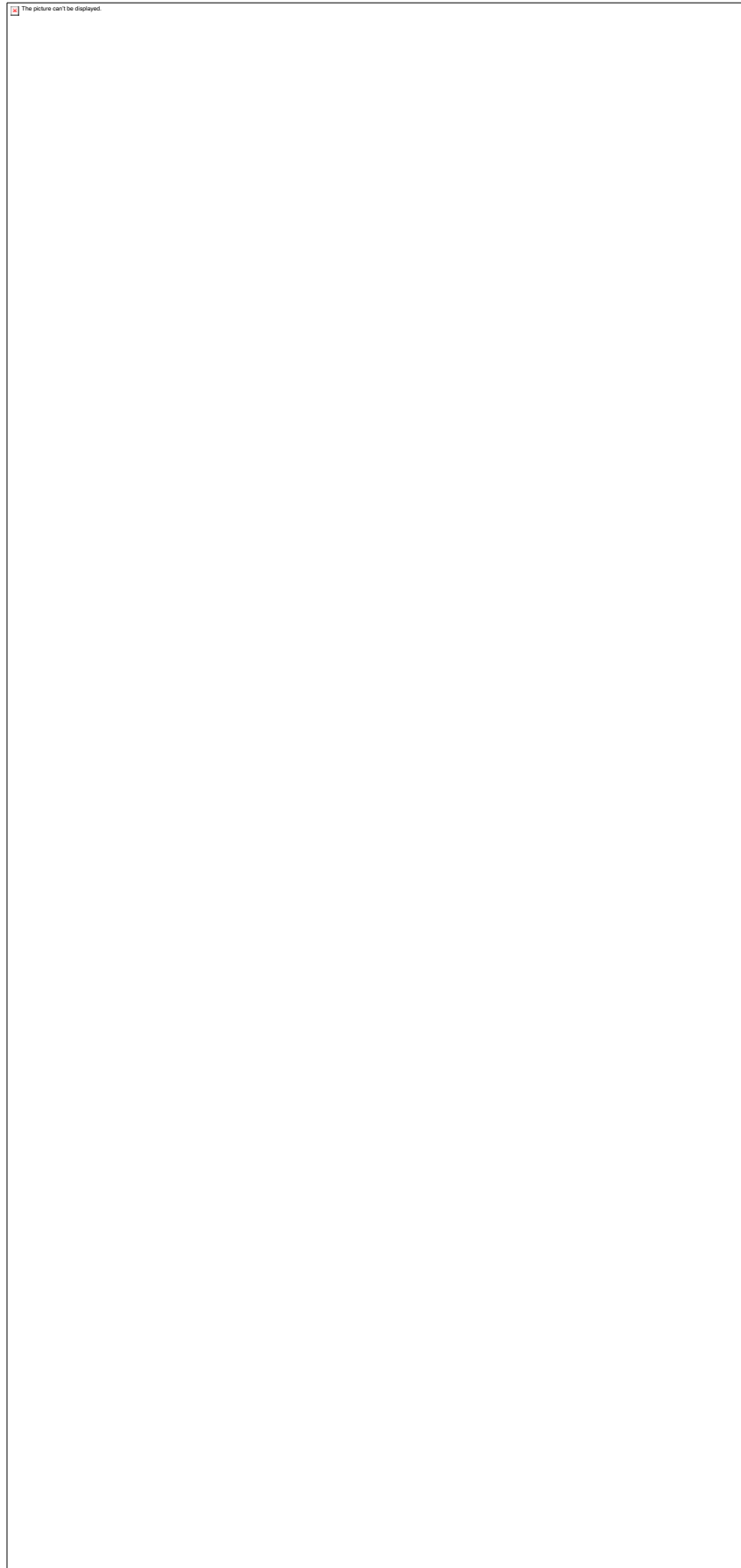




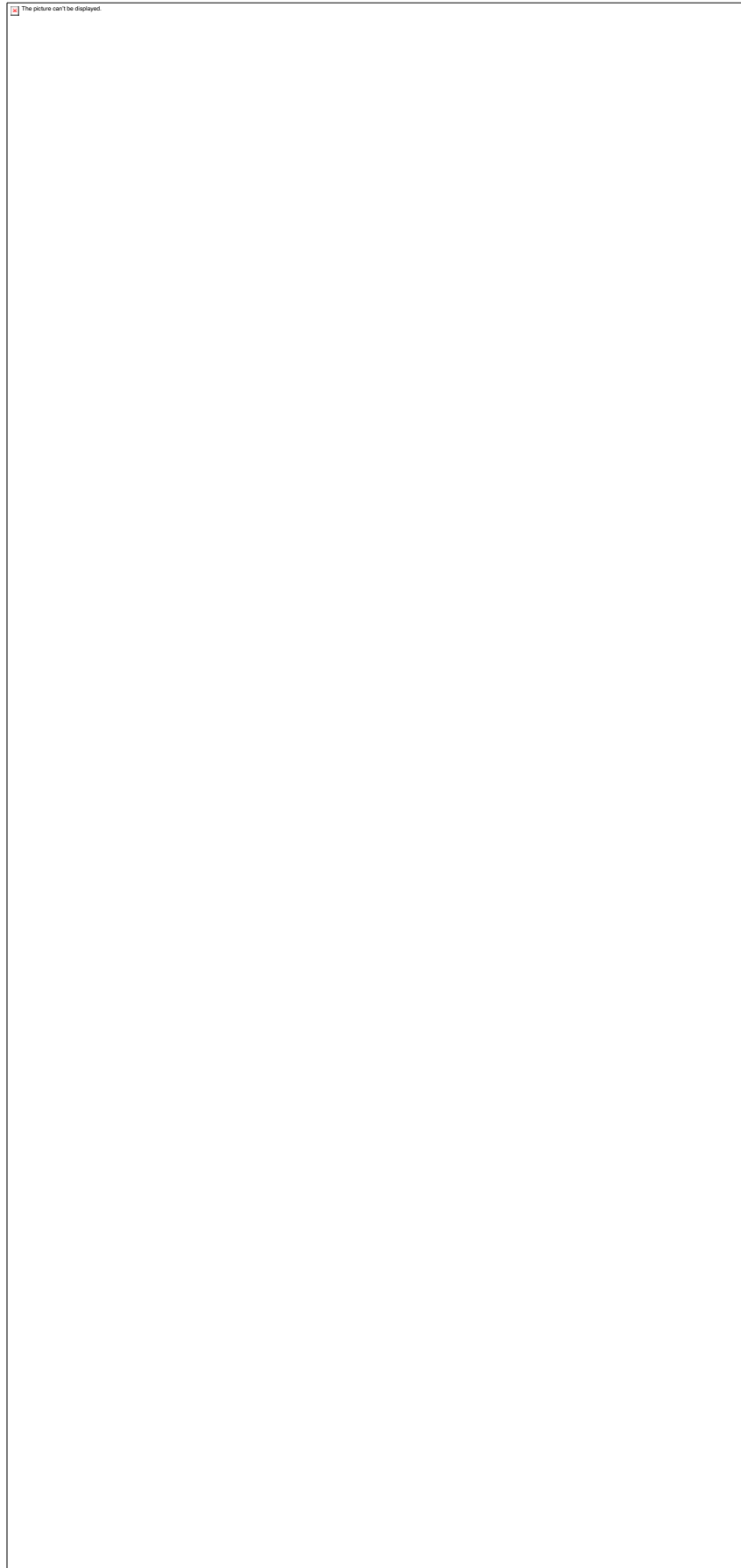


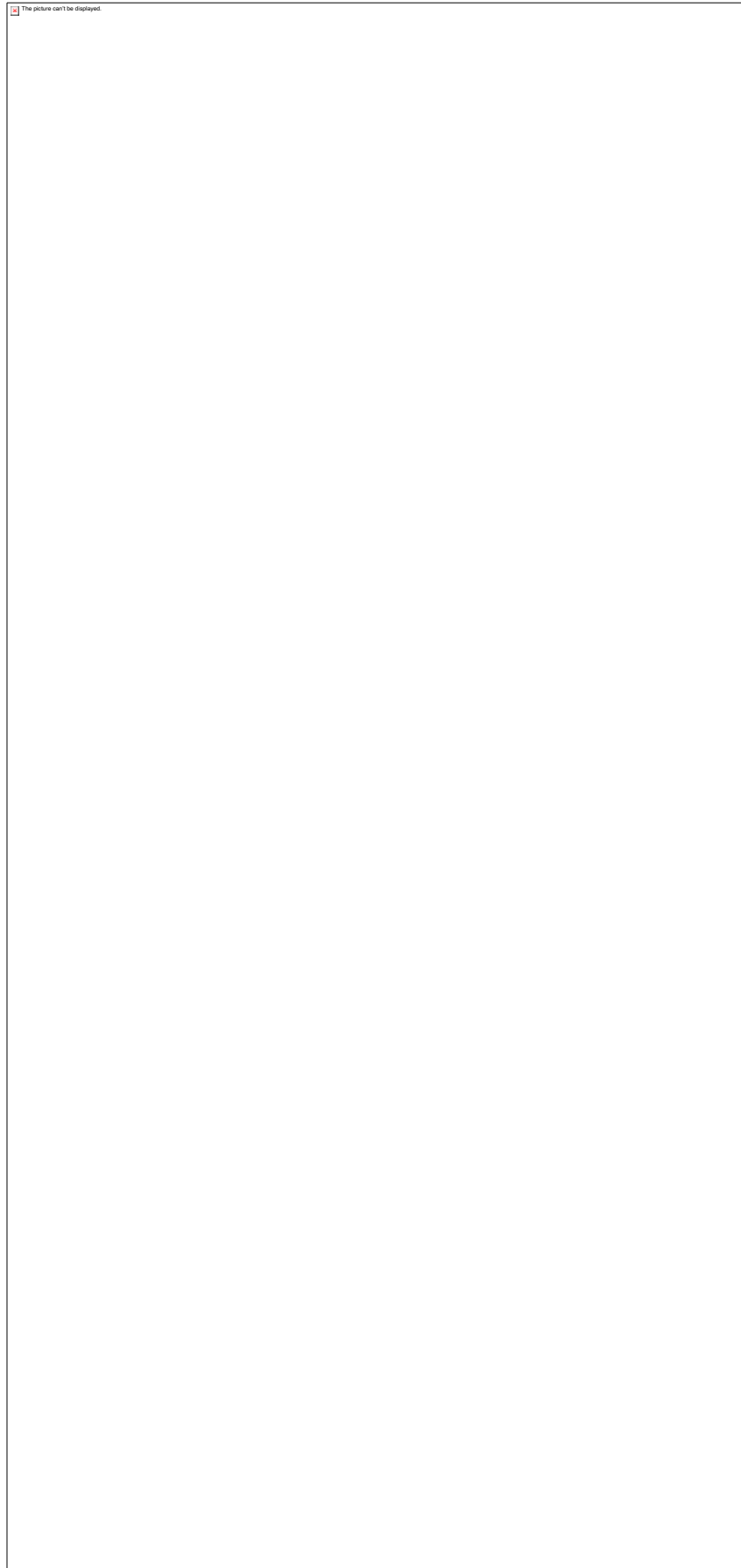


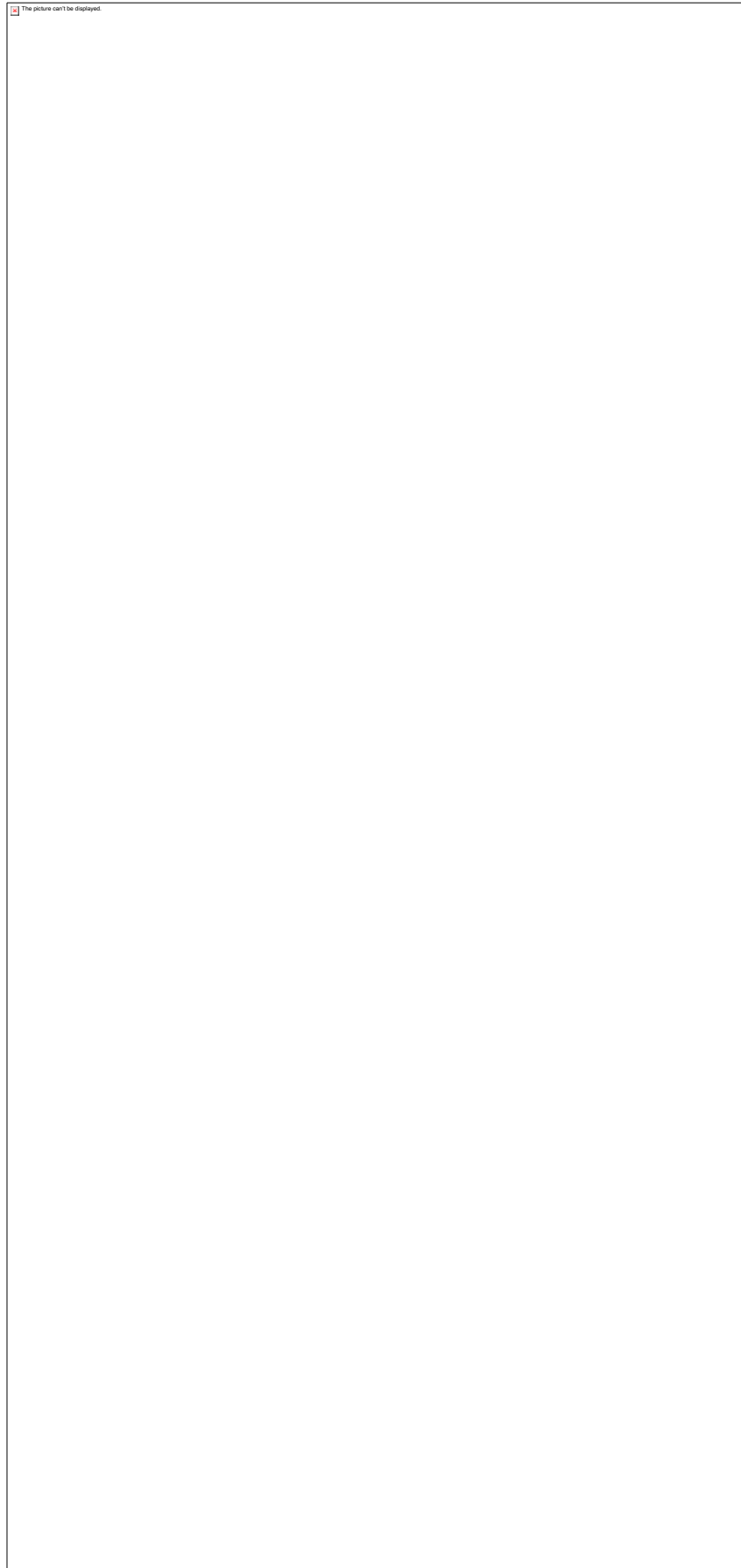


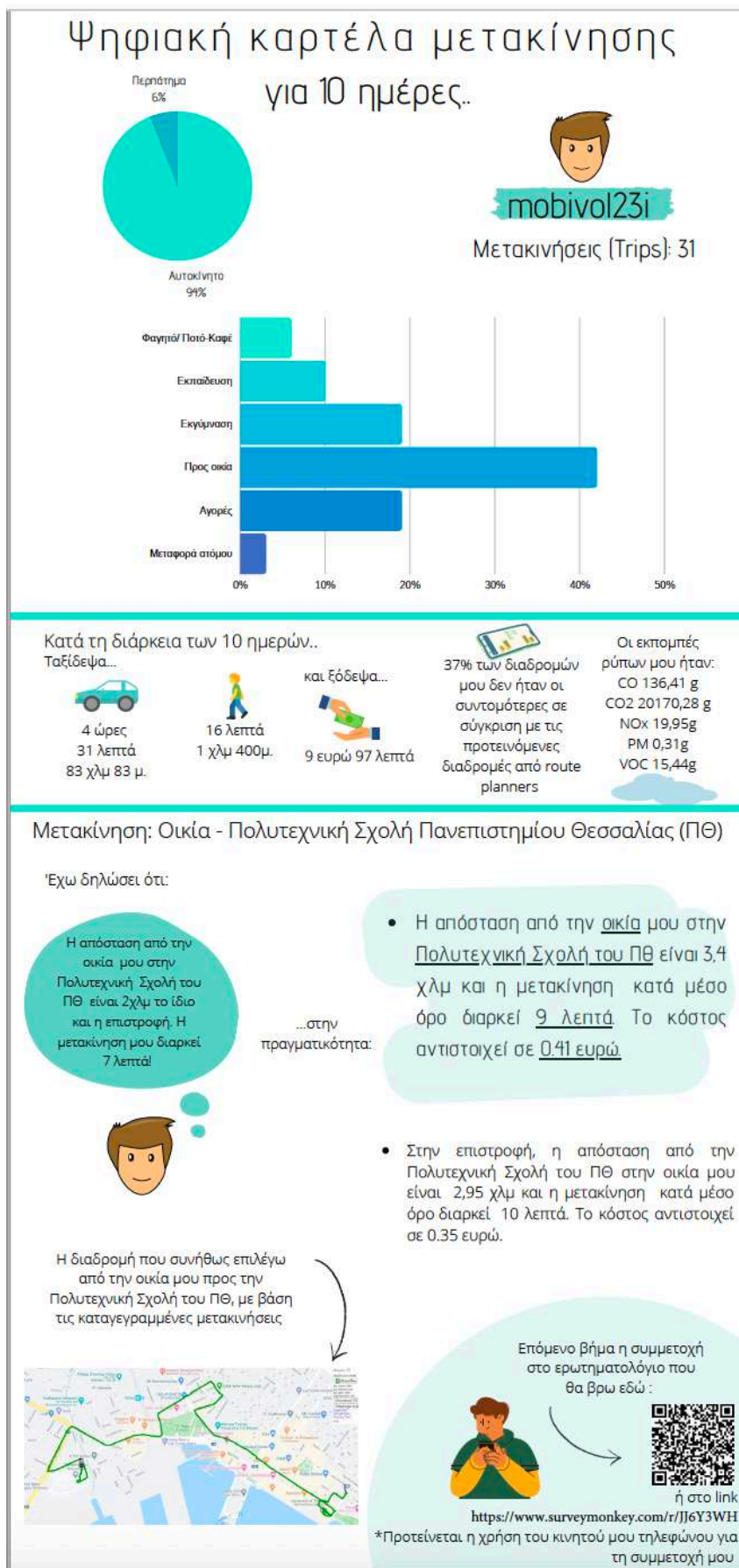


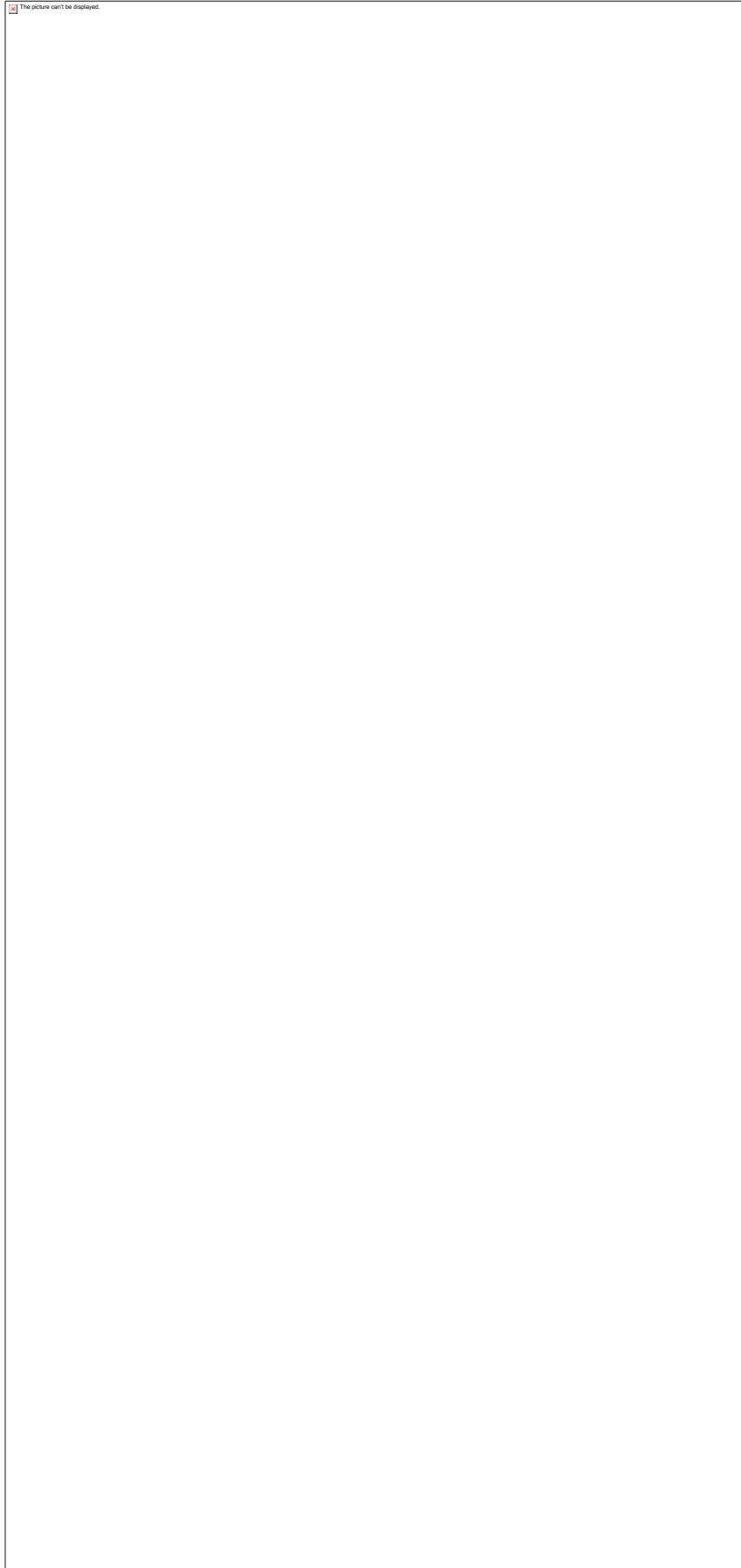


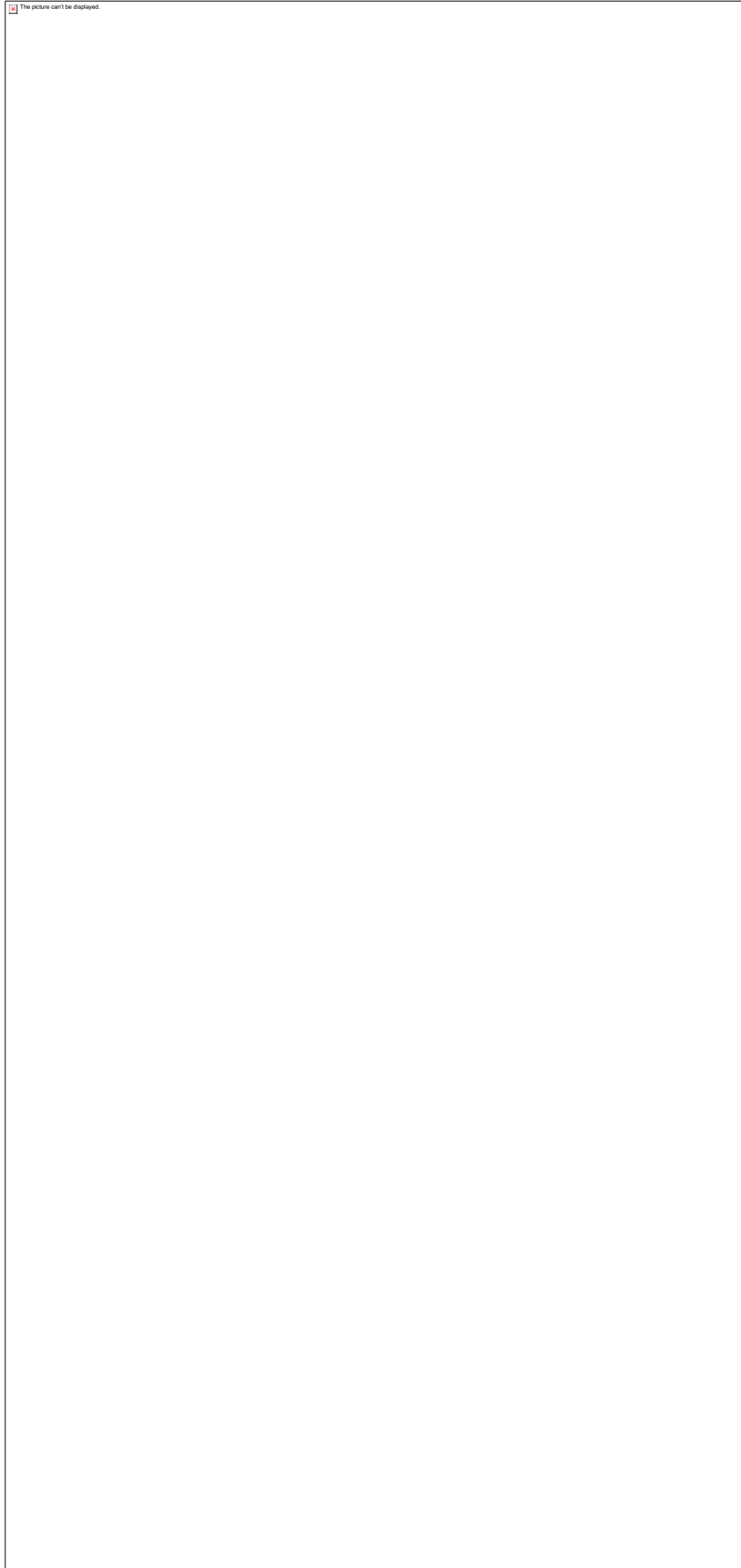


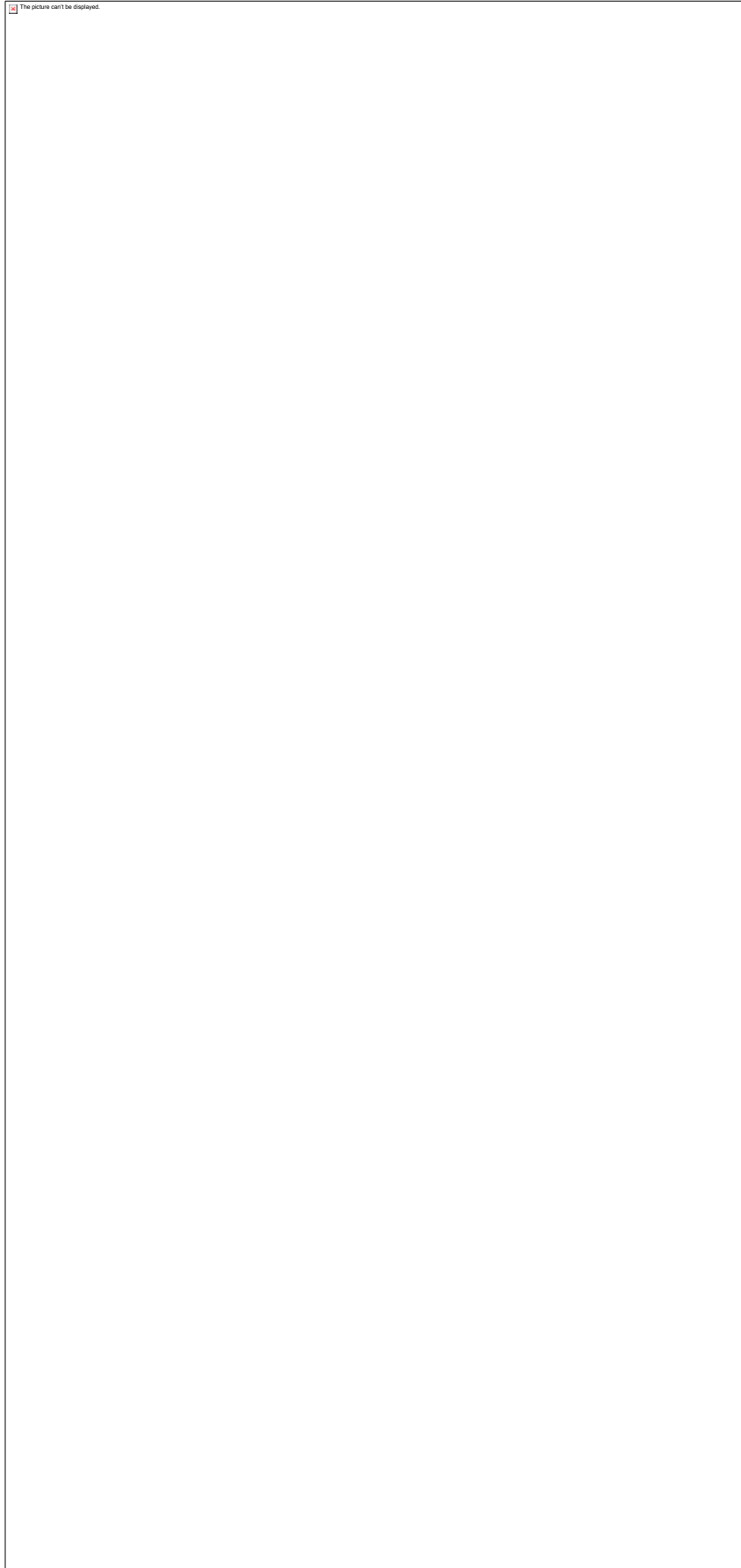


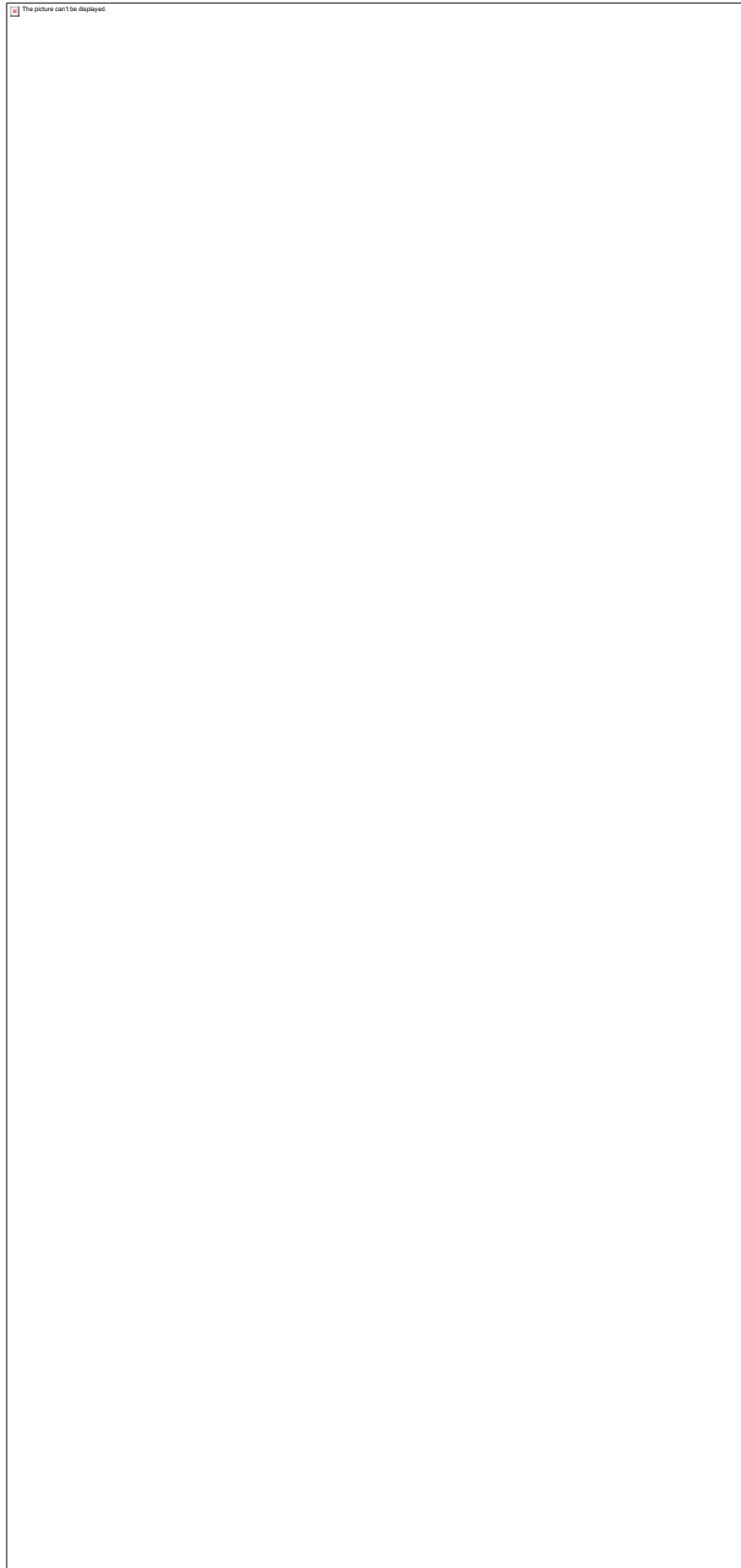














