



Driving Equitable and Accessible 15 Minute Neighbourhood Transformations

WP3.2/WP4.2

Deliverable D4.2.

Perceived accessibility of 15-minute neighbourhoods from residents living in the urban outskirts

Date: 05/06/2026

Responsible partners:

Universiteit Twente (UT),

Budapest University of Technology and Economics (BME)

Authors:

Daniela Arias Molinares (UT)

Dylan van Bezooijen (UT)

Ognjen Bobičić (BME)

Domokos Esztergár-Kiss (BME)



Document change record

Version	Date	Status	Author	Description
0.1	09/02/2026	Template	Daniela Arias Molinares,	Original draft
0.2	18/02/2026	Draft	Domokos Esztergár-Kiss, Ognjen Bobičić	Extended draft
0.3.	27/03/2026	Draft	Dylan van Bezooijen	Revised draft
0.4a	05/05/2026	Review	Yusak Susilo (BOKU)	Deliverable review
1.0.	05/06/2026	Final version	Domokos Esztergár-Kiss, Ognjen Bobičić, Dylan van Bezooijen	Revised after review

The DUT Partnership is supported by the European Commission and funded under the Horizon Europe co-funded Partnership scheme (Topic HORIZON-CL5-2021-D2-01-16).

TABLE OF CONTENTS

SUMMARY	9
1. INTRODUCTION	11
1.1. Background: The 15-Minute Neighbourhood and the DREAMS project	11
1.2. Objectives of the cross-city survey	11
1.3. Scope of the deliverable	12
1.4. Structure.....	12
1.5. The surveyed areas: DREAMS living labs	13
2. METHODOLOGY	14
2.1. Survey design	14
2.1.1. Survey perceived accessibility content	15
2.1.2. Survey choice experiment	15
2.2. Perceived accessibility model.....	20
2.3. Persona clustering.....	21
2.4. Choice experiment analysis.....	21
2.5. Data collection process.....	23
2.5.1. Sources	23
2.5.2. Data cleaning and valid sample	24
3. PERCEIVED ACCESSIBILITY	27
3.1. Description of the survey respondents.....	27
3.2. Reach and barriers	43
3.3. Key services, location criteria, and neighbourhood perceptions.....	47
3.4. Modelling perceived accessibility	52
3.5. Service-preference personas	53
4. CHOICE EXPERIMENTS	57
4.1. Brussels.....	57
4.2. Budapest.....	58
4.3. Munich.....	61
4.4. Paris.....	63
4.5. Utrecht.....	65
4.6. Vienna.....	67
4.7. Main finding from the choice experiments	69
5. CONCLUSIONS AND DISCUSSION	71
5.1. Importance of everyday services	71
5.2. Perceived accessibility.....	71
5.3. Service bundles and the relevance of personas	72
5.4. Behavioural validation through discrete choice modelling	72

5.5.	Limitations.....	73
6.	REFERENCES.....	73
7.	APPENDICES	75

LIST OF FIGURES

Figure 1 DREAMS living labs and surveyed areas.....	13
Figure 2: DREAMS survey design.....	14
Figure 3 Boxplot of survey completion time (min).....	25
Figure 4 Valid sample after cleaning (n=2,181 valid responses).....	26
Figure 5 Valid sample size in each living lab (n=2181).....	26
Figure 6 Age distribution of DREAMS survey respondents.....	27
Figure 7 Gender distribution in DREAMS survey respondent.....	28
Figure 8 Migrant background of DREAMS survey respondents.....	28
Figure 9 Education level of DREAMS survey respondents.....	29
Figure 10 Employment status of DREAMS survey respondents.....	30
Figure 11 Household situation of DREAMS survey respondents.....	31
Figure 12 Net household combined monthly income from DREAMS survey respondents.....	31
Figure 13 Telework frequency of DREAMS survey respondents.....	32
Figure 14 Respondents' digital skills with smartphone for mobility tasks.....	33
Figure 15 Share of respondents reporting reduced in-person activities due to online alternatives.....	34
Figure 16 Access to mobility-related resources at the household level.....	35
Figure 17 Mobility difficulties among DREAMS survey respondents.....	35
Figure 18 Top 10 amenities selected as important to have nearby.....	36
Figure 19 Age distribution for the top 10 services.....	37
Figure 20 Gender distribution for the top 10 services.....	38
Figure 21 Migration background distribution along the top 10 services.....	38
Figure 22 Household situation distribution for the top 10 services.....	39
Figure 23 Mode share per top 10 selected amenities.....	40
Figure 24 Frequency share per top 10 amenities.....	41
Figure 25 Current and desired travel times to top 10 amenities.....	41
Figure 26 Share of residents with 15-minute walk access to key services.....	42
Figure 27 Current number of locations per service that are visited throughout a year.....	43
Figure 28 Desired number of locations per service nearby the home.....	45
Figure 29 Perceived accessibility to selected services.....	46
Figure 30 Barriers for reaching the selected relevant services.....	47
Figure 31 Acceptability of solutions for accessibility barriers.....	48
Figure 32 Top 1 service to have nearby home.....	48
Figure 33 Criteria for choosing a specific location for their top 1 priority service.....	49

Figure 34 Desired services to have nearby that are not currently available.	50
Figure 35 Reasons behind the selection of a desired service.....	51
Figure 36 Overall neighbourhood walking accessibility rating	51
Figure 37: Persona reports for cluster 1: Essential needs-oriented persona.....	92
Figure 38: Persona reports for cluster 2: Family and child-oriented persona.....	93
Figure 39: Persona reports for cluster 3: Social oriented persona.....	94

LIST OF TABLES

Table 1 States Preferences Choice Experiment Design - Brussels	16
Table 2 Stated Preferences Choice Experiment Design – Budapest	16
Table 3 Stated Preferences Choice Experiment Design – Munich.....	17
Table 4 Stated Preferences Choice Experiment Design – Paris.....	18
Table 5 Stated Preferences Choice Experiment Design – Utrecht.....	19
Table 6: Stated Preferences Choice Experiment 1 Design – Vienna.....	19
Table 7 Stated Preferences Choice Experiment 2 Design – Vienna	20
Table 8: OLM parameters.....	52
Table 9 Persona sizes	54
Table 10 Top 10-prioritised services by global service-preference personas (ARC1-based clustering)	54
Table 11 Persona overview	56
Table 12 The transformed observed variables used in the model - Brussels	57
Table 13 Model fit statistics - Brussels.....	57
Table 14 MXL estimates for core choice attributes and random parameters - Brussels	57
Table 15 Estimated effects of socio-demographics and trip purpose on mode utilities - Brussels	58
Table 16 The transformed observed variables used in the model - Budapest.....	59
Table 17 Choice Model fit statistics - Budapest	59
Table 18 MXL estimates for core choice attributes and random parameters - Budapest.....	59
Table 19 Estimated effects of socio-demographics and trip purpose on mode utilities - Budapest	60
Table 20 The transformed observed variables used in the model - Munich.....	61
Table 21 Model fit statistics - Munich.....	61
Table 22 MXL estimates for core choice attributes and random parameters - Munich.....	61
Table 23 Estimated effects of socio-demographics and trip purpose on mode utilities - Munich	62
Table 24 The transformed observed variables used in the model - Paris.....	63
Table 25 Model fit statistics - Paris	63
Table 26 MXL estimates for core choice attributes and random parameters - Paris.....	64
Table 27 Estimated effects of socio-demographics and trip purpose on mode utilities - Paris	64
Table 28 The transformed observed variables used in the model - Utrecht.....	65
Table 29 Model fit statistics - Utrecht	65
Table 30 MXL estimates for core choice attributes and random parameters – Utrecht	66
Table 31 Estimated effects of socio-demographics and trip purpose on mode utilities - Utrecht	66

Table 32 The transformed observed variables used in the CE1 model - Vienna	67
Table 33 Model fit statistics CE1 - Vienna.....	67
Table 34 MNL estimates CE1 - Vienna.....	68
Table 35 The transformed observed variables used in the CE2 model - Vienna.....	68
Table 36 Model fit statistics for CE2 - Vienna	68
Table 37 MNL estimates for CE2 - Vienna.....	69

SUMMARY

This deliverable presents the results of the cross-city survey conducted within the DREAMS project, focusing on residents' perceived accessibility to everyday services in urban outskirts (Layer 2 of the DREAMS decision-support tool). Building on the conceptual framework established in Deliverable 2.1, the analysis provides empirical evidence on how proximity, mobility options, and service availability are experienced by residents across six European Living Labs: Brussels, Budapest, Munich, Paris, Utrecht, and Vienna.

Based on a cleaned and validated sample of 2,181 respondents, the findings show that daily necessities and essential services dominate proximity preferences. Grocery stores are by far the most important service to have within walking or cycling distance, followed by basic healthcare services (pharmacies and general practitioners) and everyday retail such as bakeries. Leisure, cultural, and specialised services are valued, but consistently rank lower as top-priority proximity needs. Overall, respondents express a strong preference for short travel times, with walking emerging as the dominant mode for accessing nearby everyday services.

Across cities, perceived accessibility to core daily services is generally high. Most respondents report being able to reach essential amenities often or always using their preferred transport mode, indicating a relatively strong baseline of walkable and cyclable access in the surveyed urban-outskirts areas. At the same time, clear differences emerge between service domains: commercial and leisure services show relatively consistent 15-minute walking access across cities, whereas healthcare and especially education-related services display greater variability, pointing to more uneven accessibility conditions.

Reported accessibility barriers are mentioned by a relatively small share of respondents, with distance and transport connectivity emerging as the most common constraints. While this may suggest that most residents do not experience severe accessibility problems in their daily lives, it should not be interpreted as an absence of structural issues. Rather, the low prevalence of reported barriers likely reflects a combination of adaptation strategies, selective activity choices, and the normalisation of longer trips for certain services.

For policy makers results suggest improving access to transport modes does not necessarily improve perceived accessibility. The strongest effects on perceived accessibility come from equity issues such as income, mobility issues and gender. Hence, the findings suggest the most effective measures should focus on improving proximity to services disadvantaged population groups find important rather than improving transport options.

The analysis further highlights that residents' accessibility needs are best understood through bundles of services rather than single amenities. The personas presented in this report align closely with identifiable life situations, such as ageing in place or households with children, while others cut across socio-demographic groups, reflecting more universal or lifestyle-driven accessibility logics. These results can guide policymakers in finding the right balance of services corresponding to different lifestyles.

Discrete choice model results across the five living labs show clear sensitivity to travel time and travel cost. Respondents consistently prefer faster and more affordable options. At the same time, the models reveal substantial heterogeneity, particularly in cost sensitivity. While average effects follow expected behavioural patterns, individuals differ markedly in how they value time and monetary trade-offs.

Service functionalities have context-dependent effects. In Paris, infrastructure improvements, such as protected bike lanes significantly increase the attractiveness of shared micromobility. In Brussels, bundled discounts produce modest positive effects. In Munich and Budapest, most financial incentives remain statistically insignificant. Utrecht shows selective sensitivity, with flexible parking increasing shared moped utility while other incentives have limited influence, implying that infrastructure

improvements and spatial convenience tend to generate stronger behavioural responses than pricing incentives alone. In Vienna's retail experiments, larger store size, greater product variety, lower prices, shorter travel duration, and non-crowded environments significantly increase utility.

Socio-demographic and activity-based interactions further underline the importance of context. Younger individuals often show stronger preferences for shared and public modes in mobility settings, while in Vienna younger respondents display a greater preference for chain-branded establishments. Grocery and commerce trips consistently reduce the attractiveness of active and shared modes, whereas leisure and health-related trips often increase walking or public transport utility.

Taken together, the findings underscore that perceived accessibility in urban outskirts is shaped less by the mere availability of transport options and more by the spatial alignment of essential services with residents' everyday needs and life situations. While most respondents report satisfactory access to core amenities, the observed variations across service domains and population groups highlight persistent inequities that remain insufficiently addressed. The results point toward a clear policy implication: enhancing proximity to key services, particularly for disadvantaged groups, offers greater potential to improve perceived accessibility than transport-focused interventions alone. Furthermore, policy makers should consider that infrastructure quality and spatial convenience tend to be more effective in shaping behaviour than pricing incentives.

By integrating survey insights with behavioural modelling, the DREAMS framework provides a robust, evidence based foundation for designing more inclusive and context-sensitive accessibility strategies in European urban outskirts. By recognising the importance of service bundles, contextual preferences, and heterogeneous sensitivities to time and cost, the DREAMS framework provides a nuanced, evidence based foundation for designing more inclusive and effective accessibility strategies in European urban outskirts.

1. INTRODUCTION

This section introduces the context and objectives of this deliverable, its connection to the DREAMS project, and clarifies the analytical scope and structure of the report. Building on the conceptual and theoretical foundations developed in [Deliverable 2.1](#), this report focuses on residents' perceived accessibility in urban outskirts and contributes empirical evidence to support equitable and accessible 15-minute neighbourhood (15mN) transformations.

1.1. Background: The 15-Minute Neighbourhood and the DREAMS project

The 15-minute city (15mC) concept has gained substantial attention in recent years as a planning approach aimed at reducing car dependency and improving access to essential services through proximity-centred urban development. While the concept has been widely applied and discussed in dense urban cores, its applicability to urban outskirts remains contested due to lower densities, dispersed amenities, and higher levels of car dependency.

The DREAMS project ("[Driving Equitable and Accessible 15-Minute Neighbourhood Transformations](#)") addresses this gap by explicitly focusing on urban outskirts and by placing equity, accessibility, and user perspectives at the centre of the analysis. DREAMS conceptualises the 15-minute neighbourhood not as a rigid time threshold, but as a flexible framework that combines proximity, active mobility, local public transport, shared mobility services, and governance mechanisms to reduce car dependency while improving access to daily activities.

Deliverable 2.1 established the conceptual and theoretical foundations of the DREAMS framework through a systematic literature review. It introduced the DREAMS 15-minute neighbourhood (15mN) definition and identified six key components shaping 15mN transformations: density, diversity, design, human perspectives and needs, governance, and business models. Among these components, human perspectives and perceived accessibility emerged as a major knowledge gap in existing research, particularly in the context of urban outskirts. Moreover, in Work Package 3, the team is developing a decision-support tool to assess accessibility in urban outskirts from multiple complementary perspectives. This tool is structured around several analytical layers that jointly capture both objective and subjective dimensions of accessibility. The first layer of information in this tool is the current (objective) accessibility, measured through spatial and transport indicators that reflect the existing land-use and mobility system. In other words, this layer represents the services, opportunities and infrastructure that is currently there derived from land-use and transport data (e.g., OSM-based opportunities and network indicators, etc.). The second layer is called perceived accessibility, consists of survey-based perceived accessibility data, offering the subjective perceptions or residents' own assessments of how easily they can reach everyday amenities, considering individual needs, preferences, constraints, and lived experiences. Perceived accessibility is measured through a cross-city survey conducted in all DREAMS living labs. For more information about the layers, this report refers to [Deliverable 3.1](#)

Hence, this deliverable directly builds on that gap by empirically investigating how residents in urban outskirts perceive their accessibility to amenities, how these perceptions differ across population groups, and how they relate to potential pathways towards more equitable 15-minute neighbourhoods.

1.2. Objectives of the cross-city survey

This report presents the results of the DREAMS cross-city survey, and it presents the outputs of two tasks of the DREAMS project: Task 3.2 and Task 4.2. Task 3.2 "Perceived 15mC accessibility" examines perceived accessibility to everyday amenities across population groups and barriers to achieve 15-minute neighbourhoods in urban outskirts. This task provides input to Layer 2 of the DREAMS Decision Support Model: Perceived 15-minute neighbourhood accessibility. The main objectives of this task are to:

- Assess residents' perceived accessibility to everyday amenities in selected DREAMS living labs located in urban outskirts

- Examine how perceived accessibility varies across socio-demographic groups, travel needs, and activity preferences
- Identify perceived barriers and opportunities for achieving 15-minute neighbourhoods from a user-centred perspective
- Provide empirical insights into how proximity-centred planning and mobility services may contribute to more equitable and accessible 15mN transformations.

By focusing on perceptions rather than solely on objective accessibility indicators, this deliverable complements spatial and modelling-based analyses developed in the decision-support tool. It acknowledges that accessibility is not only shaped by infrastructure and land-use patterns, but also by individual needs, capabilities, constraints, and lived experiences. Task 4.2 “Pricing Strategies, societal and environmental goals” aims to examine the impacts of different pricing strategies of the uptake of shared mobility services and flexible activity hubs.

1.3. Scope of the deliverable

The analysis presented in this report reflects the layered design of the DREAMS survey, which was originally conceived as two separate survey instruments, corresponding to different work packages and tasks within the project. The DREAMS survey was implemented as one integrated survey consisting of two sequential components:

- Part I – Perceived Accessibility: a first part focusing on residents’ self-reported perceptions of accessibility to key amenities within their neighbourhoods. It captures perceived travel times, modal options, and satisfaction with access to daily activities, with particular attention to differences across socio-economic characteristics, gender, household composition, and mobility resources (corresponding to WP3, Task 3.2), and
- Part II – Choice Experiment: a second part consisting of the choice experiment results with findings focusing on how perceptions of accessibility relate to potential behavioural responses and future mobility choices (corresponding to WP4, Task 4.2.2).

This report is structured to first present the results from the perceived accessibility survey component, followed by the analysis of the choice experiment, reflecting the actual sequence experienced by respondents and the integrated nature of the data collection process. Overall, the scope of this deliverable is descriptive and analytical rather than evaluative. It does not aim to assess the performance of specific interventions, but rather to identify pathways and conditions under which 15-minute neighbourhood principles may become meaningful and feasible for residents living in urban outskirts.

1.4. Structure

The remainder of this deliverable is structured as follows. Section 2 presents the methodology. It first introduces the DREAMS living labs and the surveyed urban-outskirts areas, followed by a description of the integrated cross-city survey design. This includes the perceived accessibility survey (WP3, Task 3.2) and the stated preference choice experiment (WP4, Task 4.2), as well as the data collection strategy, sampling approach, and data cleaning procedures used to obtain the final valid sample. Section 3 reports the results of the survey and is divided into two main parts, reflecting the layered structure of the decision-support tool and the integrated survey design.

Section 3.1 (Part I) presents the perceived accessibility results. It starts with an overview of the sample characteristics and then analyses the importance of everyday services, current mobility behaviour, perceived reach and barriers, neighbourhood satisfaction, and residents’ priorities regarding proximity. The section concludes with a persona-based analysis that identifies bundles of service preferences and their socio-demographic profiles across cities. Section 3.2 (Part II) presents the stated preference choice experiment results, examining how respondents trade off accessibility, mobility, and service attributes under hypothetical scenarios, and how these behavioural preferences relate to the perceived accessibility patterns and personas identified in Part I. The deliverable concludes by synthesising the key findings and discussing their implications for equitable and accessible 15-minute neighbourhood transformations in urban outskirts, with supporting material provided in the appendices.

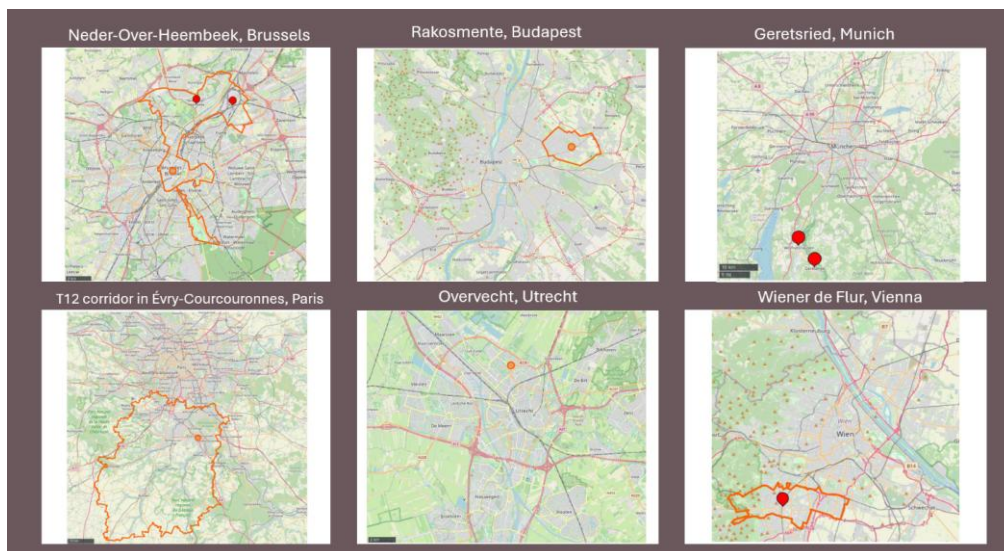
1.5. The surveyed areas: DREAMS living labs

Within the DREAMS project, living labs were selected in six European cities and regions to investigate accessibility, mobility behaviour, and 15-minute neighbourhood (15mN) dynamics in urban outskirts (see Deliverable 2.3 for more detail on the living labs). The selected living labs (see Figure 1) represent diverse metropolitan contexts, governance settings, and spatial structures, while sharing common challenges related to car dependency, dispersed amenities, and unequal access to services. An overview of the Living Lab locations is provided next.

- Brussels Capital Region (Belgium): The Living Lab is situated in Neder-Over-Heembeek, a northern peripheral area of Brussels combining residential neighbourhoods with industrial and port-related functions, and facing challenges related to connectivity and access to everyday amenities.
- Budapest (Hungary): The Living Lab is located in Rákosszentimre (17th district), a peripheral district of Budapest characterised by suburban housing patterns, limited local service concentration, and high levels of car dependency.
- Munich metropolitan region (Germany): The Living Lab is located in Geretsried, a town at the southern edge of the Munich metropolitan region, representing a suburban context with limited rail accessibility and strong reliance on car-based mobility.
- Île-de-France / Paris region (France): The Living Lab focuses on the T12 corridor in Évry-Courcouronnes, a suburban area south of Paris structured around a regional transport corridor, with dispersed activity locations and strong commuter-oriented mobility patterns.
- Utrecht (The Netherlands): The Living Lab is situated in Overvecht, a northern district of Utrecht characterised by post-war housing developments, socio-economic diversity, and ongoing urban regeneration efforts aimed at improving accessibility and local services.
- Vienna (Austria): The Living Lab is located in Wiener Floridsdorf, Liesing, an outer area of Vienna characterised by low-density residential development, limited local service provision, and a strong reliance on private motorised transport, typical of urban fringe conditions.

Together, these living labs form a comparative framework that captures a wide range of urban-outskirts conditions across Europe. This diversity enables the DREAMS project to analyse how perceived accessibility, mobility behaviour, and preferences differ across contexts, and to identify transferable pathways towards more equitable and accessible 15-minute neighbourhood transformations.

Figure 1 DREAMS living labs and surveyed areas



2. METHODOLOGY

2.1. Survey design

This section describes the standardised cross-city survey developed within the DREAMS project, which provided the empirical data required to analyse residents' perceived accessibility and mobility preferences across the DREAMS living labs in the context of 15-minute neighbourhood transformations in urban outskirts (see Figure 2). The full set of questions included in the survey can be found in the appendices.

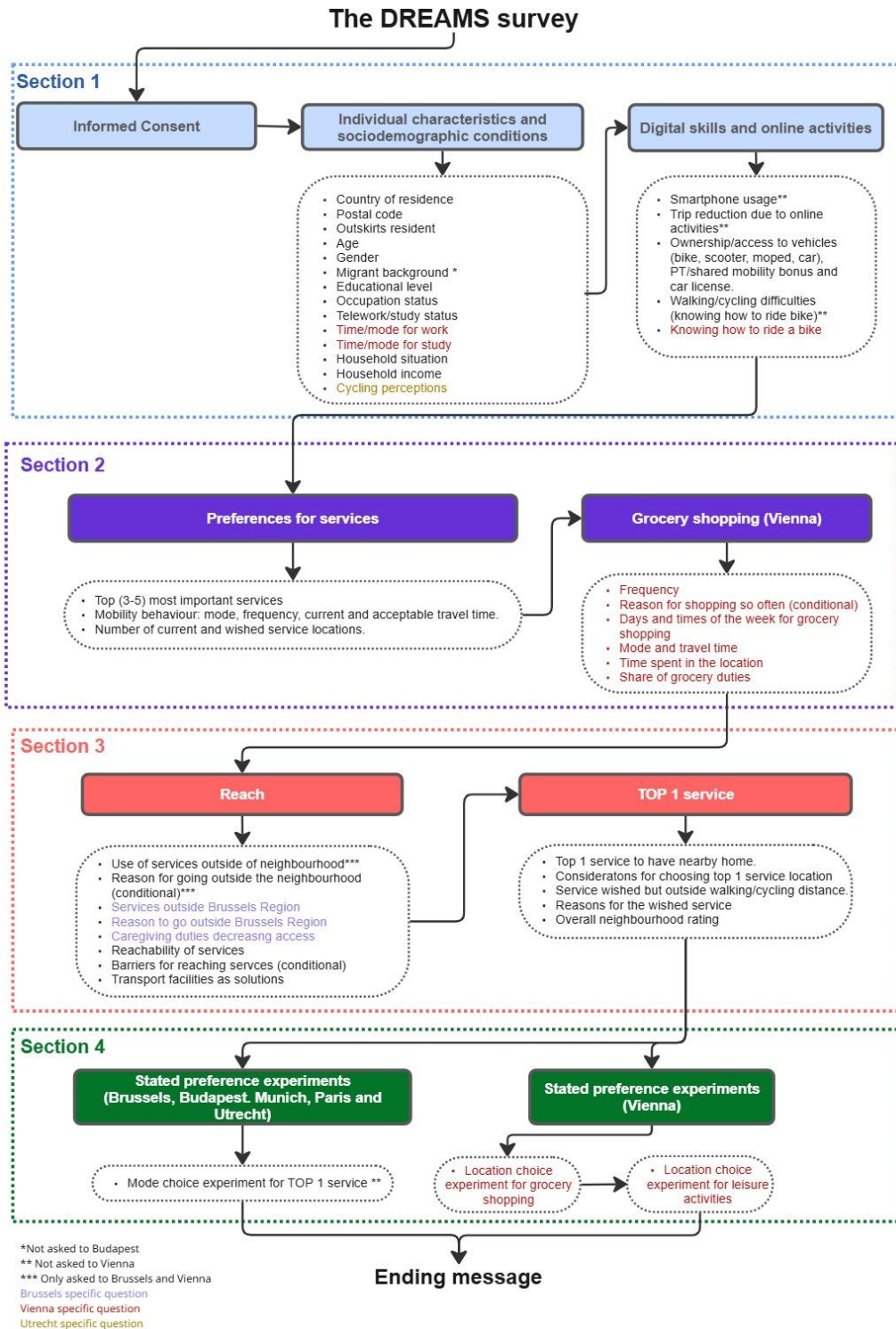


Figure 2: DREAMS survey design

2.1.1. Survey perceived accessibility content

The survey design aimed to collect harmonised and comparable data across the DREAMS living labs to analyse perceived accessibility, mobility behaviour, and stated preferences in the context of 15-minute neighbourhood (15mN) transformations in urban outskirts. The survey was designed as a standardised cross-city instrument, while allowing for limited city-specific adaptations where required by the local context.

As described in Section 1.3, the survey was originally conceived as two separate instruments corresponding to different project tasks: a survey addressing perceived accessibility under WP3, Task 3.2, and a separate stated preference choice experiment under WP4, Task 4.2.2. To reduce respondent burden and mitigate survey fatigue, both instruments were ultimately integrated into one joint survey, implemented as a single data collection effort. The final survey was therefore structured into four main sections, reflecting a sequential logic experienced by all respondents.

The first section introduced respondents to the context and objectives of the survey and provided information on data protection and privacy in accordance with GDPR requirements. Proceeding to the remainder of the survey was only possible after respondents provided informed consent. Following consent, this section collected information on individual characteristics and sociodemographic conditions, including country of residence, postcode, confirmation of residence in urban outskirts, age, gender, migration background, education level, occupation, telework or study status, household composition, and household income. In addition, respondents reported their time and mode of travel for work and study, as well as perceptions related to cycling. This section also included questions on digital skills and online activities, capturing respondents' smartphone use, engagement in online activities that may substitute travel, ownership or access to transport modes (including private vehicles, public transport, and shared mobility), possession of a driving licence, and physical abilities related to walking, cycling, and riding a bicycle.

The second section focused on respondents' preferences for local services and everyday activities, which are central to the 15-minute neighbourhood concept. Respondents were asked to identify their top three to five most important services, report current mobility behaviour related to these services (mode choice, frequency, and acceptable travel time), and indicate the number of existing and desired service locations. For selected living labs (Vienna), this section also included a more detailed module on grocery shopping behaviour, capturing shopping frequency, timing, travel mode and travel time, time spent at the location, reasons for shopping patterns, and the division of grocery-related responsibilities within the household.

The third section addressed perceived accessibility and reach, forming the empirical core of WP3, Task 3.2 (Layer 2: Perceived accessibility). In the case of Brussels and Vienna, respondents were asked about their use of services outside their neighbourhood, reasons for travelling beyond the neighbourhood boundaries, while in general all living labs answered about perceived reachability of services, and barriers encountered when accessing amenities. The section also explored perceived accessibility constraints related to caregiving responsibilities (again, only for Brussels and Vienna) and transport availability, as well as respondents' views on transport-related solutions that could improve access. In addition, respondents were asked to identify their top one service they would like to have closer to home, the considerations influencing the choice of service location, acceptable walking and cycling distances, and overall neighbourhood satisfaction. These questions provided insight into residents' priorities and perceived gaps in local accessibility. The choice of having or not having specific questions asked was made by living lab leaders with respect to topics of interest for their own context and their interest also for shorter surveys to get more respondents.

2.1.2. Survey choice experiment

The final section (section 4) consisted of stated preference choice experiments, corresponding to WP4, Task 4.2.2, and was implemented after the perceived accessibility questions. Depending on the living lab, respondents participated in one or more choice experiments focusing on mode choice for reaching their top-priority service (all living labs but Vienna) or location choice for grocery shopping or leisure activities (Vienna's particular choice experiment).

The experiments presented respondents with hypothetical but realistic scenarios in which key attributes - such as travel time, access conditions, and service availability- were systematically varied. This allowed the analysis of trade-offs and preferences under different accessibility and mobility configurations, complementing the perception-based data collected in the earlier sections.

- Brussels

In the Brussels SP choice experiment design (Table 1), participants also evaluated five alternatives: walking, public transport (PT), shared cargo bike (SCB), car sharing (CS), and an opt-out. Each mode included following travel attributes (travel time, cost, and walking time to access), while SCB and CS incorporated service functionalities focused on group plans (Get one plan for everyone - family or group subscriptions with 20%/30% savings!) and bundled discounts (Get car-sharing & cargo-bike package with special discounts of 20%/30%!). The opt-out option was included without attributes to represent a respondent's choice to maintain their current travel behaviour or to indicate that none of the available alternatives represented a suitable choice.

Table 1 States Preferences Choice Experiment Design - Brussels

Alternative	Attribute	Attribute level
Walking	On vehicle/ travel time (min)	26/32/38
	Travel cost (EUR)	0
	Walking time to PT stop/ docking station (min)	0
Public transport	On vehicle/ travel time (min)	13/16/19
	Travel cost (EUR)	1.8/2.3/2.8
	Walking time to PT stop/ docking station (min)	2/4/6
Shared cargo bike (SCB)	On vehicle/ travel time (min)	13/16/19
	Travel cost (EUR)	2.8/3.5/4.2
	Walking time to PT stop/ docking station (min)	2/4/6
Car sharing (CS)	Service functionalities and pricing options	-/SF1/SF2/SF3/SF4
	On vehicle/ travel time (min)	7/9/11
	Travel cost (EUR)	2.7/3.4/4.1
Opt-out	Walking time to PT stop/ docking station (min)	5/6/7
	Service functionalities and pricing options	-/SF1/SF2/SF3/SF4
		-
SF1 - Get one plan for everyone - family or group subscriptions with 20% savings!		
SF2 - Get one plan for everyone - family or group subscriptions with 30% savings!		
SF3 - Get car-sharing & cargo-bike package with special discounts of 20%!		
SF4 - Get car-sharing & cargo-bike package with special discounts of 30%!		

- Budapest

In the Budapest stated preference experiment (Table 2), participants chose between walking, public transport, shared bikes (SB), shared electric scooters (SES), and an opt-out option. The attributes included travel time, travel cost (expressed in HUF), and walking time to access points. SEB and SES also featured four service functionalities/pricing options each, such as promotional ride offers (Try shared services and get first 5/10 rides free of charge!) and reward-based incentives (Get additional free ride after completing 5/10 trips!).

Table 2 Stated Preferences Choice Experiment Design – Budapest

Alternative	Attribute	Attribute level
Walking	On vehicle/ travel time (min)	26/32/38
	Travel cost (HUF)	0

Public transport	Walking time to PT stop/ docking station (min)	0
	On vehicle/ travel time (min)	13/16/19
	Travel cost (HUF)	360/450/540
Shared bike (SB)	Walking time to PT stop/ docking station (min)	2/4/6
	On vehicle/ travel time (min)	9/11/13
	Travel cost (HUF)	440/550/660
Shared electric scooter (SES)	Walking time to PT stop/ docking station (min)	1/3/5
	Service functionalities and pricing options	-/SF1/SF2/SF3/SF4
	On vehicle/ travel time (min)	9/11/13
Opt-out	Travel cost (HUF)	640/800/960
	Walking time to PT stop/ docking station (min)	1/3/5
	Service functionalities and pricing options	-/SF1/SF2/SF3/SF4
SF1 - Try shared services and get first 5 rides free of charge!	-	-
SF2 - Try shared services and get first 10 rides free of charge!	-	-
SF3 - Get additional free ride after completing 5 trips!	-	-
SF4 - Get additional free ride after completing 10 trips!	-	-

- Munich

In the Munich stated preference experiment (Table 3), respondents chose between walking, public transport, shared bikes (SEB), car sharing (CS), and an opt-out alternative. The design included standard travel attributes (on vehicle/travel time, travel cost and walking time to PT stop or docking station), and four service functionalities tied to integrated subscriptions (One subscription for every car-sharing & public transport & shared bike with special discount of 20%/ 30%!) and bonus credits (Get 20%/30% bonus credit after completing trip to less-connected areas!).

Table 3 Stated Preferences Choice Experiment Design – Munich

Alternative	Attribute	Attribute level
Walking	On vehicle/ travel time (min)	26/32/38
	Travel cost (EUR)	0
	Walking time to PT stop/ docking station (min)	0
Public transport	On vehicle/ travel time (min)	13/16/19
	Travel cost (EUR)	1.6/2/2.4
	Walking time to PT stop/ docking station (min)	2/4/6
Shared bike (SEB)	On vehicle/ travel time (min)	9/11/13
	Travel cost (EUR)	1.6/2/2.4
	Walking time to PT stop/ docking station (min)	1/3/5
Car sharing (CS)	Service functionalities and pricing options	-/SF1/SF2/SF3/SF4
	On vehicle/ travel time (min)	7/9/11
	Travel cost (EUR)	2.2/2.8/3.4
Opt-out	Walking time to PT stop/ docking station (min)	5/6/7
	Service functionalities and pricing options	-/SF1/SF2/SF3/SF4
	-	-

-
- SF1 - One subscription for every car-sharing & public transport & shared bike with special discount of 20%!
 - SF2 - One subscription for every car-sharing & public transport & shared bike with special discount of 30%!
 - SF3 - Get 20% bonus credit after completing trip to less-connected areas!
 - SF4 - Get 30% bonus credit after completing trip to less-connected areas!
-

- Paris

The SP choice experiment conducted in Paris (Table 4) was designed to assess individuals' preferences among five travel alternatives: walking, public transport (PT), shared electric bike (SEB), shared electric scooter (SES), and an opt-out option. Each alternative was described using key travel-related attributes, including on-vehicle travel time, travel cost, and walking time to the nearest PT stop or docking station. The attribute levels were constructed using a baseline value with $\pm 20\%$ variation to reflect realistic fluctuations in travel experience. For the shared micromobility modes (SEB and SES), an additional attribute captured specific service functionalities and pricing incentives. These functionalities include provisions such as infrastructure improvements (e.g., the presence of shared or protected bike lanes) and promotional offers like free initial rides (five or ten).

Table 4 Stated Preferences Choice Experiment Design – Paris

Alternative	Attribute	Attribute level
Walking	On vehicle/ travel time (min)	26/32/38
	Travel cost (EUR)	0
	Walking time to PT stop/ docking station (min)	0
Public transport	On vehicle/ travel time (min)	13/16/19
	Travel cost (EUR)	2/2.5/3
	Walking time to PT stop/ docking station (min)	2/4/6
Shared electric bike (SEB)	On vehicle/ travel time (min)	9/11/13
	Travel cost (EUR)	2.8/3.5/4.2
	Walking time to PT stop/ docking station (min)	1/3/5
	Service functionalities and pricing options	-/SF1/SF2/SF3/SF4
Shared electric scooter (SES)	On vehicle/ travel time (min)	9/11/13
	Travel cost (EUR)	2.8/3.5/4.2
	Walking time to PT stop/ docking station (min)	1/3/5
	Service functionalities and pricing options	-/SF1/SF2/SF3/SF4
Opt-out	-	-

-
- SF1 - Be provided at the stops and stations with shared bike lanes
 - SF2 - Be provided at the stops and stations with a dedicated and protected bike lanes with buffer zones
 - SF3 - Try shared services and get first 5 rides free of charge!
 - SF4 - Try shared services and get first 10 rides free of charge!
-

- Utrecht

In the Utrecht stated preference choice experiment (Table 5), respondents evaluated five alternatives: walking, public transport (PT), shared electric bike (SEB), shared moped (SM), and an opt-out option. All modes were described using standard attributes, travel time, travel cost, and walking time to the access point, while SEB and SM also included service functionalities/ pricing options related to financial

incentives (Get a 30%/50% in your next ride if you return the bike to the station and dock it!) and parking conditions (Park anywhere within a 1-min/5-min walk to your final destination!).

Table 5 Stated Preferences Choice Experiment Design – Utrecht

Alternative	Attribute	Attribute level
Walking	On vehicle/ travel time (min)	26/32/38
	Travel cost (EUR)	0
	Walking time to PT stop/ docking station (min)	0
Public transport	On vehicle/ travel time (min)	13/16/19
	Travel cost (EUR)	1.4/1.7/2.0
	Walking time to PT stop/ docking station (min)	2/4/6
Shared electric bike (SEB)	On vehicle/ travel time (min)	7/9/11
	Travel cost (EUR)	2.7/3.3/4.0
	Walking time to PT stop/ docking station (min)	1/3/5
	Service functionalities and pricing options	-/SF1/SF2/SF3/SF4
Shared moped (SM)	On vehicle/ travel time (min)	7/9/11
	Travel cost (EUR)	2.7/3.3/4.0
	Walking time to PT stop/ docking station (min)	1/3/5
	Service functionalities and pricing options	-/SF1/SF2/SF3/SF4
Opt-out	-	-
SF1 - Get a 30% in your next ride if you return the bike to the station and dock it!		
SF2 - Get a 50% in your next ride if you return the bike to the station and dock it!		
SF3 - Park anywhere within a 1-min walk to your final destination!		
SF4 - Park anywhere within a 5-min walk to your final destination!		

- Vienna

In Vienna's first stated preference SP choice experiment (Table 6), participants evaluated three alternatives for shopping destinations: independent establishments (IE), chain-branded establishments (CBE), and shopping centres (SC). Each alternative was defined by five attributes: size, variety of items, price, walking duration, and quality (crowdedness). Attribute levels were designed to reflect realistic variations in the shopping experience.

Table 6: Stated Preferences Choice Experiment 1 Design – Vienna

Alternative	Attribute	Attribute level
Independent Establishment	Size	Small/Medium/Large
	Variety of Items	Small Variety/Large Variety
	Price	Cheaper than expected/As expected/More expensive than expected
	Walking duration (min)	10 or less/ 10-30 / 30 or more
	Quality	Crowded/Non-Crowded
Chain Branded Establishment	Size	Small/Medium/Large
	Variety of Items	Small Variety/Large Variety
	Price	Cheaper than expected/As expected/More expensive than expected
	Walking duration (min)	10 or less/ 10-30 / 30 or more
	Quality	Crowded/Non-Crowded
	Size	Small/Medium/Large

Shopping Centre (Einkaufszentrum)	Variety of Items	Small Variety/Large Variety
	Price	Cheaper than expected/As expected/More expensive than expected
	Walking duration (min)	10 or less/ 10-30 / 30 or more
	Quality	Crowded/Non-Crowded

In Vienna's second stated preference choice experiment (Table 7), similarly designed as CE1, participants evaluated two types of shopping destinations, independent establishments (IE) and chain-branded establishments (CBE), based on four attributes: size, price, travel duration, and ambience/atmosphere (crowded vs. non-crowded).

Table 7 Stated Preferences Choice Experiment 2 Design – Vienna

Alternative	Attribute	Attribute level
Independent Establishment	Size	Small/Medium/Large
	Price	Cheaper than expected/As expected/More expensive than expected
	Travel duration (min)	10 or less/ 10-30 / 30 or more
	Ambience/Atmosphere	Crowded/Non-Crowded
Chain Branded Establishment	Size	Small/Medium/Large
	Price	Cheaper than expected/As expected/More expensive than expected
	Travel duration (min)	10 or less/ 10-30 / 30 or more
	Ambience/Atmosphere	Crowded/Non-Crowded

2.2. Perceived accessibility model

To move beyond a descriptive understanding of perceived accessibility an ordered logit model (OLM) can be fit. The aim of such a model is to assess how socio-economic and environmental factors impact the perceived accessibility for each respondent. The perceived accessibility is measured using results from the questions: "In general, how often can you reach(access) these services using your preferred mode of transportation?", where 'services' refers to the amenities respondents personally found to be important for themselves. The answer options was a 5-point Likert scale (Always – Never). Since the dependent variable is naturally ordered an OLM is an appropriate model choice, since it does not assume equal distances between categories the same way an ordinary least square (linear) model would. Formally, the cumulative probabilities of an OLM are given by:

$$P(y \leq j|X) = \frac{\exp(\tau_j + X\beta)}{1 + \exp(\tau_j - X\beta)} \quad (1)$$

Where y denotes the observed ordinal outcome (dependent variable), j is an index for the independent variables, τ_j are the estimated threshold parameters separating the categories, X is a vector containing the value of the independent variables and β is a vector containing the estimated variable coefficients. The model was estimated using maximum likelihood estimation. A key assumption of the OLM is that of proportional odds. Which entails that the effects of the independent variables across different outcome variables is the same, regardless of the value of the independent variable. In this study, this assumption was not formally tested, as the independent variables are expected to have a consistent directional effect across the ordered accessibility categories (e.g. income always improves accessibility). For more details regarding OLMs in general this report refers to the work by Williams & Quiroz (2020).

Prior to model estimation, several transformations were applied to the independent variables to ensure comparability across countries and improve interpretability as well as prepare data for the OLM model. First, demographic variables were standardised. Since most variables will be using dummy coding (0 or

1) age was also rescaled to a 0–1 range using min–max normalization to ensure variable coefficient estimates remain comparable. Gender was recoded into categorical groups (woman, man, other) and later transformed into dummy variables for inclusion in the regression model.

Second, household income was harmonised across different countries. Reported income categories adjusted for household size using an equivalence scale (square root of household size). To ensure cross-country comparability, income was further adjusted using purchasing power parity (PPP) indices for all cities retrieved from an open-source cost of living database (NUMBEO). Finally, respondents were grouped into country-specific income terciles (low, medium, high), capturing relative income positions within each living lab. Also, these were subsequently converted to dummy variables.

Third, education levels were unified across countries. Given differences in national education systems, country-specific education categories were mapped to a common classification consisting of primary, secondary, vocational, and tertiary (university/college) education levels. These were subsequently encoded as dummy variables.

Fourth, mobility-related variables were transformed into binary indicators. Access to different transport modes (e.g., bicycle, public transport, car) was converted to 0/1 variables indicating availability. Car ownership was simplified to a binary indicator (no car vs. at least one car), regardless of the number of vehicles. Additionally, a variable capturing mobility constraint was constructed, indicating whether respondents have trouble walking or cycling (physically, or because they do not know how to cycle).

Fifth, built environment were derived. Respondents' postal codes were geocoded to obtain geographic coordinates, which were used to calculate the distance to the respective city centre. This distance was normalised within each country to account for differences in city size. Furthermore, population density was assigned using spatial joins with a 1 km² grid dataset and similarly normalised at the country level.

2.3. Persona clustering

To identify distinct groups of individuals based on their accessibility preferences, a k-means clustering approach was applied using the scikit-learn package in Python. For detailed information on the workings of the algorithm this report refers to. K-means is an unsupervised machine learning algorithm that partitions a sample into a predefined number of clusters (k), such that individuals within a cluster are more similar to each other than to those in other clusters (Ikotun, Ezugwu, Abualigah, Abuhajja, & Heming, 2023).

The clustering was performed in two steps. First, using amenity preferences of respondents (encoded as 0/1 per amenity). A second clustering step was performed using the outcome of these clusters as subsets. This second clustering step used socio-demographic variables such as age, living situation (e.g. single household, couple, couple with children) and income level (encoded as in the OLM model). Prior to clustering, all variables were standardised using z-score normalisation. This step ensures that each variable contributes equally to the clustering process and prevents variables with larger scales from dominating the results. The optimal number of clusters was determined by combining the elbow method and silhouette analysis. The elbow method evaluates the within-cluster sum of squares (inertia) across different values of k, identifying the point at which additional clusters yield diminishing improvements. Complementarily, the silhouette score assesses how well each observation fits within its assigned cluster relative to other clusters, with higher values indicating better-defined cluster structures. Cluster profiles were subsequently interpreted by examining the mean values of the input variables and the distribution of demographic characteristics within each cluster. This enabled the identification of distinct “personas” representing different accessibility needs and socio-demographic contexts.

2.4. Choice experiment analysis

To analyse the SP experiment data, the study employs discrete choice models grounded in random utility theory. The APOLLO package (Hess & Palma, 2019) realized in R is applied to estimate the choice

models. Discrete choice models (such as logit models) are a cornerstone of transportation research for modelling and predicting people's choices among alternatives. In a random utility framework, each decision-maker n is assumed to associate a latent utility U_{nj} with each alternative j in a choice set. This utility is typically expressed as (McFadden, 1974):

$$U_{nj} = V_{nj} + \varepsilon_{nj}, \quad (2)$$

where V_{nj} is the systematic, observable component of utility (a function of measured attributes and coefficients) and ε_{nj} is an unobserved error term (random component) (Train, 2009). The decision-maker is assumed to choose the alternative with the highest utility. The multinomial logit (MNL) model arises when the ε_{nj} terms are independently and identically distributed. Under this assumption, the choice probability of individual n choosing alternative j takes the closed-form logit formula (McFadden, 1974):

$$P_n(j) = \frac{e^{(V_{nj})}}{\sum_k^J e^{(V_{nk})}}, \quad (3)$$

for $j=1,2,\dots,J$, where J is number of alternatives. In practice, V_{nj} is often specified as a linear function of attributes and parameters (e.g. $V_{nj} = \beta' x_{nj}$, where x_{nj} is a vector of attributes for alternative j and β a vector of coefficients). The MNL model's parameters (taste coefficients β) are typically estimated by maximum likelihood estimation, using the observed choices in the sample to find the β values that maximize the likelihood of the data. In particular, the MNL assumes homogeneous preferences across all individuals (each individual shares the same β coefficients once estimated) and exhibits the property of independence of irrelevant alternatives (IIA). IIA implies that the odds of choosing between any two alternatives are unaffected by the presence or attributes of other alternatives, an assumption that can be unrealistic in many transport settings (Train, 2009).

On another side, Mixed Logit (MXL) models introduce random coefficients to capture taste heterogeneity and more flexible substitution patterns (McFadden & Train, 2000). In a mixed logit model, some or all of the β coefficients are treated as random variables that vary across individuals (or choice situations) according to a specified distribution (Train, 2009; Vij & Walker, 2016). This means each individual n has their own realization β drawn from a population distribution $f(\beta|\Omega)$ characterized by parameters Ω (e.g. a mean and covariance if f is normal). The utility can be written as $V_{nj} = \beta' x_{nj} + \varepsilon_{nj}$, highlighting that different decision-makers weigh attributes differently. The MXL choice probability is then a weighted integral of the logit formula over the distribution of random parameters (McFadden & Train, 2000). Formally, the choice probability is expressed as:

$$P_n(j) = \int_{\beta} \frac{e^{(\beta' x_{nj})}}{\sum_k^J e^{(\beta' x_{nk})}} f(\beta|\Omega) d\beta, \quad (4)$$

which is an integral of the standard logit probability evaluated at a given β (inside the fraction) weighted by the density $f(\beta)$. In other words, mixed logit probabilities are integrals of MNL probabilities over a distribution of preferences. Hence, the MXL model represents a mixture of many possible preference realizations, which effectively averages the logit choice probabilities across the population's taste distribution. This flexibility means that mixed logit does not exhibit IIA in general, since introducing or changing an alternative can affect choice probabilities in a non-proportional way, and it can capture complex substitution effects between alternatives (Hess et al., 2006).

To better understand variations in mode choice utility, the model includes interaction terms between transport alternatives and both socio-demographic characteristics and activity types. For the activity-related interactions, participants in all living labs were asked to select the most important activity from a list of 25 options. Their top-ranked activity was used as the reference destination in the SP choice experiment, on individual level. Grocery shopping was the most frequently chosen activity across all cities. The remaining activities were grouped into five broader categories: (other) commerce, education, health, leisure, and services. These categories were used to construct interaction terms in the model, enabling the analysis to test how different destination purposes influence mode preferences and to identify which activity-mode combinations have significant effects on utility.

In order to ensure the most robust and interpretable model, several alternative specifications were estimated and compared using model fit criteria, including the log-likelihood, Akaike Information

Criterion (AIC), and Bayesian Information Criterion (BIC). These metrics provide a trade-off between model accuracy and complexity, where lower values of AIC and BIC indicate better-fitting models. The final model was selected based on its superior performance across these criteria after multiple rounds of refinement, ensuring both statistical soundness and behavioural plausibility.

Prior to the general modelling procedure described above, a refinement process was applied to ensure the behavioural validity and robustness of the estimated models in selected living labs. The initial dataset used for model estimation consisted of cleaned and validated survey responses following standard data preparation procedures (e.g., removal of incomplete responses and basic consistency checks). A first round of model estimation was conducted using these datasets for all cities.

However, during model diagnostics and preliminary result interpretation, specific behavioural patterns were identified in the datasets for Budapest, Brussels, and Utrecht. A subset of respondents consistently selected the opt-out alternative across all choice tasks, suggesting non-engagement with the stated preference scenarios or potential protest responses. To address these issues and improve model interpretability, a second round of data filtering was conducted for these three living labs. This additional filtering excluded (i) respondents who always selected the opt-out option across all choice tasks and (ii) respondents reporting mobility-related disabilities. This last step was performed because these respondents might bias the results from choice experiment due to them being physically unable to choose an alternative. Following this refinement, the discrete choice models in these three cities were re-estimated using the adjusted datasets, Budapest (359), Brussels (335), and Utrecht (228).

2.5. Data collection process

The following two sections describe the minimum sample requirements of the survey data and the procedure followed to achieve the defined goals.

2.5.1. Sources

In contrast to conventional accessibility surveys aiming at full population representativeness, the DREAMS survey explicitly prioritised the analysis of specific target groups relevant to each Living Lab, as defined in the project proposal. These groups reflect local policy priorities and context-specific challenges related to accessibility and equity. Accordingly, the survey design did not follow a stratified sampling approach, nor were the results weighted using census data. Instead, the emphasis was placed on collecting sufficiently rich samples for the population groups of interest in each Living Lab.