**Annex J:** Questionnaire- “A Stated Preference survey- GPS group of motorized users”.



The picture can't be displayed

 The picture can't be displayed

 The picture can't be displayed

The picture can't be displayed

The picture can't be displayed

 The picture can't be displayed

 The picture can't be displayed







 The picture can't be displayed

The picture can't be displayed

The picture can't be displayed



 The picture can't be displayed

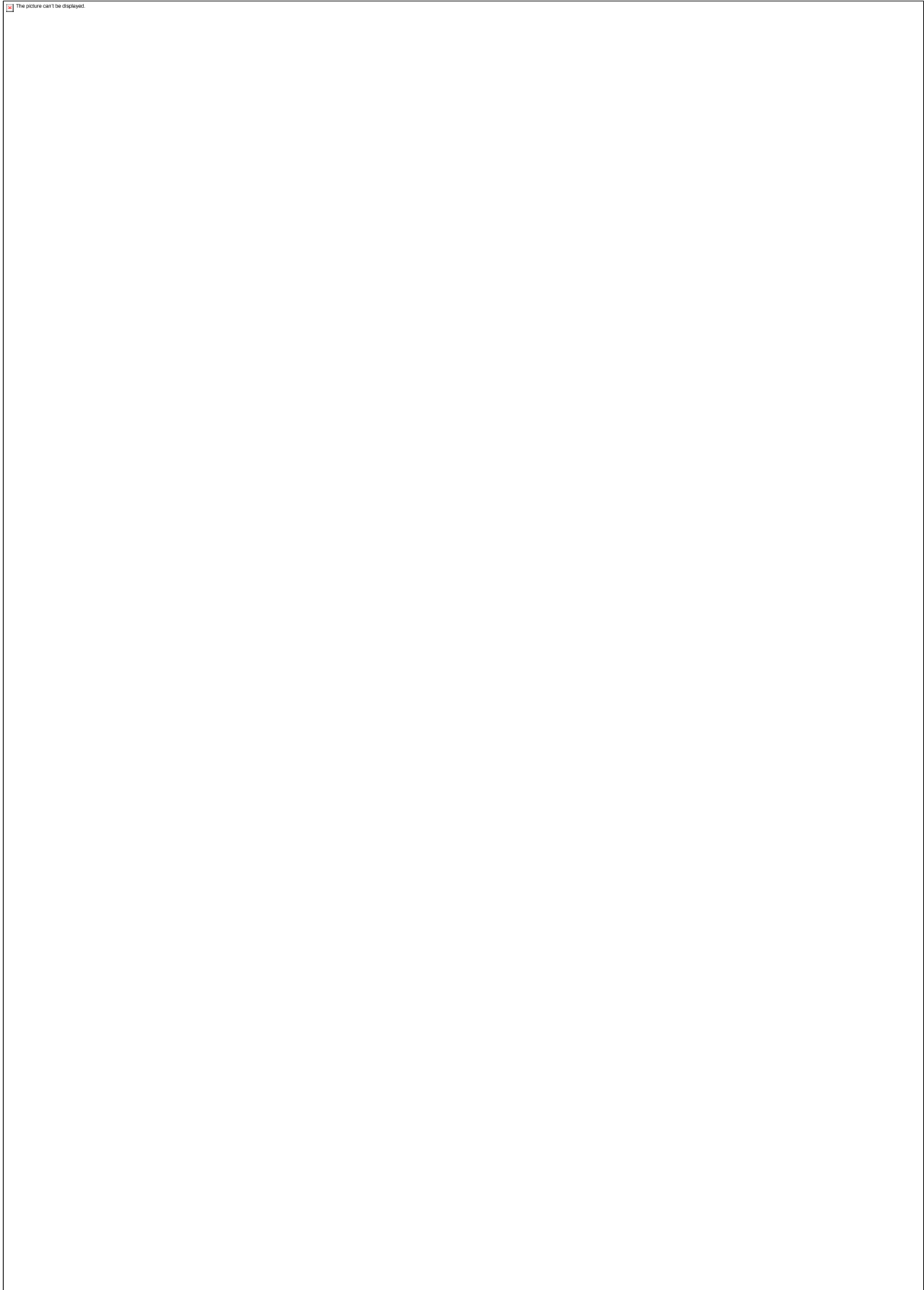
The picture can't be displayed



 The picture can't be displayed

 The picture can't be displayed

The picture can't be displayed





 The picture can't be displayed

 The picture can't be displayed

 The picture can't be displayed







 The picture can't be displayed

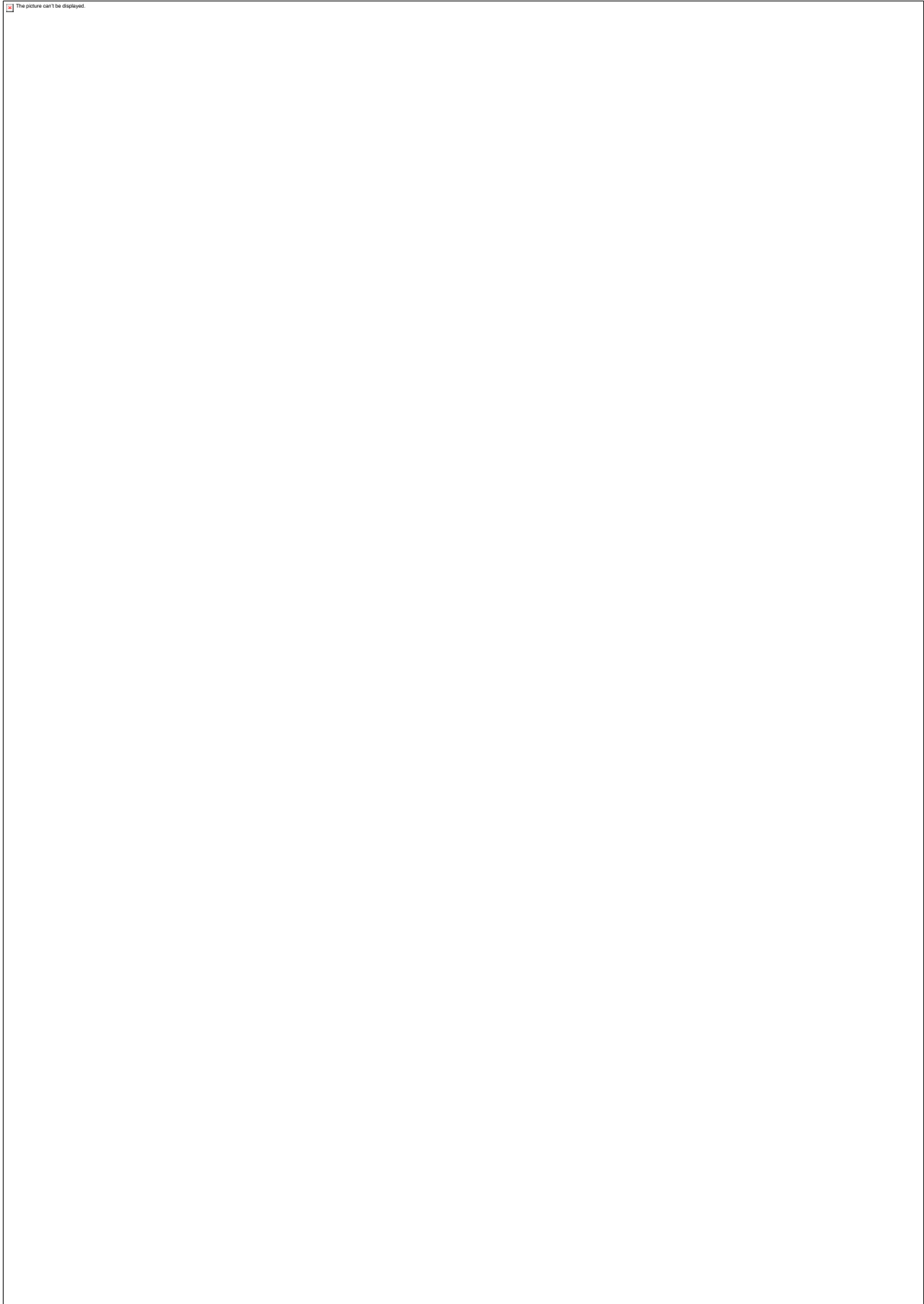
**Annex K:** Questionnaire- “COVID-19: A Stated Preference survey about the daily main trip”.