The target groups addressed across the DREAMS living labs were as follows:

- Munich (Geretsried): older adults and migrants
- Utrecht (Overvecht): migrants and low-income households
- Brussels (Neder-Over-Heembeek): caregivers
- Paris (T12 corridor – Évry-Courcouronnes): young people
- Budapest (Rákosmente): general population
- Vienna (Wiener Flur): grocery shopping behaviour and daily activity access

This targeted approach allowed the project to capture in-depth insights into accessibility experiences that are often underrepresented in general population surveys, while remaining consistent with the equity-oriented objectives of the DREAMS framework. For the stated preference choice experiment component, a minimum threshold of 120 valid responses per Living Lab was defined as necessary to ensure the statistical validity of the estimated models. An ideal target of more than 300 responses was set where feasible, in order to support more robust subgroup analyses. While not all living labs reached the ideal sample size, all achieved at least the minimum number of responses required for the choice experiment analysis.

Data collection for the DREAMS cross-city survey was conducted through a combination of panel-based recruitment, targeted local outreach, and assisted fieldwork, depending on the specific context and feasibility conditions of each Living Lab. While the survey was initially designed to be implemented strictly within the predefined Living Lab areas, practical constraints related to respondent availability,

survey fatigue, and the need to reach specific target groups required context-sensitive adaptations across cities.

In contrast to surveys aiming at population representativeness, the DREAMS data collection strategy prioritised the inclusion of specific target groups identified in the project proposal and relevant to each Living Lab. Consequently, the survey did not follow a stratified sampling design, nor were the results weighted using census data. This approach allowed the project to collect in-depth evidence on accessibility perceptions and mobility preferences among groups often underrepresented in standard surveys. The city-specific data collection processes are summarised next:

- Vienna (Wiener Flur): data collection was conducted primarily through a panel company. Due to insufficient response rates within the Living Lab area alone, the recruitment area was expanded to the entire city of Vienna and Lower Austria. To maintain the focus on urban outskirts, the panel provider received explicit instructions regarding the inclusion and exclusion of specific postal codes, ensuring that responses from central districts were avoided. The survey was launched on 18 July and yielded 653 responses prior to data cleaning.
- Utrecht (Overvecht): data collection initially relied on recruitment efforts led by the Living Lab Leader within the Living Lab area. However, persistent survey fatigue and low willingness to participate- particularly pronounced in Overvecht, where residents are frequently approached for research- made it necessary to expand the recruitment area to the entire municipality of Utrecht. A panel company was subsequently engaged, with strict geographic filtering applied to exclude the city centre. The survey was launched on 10 September and collected 400 responses.
- Budapest (Rákosmente): data collection was conducted using a panel company, targeting the Living Lab area directly through postcode-based filtering. The survey was launched on 11 July and resulted in 505 responses.
- Brussels (Neder-Over-Heembeek): recruitment was also conducted through a panel provider, with clear geographic constraints to ensure coverage of the Living Lab area and exclusion of central city neighbourhoods. The survey was launched on 24 October and collected 660 responses.
- Paris (T12 corridor – Évry-Courcouronnes): a different approach was adopted. Professional interviewers with local expertise were contracted to recruit respondents directly within the study area. This targeted field-based strategy ensured appropriate coverage of the corridor and facilitated participation in a context where online recruitment alone would have been insufficient. The survey was launched on 25 August and yielded 200 responses.
- Munich (Geretsried): data collection was coordinated directly by the Living Lab Leader, without the use of a panel company. Respondents were recruited through local outreach activities and invited to complete the survey online via QR codes and direct links. Participation was encouraged through small incentives, such as vouchers for ice-creams etc. The survey was launched on 8 July and resulted in 183 responses.

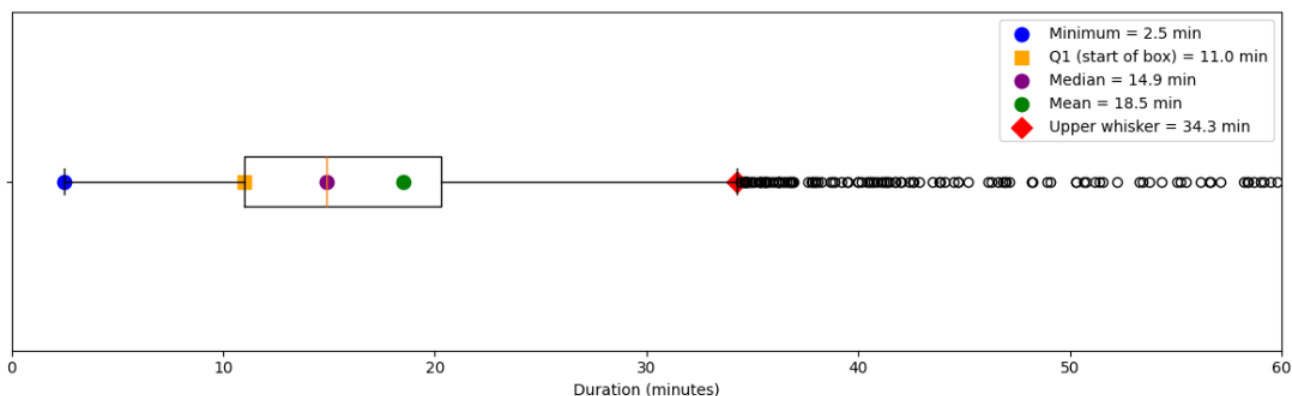
Although survey launch dates differed across living labs due to local implementation strategies, data collection was harmonised by applying a common closing date of 15 November across all cities. In total, the DREAMS survey collected over 2,600 responses across the six living labs, prior to data cleaning. All living labs achieved at least the minimum required number of valid responses for the stated preference choice experiment, ensuring the robustness of subsequent analyses.

2.5.2. Data cleaning and valid sample

The data cleaning process of the collected raw data consisted in (i) downloading the results separately for each city, (ii) filtering the dataset to include only consented responses and from the corresponding city (IC), (iii) removing all test entries submitted prior to the official launch dates, and (iv) excluding incomplete responses by retaining only those that submitted the entire survey. Additionally, open-ended responses were inspected, and additional filtering was applied to remove straight-lining cases, nonsensical entries and responses that failed to complete required fields. After general cleaning two additional cleaning steps were performed to ensure a valid sample; one based on survey completion time and one based on respondents' location.

Figure 3 presents the distribution of survey completion times using a boxplot. The shortest observed completion time was 2.5 minutes, whereas the upper whisker, representing the upper limit of non-outlier values based on the $1.5 \times \text{IQR}$ rule, extended to approximately 34 minutes. A small number of responses above this value were identified as extreme outliers, likely caused by interruptions or respondents leaving the survey open for extended periods. The first quartile (Q1) occurred at 11 minutes, meaning that 25% of respondents completed the survey in less than 11 minutes. The median completion time was 14.9 minutes, and the mean was 18.5 minutes, indicating a distribution with a long right tail driven by very slow completions.

Figure 3 Boxplot of survey completion time (min)



While $Q1 = 11$ minutes marks the beginning of the interquartile range and is commonly used as a threshold for identifying unusually fast responses, applying this cutoff would have excluded approximately 25% of the dataset, which we considered excessively strict. Common practice in survey data cleaning recommends removing approximately 1–5% of responses based on duration-based quality checks. Using this rationale, we selected 7 minutes as a more conservative and methodologically appropriate lower-bound threshold. Responses shorter than 7 minutes were classified as unusually fast and potentially low-quality (139 outliers). No upper-duration filter was applied. We therefore retained all responses with a completion time of 7 minutes or more. After cleaning, the cleaned sample included 2,542 responses.

Finally, whilst the survey in all living labs theoretically ensures that all respondents lived in urban outskirts, an additional validation step was performed to check this assumption. Matching the postcodes given in the survey to a Eurostat dataset containing geolocations of all European postcodes (European Union - GISCO, 2024), allowed for manual verification. This way, 361 respondents were manually identified to be living in city/urban centres. An overview of which postcodes were removed. A visual map of this filtering step is provided in Appendix 1 together with removed postcodes. Figure 4 shows the locations of the valid responses.

Figure 4 Valid sample after cleaning (n=2,181 valid responses)

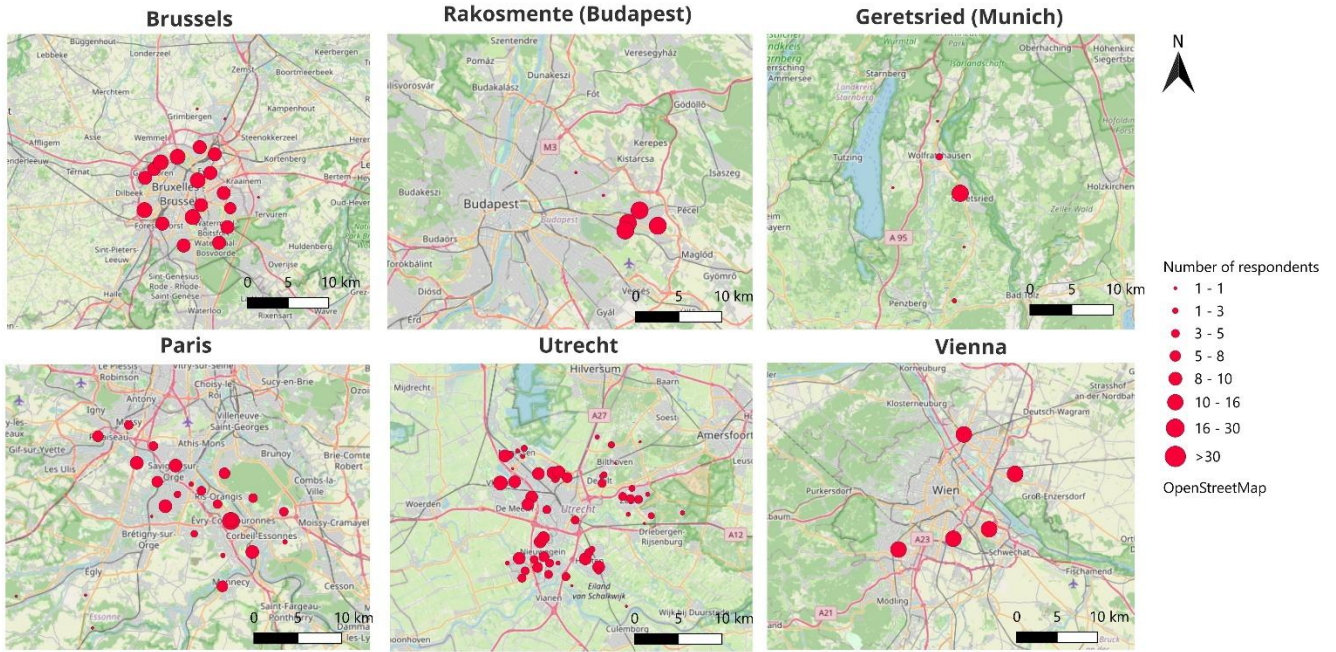
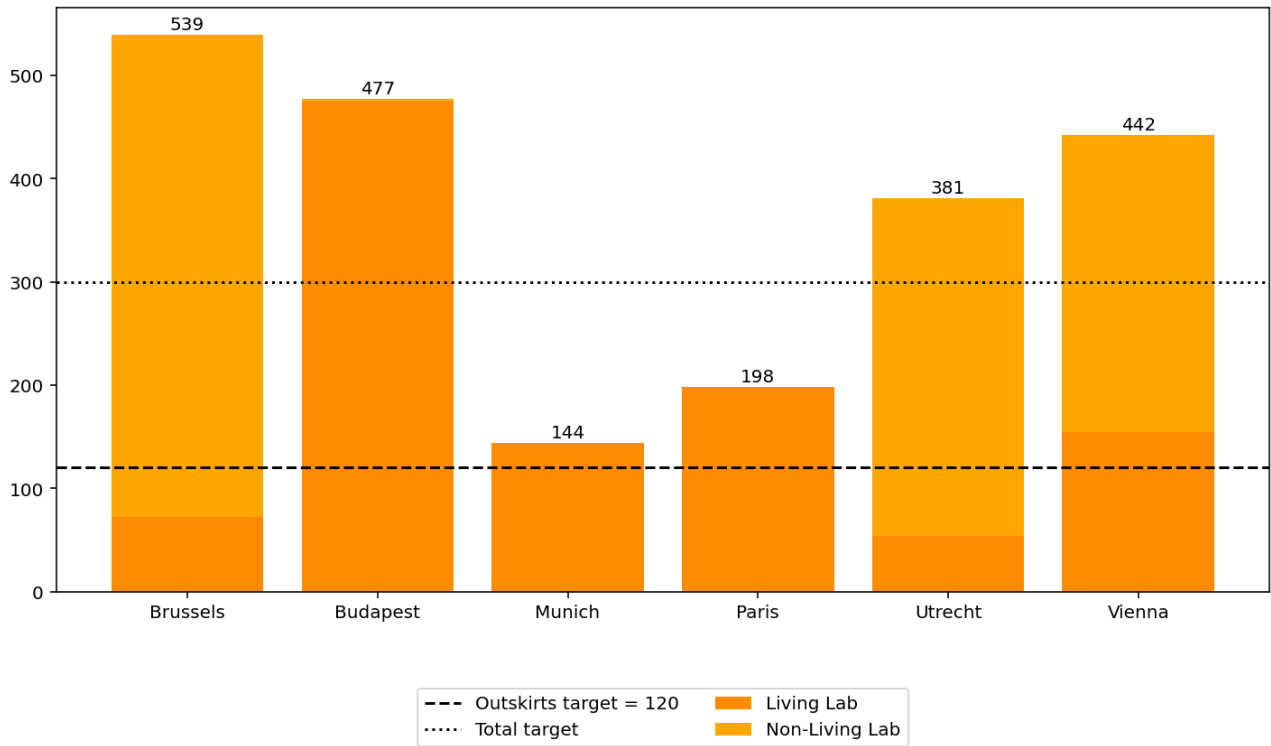


Figure 5 Valid sample size in each living lab (n=2181)



3. PERCEIVED ACCESSIBILITY

This chapter presents findings from the general survey questions related to perceived accessibility. First, this section provides a sociodemographic description of the survey respondents, offering contextual information to support the interpretation of the perceived accessibility results, which are presented in the later sections.

3.1. Description of the survey respondents

Age and Gender

Across the surveyed cities, respondents were predominantly concentrated in the middle age groups, with those aged 25–44 and 45–64 together accounting for the clear majority in every case. The 45–64 age group was particularly prominent in Brussels, Munich, and Utrecht, while Paris stood out for having a larger share of respondents aged 25–44. Younger respondents under 25 were consistently underrepresented across all cities, whereas the share of respondents aged 65 and over remained substantial, especially in Brussels, Munich, Vienna, and in the overall sample (see Figure 6).

In terms of gender (see Figure 7), the sample showed a systematic predominance of women in all cities, ranging from just over half of respondents in Brussels, Munich, and Vienna to nearly two-thirds in Paris. Men represented a smaller but still significant proportion across the board. Overall, the respondent profile reflected a mature, working-age population with a moderate overrepresentation of women, a pattern that was broadly consistent across cities while still exhibiting some local variation.

Figure 6 Age distribution of DREAMS survey respondents

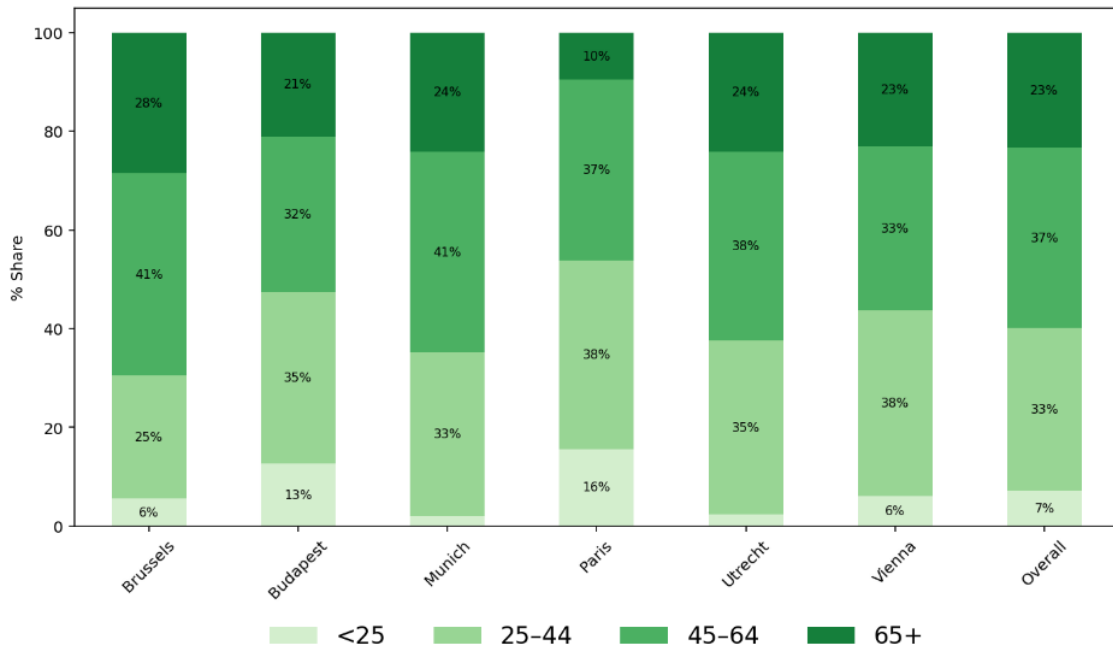
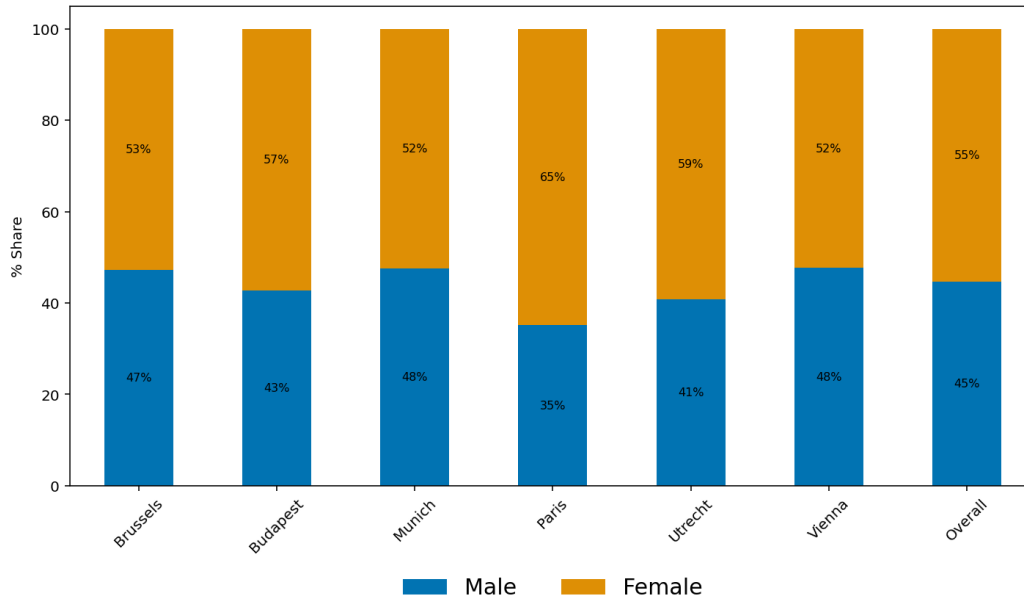


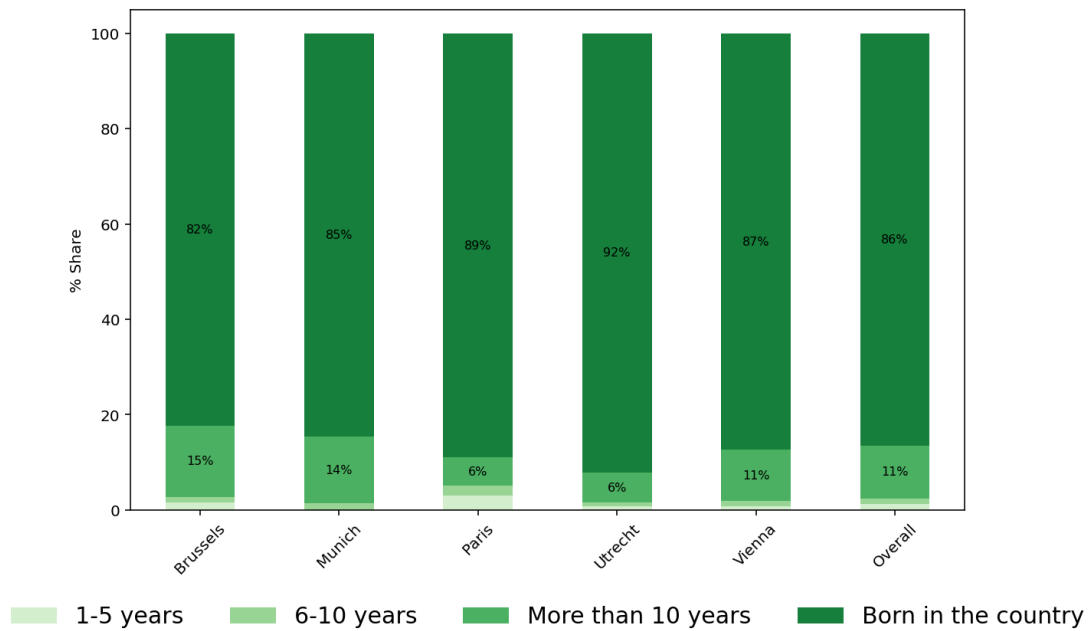
Figure 7 Gender distribution in DREAMS survey respondent



Migration background

The results on migration background (see Figure 8) indicated that many respondents had long-term ties to their country of residence. Across the cities included in this analysis, most participants reported being born in the country, with shares exceeding four-fifths in all cases and reaching particularly high levels in Paris and Utrecht. Among those not born in the country, the most common situation was long-term residence of more than ten years, while shorter residence durations were comparatively rare. This pattern suggested that the sample was largely composed of residents with substantial local experience and familiarity with their urban context, rather than recent arrivals. Overall, the distribution pointed to a stable population profile, which was relevant when interpreting perceptions and responses related to neighbourhood conditions and daily mobility.

Figure 8 Migrant background of DREAMS survey respondents

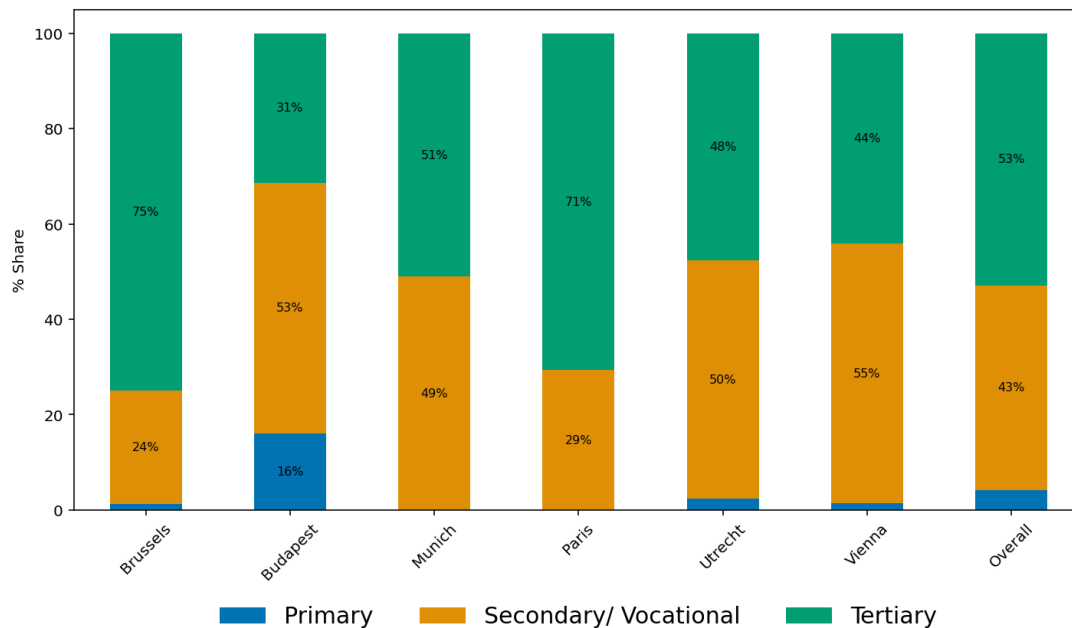


Note: This question was not asked in Budapest for privacy issues. The response options “prefer not to say” and “less than 1 year” were excluded because no respondents selected them.

Education

Across all cities, respondents are predominantly highly educated (see Figure 9), with tertiary education (Bachelor or higher) representing the largest share of the sample in most cases. This was particularly pronounced in Brussels and Paris, where a clear majority of respondents held a tertiary degree, and remained substantial in Munich, Utrecht, Vienna, and in the overall sample. Secondary or vocational education constituted the second most common category, accounting for a sizeable proportion across cities and forming the majority only in Budapest. The results indicated that the sample largely reflected a well-educated population, with some variation in the balance between secondary and tertiary education across cities.

Figure 9 Education level of DREAMS survey respondents

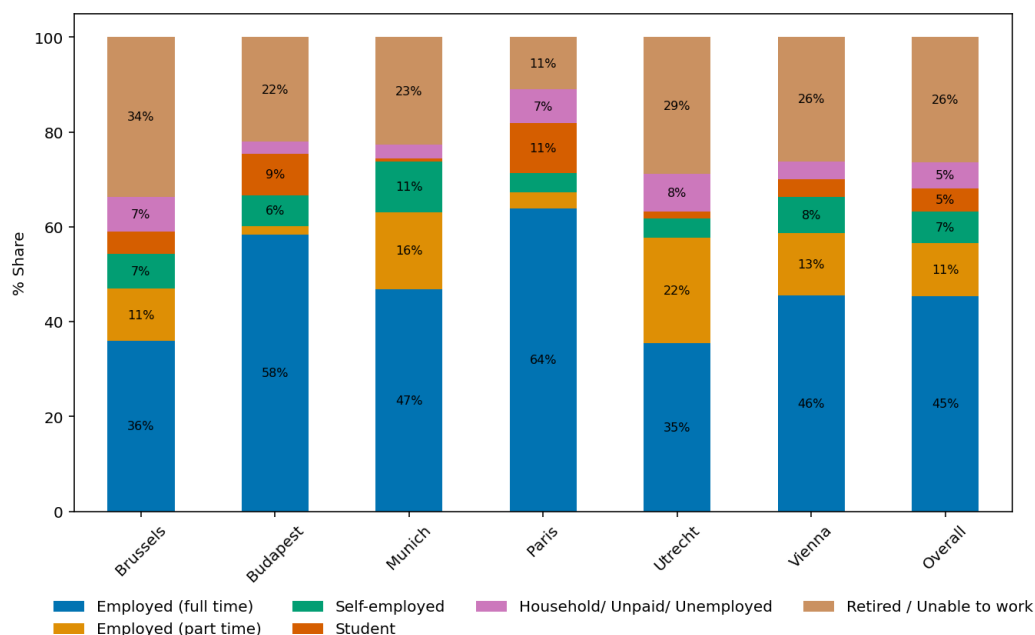


Note: Primary or less = primary / elementary (and pre-primary if present). Secondary/vocational = lower and upper secondary, Matura, apprenticeship, technical/commercial, post-secondary non-tertiary. Tertiary (Bachelor+): short-cycle tertiary, degree from university/college, Bachelor, generic "tertiary" (when undifferentiated), Master and PhD.

Employment status

In terms of employment, most respondents are economically active, with full-time employment being the most common status across all cities and in the overall sample (see Figure 10). Part-time employment and self-employment together represented a smaller but non-negligible share, with some city-specific variation. Students and respondents classified as household, unpaid, or unemployed accounted for relatively limited proportions, while a substantial minority of participants were retired or unable to work, particularly in Brussels, Utrecht, and Vienna. Overall, the employment profile was dominated by working-age, economically active individuals, complemented by a meaningful presence of retired respondents, reflecting the age structure observed in the sample.).

Figure 10 Employment status of DREAMS survey respondents

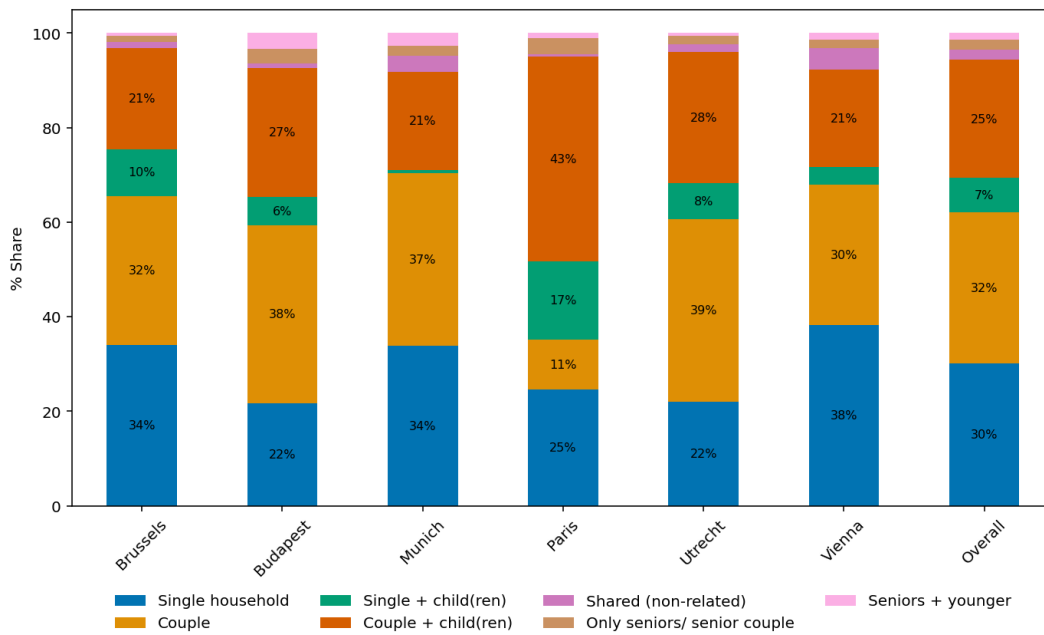


Household situation

illustrates household situation of the respondents across the living labs. Single-person households accounted for 30% of respondents, followed closely by couples without children at 32%, meaning that more than 60% of participants lived in households without children. Households with children nevertheless represented a substantial share of the sample. Couples with children made up 25% overall, with markedly higher proportions in Paris (43%) and Utrecht (28%). Single-parent households remained relatively uncommon across all cities, ranging from 6% in Budapest to around 17% in Paris. Other household arrangements were marginal in all study areas, each accounting for only a small fraction of respondents. Overall, the distribution suggested a sample dominated by small and medium-sized households, with family households playing a more prominent role in specific urban contexts.

Figure 11 illustrates household situation of the respondents across the living labs. Single-person households accounted for 30% of respondents, followed closely by couples without children at 32%, meaning that more than 60% of participants lived in households without children. Households with children nevertheless represented a substantial share of the sample. Couples with children made up 25% overall, with markedly higher proportions in Paris (43%) and Utrecht (28%). Single-parent households remained relatively uncommon across all cities, ranging from 6% in Budapest to around 17% in Paris. Other household arrangements were marginal in all study areas, each accounting for only a small fraction of respondents. Overall, the distribution suggested a sample dominated by small and medium-sized households, with family households playing a more prominent role in specific urban contexts.

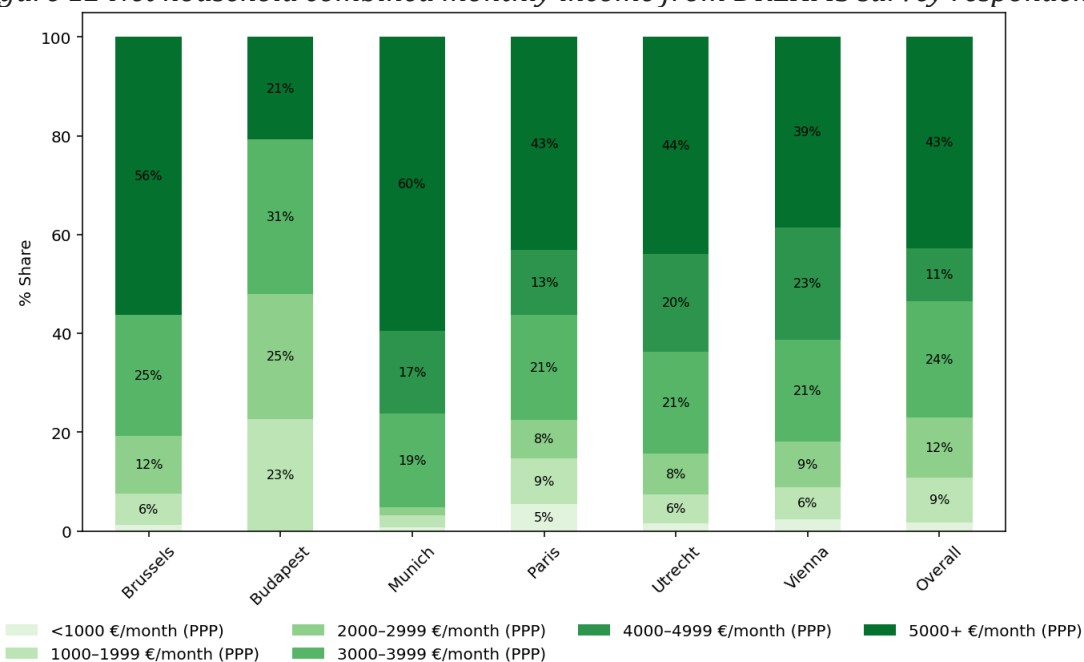
Figure 11 Household situation of DREAMS survey respondents



Household income

The distribution of net combined monthly household income, adjusted for purchasing power parity (PPP) for each city can be seen in Figure 12. Results show clear differences across cities while consistently capturing a broad range of income categories. In most study areas, the largest shares of respondents are concentrated in the upper income bracket. Lower income brackets below 3000 €/month represent a smaller but non-negligible share, with higher proportions observed in Budapest. At the upper end of the distribution, households reporting €4,000–4,999 and €5,000 or more per month are especially prominent in Munich, where 60% of respondents fall into the highest category, and are also well represented in Paris, Utrecht and Vienna. By contrast, these higher income categories are less common in Budapest. Non-response remains limited across cities, with “prefer not to say” accounting for a relatively small share overall. Taken together, the results indicate adequate variation in reported household income across cities

Figure 12 Net household combined monthly income from DREAMS survey respondents



Telework arrangement, digital skills and online activities

Teleworking shows marked differences across cities while being well established among a substantial share of respondents (see Figure 13). Overall, 27% of respondents work remotely 1–2 days per week and 13% work remotely 3–4 days per week, while more than 7% report working almost always remotely. At the same time, 34% of the sample indicate that they never telework. Budapest stands out with a particularly high share of respondents who never work remotely (63%). In contrast, Paris, Utrecht, and Vienna display higher levels of regular teleworking, with between 34% and 38% of respondents working remotely 1–2 days per week. Near-daily teleworking is most common in Brussels and Vienna (10 and 8% respectively). Overall, the results point to uneven adoption of teleworking across cities, ranging from predominantly on-site work patterns to more hybrid arrangements.

Regarding digital skills from respondents (see Figure 14), the results indicate generally high knowledge levels related to mobility tasks across all cities. Most respondents report being able to look up travel information online, with shares exceeding 80% in all cities and reaching over 90% in Brussels, Munich, Paris, and Utrecht. Similarly, the use of journey planners- both for public transport and for private vehicles -is widespread, although with some variation across cities. More advanced digital tasks, such as booking shared mobility services and buying public transport tickets or transfers online, are less common but still reported by a substantial proportion of respondents, particularly in Paris and Brussels. Only a very small share of respondents reported not having a smartphone or being unable to perform these digital tasks, both at the city level and overall, indicating that digital exclusion is limited within the sample.

Figure 13 Telework frequency of DREAMS survey respondents

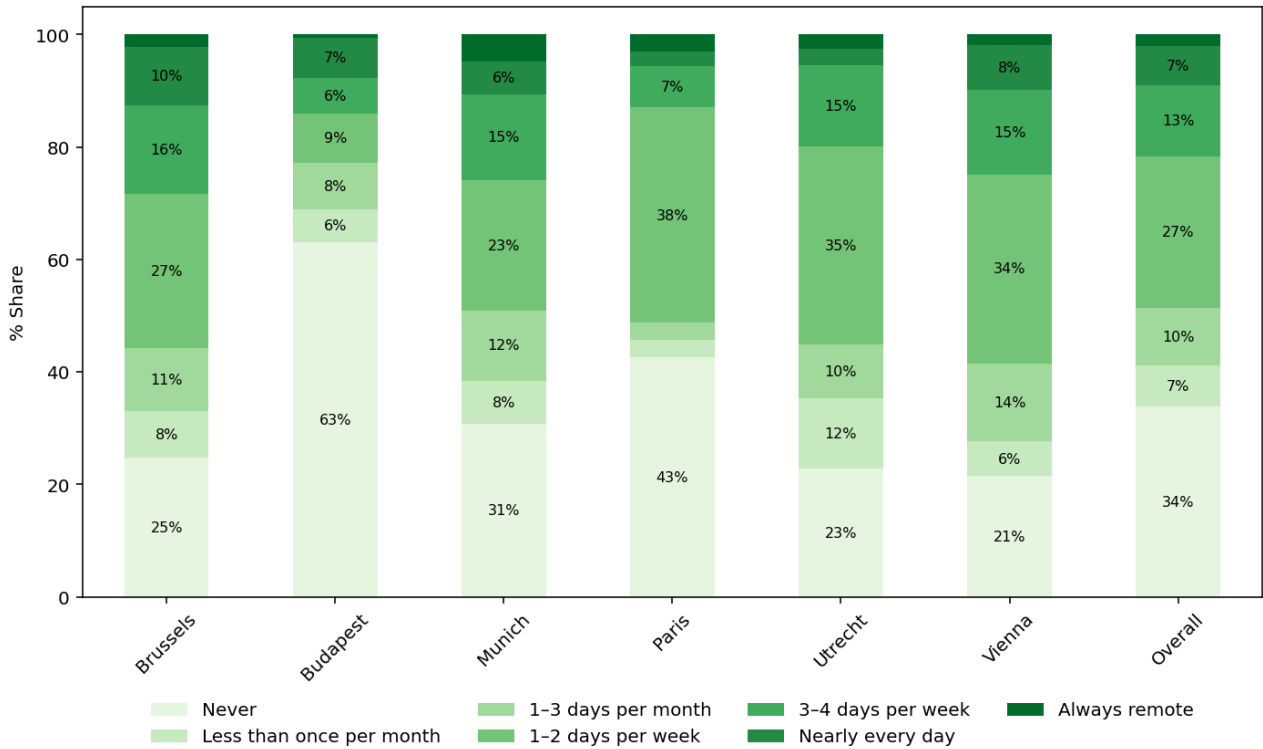
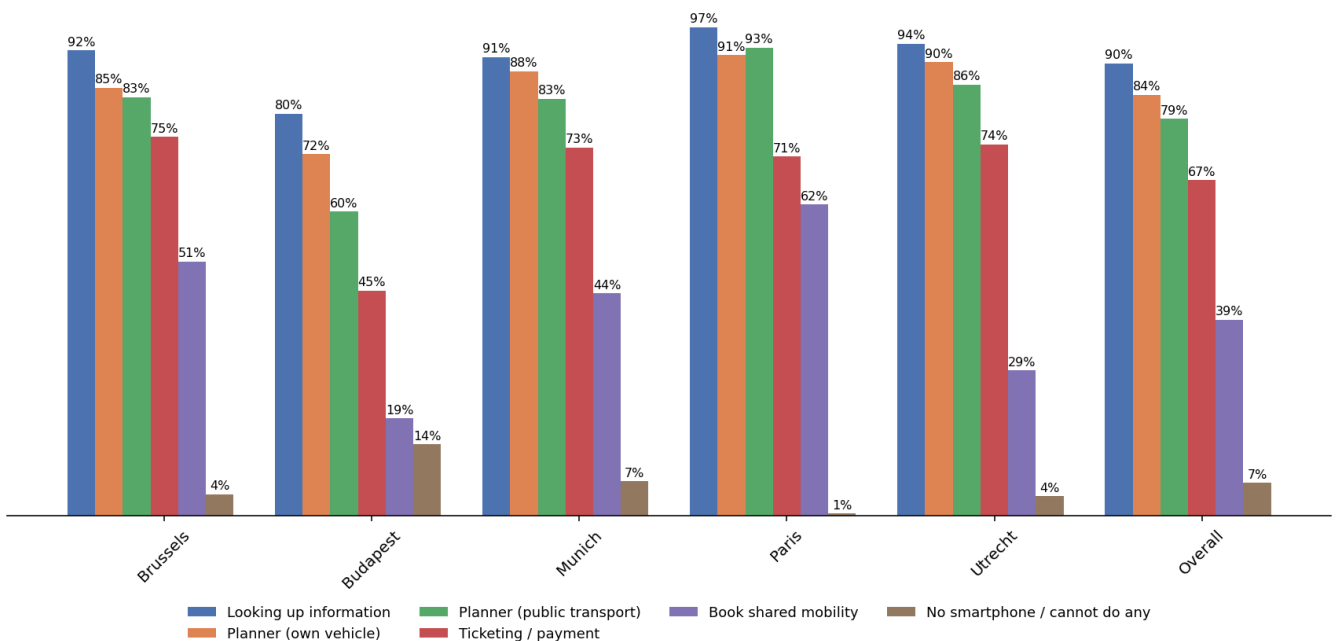


Figure 14 Respondents' digital skills with smartphone for mobility tasks

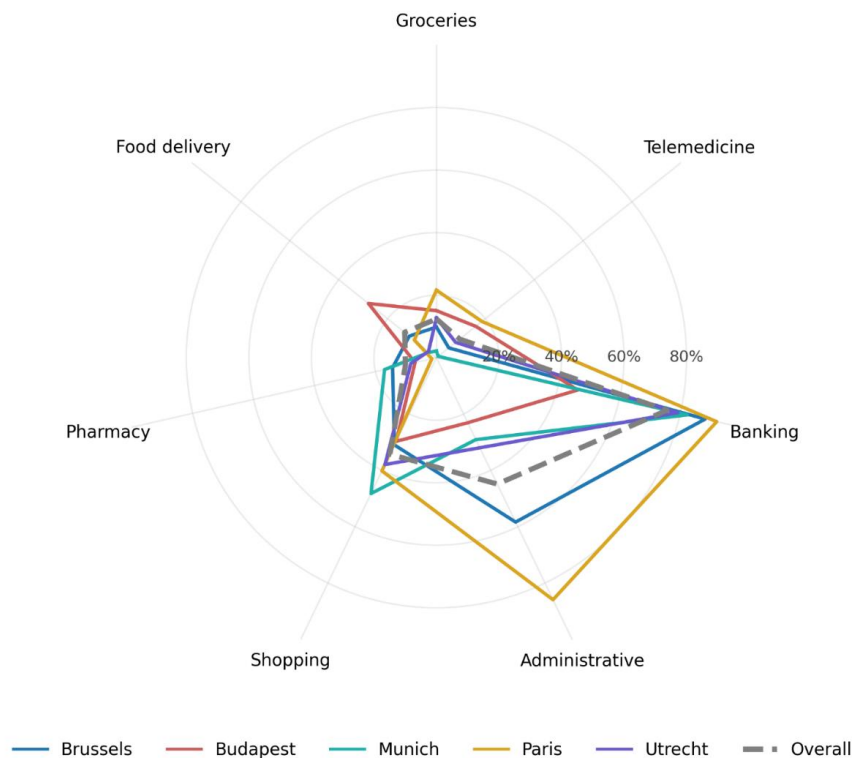


The impact of online activities on the frequency of out-of-home activities was examined by asking respondents to indicate their level of agreement with the statement “I go less often to this activity because I do it online” for a range of specific activities. For the analysis, responses indicating agree and strongly agree were combined, capturing the share of respondents who reported a reduced need to physically travel due to the availability of online alternatives.

Overall, the results (see Figure 15) show that banking is the activity most strongly affected by online substitution, with very high shares of agreement across all cities, generally ranging between around 70% and 90%. Administrative activities also show a strong impact of online alternatives, particularly in Paris and Brussels, where a large proportion of respondents report going less often in person. Shopping presents a more moderate level of substitution, with roughly 30–45% of respondents indicating fewer trips due to online options, especially in Munich and Paris. In contrast, groceries, pharmacy visits, and telemedicine show considerably lower levels of substitution, typically below 20–25%, indicating that these activities remain largely place-based despite increasing digitalisation. Overall, the findings suggest that online services mainly reduce travel for administrative and financial purposes, while their influence on everyday activities remains more limited.

Figure 15 Share of respondents reporting reduced in-person activities due to online alternatives

"I agree / strongly agree that I go less often to this activity because I do it online"



Mobility resources and difficulties

Figure 16 shows high levels of access to private and public transport resources across cities, with clear differences by item and location. Licence ownership is widespread, exceeding 70% in all cities and reaching over 85% in Munich, Paris, and Vienna. Car access is also high overall, although more unevenly distributed, ranging from around half of respondents in Budapest to more than three quarters in Utrecht and Paris. Public transport passes or subscriptions are common, particularly in Brussels, Paris, Utrecht and Budapest. Access to bicycles is substantial across all cities, with bike or cargo-bike availability especially high in Munich and Utrecht, and moderate to high levels also observed in Paris and Vienna. E-bikes and e-cargo bikes are less common but still present for a notable share of respondents, particularly in Utrecht and Munich. In contrast, access to scooters, motorcycles, and shared mobility subscriptions remains relatively limited in all cities. Overall, the findings indicate a diverse set of mobility resources available at the household level, combining high access to cars and public transport with strong availability of bicycles in several urban contexts.

Moreover, regarding mobility difficulties, most of the respondents report having no mobility-related difficulties (see Figure 17). Reported difficulties for both walking and cycling are reported higher in

Utrecht and Brussels, while in the rest of the cities it remains relatively low. Overall, the findings suggest that mobility-related physical constraints affect only a small minority of respondents, indicating generally high physical accessibility within the sample.

Figure 16 Access to mobility-related resources at the household level

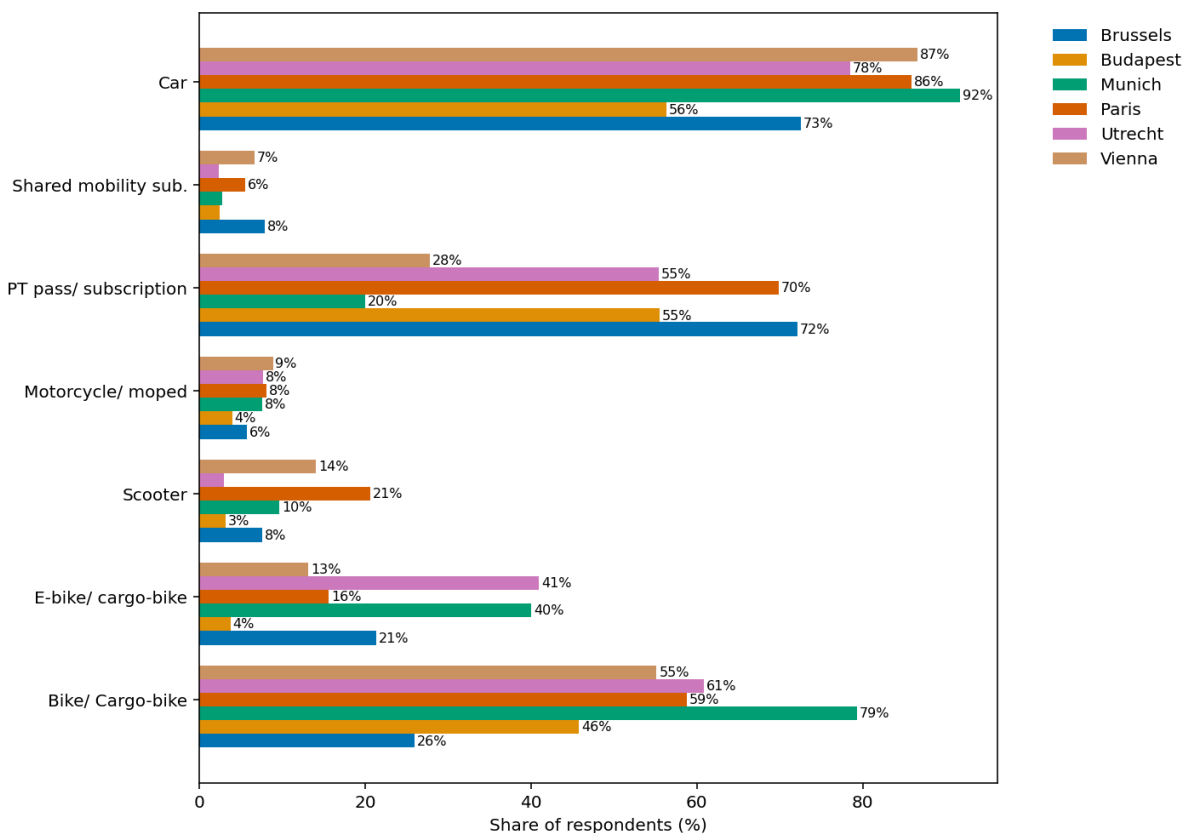
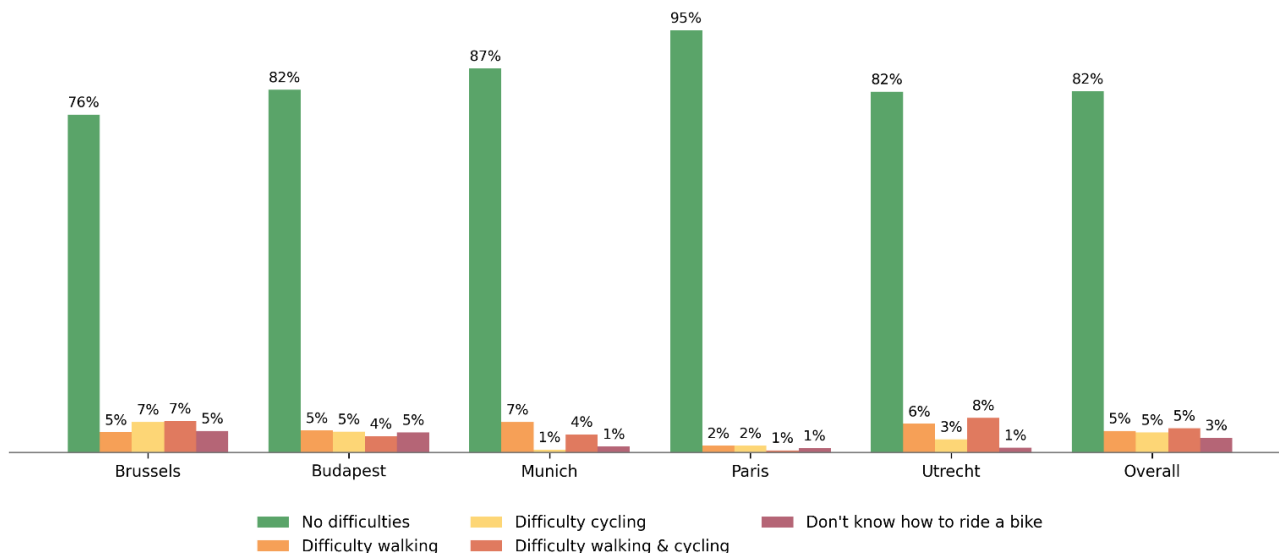


Figure 17 Mobility difficulties among DREAMS survey respondents



1.1. Importance of amenities

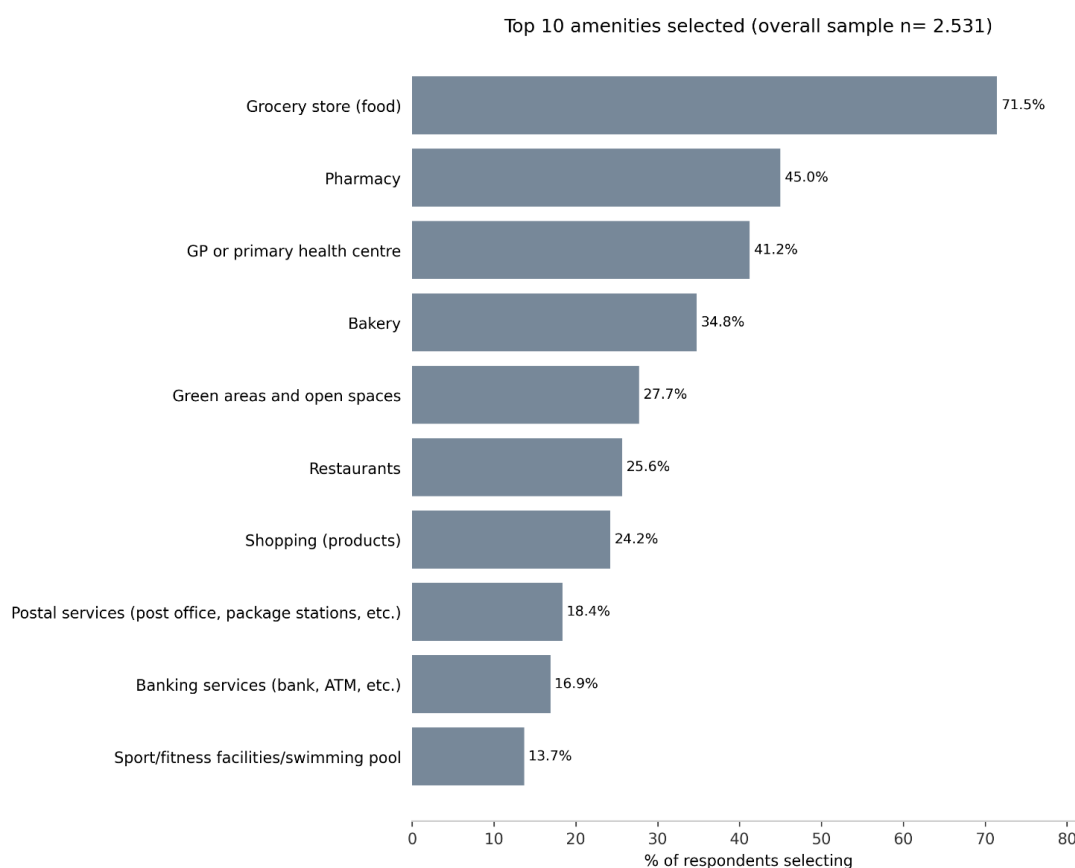
Up to this point, the results presented characterise the sample of the survey, describing their main socio-demographic characteristics and contextual attributes. In this section, the focus shifts to the core results of the survey, which address respondents' perceived accessibility and their experiences in accessing amenities. To capture which amenities play a key role in driving perceived accessibility, respondents were asked to identify the services they consider most important to have close to their home.