 The picture can't be displayed

 The picture can't be displayed





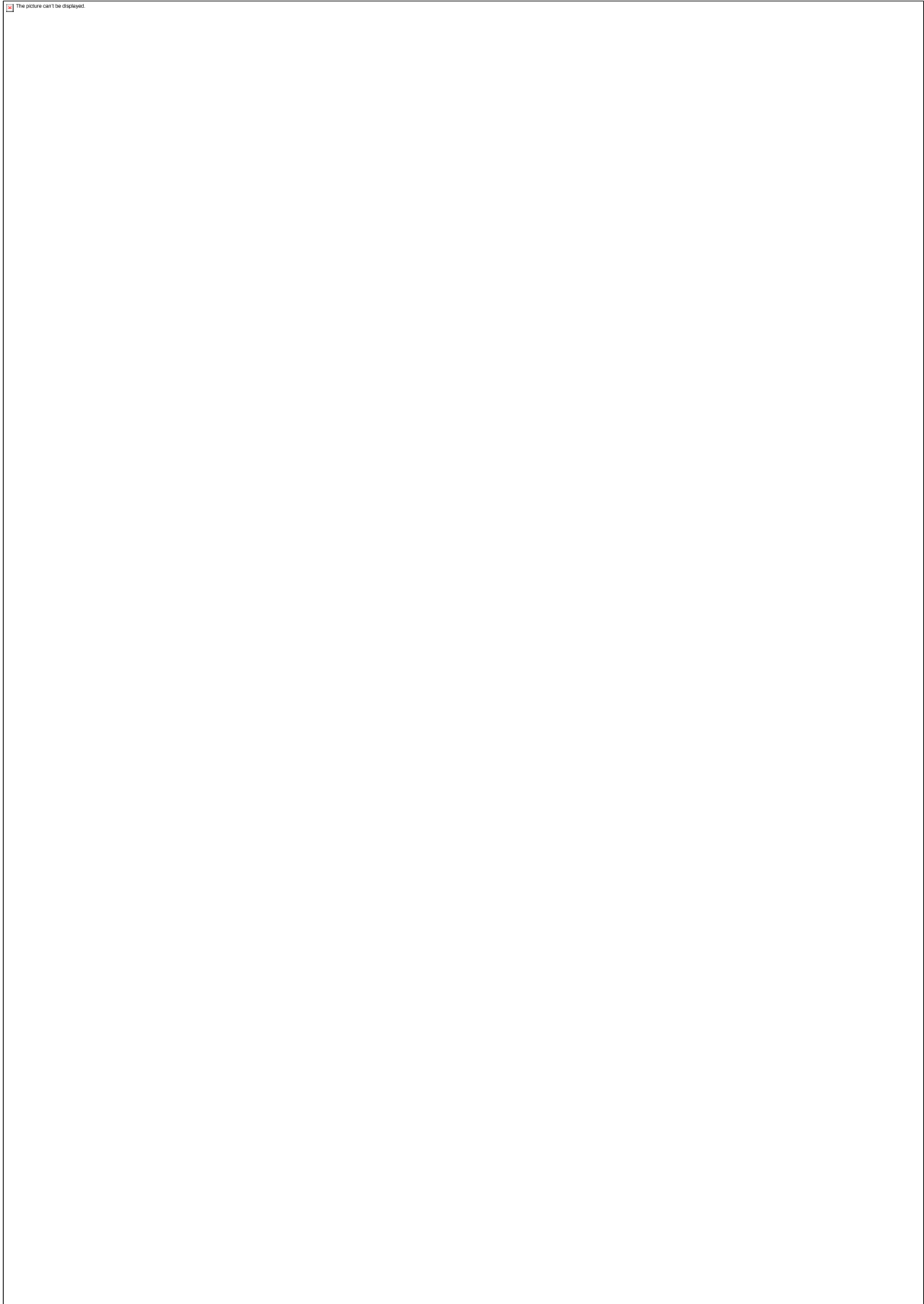
 The picture can't be displayed

 The picture can't be displayed

The picture can't be displayed

The picture can't be displayed

The picture can't be displayed



 The picture can't be displayed

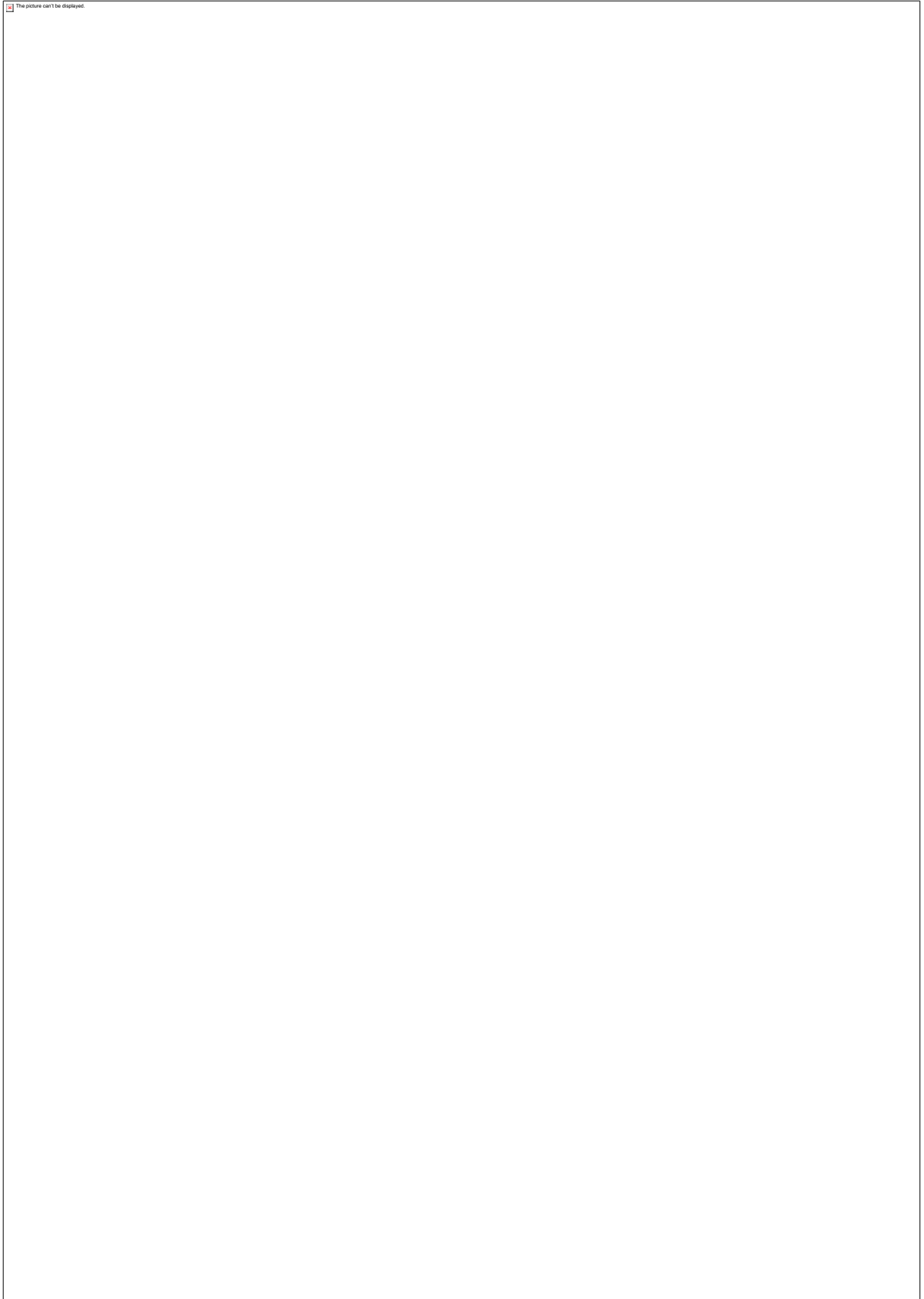
 The picture can't be displayed



 The picture can't be displayed

 The picture can't be displayed

 The picture can't be displayed



 The picture can't be displayed

 The picture can't be displayed

 The picture can't be displayed

 The picture can't be displayed



 The picture can't be displayed

**COVID-19 Έρευνα δεδηλωμένων προτιμήσεων σχετικά με την καθημερινή κύρια μετακίνησή σας**

**Μέρος Β: Χαρακτηριστικά μετακίνησης - Ποδήλατο**

\* 41. Ποιο από τα παρακάτω περιγράφει τη δική σας περίπτωση σχετικά με την καθημερινή κύρια μετακίνησή σας;

Χρησιμοποιώ πάντα την ίδια διαδρομή

Χρησιμοποιώ συχνά την ίδια διαδρομή, καμιά φορά επιλέγω εναλλακτική διαδρομή

Επιλέγω συχνά διαφορετικές διαδρομές

\* 42. Πόσο υπολογίζετε ότι διαρκεί η κύρια μετακίνησή σας σε λεπτά;  
πχ. Συμπληρώστε 10, αν είναι 10 λεπτά

\* 43. Πόση υπολογίζετε ότι είναι η χιλιομετρική απόσταση που διανύετε για την κύρια μετακίνησή σας;  
πχ. Συμπληρώστε 3.5, αν είναι 3.5 χλμ

\* 44. Αξιολογήστε την κύρια μετακίνησή σας ως προς τα παρακάτω:

	1 - Καθόλου ικανοποιητική	2 - Λίγο ικανοποιητική	3 - Μέτρια ικανοποιητική	4 - Ικανοποιητική	5 - Πολύ ικανοποιητική
Επίπεδα συνωστισμού	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Χρόνος διαδρομής	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Περιβάλλον διαδρομής	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

\* 45. Πόσο πρόθυμος/η είστε να αλλάξετε την ώρα της κύριας μετακίνησής σας λόγω συνωστισμού μετά από την προτροπή μηνύματος πληροφόρησης;

Καθόλου  Πολύ

Λίγο  Πάρα πολύ

Αρκετά

\* 46. Πόσο πιθανό είναι να αλλάζατε την ώρα της κύριας μετακίνησής σας μετά από λήψη ειδοποίησης για αποφυγή **υψηλού** συνωστισμού και μετάβαση σε **χαμηλό**.

	Καθόλου	Λίγο	Αρκετά	Πολύ	Πάρα πολύ
εώς 10 λεπτά νωρίτερα	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
εώς 30 λεπτά νωρίτερα	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
εώς 10 λεπτά αργότερα	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
εώς 30 λεπτά αργότερα	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

\* 47. Πόσο πιθανό είναι να αλλάζατε την ώρα της κύριας μετακίνησής σας μετά από λήψη ειδοποίησης για αποφυγή **υψηλού** συνωστισμού και μετάβαση σε **μέτριο**.

	Καθόλου	Λίγο	Αρκετά	Πολύ	Πάρα πολύ
εώς 10 λεπτά νωρίτερα	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
εώς 30 λεπτά νωρίτερα	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
εώς 10 λεπτά αργότερα	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
εώς 30 λεπτά αργότερα	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

\* 48. Πόσο πιθανό είναι να αλλάζατε την ώρα της κύριας μετακίνησής σας μετά από λήψη ειδοποίησης για αποφυγή **μέτριου** συνωστισμού και μετάβαση σε **χαμηλό**.

	Καθόλου	Λίγο	Αρκετά	Πολύ	Πάρα πολύ
εώς 10 λεπτά νωρίτερα	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
εώς 30 λεπτά νωρίτερα	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
εώς 10 λεπτά αργότερα	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
εώς 30 λεπτά αργότερα	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

\* 49. Θα επιθυμούσατε να ενημερώνεστε μέσω εφαρμογών τύπου Google maps ή κάποιου μέσου κοινωνικής δικτύωσης σχετικά με τα επίπεδα συνωστισμού της διαδρομής που χρησιμοποιείτε στην κύρια μετακίνησή σας;

<input type="radio"/> Καθόλου	<input type="radio"/> Πολύ
<input type="radio"/> Λίγο	<input type="radio"/> Πάρα πολύ
<input type="radio"/> Αρκετά	

\* 50. Ποιο είδος ενημέρωσης θα προτιμούσατε για να λάβετε πληροφορίες σχετικά με τα επίπεδα συνωστισμού κατά την κύρια μετακίνησή σας;

- Εφαρμογές τύπου Google maps
- Μέσα κοινωνικής δικτύωσης
- Κανένα

**COVID-19 Έρευνα δεδηλωμένων προτιμήσεων σχετικά με την καθημερινή κύρια μετακίνησή σας**

**Μέρος Δ: Πληροφορία και εμφάνιση μηνύματος**

**\* 51. Σε τι βαθμό διαφωνείτε/συμφωνείτε με τα παρακάτω;**

	Διαφωνώ απόλυτα	Διαφωνώ αρκετά	Ουδέτερη γνώμη	Συμφωνώ αρκετά	Συμφωνώ απόλυτα
Η χρήση χρωμάτων και γραφικών στις καρτέλες επιλογών έκανε πιο κατανοητό το περιεχόμενο τους	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Η χρήση χρωμάτων και γραφικών στις καρτέλες επιλογών έκανε πιο ελκυστικό και ευχάριστο οπτικά το περιεχόμενο τους	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Η χρήση χρωμάτων και γραφικών στις καρτέλες επιλογών επηρέασε την τελική μου επιλογή	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Η χρήση ιδίων χρωμάτων και γραφικών στις καρτέλες επιλογών ενισχύει την αντικειμενικότητα των τελικών σας επιλογών	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

**COVID-19 Έρευνα δεδηλωμένων προτιμήσεων σχετικά με την καθημερινή κύρια μετακίνησή σας****Μέρος Ε: Επίδραση της νόσου COVID-19 στην κύρια μετακίνηση**

\* 52. Η κύρια μετακίνησή σας μετά την εξάπλωση της νόσου COVID-19 σε **περίοδο lockdown** πραγματοποιείται:

- με την ίδια συχνότητα
- με μικρότερη συχνότητα
- καθόλου

\* 53. Η κύρια μετακίνησή σας μετά την εξάπλωση της νόσου COVID-19 σε **περίοδο εκτός lockdown** πραγματοποιείται:

- με την ίδια συχνότητα
- με μικρότερη συχνότητα
- καθόλου

\* 54. Υπήρξε αλλαγή στο μέσο της κύριας μετακίνησής σας λόγω της εξάπλωσης της νόσου COVID-19;

- Ναι
- Όχι

\* 55. Πόσο σημαντικά είναι για εσάς τα παρακάτω **META** την εξάπλωση της νόσου COVID-19;

	1 - Καθόλου	2 - Λίγο	3 - Αρκετά	4 - Πολύ	5 - Πάρα πολύ
Υποχρεωτική χρήση μάσκας σε εξωτερικούς χώρους	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Υποχρεωτική χρήση μάσκας σε εσωτερικούς χώρους (Μέσα Μαζικής Μεταφοράς, συνεπιβάτες αυτοκινήτου)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Κοινωνική απόσταση (Social distancing)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Επίπεδα καθαριότητας και απολύμανσης σε δημόσιους χώρους	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Δημόσια υγεία	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Αίσθημα ασφάλειας (απουσία ανησυχίας μόλυνσης/ εμφάνιση ασθένειας)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Αίσθημα ατομικής ευθύνης των ανθρώπων γύρω σας	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Μέτρα προσωπικής υγιεινής (πλύσιμο χεριών, αποστείρωση κτλ)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

\* 56. Πόσο ικανοποιημένοι είστε με τα παρακάτω **META** την εξάπλωση της νόσου COVID-19;

	1 - Καθόλου	2 - Λίγο	3 - Μέτρια	4 - Πολύ	5 - Πάρα πολύ
Υποχρεωτική χρήση μάσκας σε εξωτερικούς χώρους	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Υποχρεωτική χρήση μάσκας σε εσωτερικούς χώρους (Μέσα Μαζικής Μεταφοράς, συνεπιβάτες αυτοκινήτου)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Κοινωνική απόσταση (Social distancing)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Επίπεδα καθαριότητας και απολύμανσης σε δημόσιους χώρους	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Δημόσια υγεία	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Αίσθημα ασφάλειας (απουσία ανησυχίας μόλυνσης/ εμφάνισης ασθένειας)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Αίσθημα ατομικής ευθύνης των ανθρώπων γύρω σας	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Μέτρα προσωπικής υγιεινής (πλύσιμο χεριών, αποστείρωση κτλ)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

**COVID-19 Έρευνα δεδηλωμένων προτιμήσεων σχετικά με την καθημερινή κύρια μετακίνησή σας**

**Μέρος ΣΤ: Πληροφορίες συμμετέχοντα**

**\* 57. Φύλο**

Γυναίκα

Άνδρας

**\* 58. Ηλικία**

18-23

24-40

41-65

66 και άνω

**\* 59. Επάγγελμα / Κύρια ασχολία**

Φοιτητής/ -τρια

Εργαζόμενος/ -η μερικής απασχόλησης (ιδιωτικού τομέα)

Εργαζόμενος/ -η πλήρους απασχόλησης (ιδιωτικού τομέα)

Εργαζόμενος/ -η μερικής απασχόλησης (Δημοσίου τομέα)

Εργαζόμενος/ -η πλήρους απασχόλησης (Δημοσίου τομέα)

Ελεύθερος Επαγγελματίας

Οικιακά

Άνεργος

Συνταξιούχος

Άλλο

**\* 60. Τόπος διαμονής**  
π.χ. Βόλος

**\* 61. Μηνιαίο εισόδημα**

0-500

501-1000

1001-1500

>1501



COVID-19 Έρευνα δεδηλωμένων προτιμήσεων σχετικά με την καθημερινή κύρια μετακίνησή σας

Τέλος ερωτηματολογίου

Σας ευχαριστούμε πολύ για τη συμμετοχή σας.

**Annex L:** Mobility in the COVID-19 era- tables and charts.

The COVID-19 pandemic has had a significant impact on transportation and mobility patterns around the world. Pedestrians, public transport users, cyclists, car/motorbike users have all been affected by the pandemic, with restrictions significantly impacting their mobility. COVID-19 related aspects that affected the mobility of different transport mode users and emerged due to the pandemic can be found in the following tables. The collected data from 925 individuals in Greece that participated to the online survey were used to detect differences among groups of pedestrians, public transport users, cyclists, car/motorbike users. Results showed that public health and safety measures such as social distancing, mask-wearing, increased cleaning, etc. are essential to ensure the safety of all mobility users. The performance analysis also highlighted areas where improvements are needed such as social distancing, cleanliness/ disinfection in public spaces and Public Health. Crowd avoidance plays a significant role in shaping mobility decisions for pedestrians, public transport users and cyclists. A thorough analysis for pedestrians and public transport users can be found in Chapter 7. Annex M includes the descriptive statistics of bicyclists’ group.

Table L1. Descriptive statistics of pedestrians, public transport users, cyclists, other.

<b>Variables</b>	<b>Pedestrians (%)</b>	<b>Public transport users (%)</b>	<b>Car/motorbike users (%)</b>	<b>Cyclists (%)</b>	<b>Other (%)</b>
<i>Gender</i>					
Female	56	49	56	60	67
Male	44	51	44	40	33
<i>Age</i>					
18-23	52	40	18	42	17
24-40	41	58	61	44	50
41-65	7	2	19	14	33
>66	0	0	2	0	0
<i>Monthly income</i>					
0-500	66	53	25	58	33
501-1000	21	29	39	26	17
1001-1500	8.5	11	25	12	50
>1501	4.5	7	11	4	0
<i>Occupation</i>					
Students	58	46	20	56	33
Part-time job (private sector)	4	12	6	0	0
Full-time job (private sector)	15	30	30	10	17
Part-time job (public sector)	1	1	3	2	0
Full-time job (public sector)	5	5	21	12	50
Freelancer	7	6	12	12	0
Household	1	0	1	0	0

<b>Variables</b>	<b>Pedestrians (%)</b>	<b>Public transport users (%)</b>	<b>Car/motorbike users (%)</b>	<b>Cyclists (%)</b>	<b>Other (%)</b>
Unemployed	6	0	4	6	0
Retired	1	0	2	2	0
Other	1	0	1	0	0
<i>Place of residence</i>					
Large-sized (Athens)	23	49	24	4	33,3
Medium-sized (Thessaloniki, Patra, Heraklion, Larisa, Volos)	50	45	37	68	33,3
Small-sized	27	6	39	28	33,3

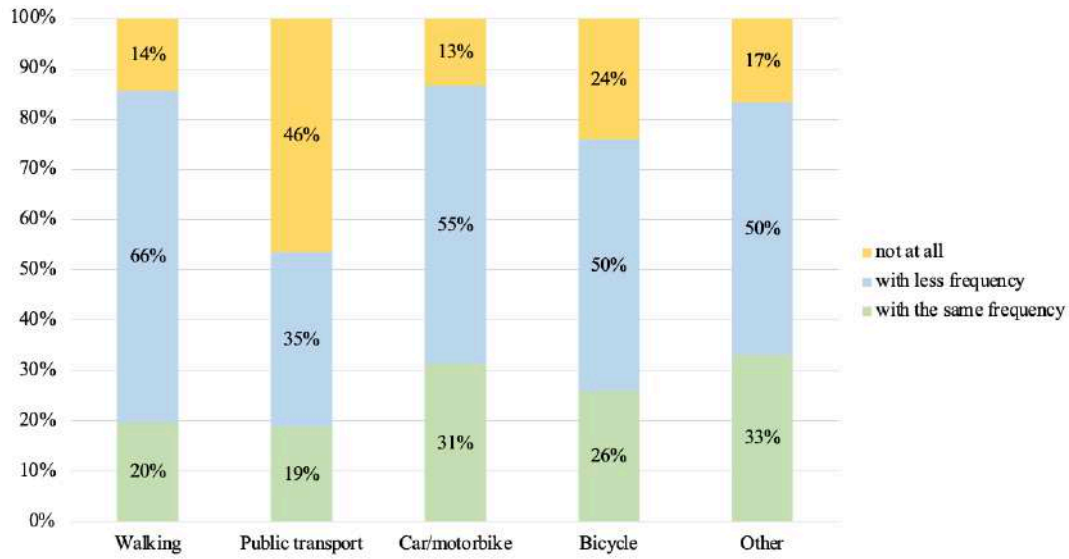


Figure L1. Frequency of daily main trip after the spread of COVID-19 during a lockdown period.

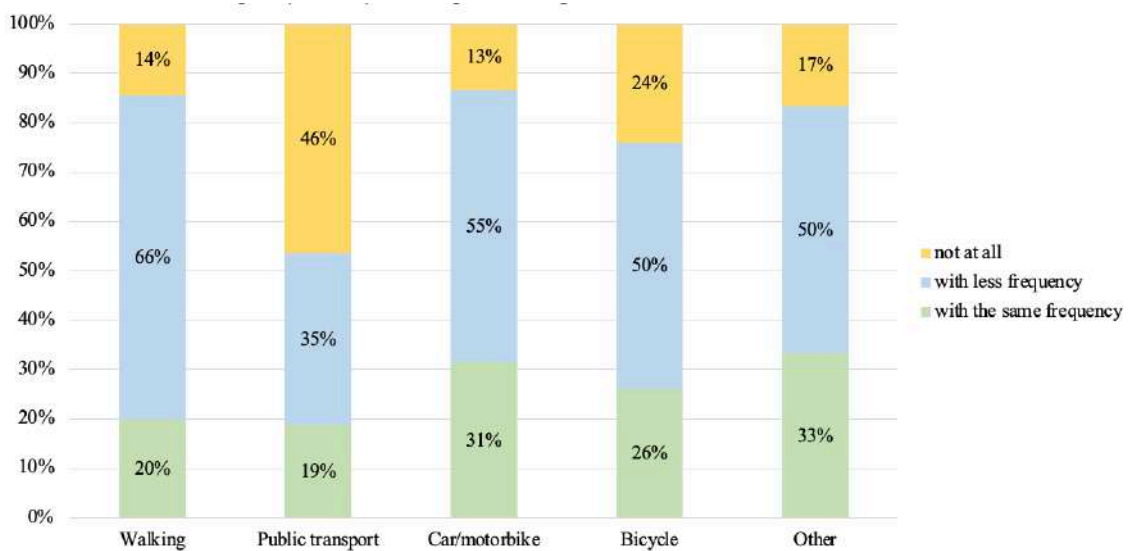


Figure L2. Frequency of daily main trip after the spread of COVID-19 without a lockdown.

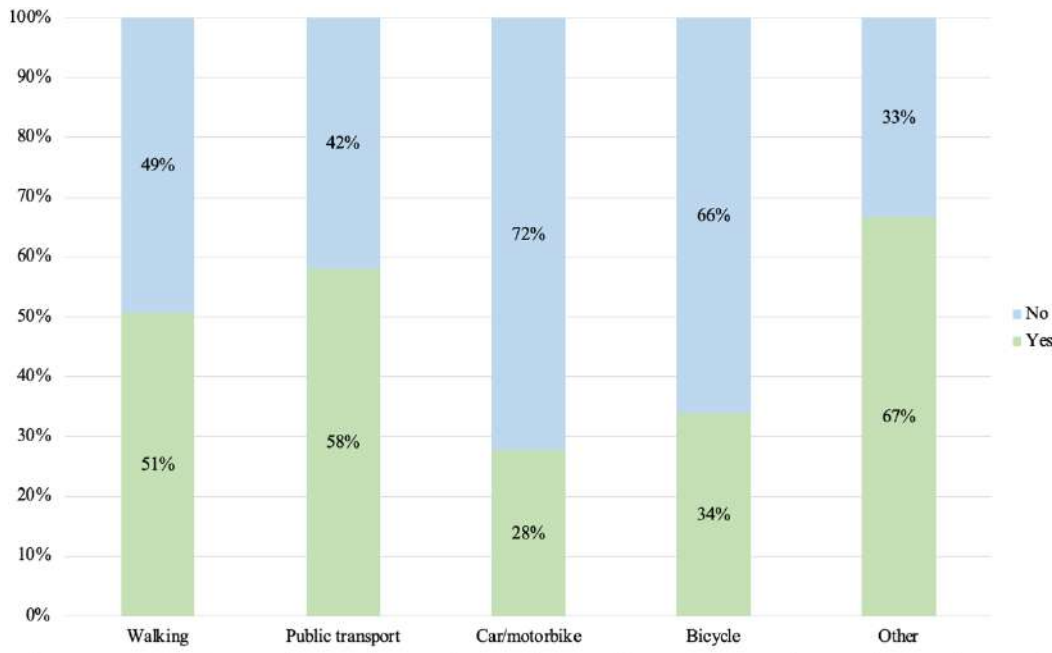
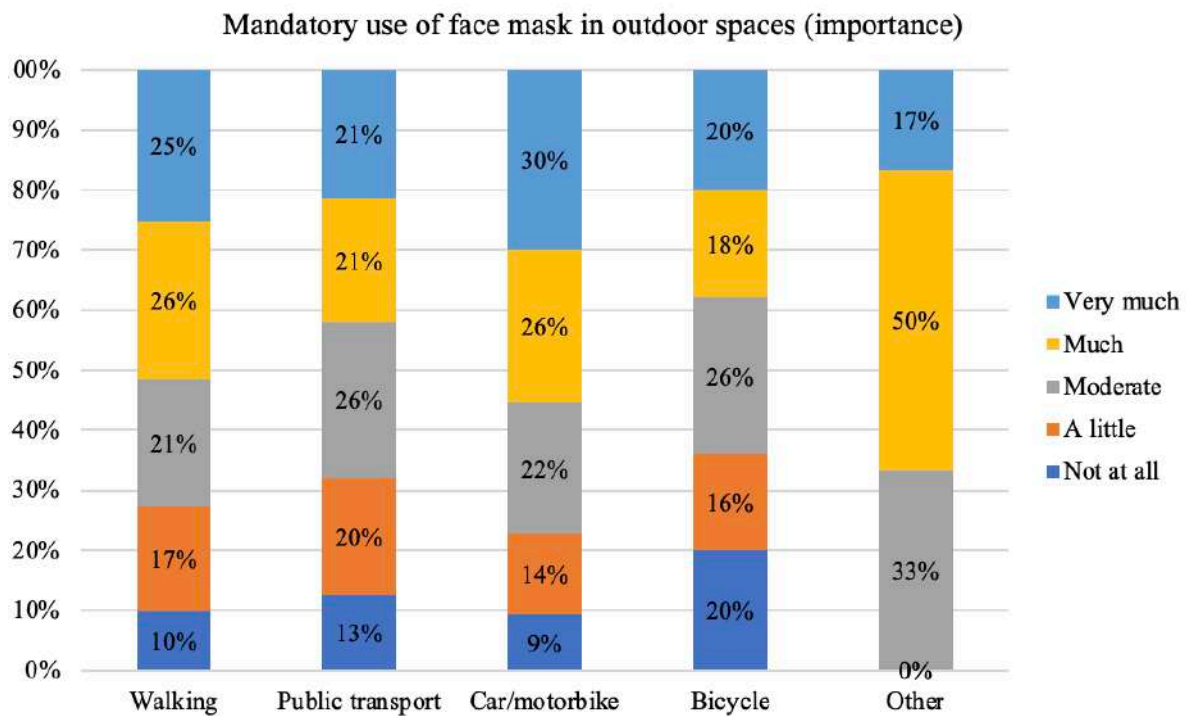
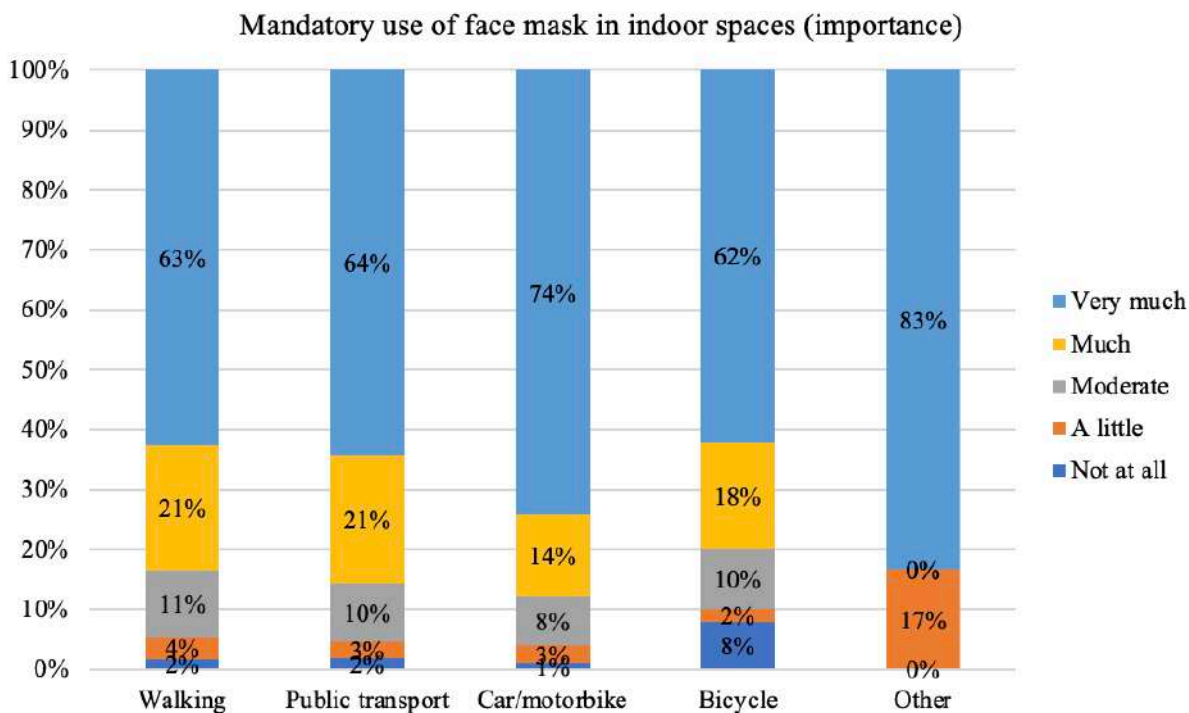


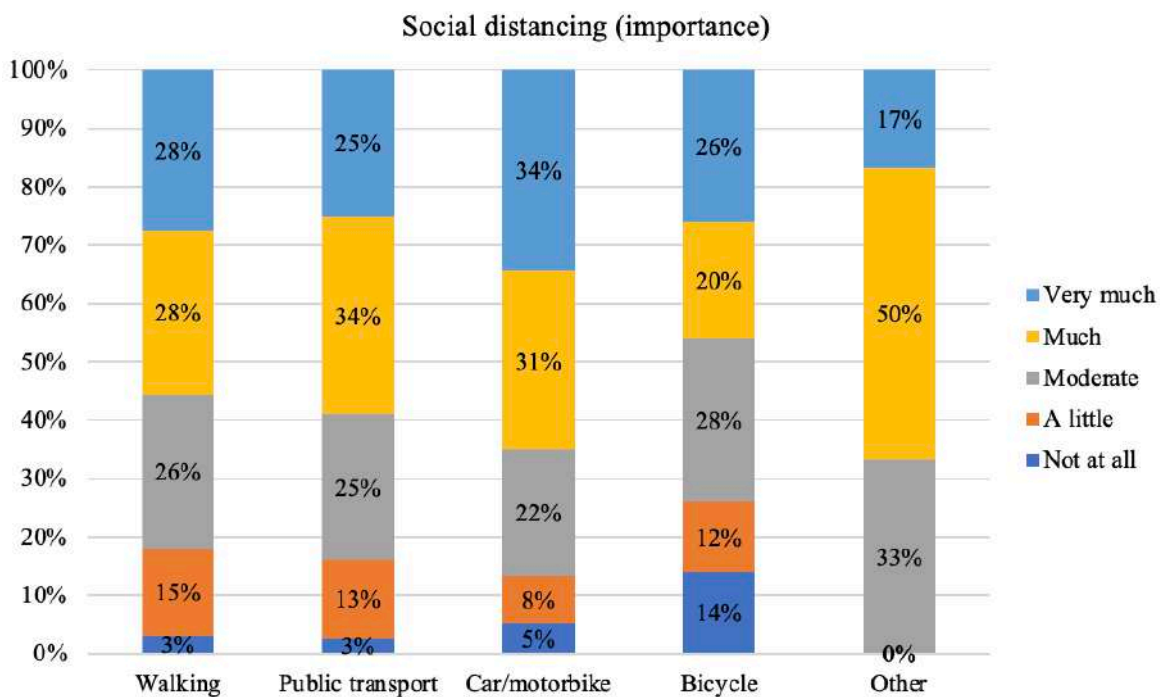
Figure L3. Change of transport mode of daily main trip due to the spread of COVID-19