Specifically, they were asked to select between three and five amenities that they regularly travel to and would prefer to access within walking or cycling distance. The sample that responded to this question correctly (by selecting between three and five amenities) consisted of n = 2.340 respondents, 11 respondents were excluded.

The question was phrased as follows: *“Based on your current living situation, select your topmost important amenities or services that you travel to and would like to have close to your home, within walking/cycling distance”*. As an initial diagnosis, most respondents selected the maximum number of amenities allowed, with 60.1% identifying five amenities as most important to have nearby. A smaller share selected exactly three amenities (27.4%), while only 12.5% chose four amenities, indicating a clear tendency to prioritise a broader set of local services.

Figure 18 shows a clear prioritisation of essential, everyday services among respondents. Grocery stores stand out as the most important amenity to have close to home, selected by 71.5% of respondents, indicating the central role of food-related activities in daily life. Health-related services are also highly valued, with pharmacies (45%) and GP or primary health centres (41.2%) ranking second and third, respectively.

Figure 18 Top 10 amenities selected as important to have nearby



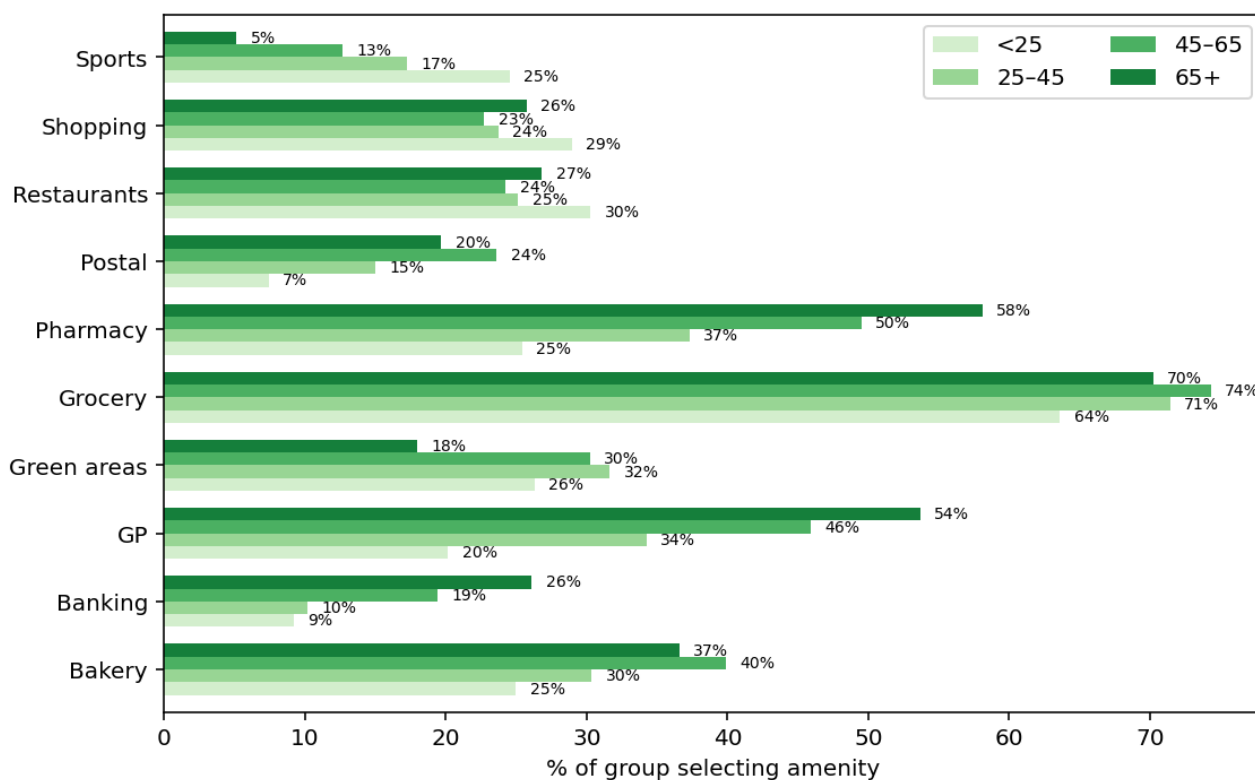
Local retail and leisure-oriented amenities follow at some distance, including bakeries (34.8%), green areas and open spaces (27.7%), restaurants (25.6%), and non-food shopping (24.2%). Services related to administration and finance, such as postal services (18.4%) and banking services (16.9%), are selected less frequently, while sport and fitness facilities appear as a lower priority overall (13.7%). Taken together, the findings suggest that proximity to basic daily needs and health services is valued more strongly than access to discretionary or less frequently used amenities. To see the full set of amenities prioritised by respondents see.

Sociodemographic characteristics and relevance of amenities

In the following section, we describe how diverse sociodemographic characteristics are distributed across the most frequently selected amenities. Focusing on the top 10 services, this analysis explores how different population segments relate to and prioritise nearby everyday services.

First, as seen in Figure 19, there exist significant differences in the importance different age groups assign to amenities. All groups assign relatively high importance to having a grocery store, pharmacy and GP nearby. Older generation assign marginally more importance to the former two amenities than younger generations. Also, older generation place relatively more importance into having banking services nearby. In contrast, sport related amenities, as well as shops and restaurants, are more important for younger age groups than older age groups. In general, the results indicate that all age group find essential services important. The differences between age groups reflect the changes in lifestyle and mobility that occur when ageing, where older generations generally place more importance in having essential amenities close by and younger generation assign more importance to recreational activities.

Figure 19 Age distribution for the top 10 services



In regard to gender (Figure 19), women represent most respondents for every service, with particularly strong overrepresentation for GP visits, pharmacies and green areas. The gender gap is smallest for sports, shopping, banking. Male respondents indicated restaurants, bakeries and shopping were important more often than female respondents. Overall, the findings suggest that female respondents tend to prioritise proximity to a broader range of everyday services such as healthcare and daily-needs amenities.

With respect to migration background (Figure 21) respondents who have lived longer in their country of residence show higher engagement across most essential services, including groceries, pharmacies, GPs and banking services. Grocery shopping remains consistently important across all groups. Recently immigrated respondents indicated significantly more importance towards shopping and green areas. This could be caused by newly migrated respondents being of relatively young age.

Regarding household situation, Figure 22 shows similar results as seen previously in Figure 18. Where essential services such as grocers, pharmacies and GPs are important across almost every household type. There are some differences between household when it comes to amenity importance, where

seniors tend to select pharmacies (54%) and GPs (56%) as important relatively more. Households with children most often indicate green and open areas as important, reflecting a more family-oriented lifestyle.

Figure 20 Gender distribution for the top 10 services

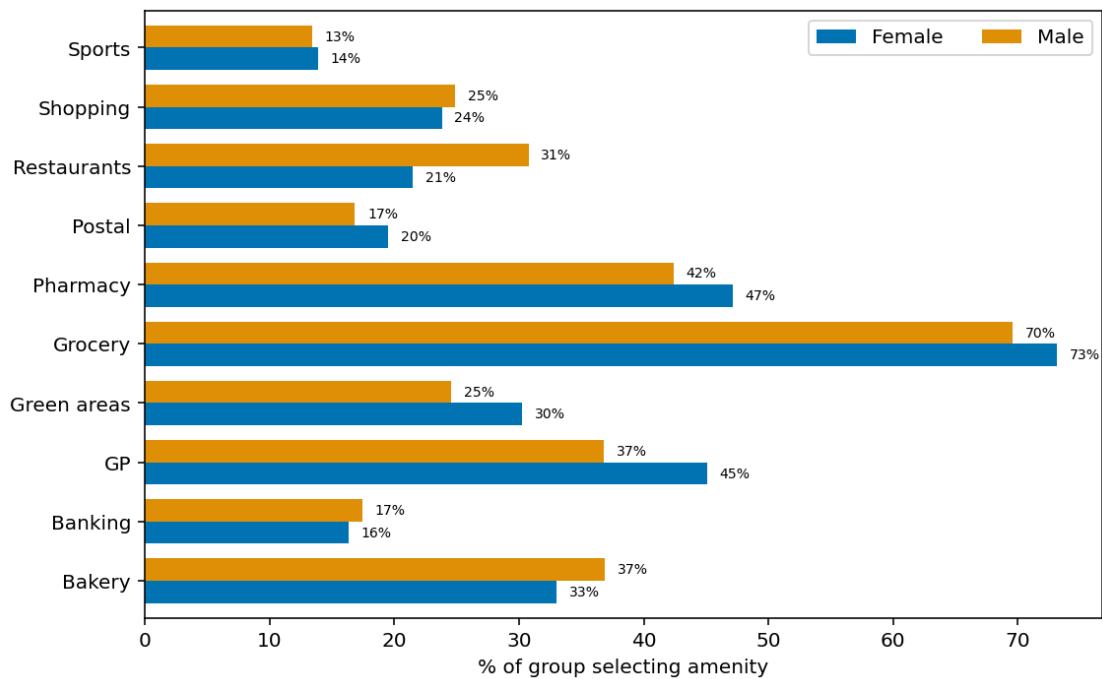


Figure 21 Migration background distribution along the top 10 services

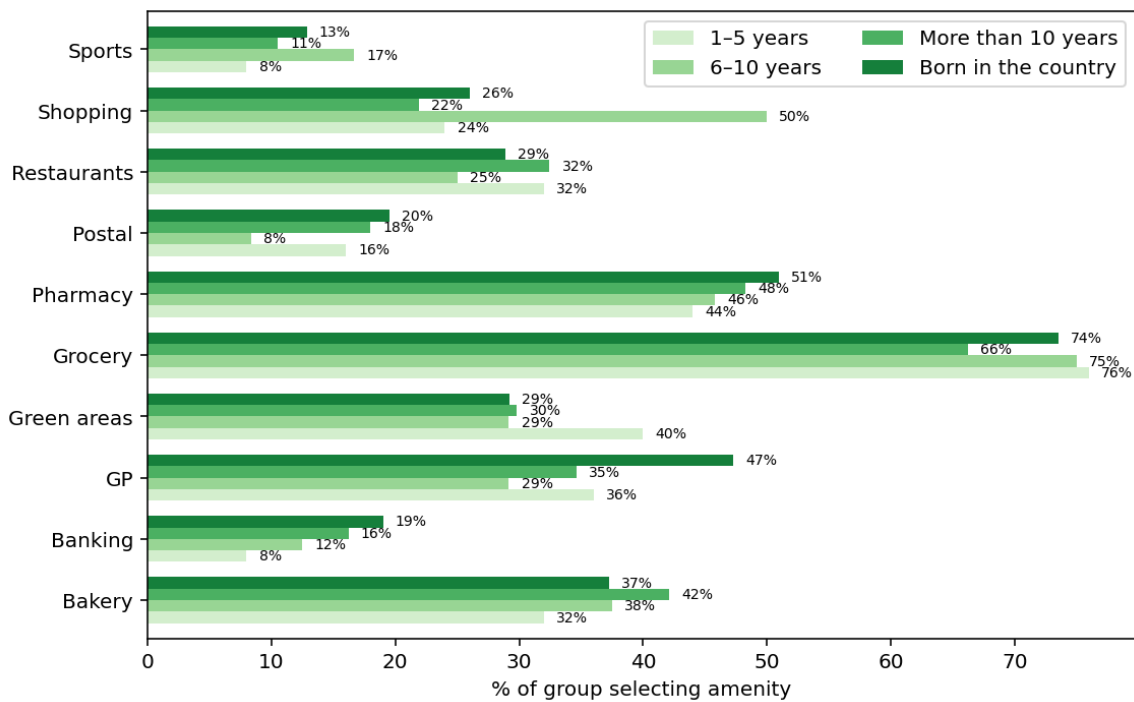
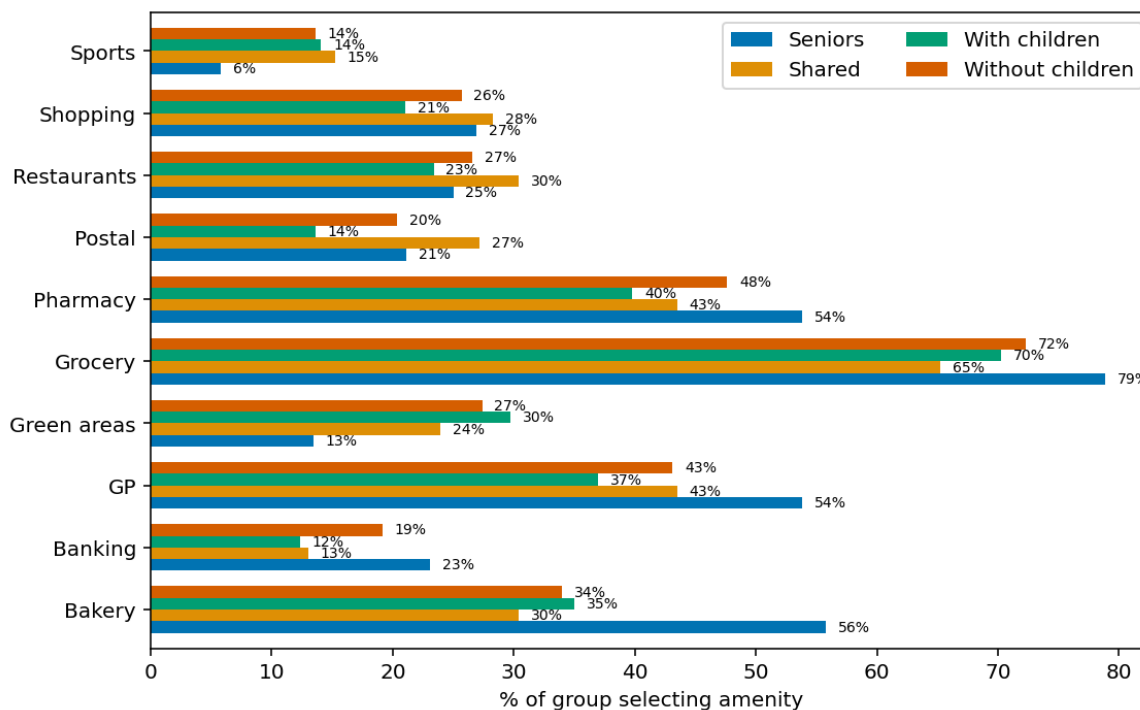


Figure 22 Household situation distribution for the top 10 services



These results presented in this section have shown the importance of everyday services such as grocery stores, GPs and pharmacies to be present amongst all respondents, cutting across socio-demographic layers. Some groups place more importance in specific amenities depending mostly on differences in lifestyles between respondent groups.

1.2. Current mobility behaviour

In this section, we describe how people currently travel to their selected services, as well as their desired travel times and the maximum acceptable walking time to reach these amenities. Specifically, we analyse the transport modes used to access everyday services, the frequency of these trips, and both current and desired travel times. This approach allows us to compare existing mobility patterns with respondents' aspirations, providing insight into how current travel behaviour aligns with, or diverges from, people's preferences and expectations regarding access to everyday services.

Firstly, Figure 23 shows that walking is the dominant mode for nearby, everyday services, particularly green areas and open spaces (81%), bakeries (63%), and grocery stores (51%), indicating strong local accessibility for these activities. Walking also plays an important role for access to GPs and banking services, where around 40–45% of trips are made on foot.

In contrast, pharmacies, restaurants, shopping, and postal services display a more balanced modal split, with substantial shares of both car use (around 33–45%) and public transport (around 21–30%). Cycling and e-biking contribute a moderate but consistent share across most services, reaching up to 22% for sport and fitness facilities. Overall, the pattern suggests that services perceived as closer and more routine are primarily accessed by active modes, while more dispersed or less frequent activities rely more on motorised transport.

Figure 23 Mode share per top 10 selected amenities.

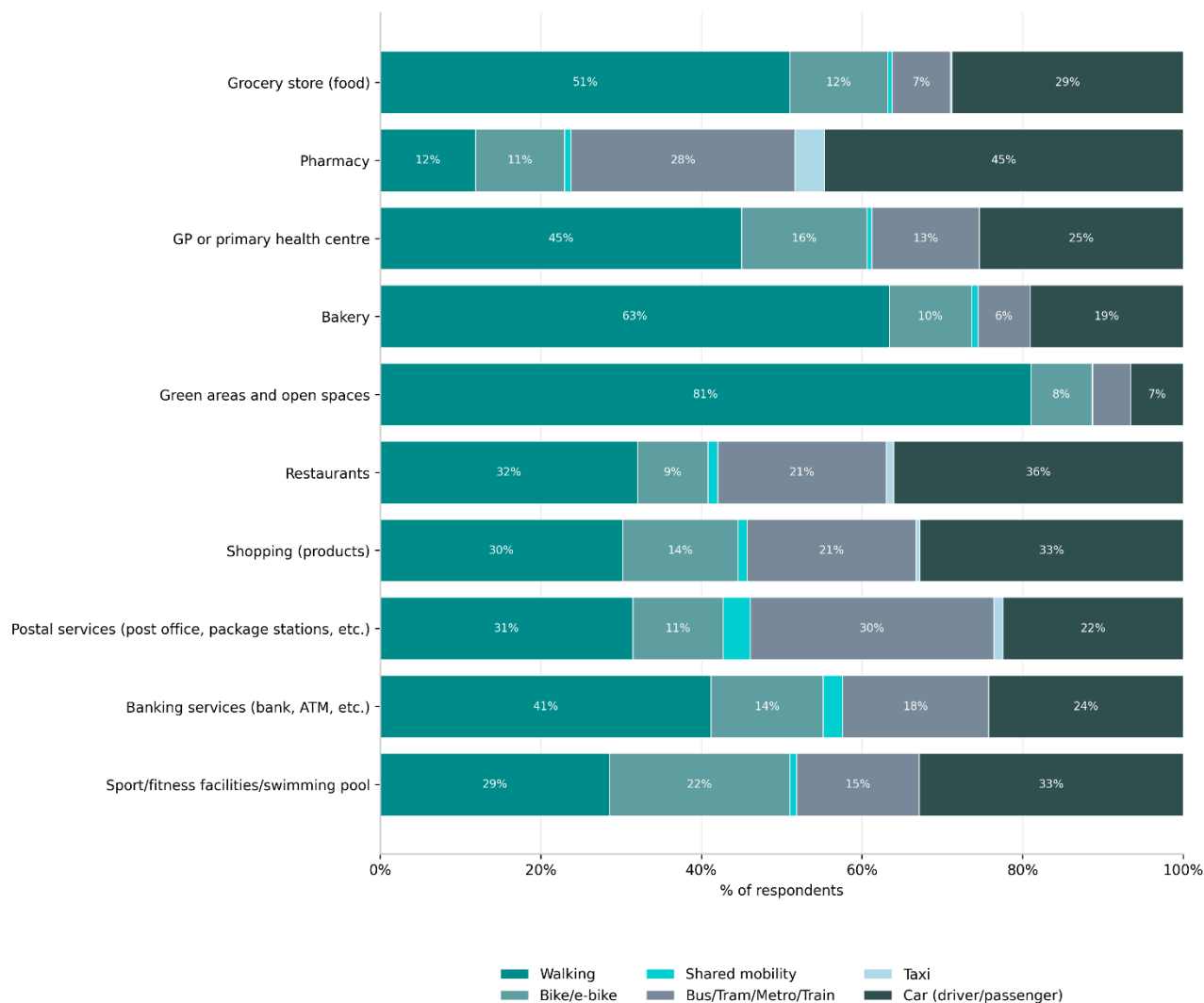


Figure 24 indicates that everyday services are used very regularly, with grocery stores (95%), bakeries (83%), green areas (82%), and sport and fitness facilities (88%) predominantly accessed on a weekly or more frequent basis. Health-related services show a different pattern, as visits to pharmacies and GPs are largely less frequent, with around 74–77% occurring less than monthly. Restaurants and shopping display a mixed pattern, combining regular use with a substantial monthly component (around 35–51%). Postal and banking services are mainly accessed monthly or less often, reflecting their more occasional nature. Overall, the findings distinguish clearly between routine, proximity-based services and more episodic activities.

When analysing current and maximum acceptable travel times to the amenities we observe in Figure 25 that most services are currently accessed within 15 minutes, particularly daily and essential amenities. At the same time, respondents generally report a higher maximum acceptable walking time than their current travel time, especially for non-daily services such as restaurants, shopping, and administrative services. This suggests some flexibility in acceptable proximity, while still indicating a strong preference for short travel times.