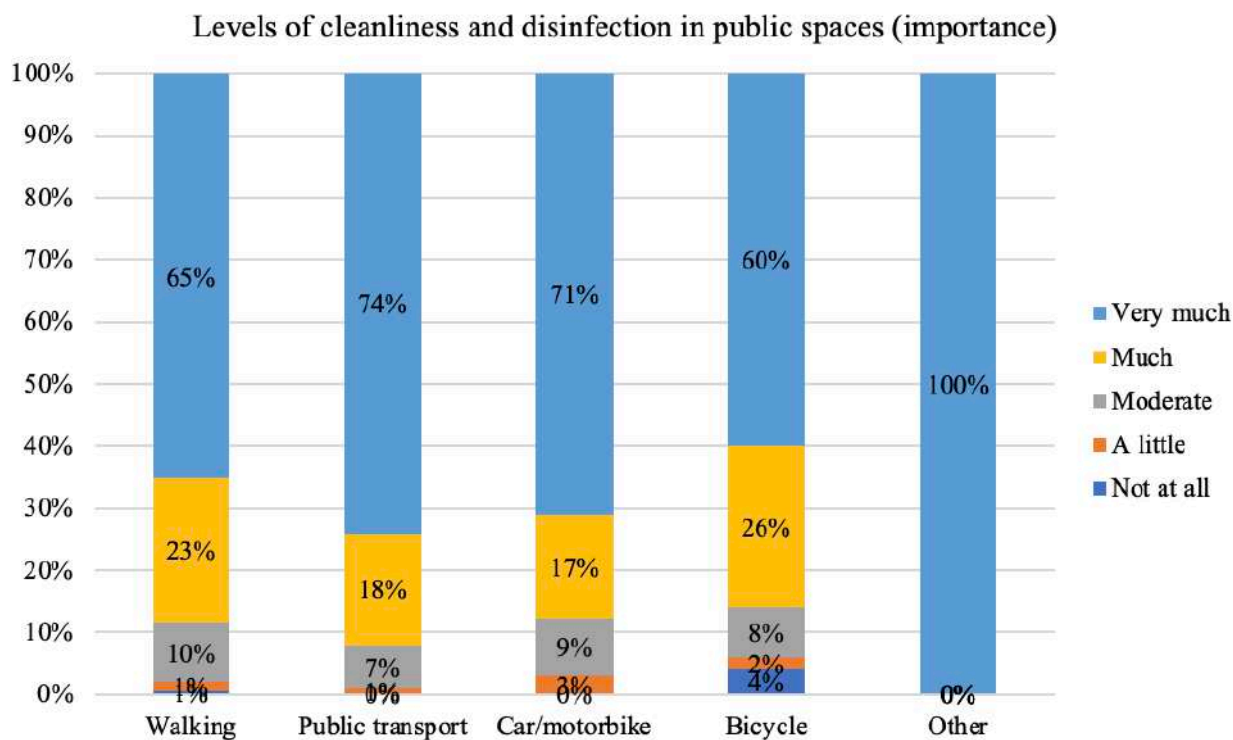
(a)



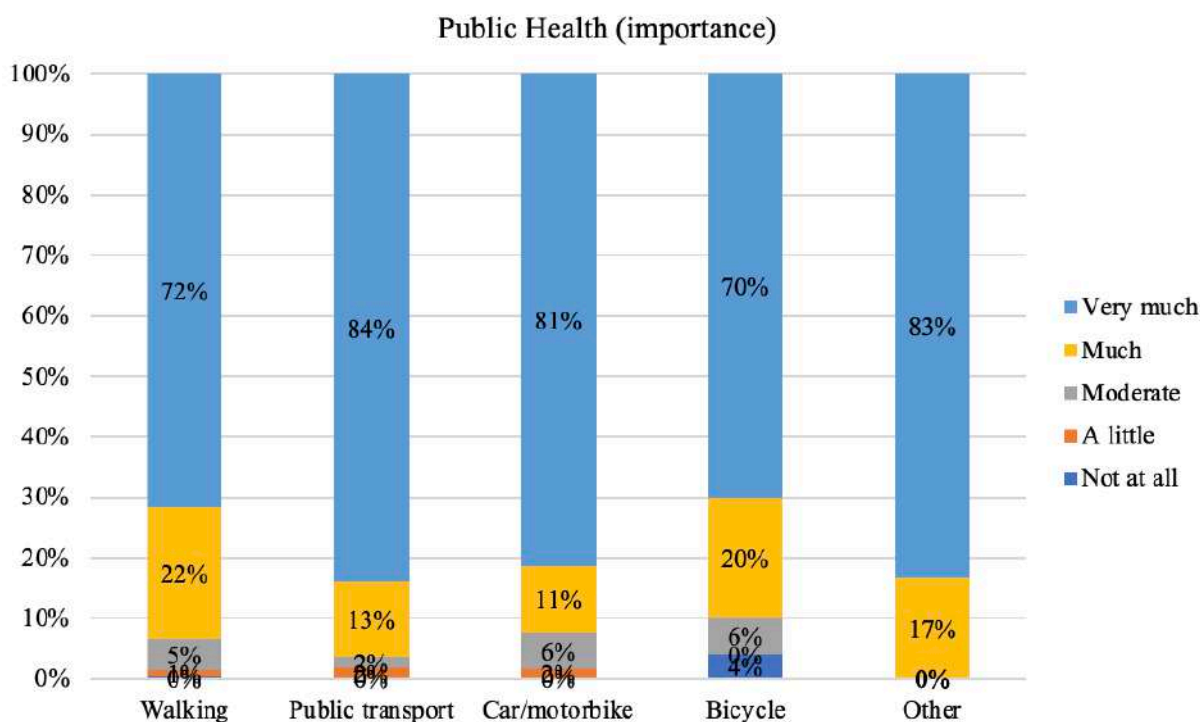
(b)



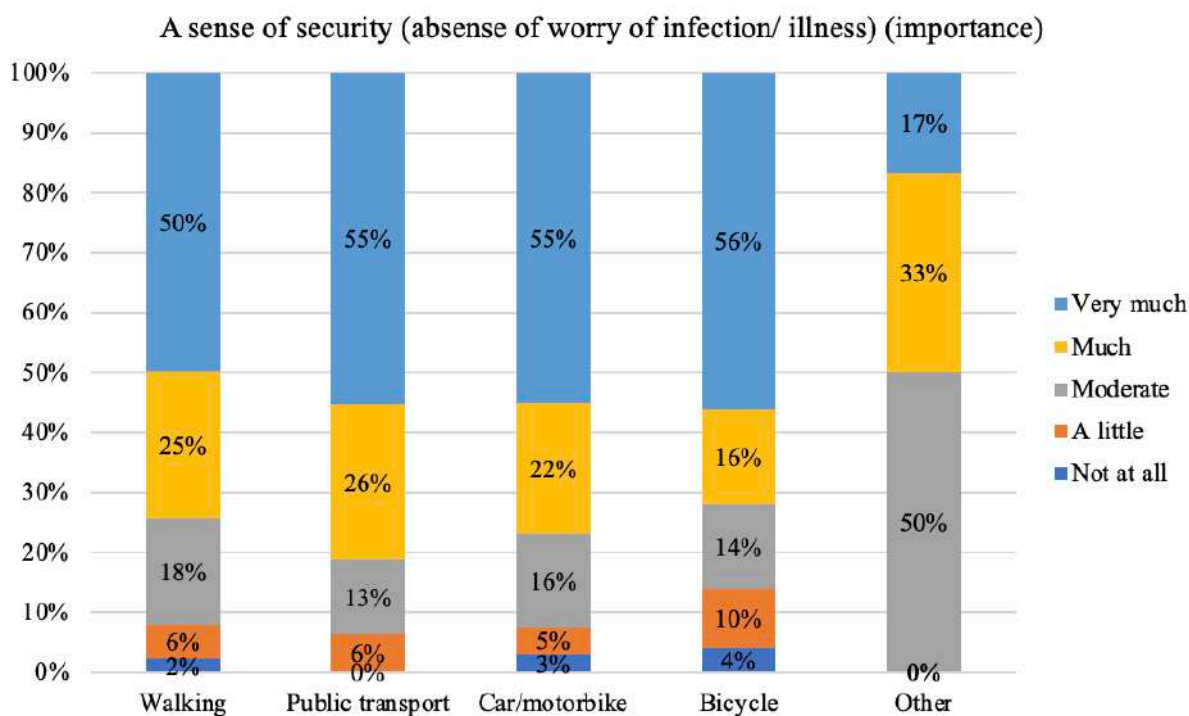
(c)



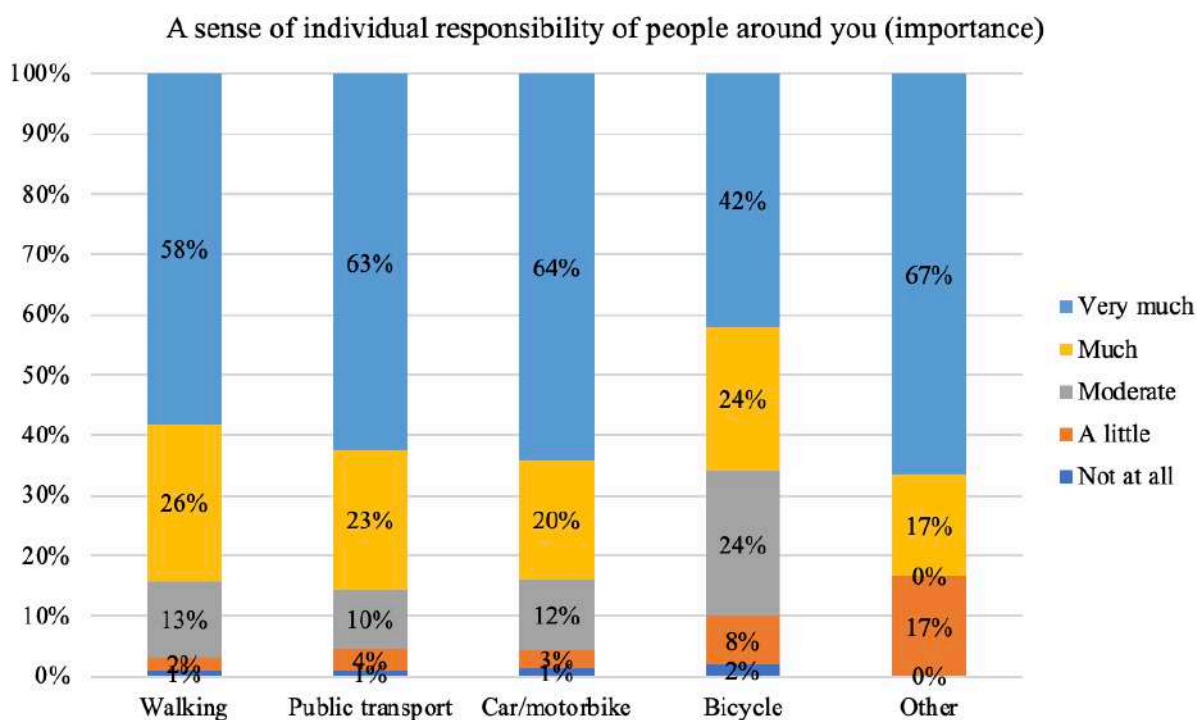
(d)



(e)

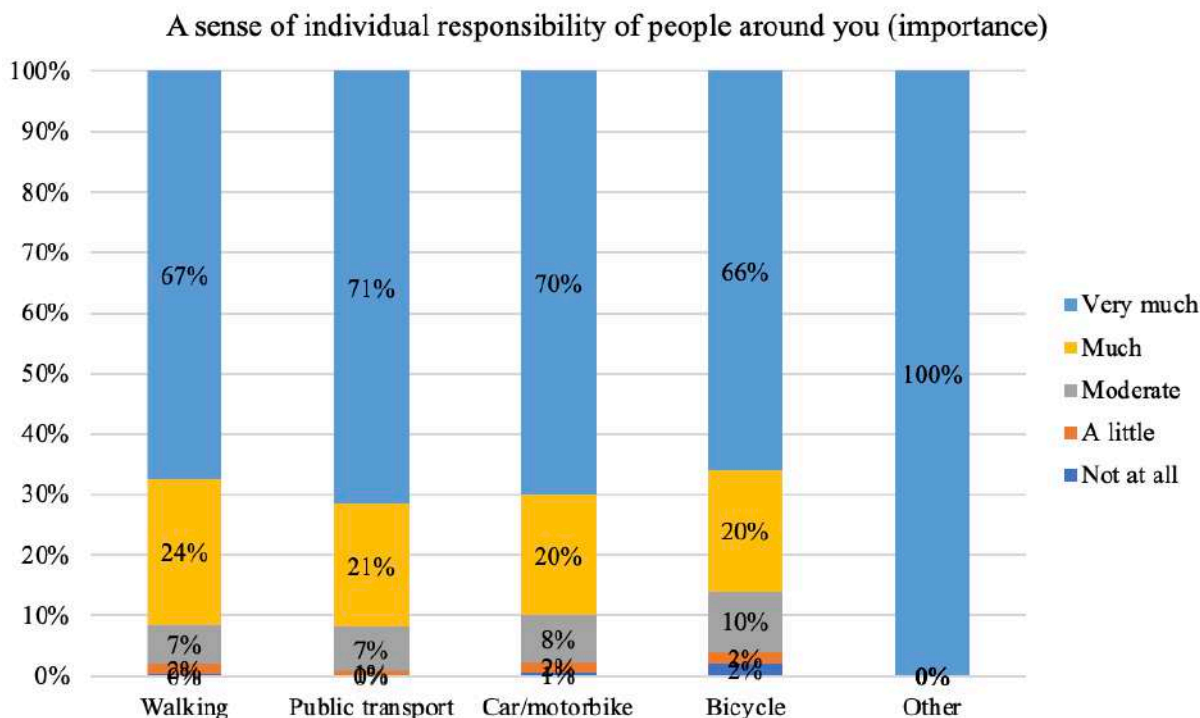


(f)



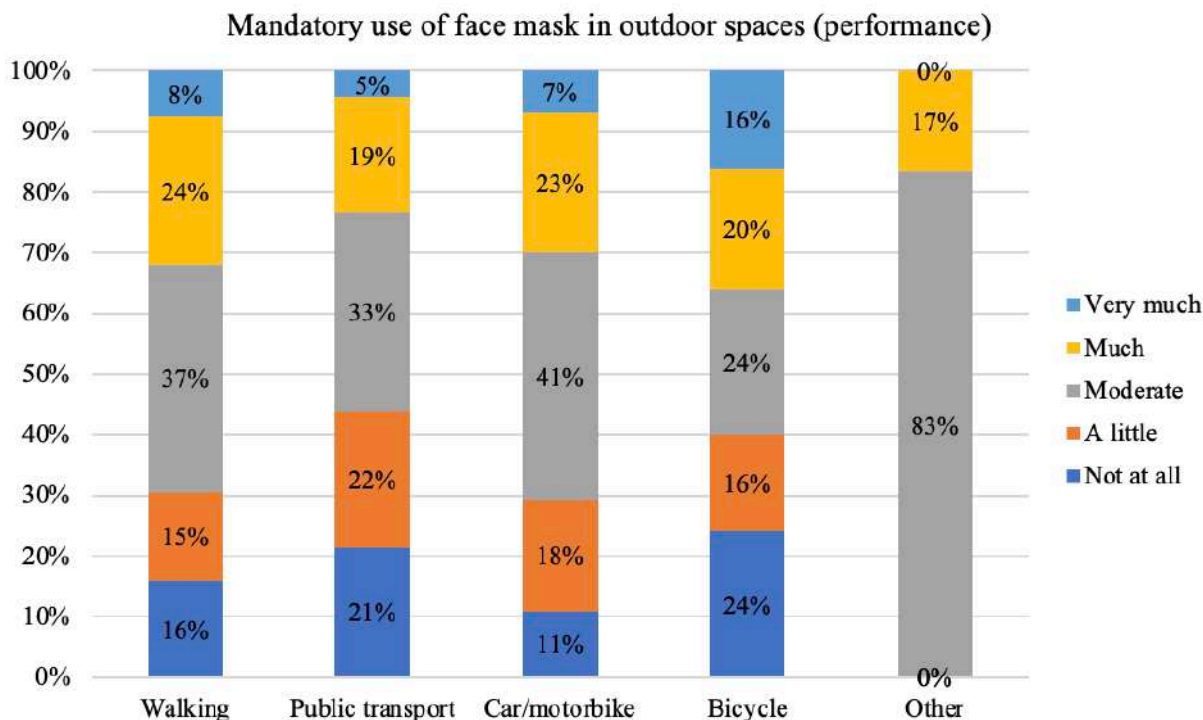
(g)



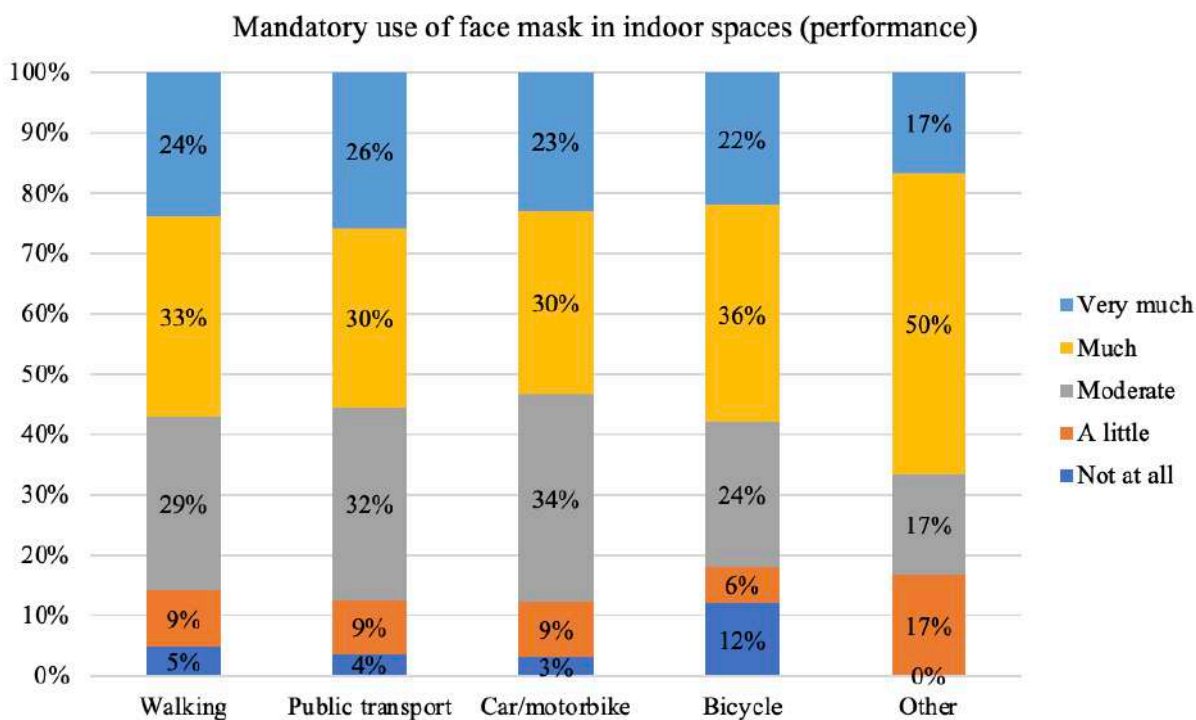


(h)

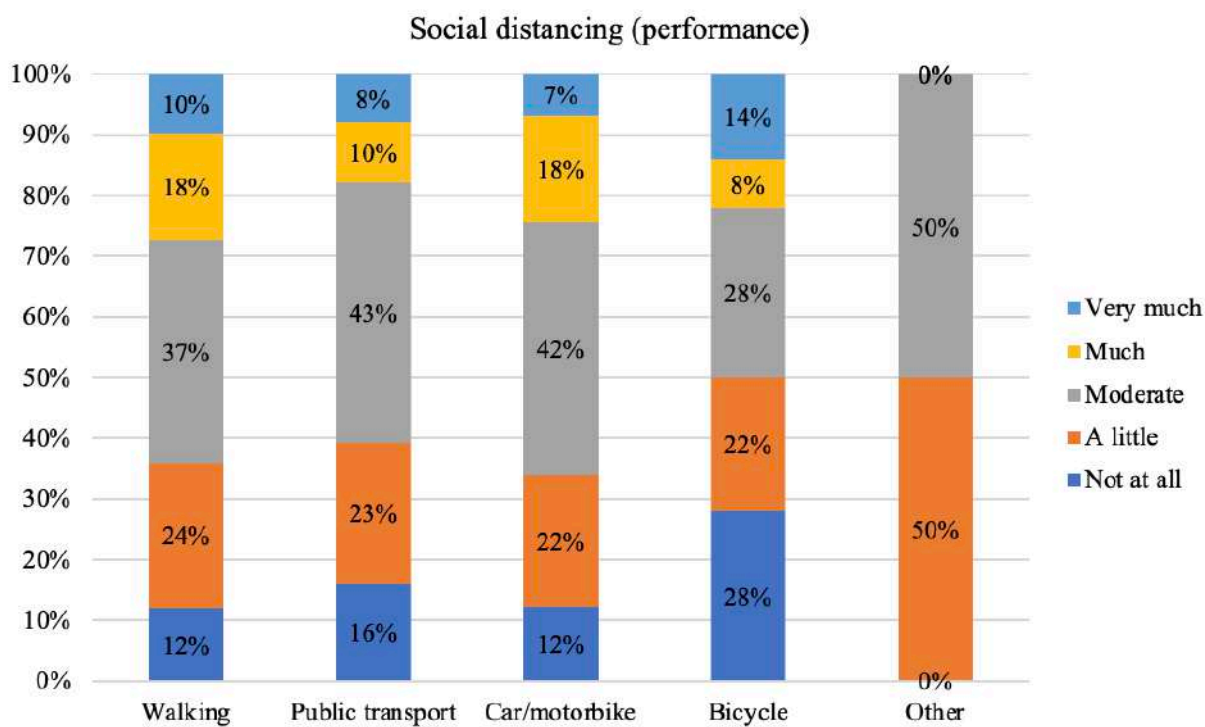
Figure L4. Importance of COVID-19 related parameters: (a) Mandatory use of face mask in outdoor spaces (b) Mandatory use of face mask in indoor spaces (c) Social distancing (d) Levels of cleanliness and disinfection in public spaces (e) Public Health (f) A sense of security (absence of worry of infection/ illness) (g) A sense of individual responsibility of people around you (h) Personal hygiene measures



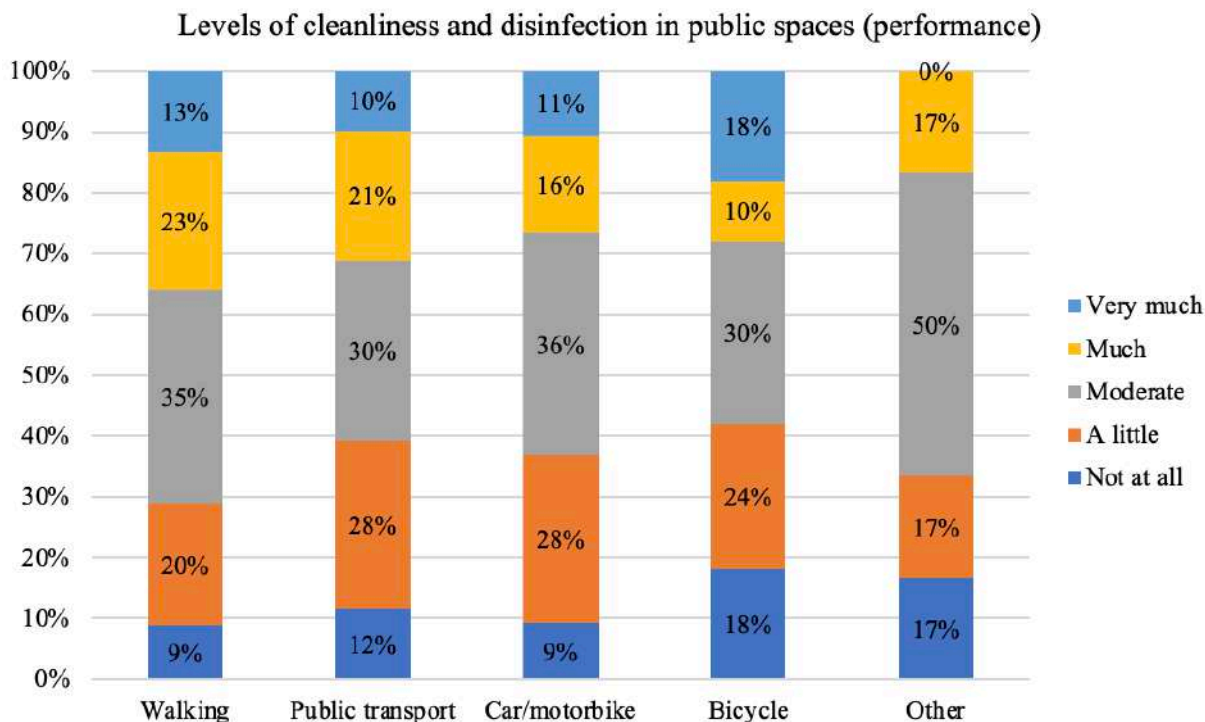
(a)



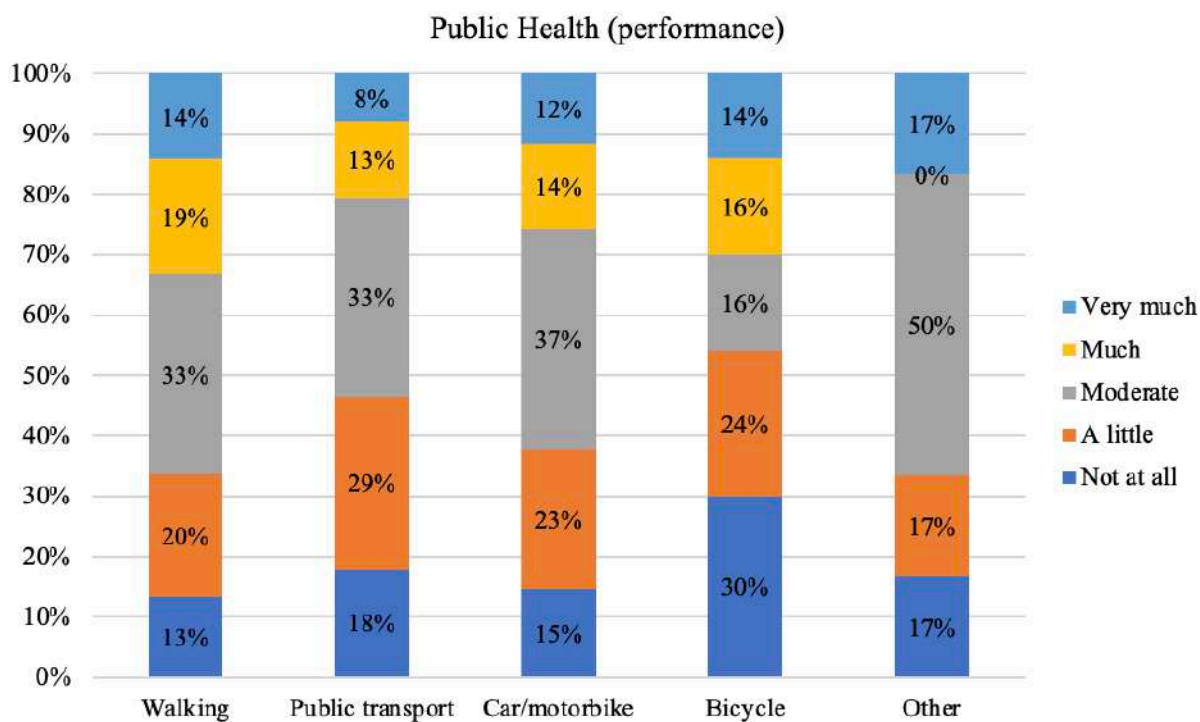
(b)



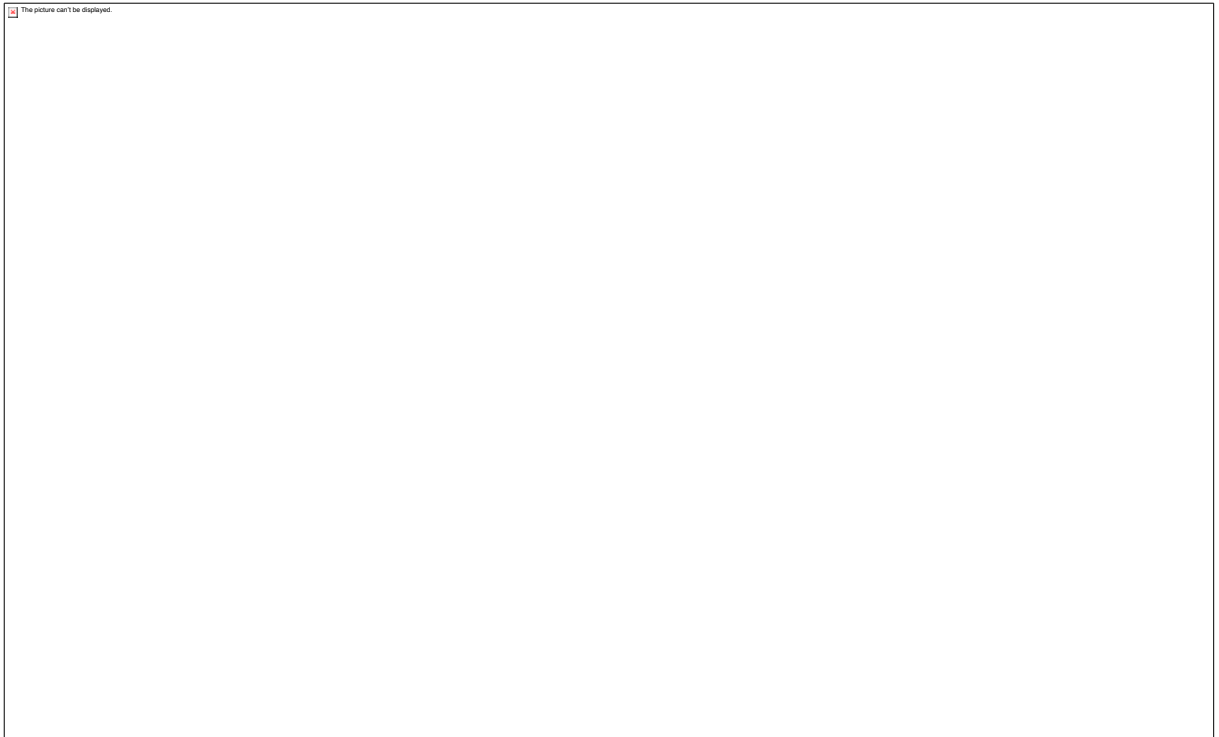
(c)