Figure 24 Frequency share per top 10 amenities

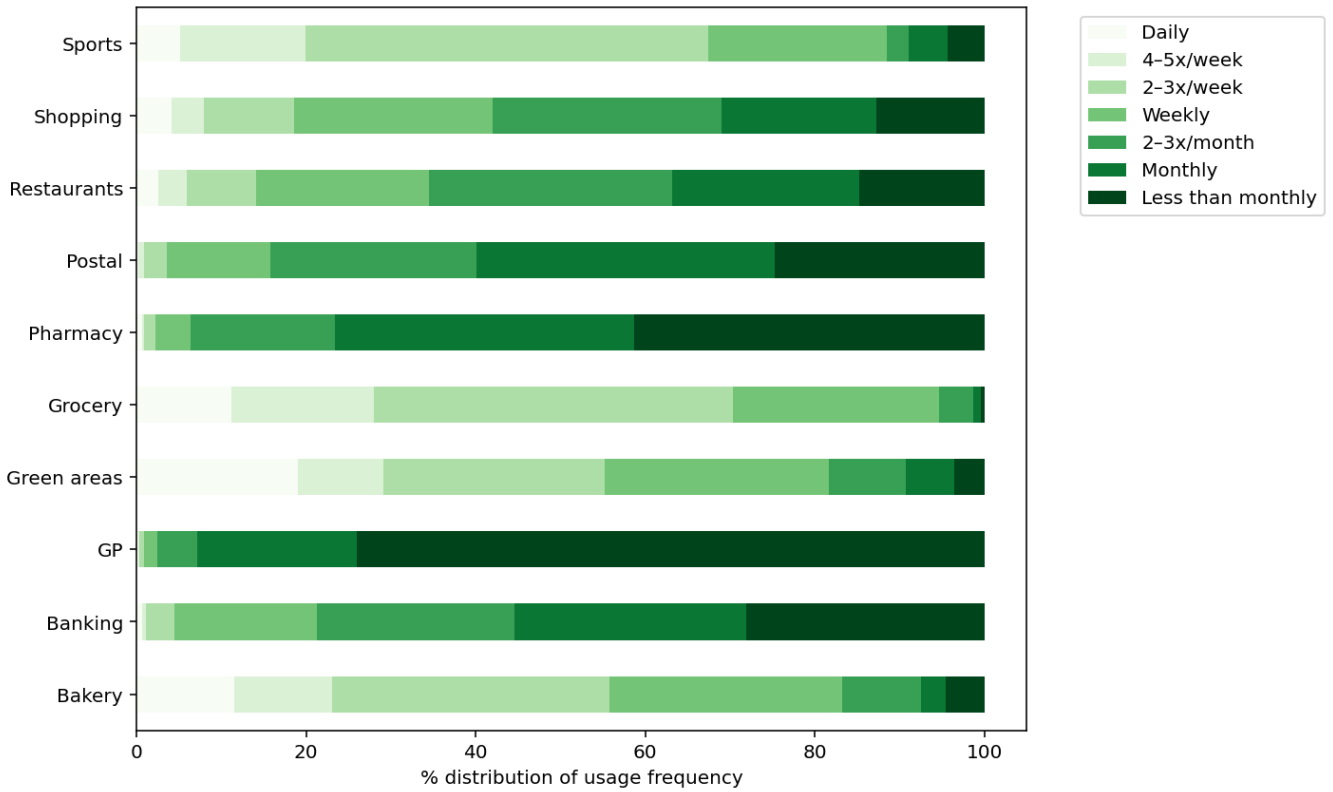
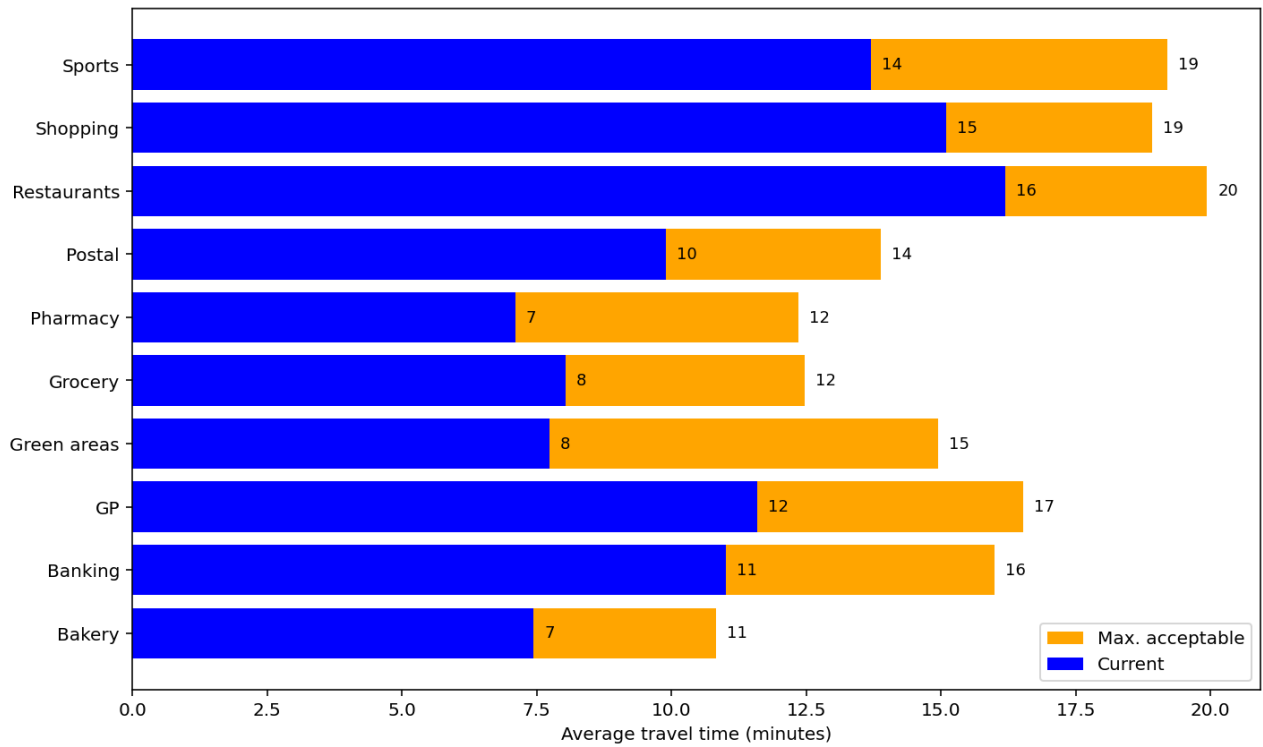


Figure 25 Current and desired travel times to top 10 amenities

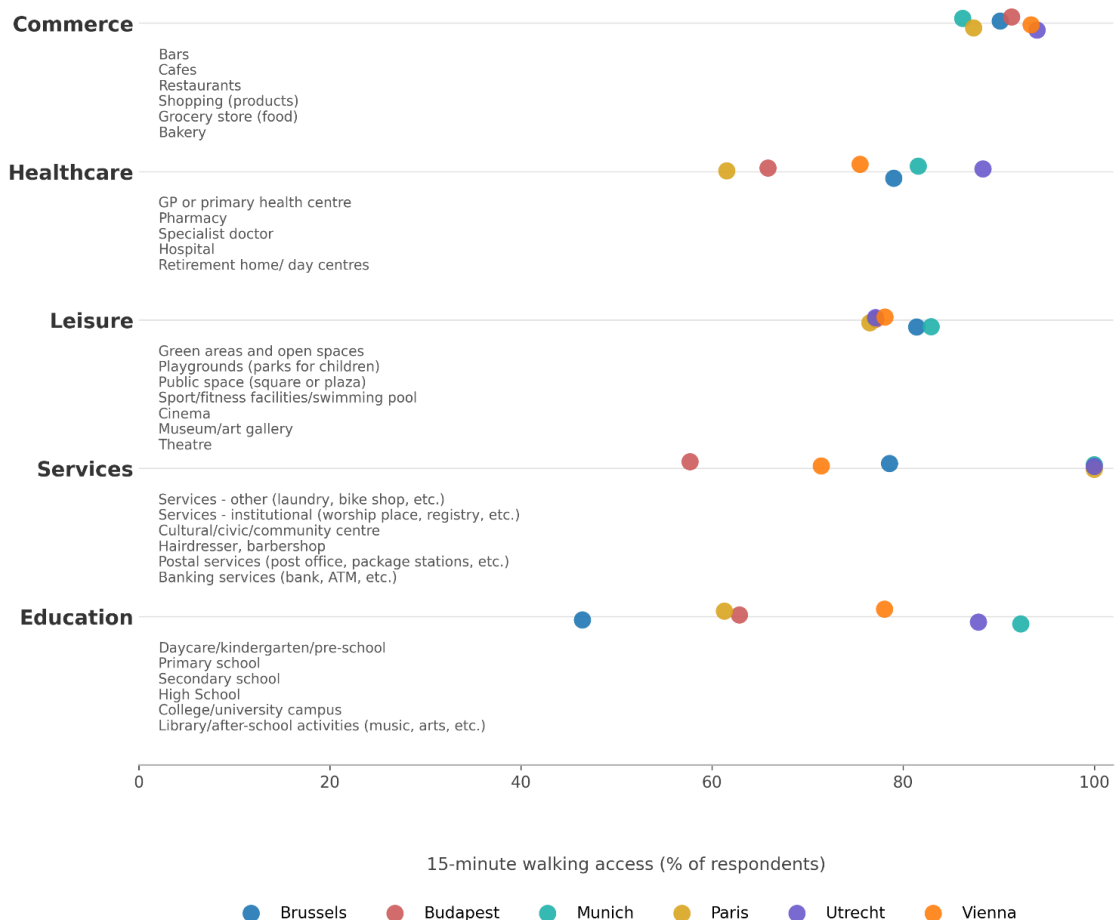


Note: Current travel times were assessed with the question "When you travel to your selected services, how long does it usually take you to get there?" and desired travel time was asked with the question "What is the maximum walking time you would spend getting there?".

As a result from the current mobility behaviour section, Figure 26 reveals clear differences in how evenly cities perform across service domains. Commerce-related amenities show a very tight clustering, with all cities grouped relatively close together and generally toward the higher end of 15-minute walking access, indicating broadly comparable and strong provision of daily commercial services. Leisure services display a similarly compact distribution, again with most cities performing well and only modest differences between them. In contrast, healthcare services are more dispersed, with some cities clearly outperforming others, pointing to greater inequalities in access to health-related amenities. Education exhibits the widest spread of all domains, showing substantial variation between cities and highlighting that walkable access to schools and educational facilities is far more uneven across contexts. Services fall somewhere in between, with noticeable but less extreme differences than education, and a moderate separation among cities. These patterns likely reflect differences in urban form, service distribution, and transport supply; however, the analysis is descriptive and not intended to infer causal drivers.

If we were to read this graph as a comparative “race” between cities in terms of how consistently they provide 15-minute walking access to key services, Utrecht and Munich will occupy leading positions. Brussels and Vienna frequently perform solidly but show more variability depending on the service type, sometimes keeping pace with the leaders (commerce, healthcare, leisure) and sometimes falling slightly behind (services and education). Paris demonstrates strong results in services, commerce and leisure but is less consistent across healthcare and education. Budapest most often lags behind, particularly in education and some service categories, where the spread is largest. Overall, the combination of tight clustering in commerce and leisure and wider dispersion in healthcare and education underscores both shared strengths and persistent structural differences in walkable accessibility across the cities.

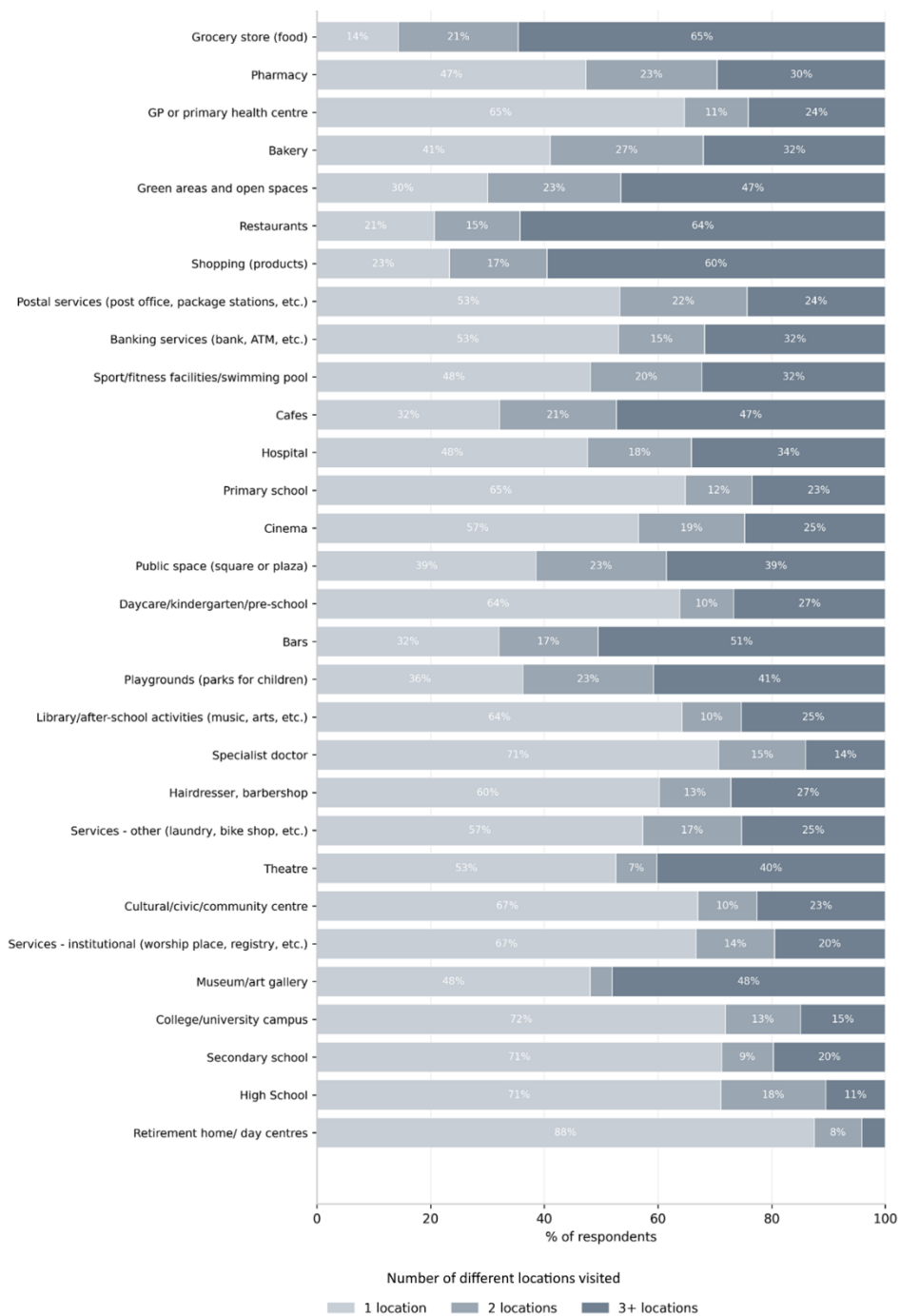
Figure 26 Share of residents with 15-minute walk access to key services



3.2. Reach and barriers

In terms of reach, Figure 27 shows that most respondents tend to rely on a limited number of locations for many everyday services, particularly for education, healthcare, and institutional services, where one single location clearly dominates (often above 65–70%, and up to 88% for retirement homes/day centres). In contrast, commercial and leisure-related services such as grocery stores, restaurants, shopping, cafés, and bars show much more diversified use patterns, with most respondents visiting three or more locations over the year (often around 50–65%). Services like pharmacies, postal services, and banking fall in between, with a more balanced mix of one, two, and multiple locations. Overall, the results suggest that people concentrate their routines for essential and specialised services in few stable places, while discretionary activities are distributed across a wider set of locations.

Figure 27 Current number of locations per service that are visited throughout a year.



Note: the framed question was "How many locations of your selected services...Do you usually visit throughout the year?"

When asked about desired number of locations (see Figure 28), respondents generally express a preference for having a limited number of locations within walking or cycling distance for most essential and institutional services, such as healthcare, education, and administrative services, where a single nearby option is sufficient for a majority of respondents (often around 55–70%). In contrast, for commercial and leisure-related services (such as restaurants, cafés, shopping, bars, green and open spaces, and cultural amenities) there is a clear desire for greater choice, with substantial shares of respondents indicating a preference for two or more nearby locations, and in several cases three or more. Services like grocery stores, pharmacies, and postal services occupy an intermediate position, combining a strong preference for at least one close option with a notable demand for additional nearby alternatives. Unexpected is the stated desire of 25% of the respondents who indicated retirement homes as being important to have 3 additional locations available in their proximity. Overall, the results suggest that while proximity to a single reliable option is valued for essential services, diversity and choice within walking or cycling distance are particularly important for everyday consumption and leisure activities.

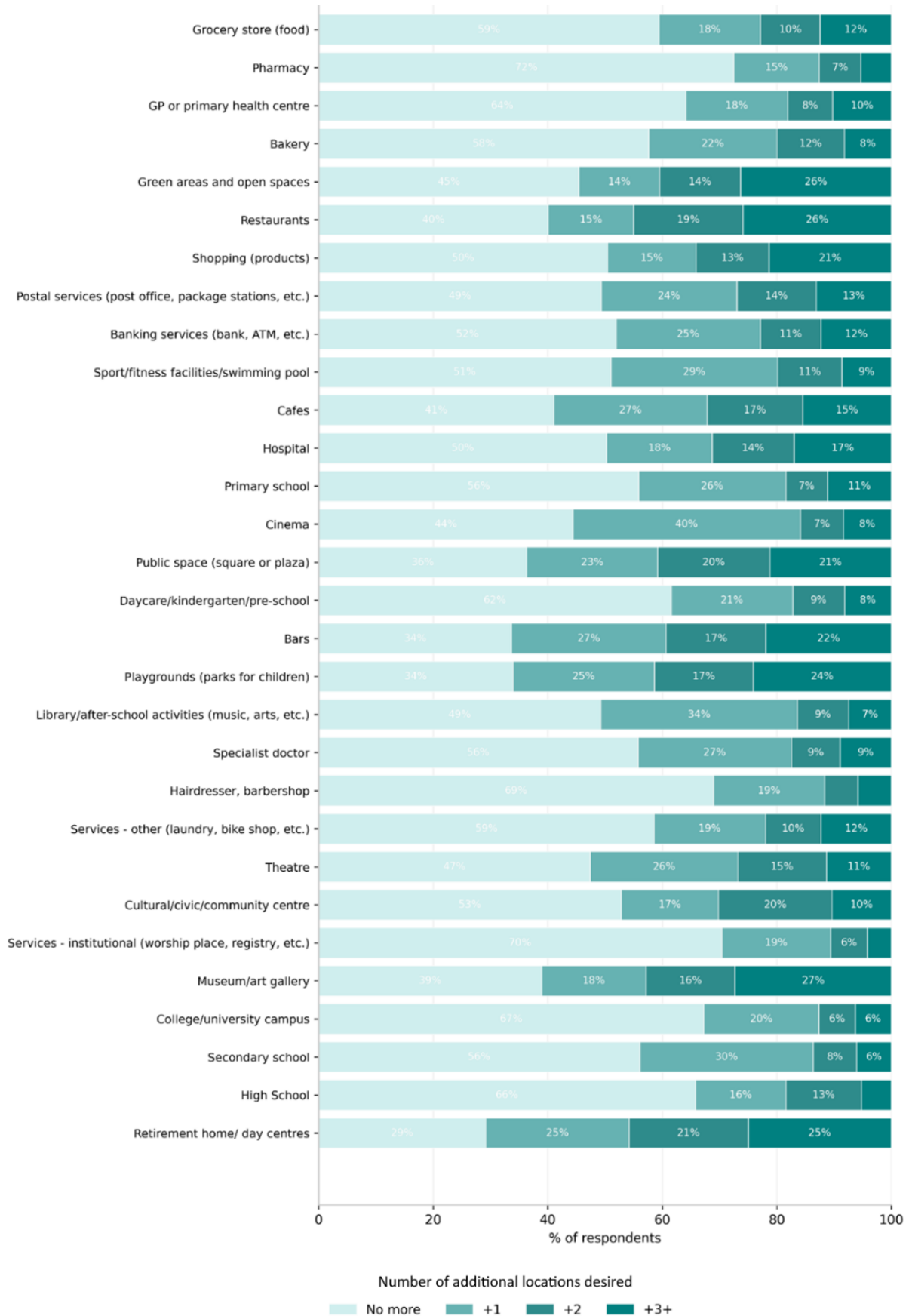
Following a current and desired approach, we asked about reachability for the selected services (see Figure 29). Overall, the graph shows very high perceived accessibility to most everyday services using respondents' preferred transport mode. Core daily needs (such as grocery stores, bakeries, pharmacies, green spaces, banking services, childcare, primary schools, and hairdresser) are reported as "always or often accessible" by around 90–100% of respondents, with almost negligible "rarely/never" responses. This suggests a strong baseline of proximity and network effectiveness for essential services.

In contrast, cultural, leisure, and specialised services (e.g. libraries/after-school activities, theatres, bars, cultural centres and museums) show lower accessibility and greater dispersion, with higher shares reporting rare or infrequent access (often 10–17%). Educational services beyond primary level (secondary/high school, university) and health services like hospitals also show slightly more mixed results, though still predominantly positive. Overall, the pattern points to highly consolidated access for daily necessities, while optional, specialised, or less frequently used services remain more unevenly accessible, highlighting where spatial or transport gaps persist.

When addressing the barriers that limit people to have good reachability for services (see Figure 30), findings indicate that spatial and transport-related barriers dominate but remain limited to a small share of respondents. The most frequently cited barrier is that services are too far from where people live (12%), followed by difficulties in reaching them by public transport, bike, or other modes (8%), and traffic congestion (6%). Other barriers, such as limited opening hours, high costs, or safety concerns during the trip, are mentioned by only small shares (around 3–4%). Barriers related to accessibility, inclusiveness, sustainability, or language are rarely reported (1–2% or less). Overall, the results suggest that while distance and transport connectivity remain the key constraints, most respondents do not perceive major systemic barriers to accessing services.

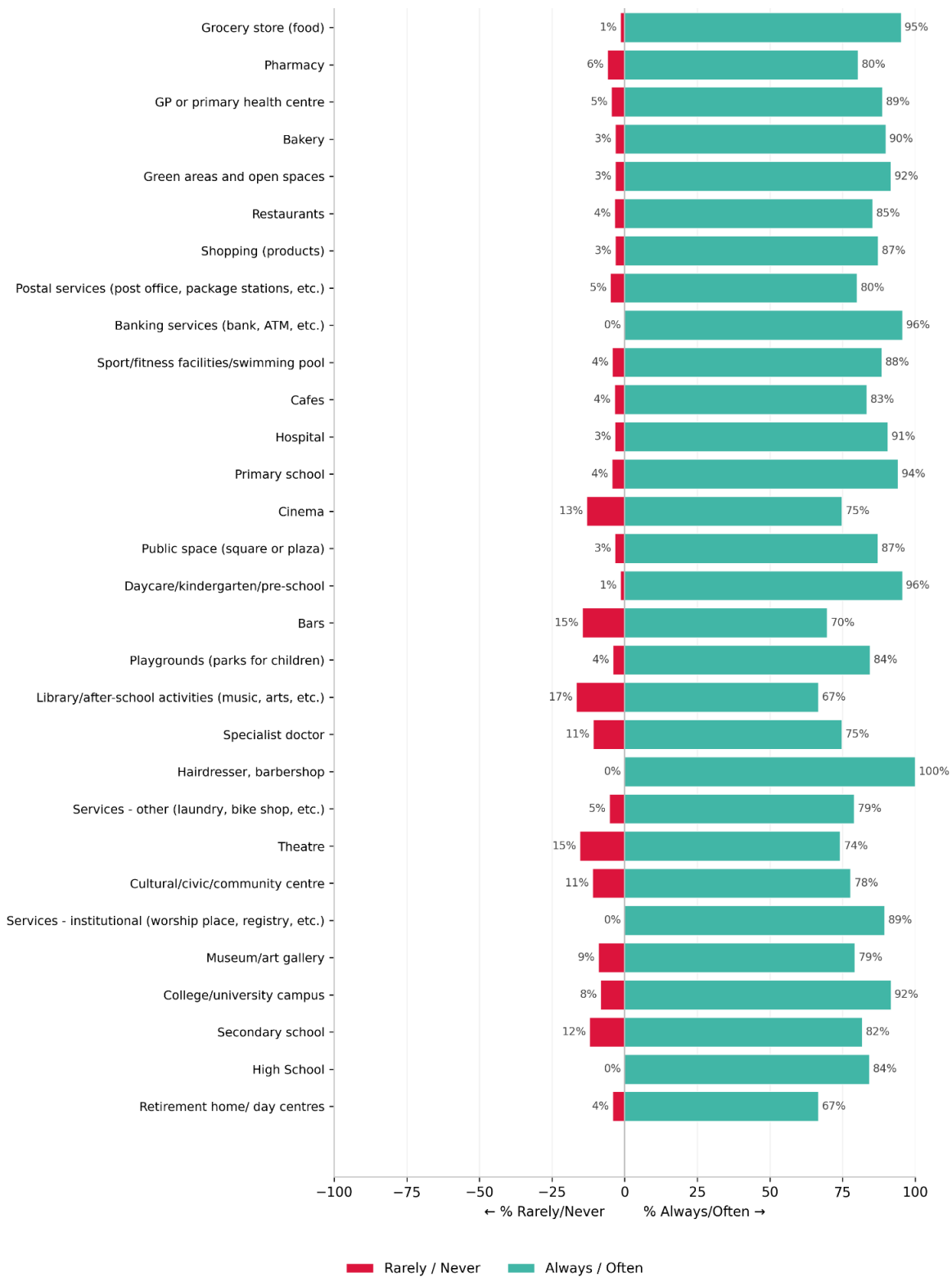
In the reported barriers to accessing urban services, the presence of amenity characteristics, e.g. related to hours of opening or cost, alongside transport options shows how developing the 15-minute city concept should engage simultaneous and coherent, urban and transport interventions. These results indicate avenues for intervention for cities willing to implement the urban concept.

Figure 28 Desired number of locations per service nearby the home.



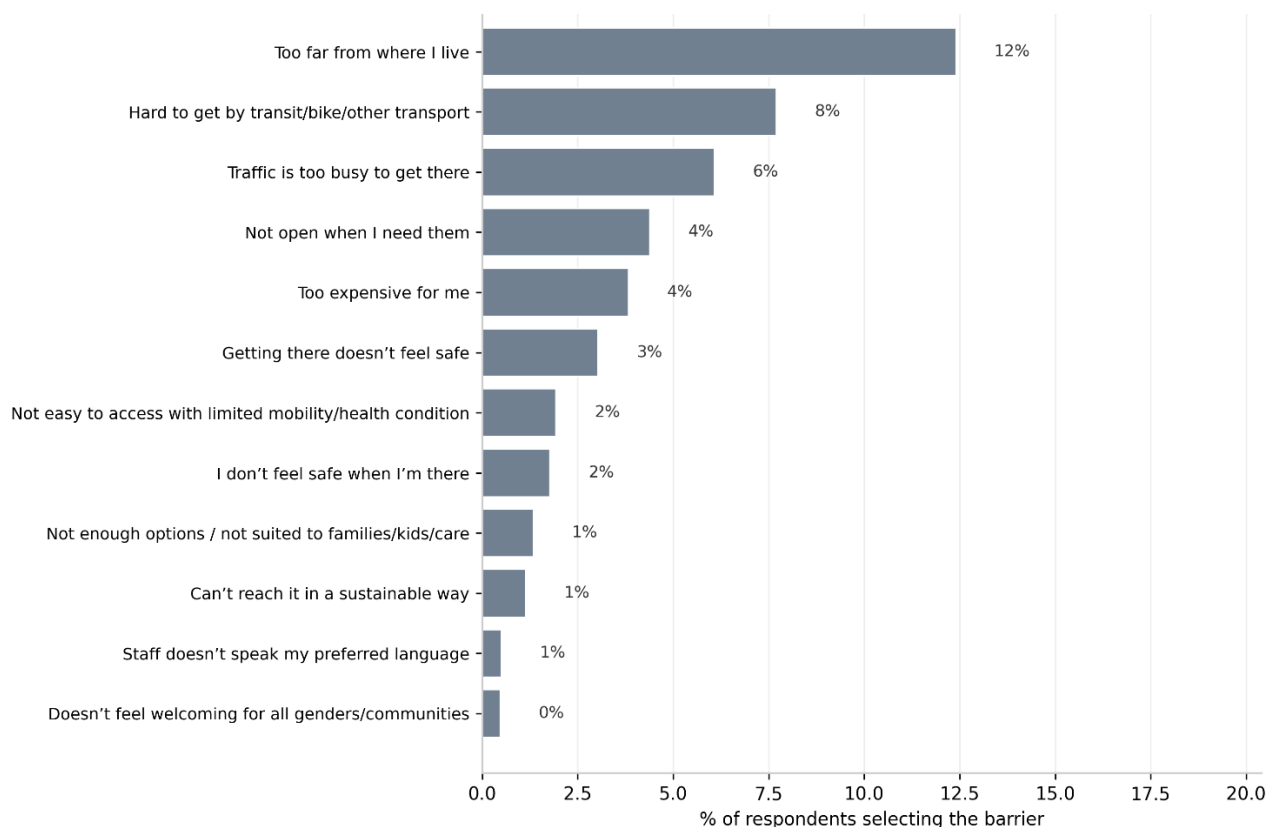
Note: the framed question was "How many locations of your selected services...Would you like to have at walking/cycling distance?"