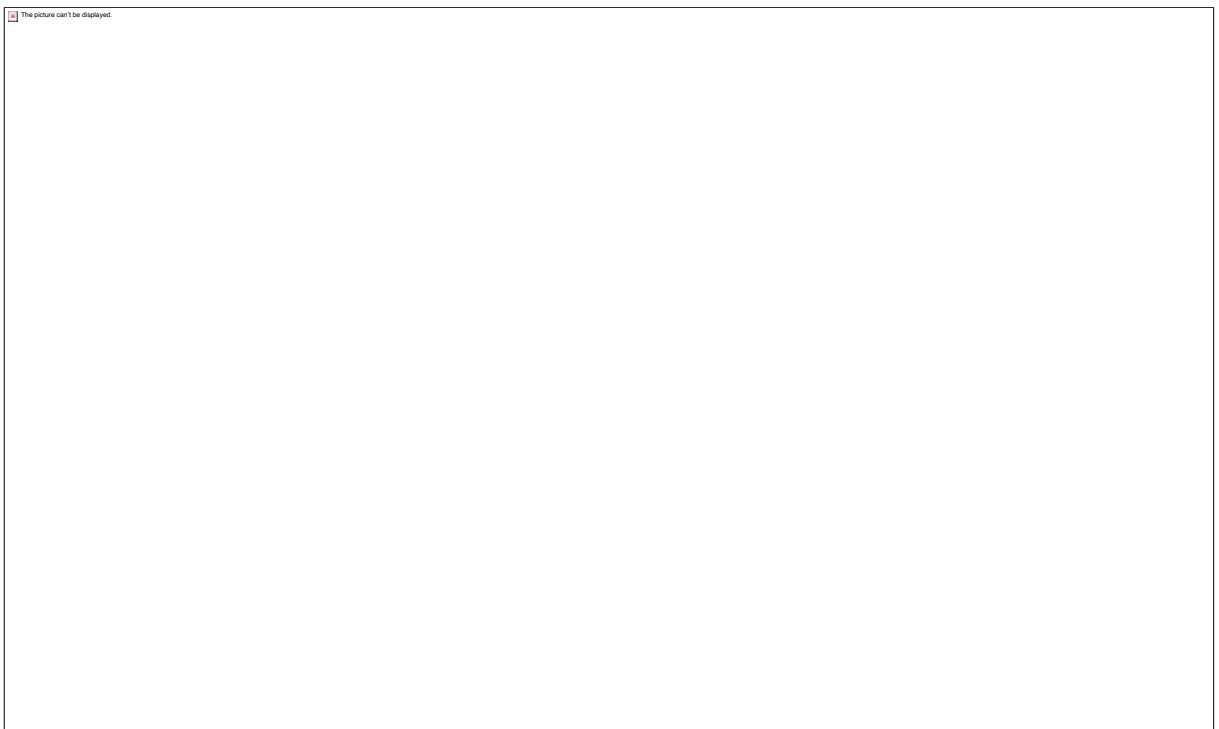
(d)



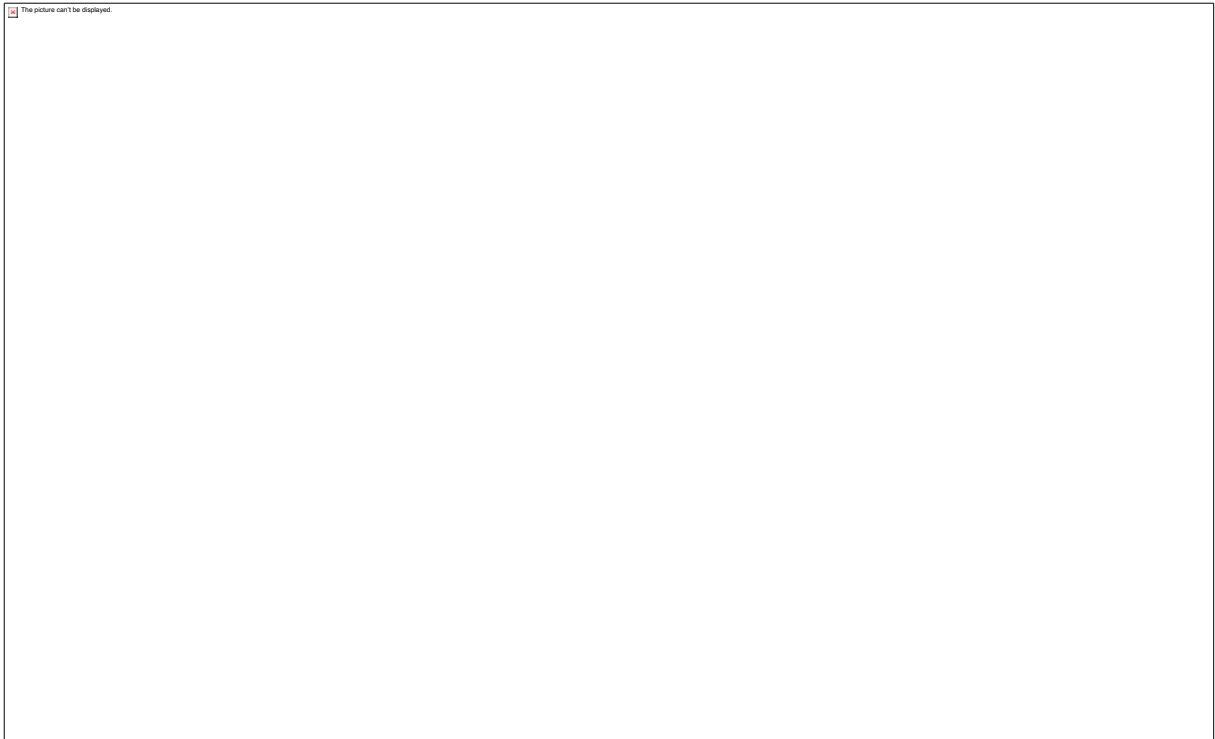
(e)



(f)



(g)



(h)

Figure L5. Performance of COVID-19 related parameters: (a) Mandatory use of face mask in outdoor spaces (b) Mandatory use of face mask in indoor spaces (c) Social distancing (d) Levels of cleanliness and disinfection in public spaces (e) Public Health (f) A sense of security (absence of worry of infection/ illness) (g) A sense of individual responsibility of people around you (h) Personal hygiene measures

**Annex M: Bicycle use in the COVID-19 era**

The descriptive statistics of the 50 bicycle users that participated in the survey can be found in the following tables.

Table M1. Bicycle use

Variable	Level	%
Which of the following sentences describes better your case regarding your daily main trip?	I always use the same route	18
	I usually use the same route, sometimes I choose another route	68
	I usually choose different routes	14

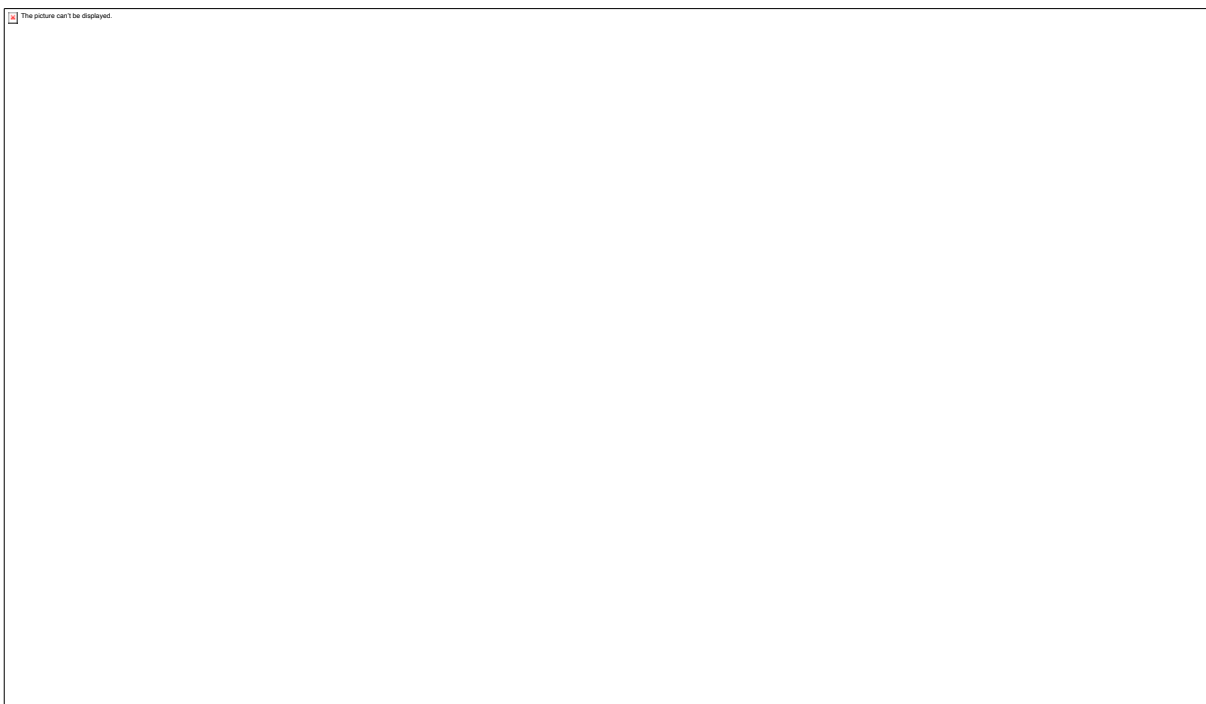
Table M2. Evaluation of bicycle daily main trip

Variable	Level	%
Evaluation of daily main trip with		
Crowdedness levels	Not at all satisfactory	6
	Slightly satisfactory	6
	Somewhat satisfactory	32
	Satisfactory	28
	Very satisfactory	28
Travel time	Not at all satisfactory	2
	Slightly satisfactory	2
	Somewhat satisfactory	18
	Satisfactory	52
	Very satisfactory	26
Biking environment	Not at all satisfactory	2
	Slightly satisfactory	16
	Somewhat satisfactory	32
	Satisfactory	30
	Very satisfactory	20

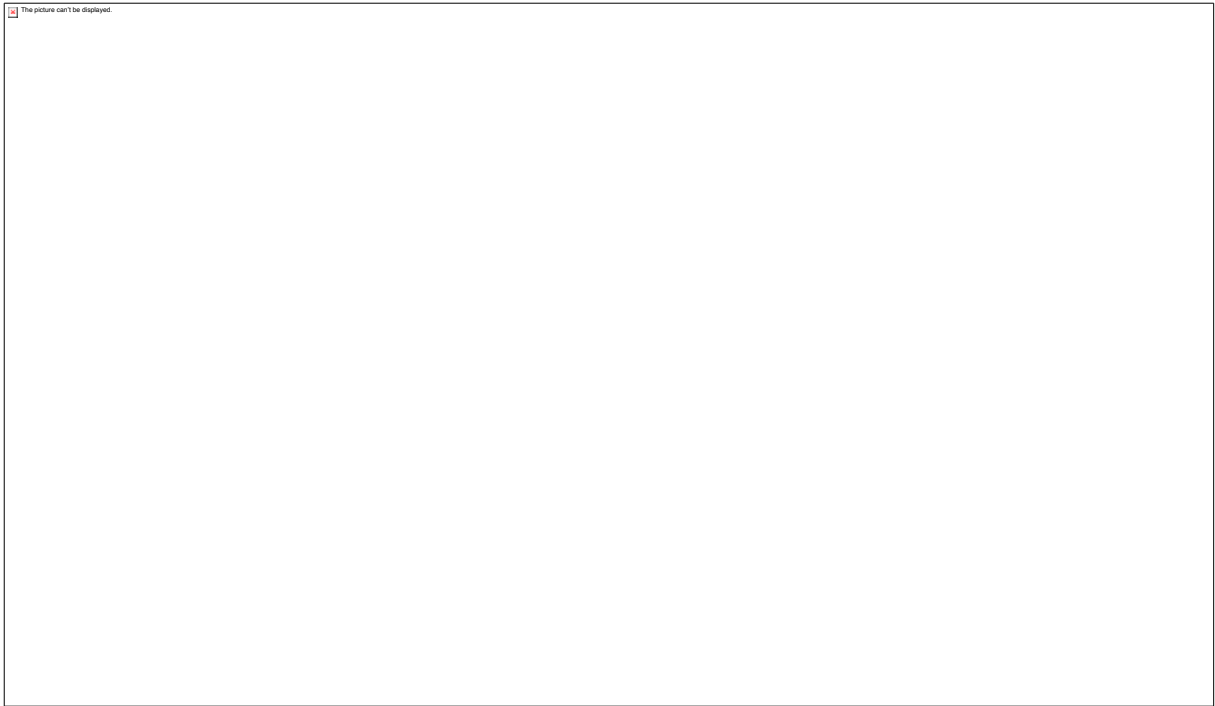
Table M3. Information about crowdedness levels on the bike route.

Variable	Level	%
Willingness to change usual route after receiving information about high levels of crowdedness on the main trip	Not at all	16
	A little	24
	Moderate	26
	Much	20
	Very much	14

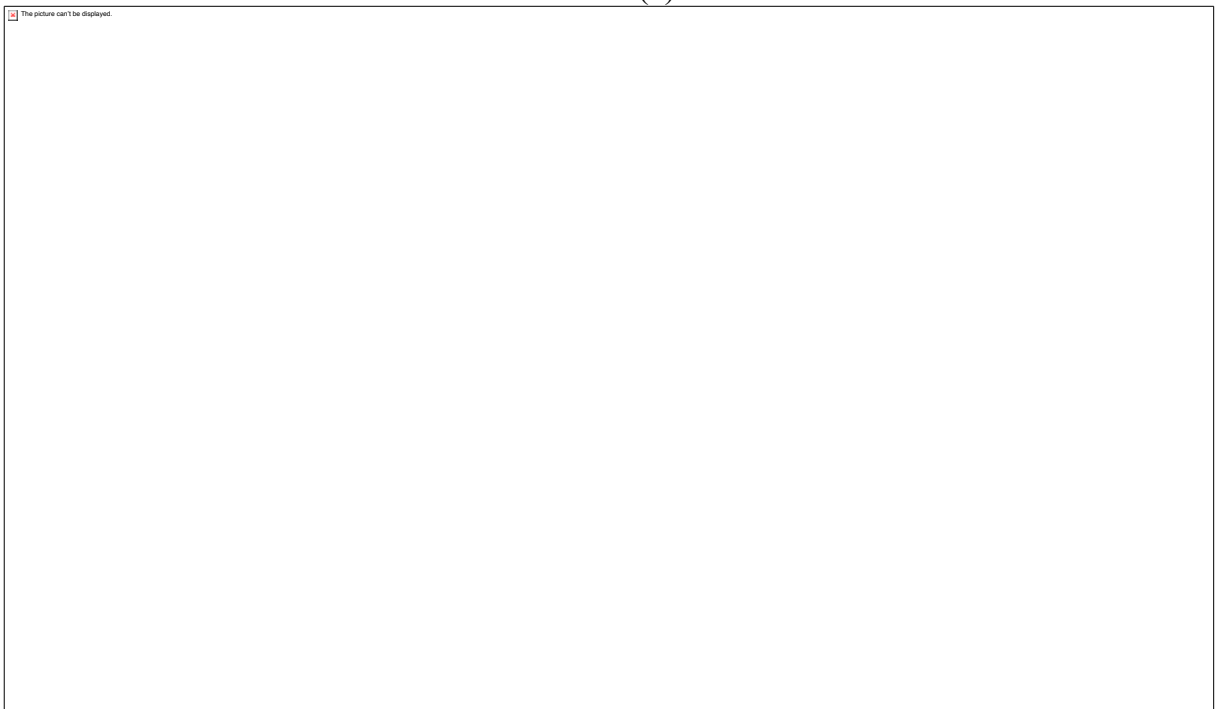
Variable	Level	%
Willingness to be informed via applications such as Google maps or social media about the crowdedness levels of the main trip	Not at all	12
	A little	20
	Moderate	34
	Much	16
	Very much	18
Source that would prefer to receive information about the crowdedness levels of the main trip	Applications such as Google maps	56
	Social media	28
	None	16



(a)



(b)



(c)

Figure M1. Willingness to change the departure time after receiving information about high levels of crowdedness on the main trip