Figure 29 Perceived accessibility to selected services



Note: the framed question was "You selected: (these services) In general, how often can you reach(access) these services using your preferred mode of transportation?"

Figure 30 Barriers for reaching the selected relevant services



Finally, when addressing the acceptability of some solutions to tackle accessibility barriers (see Figure 31), results show that improvements in public transport proximity are the most frequently identified enablers, with respondents most often selecting a bus stop near the location (7%) and a tram/metro/train stop nearby (6%). Notably, an equal share (6%) report that none of the listed facilities would improve their access, which suggests that remaining barriers may be less related to transport infrastructure and more to forms of transport poverty, such as affordability constraints, time poverty, limited mobility, or difficulties in combining trips efficiently across modes (factors that are not fully captured by proximity-based accessibility measures alone). Shared micromobility options, such as shared e-bikes or cargo bikes, are mentioned less frequently (4%), while shared cars and shared scooters/mopeds are selected by only small minorities (2% each). Overall, the findings suggest that marginal gains in accessibility are most likely to come from fine-grained public transport improvements, whereas shared mobility plays a more limited, complementary role.

3.3. Key services, location criteria, and neighbourhood perceptions

This section explores which services residents prioritise most for proximity, focusing on the single most important amenity to have within walking or cycling distance from home and the implications for perceived neighbourhood accessibility. In Figure 32 we can observe that again, daily necessities are predominant, with grocery stores overwhelmingly identified as the top priority (45.6%). Basic health services (GP or primary health centre, 9.2%), followed by bakeries (7.1%) and green/open spaces (6.9%), form a second tier of importance. All other services are selected by relatively small shares, indicating that everyday food access and essential wellbeing-related services dominate proximity preferences, while leisure, cultural, and specialised services are rarely considered the single most important amenity to have nearby.

Figure 31 Acceptability of solutions for accessibility barriers

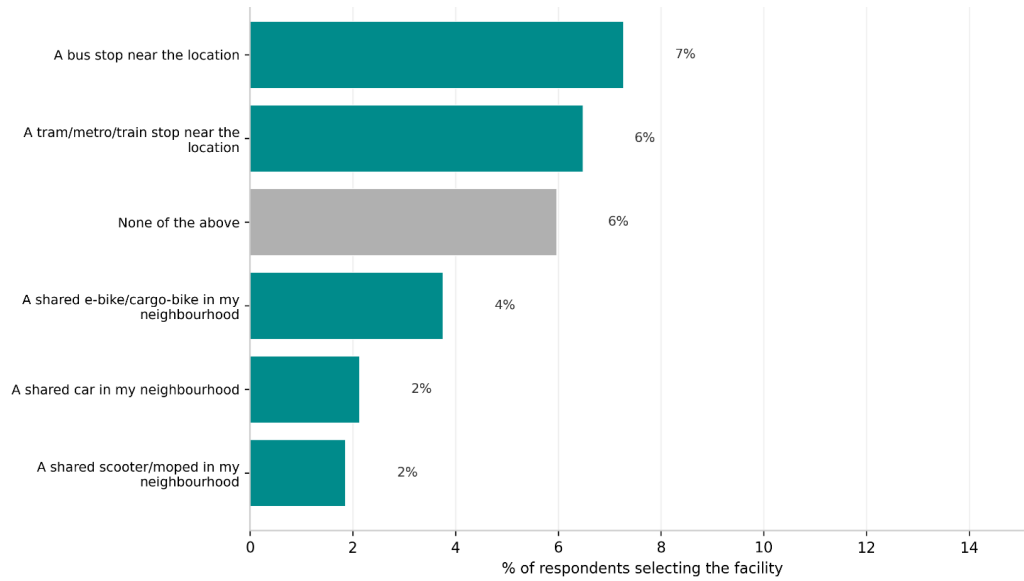


Figure 32 Top 1 service to have nearby home.

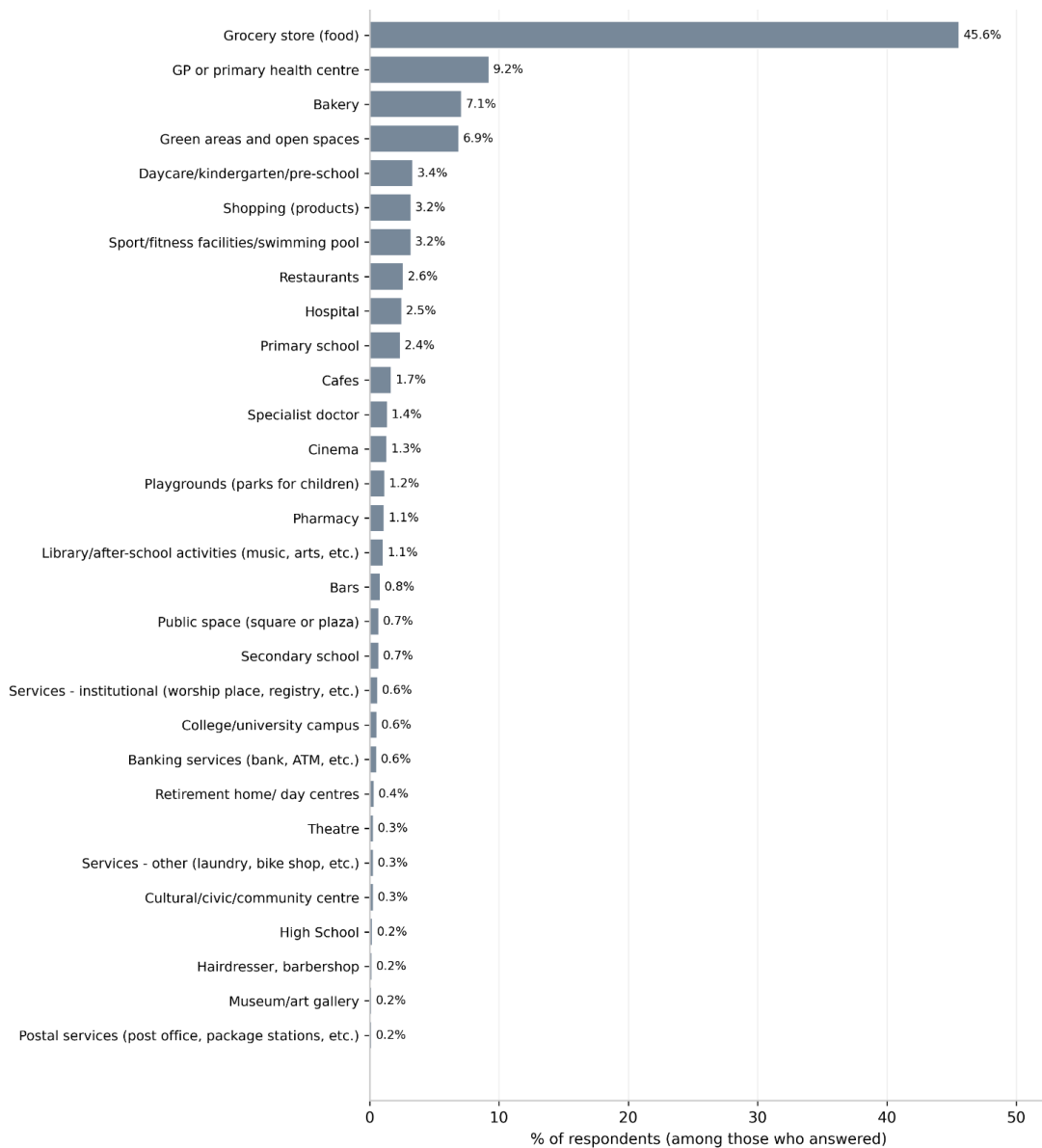
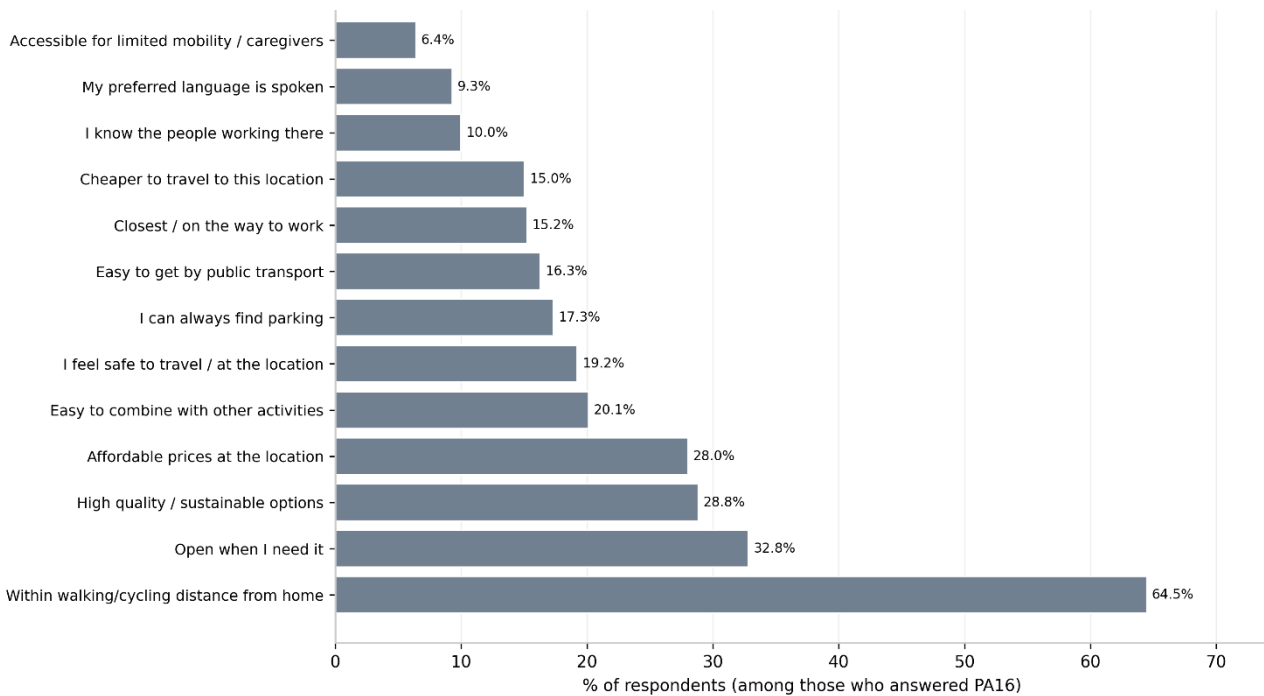


Figure 33 Criteria for choosing a specific location for their top 1 priority service

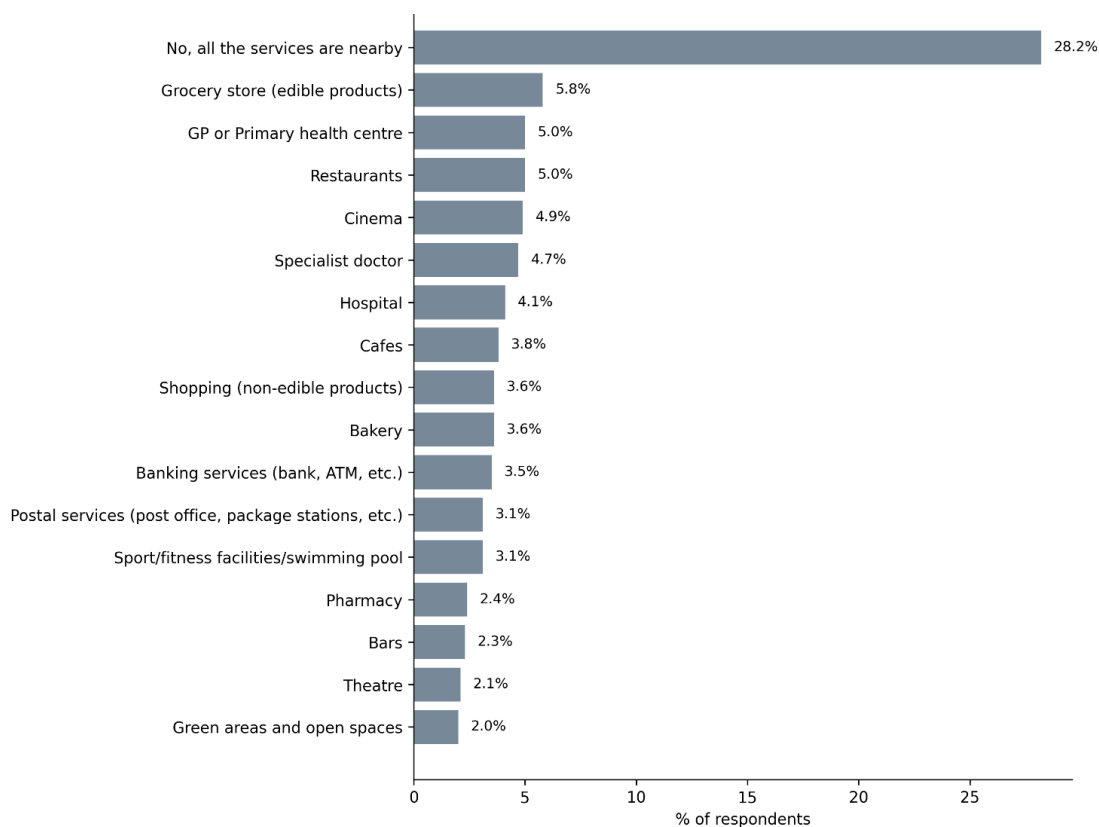


When choosing a particular location related to their top 1 priority service (Figure 33), results show that proximity is the dominant criterion when choosing the location of the most important service, with 64.5% of respondents prioritising locations within walking or cycling distance from home. Beyond proximity, temporal and quality-related factors are also important, particularly services being open when needed (32.8%), offering high-quality or sustainable options (28.8%), and having affordable prices (28.0%).

Trip efficiency and safety further shape location choice, including the ability to combine visits with other activities (20.1%), feeling safe when travelling or at the location (19.2%), and ease of access by public transport or parking (around 16–17%). In contrast, social and inclusiveness-related aspects such as language, familiarity with staff, or accessibility for limited mobility are less frequently cited, indicating that location decisions are primarily driven by proximity, convenience, and affordability.

When asked about a desired service to have nearby that is not currently within walking or cycling distance (see Figure 34), a substantial share of respondents (28.2%) indicated that all relevant services are already close to their home. Among those expressing unmet needs, the most frequently mentioned wishes relate to everyday and health-related services, particularly grocery stores (5.8%), GP or primary health centres (5.0%), and restaurants (5.0%). Leisure and cultural amenities such as cinemas (4.9%) and cafes (3.8%) are also mentioned, alongside specialised health services including specialist doctors (4.7%) and hospitals (4.1%). Overall, the findings suggest that remaining proximity gaps are relatively limited and mainly concern food, health, and selected leisure services rather than core everyday amenities.

Figure 34 Desired services to have nearby that are not currently available.



Furthermore, when asked about the reasons for selecting a desired service nearby (see Figure 35), respondents most often pointed to the service not being available within walking or cycling distance, which clearly dominates all other explanations. Secondary reasons relate to limited or inconvenient public transport options that make the service harder to reach, followed by a smaller share indicating that existing services do not align well with their lifestyle or preferences. Factors such as service quality, opening hours, personal safety, affordability, or accessibility for people with limited mobility are mentioned by relatively few respondents, while issues related to inclusiveness, language, or child-friendliness are rarely cited. Overall, the findings indicate that unmet proximity needs are driven primarily by distance and connectivity rather than by qualitative or social characteristics of services.

Finally, we explored general satisfaction levels in terms of neighbourhood walking accessibility. Results from Figure 36 show a generally positive tendency, with the majority of respondents rating accessibility as good, very good, or excellent. Utrecht and Vienna stand out with the highest shares of very good and excellent ratings, indicating particularly strong walkable access to services. Paris and Brussels also perform well overall but display a larger proportion of fair ratings, suggesting more mixed perceptions of walkability. Munich and Budapest show comparatively higher shares of fair and poor evaluations, pointing to less consistent walking accessibility across neighbourhoods. Overall, the findings highlight clear cross-city differences, with some cities exhibiting more consolidated and positively perceived walkable access to services than others.

Figure 35 Reasons behind the selection of a desired service.

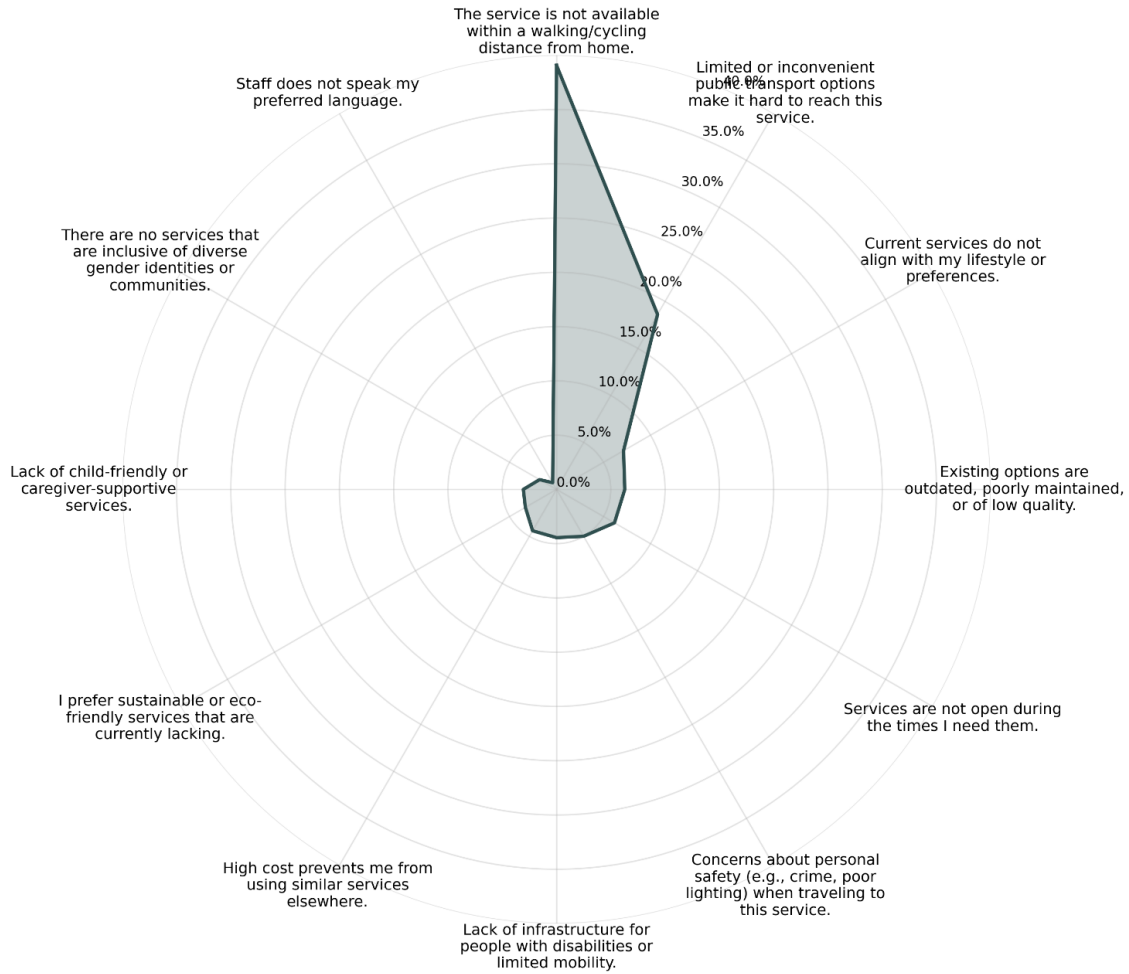
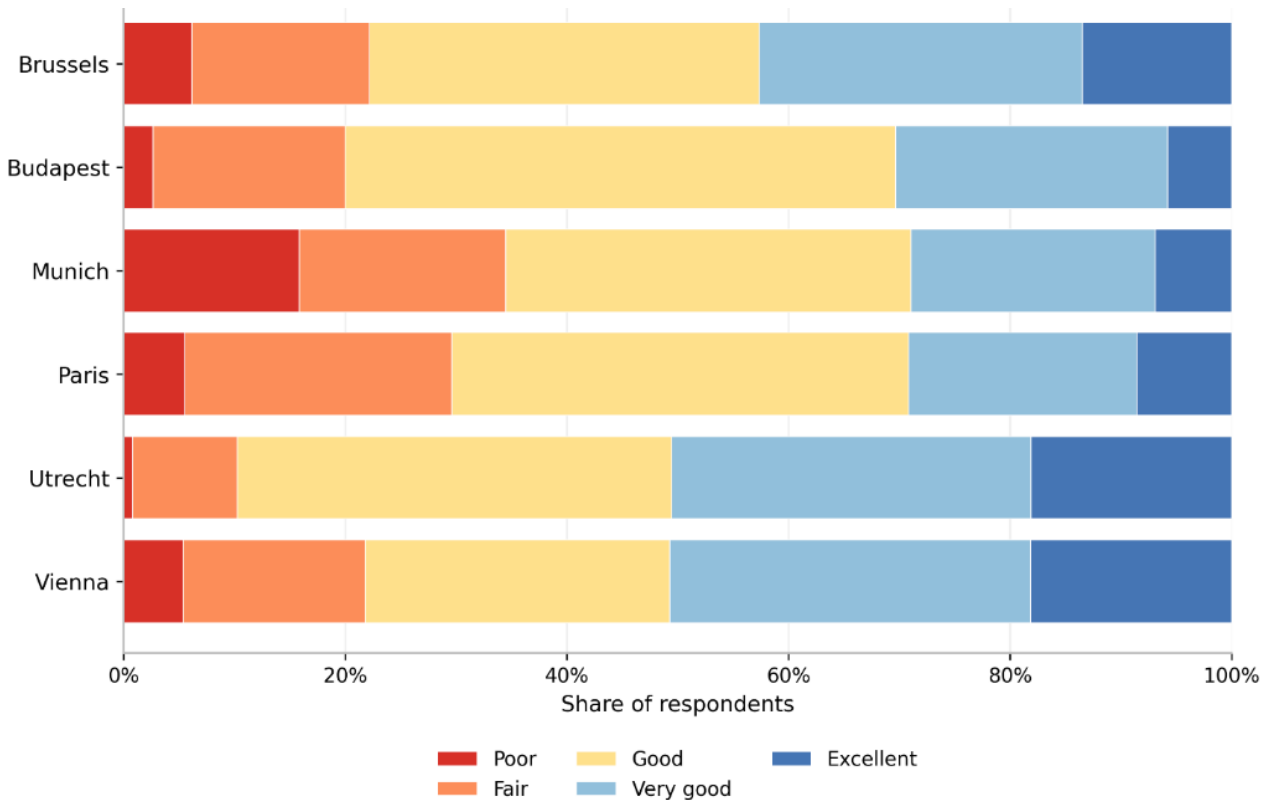


Figure 36 Overall neighbourhood walking accessibility rating



3.4. Modelling perceived accessibility

To move beyond descriptive statistics, the perceived accessibility was used as a dependent variable in an OLM, together with various socio-demographic characteristics. Specifically, the dependent variable was “how often can you reach(access) these services using your preferred mode of transportation?” (Always – Never). The OLM shows an overall moderate fit (n=2184) with a log likelihood of -2570 observations. AIC and BIC values are 5193 and 5339 respectively. The estimated coefficient estimates for the variables, together with the standard error (S.E.) and significance levels are shown in Table 8.

Access to most modes of transport did not have a significant effect on perceived accessibility. A notable exception was respondents who had a bike, which had a slight positive effect on perceived accessibility. As the dependent variable is formulated using the preferred mode of transport, this may indicate that other modes (PT, car, scooters etc.) are not the preference of users, and they might prefer walking or cycling to access their preferred services. Furthermore, respondents who indicated being impaired in their mobility, had a significantly lower perceived accessibility.

The results show that income has a positive significant effect on perceived accessibility. These respondents might live in better-connected and serviced neighbourhoods which increases their perceived accessibility. Furthermore, an increased income can result in more flexible transport-options such as private cars and ride-hailing. In contrast to income, education was not found to have a significant effect on perceived accessibility.

Whilst population density was not found to effect perceived accessibility, distance to the city centre was found to have a negative impact. This finding reflects how urban outskirts closer to the city centre are better served by amenities than urban outskirts further away. This bring nuance to the definition of “urban outskirts” because it shows outskirts are not a homogenous category. A counterintuitive finding is the positive significant effect of age on perceived accessibility. Since mobility impairments are already controlled for, this effect can be explained by the adjustments elderly make in their expectations of the accessibility of amenities. Furthermore, elderly might be more flexible in their schedules, meaning they are less dependent on closing times and mind less to spend time travelling to their amenities than their younger counterparts.

Also, women were found to statistically report a lower perceived accessibility than men, suggesting some gender-bias in the accessibility of services they find important. Using results from Figure 20, this finding suggests poor accessibility of pharmacies and GPs.

Finally, respondents from Paris reported a lower perceived accessibility than other living labs. This may reflect poor perceived accessibility of the outskirts compared to other living labs. Similar findings can be seen in Figure 26.

Table 8: OLM parameters

Variable	Coefficient Estimate (S.E.)	Sig.
Mobility related		
Access to PT pass/subscription	-0.084 (0.095)	
Access to shared mobility	-0.097 (0.20)	
Access to bike	0.18 (0.092)	*
Access to E-bike	-0.13 (0.12)	
Access to Moped	-0.24 (0.17)	
Access to Scooter	-0.23 (0.16)	
Access to a Car	-0.17 (0.13)	
Impaired mobility	-0.36 (0.14)	**
Income (ref: Low-income)		
High-income	0.34 (0.12)	**

Medium-income	0.19 (0.11)	*
Education (ref: primary education)		
Secondary education	0.57 (0.51)	
Tertiary education	0.51 (0.48)	
Vocational education	0.30 (0.49)	
Other characteristics		
Population density (normalized)	-0.18 (0.14)	
Distance to city centre (normalized)	-0.54 (0.26)	**
Age (normalized)	0.78 (0.19)	**
Gender (ref: Male)		
Gender: Female	-0.21 (0.087)	**
Gender: Other	-0.56 (0.71)	
City-effects (ref: Utrecht)		
Vienna	-0.35 (0.48)	
Brussels	-0.67 (0.48)	
Paris	-1.4 (0.47)	**
Budapest	-0.42 (0.47)	
Model cut points		
1.0/2.0	-3.9 (0.52)	**
2.0/3.0	0.23 (0.081)	**
3.0/4.0	0.15 (0.052)	**
4.0/5.0	0.15 (0.040)	**

* Significance at 10% confidence level
** Significance at 5% confidence level

3.5. Service-preference personas

To better capture differences in residents' accessibility needs, this section adopts a persona-based approach to examine service preferences. Personas are defined as groups of respondents who prioritise similar combinations of everyday services, reflecting shared patterns of what people consider important in their daily lives. Focusing on combinations of services, rather than on single amenities, provides a more holistic view of accessibility and aligns with proximity-based planning approaches such as the 15-minute city, where access to a bundle of nearby services is more relevant than access to any single service in isolation.

Given the multi-city design of the DREAMS survey, the analysis follows a two-step approach that balances comparability across cities with attention to local context. First, global service-preference personas are identified using the pooled sample from all participating cities. Personas are derived exclusively from responses to the ARC1 question, in which respondents selected the three to five services they consider most important in their daily lives (see Appendix). By relying only on service selections and excluding socio-demographic information at this stage, the clustering captures differences in service priorities themselves, rather than differences driven by population characteristics.

In a second step, the global service-preference personas identified in the pooled sample are socio-demographically characterised to support interpretation of the preference-based clusters. Socio-demographic variables, including age, gender, household situation, income, and migrant background, are analysed ex post to describe the composition of each persona and to identify population groups that are over- or under-represented within each preference profile.

In a third step, the analysis examines how the resulting personas and their socio-demographic profiles are distributed across cities. Rather than redefining personas independently for each city, respondents in each city are assigned to the global personas identified in the pooled sample. This approach enables consistent cross-city comparison while allowing the assessment of local variation in (i) the prevalence of each persona and (ii) the way shared service-preference profiles are represented within different urban and socio-demographic contexts.

Global service-preference personas

Analysis of the inertia and silhouette scores of the K-means algorithm revealed that three clusters resulted in the most robust clusters (Appendix 3). In Table 9 we can observe the main findings from the clustering analysis, resulting in 3 identified global service-preference personas in the pooled cross-city sample (n = 2.531). Each persona is defined by a distinct combination of services prioritised by respondents, reflecting different patterns of everyday needs and lifestyle orientations. Persona's belonging to cluster 1 include the largest share of respondents, consisting out of almost 80% of the respondents. The remaining two clusters share the remaining 20% of respondents.

Table 9 Persona sizes

Persona	Absolute (#)	Percentage (%)
1	2007	79.3
2	290	11.5
3	234	9.2
Total	2531	100

Source: Domokos Esztergár-Kiss, Ognjen Bobičić 2026.

Table 10 summarises for each persona, the table reports the ten services most frequently selected as priorities, together with the share of respondents within the persona who selected each service. These profiles highlight distinct bundles of everyday services, ranging from health- and food-oriented needs to leisure- and activity-focused preferences. The relative concentration of selections within personas indicates that the clustering captures meaningful and internally coherent patterns of service prioritisation.

Table 10 Top 10-prioritised services by global service-preference personas (ARC1-based clustering)

Persona	Absolute (#)	Rank	Service	Percentage (%)
1	2007	1	Grocery store	73.7%
1		2	Pharmacy	49.8%
1		3	GP or primary health centre	45.8%
1		4	Bakery	36.8%
1		5	Park	29.2%
1		6	Shopping	25.7%
1		7	Restaurants	24.3%
1		8	Postal services	21.5%
1		9	Banking services	19.7%
1		10	Sport/fitness	14.2%
2	290	1	Grocery store	67.2%
2		2	Kindergarten	60.3%
2		3	Playgrounds	59.0%
2		4	School	33.1%
2		5	GP or primary health centre	30.0%
2		6	Bakery	29.0%
2		7	Pharmacy	27.6%
2		8	Park	23.8%
2		9	Shopping	15.5%
2		10	Restaurants	13.1%
3	234	1	Bar	73.9%

3	2	Grocery store	57.3%
3	3	Restaurants	52.6%
3	4	Cafe	32.5%
3	5	College/university	28.6%
3	6	Pharmacy	25.6%
3	7	Bakery	24.4%
3	8	Shopping	22.2%
3	9	Park	20.1%
3	10	Sport/fitness	17.5%

Up to this point, service-preference personas have been identified purely based on respondents' selections of everyday services, without attaching interpretive labels or assumptions about the population groups they represent. In the following step, these personas are characterised socio-demographically to support interpretation. Labels are introduced ex post, based on the observed socio-demographic composition of each cluster and the dominant service bundles they prioritise. This approach ensures that personas remain grounded in revealed service preferences, while enabling a meaningful interpretation in relation to everyday life situations and planning-relevant population groups.

Socio-demographic characterisation of service-preference personas

To further enhance interpretability and policy relevance, the amenity clusters are further subdivided into smaller clusters driven by different socio-demographics. Selected clusters are illustrated through personas representing empirically observed life situations within each service-preference profile. These narrative personas are defined using explicit and observable socio-demographic criteria (e.g. age, income and household composition) as well as information, allowing their prevalence to be quantified within the dataset. Importantly, these personas do not imply homogeneity within clusters, nor are they intended to cover all individuals belonging to a given cluster. Rather, they serve as heuristic devices to translate abstract service-preference patterns into recognisable everyday contexts relevant for urban planning and policy discussions. A full report of socio-demographic composition per cluster can be found in Appendix 4.

- **Cluster 1: Essential needs-orientated personas (n = 2007)**

The essential needs-oriented cluster is characterised by strong preferences for grocery stores (73.7%), pharmacies (49.8%), GPs (45.8%), bakeries (36.8%), parks (29.2%), shopping (25.7%), restaurants (24.3%), postal services (21.5%), banking (19.7%), and sport facilities (14.2%). This reflects a desire for multifunctional neighbourhoods that support both daily errands, healthcare, leisure, and physical activity. Based on further sub-clustering two main personas can be identified within this cluster.

Affluent adults without children (n=747). People belonging to this persona rarely have any children living with them and generally have a medium to high income level. The age distribution is relatively heterogeneous, representing both elderly whose children have moved out as well as couples/individuals who do not have children at all.

Vulnerable adults (n=928). This group of people is generally of low income and shows a large heterogeneity in living situation and age, suggesting this persona represent vulnerable population groups in general, such as families in poverty as well as disadvantaged elderly. As a result, this group also has a relatively large share of people who are mobility impaired (18%).

- **Cluster 2 : Family- and child-oriented personas (n = 290)**

The family- and child-oriented cluster prioritises grocery stores (67.2%), kindergartens (60.3%), playgrounds (59.0%), schools (33.1%), GPs (30.0%), bakeries (29.0%), pharmacies (27.6%), parks (23.8%), shopping (15.5%), and restaurants (13.1%). This reflects accessibility needs shaped by caregiving responsibilities, and family-oriented life. Based on further sub-clustering two main personas can be identified within this cluster.

Established and upcoming families (n=58). Most people belonging to this persona are between 25 and 44 and are of high income. They are working adults and are single, a couple or a couple with children. Their preference for family-oriented amenities suggest they are either parents or are thinking about becoming parents soon.

Young families (N=197). Personas living in this cluster are generally younger families who are at the start of their career(s) and as a result prefer to have their family-oriented amenities close by. Often, they have a medium to low income.

• **Cluster 3: Social oriented personas (n = 234)**

The urban social oriented cluster is characterised by strong preferences for bars (73.9%), grocery stores (57.3%), restaurants (52.6%), cafés (32.5%), college/university amenities (28.6%), pharmacies (25.6%), bakeries (24.4%), shopping (22.2%), parks (20.1%), and sport facilities (17.5%). This reflects a social and leisure-oriented lifestyle.

Affluent Socialites (n=79). Personas belonging to this persona rarely have any children living with them and generally prefer living in the vicinity of bars and restaurants. They are of high income are generally of all age groups.

Young urban (n= 115). People belonging to these personas are relatively young and low income. They are usually single households or couples with children. Their young age suggests that they are either students going to college or university or young families who enjoy a vibrant urban lifestyle.

The personas are summarized in Table 11. The results shows that some service-preference clusters, particularly urban social and consumption-oriented personas and family and child-oriented personas, are closely aligned with identifiable and measurable life situations. In contrast, the essential needs-oriented personas exhibit substantial internal heterogeneity, showing how certain amenities cut across different socio-demographic groups.

Table 11 Persona overview

Cluster	Narrative persona	n	Share within cluster (%)	Narrative persona share within city sample (%)						Core service preferences
				Brussels (%)	Budapest (%)	Munich (%)	Paris (%)	Utrecht (%)	Vienna (%)	
1. Essential needs-oriented	Affluent adults without children	747	30%	38.5%	29.0%	33.3%	38.7%	32.1%	37.2%	Groceries, pharmacies, GP, bakeries and parks
	Vulnerable adults	928	7.79	40.9%	48.3%	39%	47.0%	49.5%	40.1%	
2. Family and child-care oriented	Established and upcoming families	58	22.27	1.7%	3.4%	8.1%	2.2%	1.6%	3.0%	Grocery, kindergarten, school, playground, GP
	Upcoming young families	197	12.97	5.9%	13.6%	12.2%	3.3%	11.5%	10.0%	
4. Urban social oriented	Affluent socialites	79	32.34	7.3%	2.6%	4.9%	8.2%	2.6%	6.1%	Grocery, restaurants, college/university, bar, cafés
	Young urban lifestyle	115	7.34	5.7%	3.1%	2.4%	1.6%	2.6%	3.5%	

4. CHOICE EXPERIMENTS

Building on these insights from perceived accessibility in section 3, this section turns to the results of the stated choice experiments, which examine how individuals trade off different service and mobility attributes when making access-related decisions.

4.1. Brussels

The model includes a set of transformed observed variables (Table 12) to capture individual-specific characteristics that may influence mode choice behaviour. These variables are binary indicators coded as 1 if a respondent falls within a specific category, and 0 otherwise.

Table 12 The transformed observed variables used in the model - Brussels

Variable (z)	Definition
Gender_woman (0/1)	1: if the participant is a woman
Age_55 (0/1)	1: if the participant's age is ≥ 55
Income_high (0/1)	1: if the participant's monthly income is ≥ 3000 EUR

The model fit (Table 13) is solid, based on 2,010 observations. The adjusted Rho-square is 0.3726, with a log-likelihood improvement from -3166.25 at start to -2004.7 at convergence. The AIC (4059.41) and BIC (4199.55) values confirm the robustness of the model.

Table 13 Model fit statistics - Brussels

Metric	Value
Number of modelled outcomes	2010
Adj. Rho-square vs equal shares	0.3726
LL start (choice)	-3166.25
LL final (choice)	-2004.7
Akaike Information Criterion (AIC)	4059.41
Bayesian Information Criterion (BIC)	4199.55

In Table 14, the alternative-specific constants for walking, public transport, SCB, and CS are statistically significant and positive, with public transport (6.0582) having the highest baseline utility, followed by walking (5.4510), SCB (4.7251), and CS (3.3651). This indicates a stronger overall preference for conventional modes, while shared mobility options exhibit comparatively lower base utility. Regarding travel attributes, both travel time (-0.1279) and travel cost (-1.7541) are statistically significant and negative, confirming their role as disutility in mode choice. In contrast, walking time to access points is not statistically significant (-0.0053), suggesting a more limited impact on choice behavior in this context.

Service functionalities show limited effects overall. For SCB, SF4 (30% discount with car-sharing & cargo-bike package) is positive and statistically significant (0.5075), while SF2 is also positive and statistically significant at the 90% confidence level (0.3812). For CS, only SF2 is statistically significant and negative (-0.6762), while all other service attributes remain insignificant. This implies that some service functionalities can affect utility, but the effects are not uniformly positive, and most service integration elements offer weak utility gain.

The estimated standard deviations of the random parameters confirm substantial heterogeneity in preferences. The highest variation is observed for travel cost (SD = 2.5678), followed by walking time to access points (SD = 0.2646) and travel time (SD = 0.1047), all statistically significant. This indicates that although travel attributes systematically affect choices, individuals differ considerably in how they value especially cost, but also time-related factors.

Table 14 MXL estimates for core choice attributes and random parameters - Brussels

Parameter	Estimates	Sig.	Rob.t.rat.
<i>Alternative-specific constants</i>			
ASC Walking	5.4510	**	8.9394
ASC Public transport	6.0582	**	10.1622

ASC Shared cargo bike (SCB)	4.7251	**	7.4722
ASC Car sharing (CS)	3.3651	**	5.4629
ASC Opt-out (base)	0	-	-
<i>Random parameters (means)</i>			
Travel time	-0.1279	**	-8.3164
Travel cost	-1.7541	**	-2.6794
Walking time to PT stop/ docking station	-0.0053		-0.1712
<i>Fixed parameters (service functionalities)</i>			
SF1 SCB	0.2163		0.7355
SF2 SCB	0.3812	*	1.6074
SF3 SCB	0.0799		0.2578
SF4 SCB	0.5075	**	2.1278
SF1 CS	0.3421		1.1864
SF2 CS	-0.6762	**	-1.9055
SF3 CS	0.1039		0.3844
SF4 CS	-0.3364		-1.0228
<i>Random parameters (standard deviations)</i>			
SD Travel time	0.1047	**	8.5362
SD Travel cost	2.5678	**	3.5565
SD Walking time to PT stop/ docking station	0.2646	**	5.7051

** significance at the 95% confidence level;

* significance at the 90% confidence level.

Following *Table 15*, socio-demographic interactions reveal differentiated mode preferences across population groups. Age group of those 55 years old or more shows a positive and statistically significant association with both walking (0.9204) and public transport (0.9344), indicating higher utility for these modes. Women show a positive but not statistically significant interaction with public transport (0.2022). For CS, the interaction with high income is negative but not statistically significant (-0.2698).

Activity-based interactions demonstrate variation in mode suitability across trip purposes. Leisure trips significantly increase the utility of walking (1.6238), indicating that walking is more attractive for discretionary activities. For SCB, grocery-related trips show a very small positive but statistically insignificant effect (0.0164), suggesting a limited impact on choice behaviour. For CS, commerce trips have a positive but statistically insignificant effect (0.3254), indicating that commerce-related activities do not increase the attractiveness of this mode.

Table 15 Estimated effects of socio-demographics and trip purpose on mode utilities - Brussels

Parameter	Estimates	Sig.	Rob.t.rat.
<i>Socio-demographic interactions</i>			
Walking x Age_55	0.9204	**	2.1257
Public transport x Age_55	0.9344	**	3.1667
Public transport x Gender_woman	0.2022		0.8215
CS x Income_high	-0.2698		-0.6901
<i>Activity interactions</i>			
Walking x Leisure	1.6238	**	3.3538
SCB x Grocery (eatable)	0.0164		0.0509
CS x Commerce	0.3254		0.7980

** significance at the 95% confidence level;

* significance at the 90% confidence level.

4.2. Budapest

In case of Budapest, *Table 16* presents transformed socio-demographic characteristics transformed into binary variables and used in the model.

Table 16 The transformed observed variables used in the model - Budapest

Variable (z)	Definition
Gender_woman (0/1)	1: if the participant is a woman
Age_18_34 (0/1)	1: if the participant's age is ≥ 18 and ≤ 34
Employed (0/1)	1: if the participant stated that they are employed
Edu_uni (0/1)	1: if the participant stated that they higher level of education is University
Income_med (0/1)	1: if the participant's monthly income is ≥ 1500 and ≤ 2990 EUR

The model (Table 17) was estimated on 2,154 choice observations and achieves an adjusted Rho-square of 0.3718. The log-likelihood improves from -4654.20 at start to -2141.93 at convergence. AIC (4355.85) and BIC (4560.16) values are in line with a model of this size and complexity.

Table 17 Choice Model fit statistics - Budapest

Metric	Value
Number of modelled outcomes	2154
Adj. Rho-square vs equal shares	0.3718
LL start (choice)	-4654.20
LL final (choice)	-2141.93
Akaike Information Criterion (AIC)	4355.85
Bayesian Information Criterion (BIC)	4560.16

All ASCs in Table 18 are statistically significant and positive, with public transport receiving the highest value (8.3975), followed by SB (6.7212), SES (5.9838), and walking (5.9461). This reflects the baseline preference for each mode compared to opting out, with public transport being the most preferred overall.

The attribute estimates show that both travel time (-0.1635) and travel cost (-1.0431) have negative and statistically significant effects on utility, confirming their role as key disutilities in mode choice. Travel cost has the largest magnitude among the attributes, indicating a particularly strong sensitivity to monetary costs. In contrast, walking time to access PT stops or docking stations is not statistically significant (0.0018), suggesting a negligible effect on choice behaviour in this case. The fixed parameters for service functionalities are largely insignificant. For SB, only SF4 is statistically significant and negative (-0.4482), which may lead to the conclusion that this specific incentive reduces utility rather than increasing it. All other SB-related service attributes are not statistically different from zero. Similarly, none of the SES-related service functionalities are statistically significant, and their estimates remain small and inconsistent in sign, which further suggests that the tested service features for both shared modes do not systematically influence preferences in this sample.

The estimated standard deviations of the random parameters in this sample also confirm significant heterogeneity in preferences across individuals. The strongest variation is observed for travel cost (SD = -0.9392), followed by walking time to access points (SD = 0.2787) and travel time (SD = 0.1416), all statistically significant, which indicates substantial differences across individuals in how they perceive cost and time-related attributes.

Table 18 MXL estimates for core choice attributes and random parameters - Budapest

Parameter	Estimates	Sig.	Rob.t.rat.
<i>Alternative-specific constants</i>			
ASC Walking	5.9461	**	6.8751
ASC Public transport	8.3975	**	13.4321
ASC Shared bike (SB)	6.7212	**	11.6826
ASC Shared electric scooter (SES)	5.9838	**	9.7448
ASC Opt-out (base)	0	-	-
<i>Random parameters (means)</i>			
Travel time	-0.1635	**	-8.8729
Travel cost	-1.0431	**	-6.8591
Walking time to PT stop/ docking station	0.0018		0.0727
<i>Fixed parameters (service functionalities)</i>			

SF1 SB	-0.1208		-0.5804
SF2 SB	-0.2973		-1.3624
SF3 SB	-0.0985		-0.4956
SF4 SB	-0.4482	**	-2.5383
SF1 SES	-0.5878		-1.5405
SF2 SES	0.0497		0.1644
SF3 SES	0.3500		1.0452
SF4 SES	0.0020		0.0054
<i>Random parameters (standard deviations)</i>			
SD Travel time	0.1416	**	9.7269
SD Travel cost	-0.9392	**	-8.3516
SD Walking time to PT stop/ docking station	0.2787	**	6.8023

** significance at the 95% confidence level;

* significance at the 90% confidence level.

Among socio-demographic interactions (Table 19), employed individuals show a significantly lower likelihood of choosing both walking (-1.5171) and public transport (-0.8088), which may lead to reduced preference for these modes among working respondents. Medium-income individuals are negatively associated with walking (-0.6965), although this effect is not statistically significant. For SB, individuals aged 35–54 exhibit a positive and weakly significant interaction (0.5653), explaining potentially higher likelihood of choosing this mode within this age group. In contrast, women show a significantly lower preference for SB (-0.7702). Other socio-demographic interactions, including education and income effects for public transport and SES, are not statistically significant.

In terms of activity interactions, several significant effects emerge. Walking is positively associated with leisure trips (1.1766), although only weakly significant, while its interactions with health and services are not statistically significant. Public transport shows strong and significant positive associations with grocery-related trips (0.8735) and especially service-related trips (4.1702), indicating its suitability for these purposes.

For SB, health-related trips significantly decrease utility (-1.0239), while service-related trips strongly increase it (4.1041), both statistically significant. Similarly, SES is negatively associated with health-related trips (-1.4785) and positively associated with service-related trips (2.7180), with both effects statistically significant. This evidence leads to conclusion that activity type plays a substantial role in shaping mode preferences in Budapest and describes sample preferences more than socio-demographic characteristics of it.

Table 19 Estimated effects of socio-demographics and trip purpose on mode utilities - Budapest

Parameter	Estimates	Sig.	Robust t.ratio.
<i>Socio-demographic interactions</i>			
Walking x Edu_uni	0.6158		0.9452
Walking x Employed	-1.5171	**	-2.3326
Walking x Income_med	-0.6965		-1.2454
Public transport x Edu_uni	0.4075		1.3599
Public transport x Employed	-0.8088	**	-2.2147
Public transport x Income_med	-0.1373		-0.4791
SB x Age_35_54	0.5653	*	1.8060
SB x Gender_woman	-0.7702	**	-3.1140
SES x Age_35_54	0.2889		0.6618
<i>Activity interactions</i>			
Walking x Health	0.8249		1.0306
Walking x Leisure	1.1766	*	1.8325
Walking x Services	2.5058		1.6443
Public transport x Grocery (eatable)	0.8735	**	3.1963
Public transport x Services	4.1702	**	3.7551
SB x Health	-1.0239	**	-2.7130

SB x Services	4.1041	**	3.2083
SES x Health	-1.4785	**	-2.3588
SES x Services	2.7180	**	1.9786

** significance at the 95% confidence level;
* significance at the 90% confidence level.

4.3. Munich

Table 20 presents transformed socio-demographic characteristics transformed into binary variables and used in the model.

Table 20 The transformed observed variables used in the model - Munich

Variable (z)	Definition
Income_med (0/1)	1: if the participant's monthly income is ≥ 1500 and ≤ 2990 EUR
Unemployed (0/1)	1: if the participant stated unemployment but not being student or retired
Edu_uni (0/1)	1: if participant holds any university degree

The model for Munich (Table 21) is based on 870 observed choices and demonstrates a strong overall fit. The adjusted Rho-square value of 0.362 indicates a good improvement over a null model, capturing a substantial portion of the variation in respondents' choices. The log-likelihood improved from -1174.81 at initialization to -857.38 at convergence, reflecting effective parameter estimation. Additionally, the model's AIC (1786.76) and BIC (1958.43) values are within a reasonable range, supporting its robustness for evaluating preferences in Munich's urban mobility context.

Table 21 Model fit statistics - Munich

Metric	Value
Number of modelled outcomes	870
Adj. Rho-square vs equal shares	0.362
LL start (choice)	-1174.81
LL final (choice)	-857.38
Akaike Information Criterion (AIC)	1786.76
Bayesian Information Criterion (BIC)	1958.43

The estimated alternative-specific constants (ASCs) (Table 22) were all positive and significant, indicating strong inherent preferences across all offered modes compared to the opt-out. Public transport received the highest ASC (8.9160), followed by car sharing (7.0667), walking (7.5594), and SEB (6.3051), a relatively balanced valuation across sustainable and shared options. Regarding core attributes, travel time (-0.2069) and walking time to the station (-0.1715) were both negative and significant, confirming user aversion to time-consuming travel components. The travel cost coefficient (0.2469) was not significant, implying that cost may not have been a decisive factor in Munich's context, due to relatively small cost differences between alternatives or a sample less sensitive to price.

None of the service functionality parameters (SF1-SF4) reached significance for either SEB or CS, suggesting that integrated subscription discounts and bonus credit incentives had no measurable effect on mode utility in this sample, which may further indicate limited interest in bundled services or low awareness of such offers.

The estimated standard deviations for the random parameters are all statistically significant, which means meaningful heterogeneity in how individuals value different travel attributes. The variation in sensitivity to travel cost is especially pronounced (SD = 1.0979, $t = 7.27$), followed by walking time to access points (SD = 0.3030) and travel time (SD = 0.2389). While the mean effect of travel cost is not statistically significant, the large and significant standard deviation suggests that respondents vary widely in their cost sensitivity, some are highly price-sensitive, while others may be indifferent or even associate higher cost with higher quality.

Table 22 MXL estimates for core choice attributes and random parameters - Munich

Parameter	Estimates	Sig.	Rob.t.rat.
<i>Alternative-specific constants</i>			

ASC Walking	7.5594	**	4.5569
ASC Public transport	8.9160	**	9.3278
ASC Shared bike (SB)	6.3051	**	6.7660
ASC Car sharing (CS)	7.0667	**	6.4734
ASC Opt-out (base)	0	-	-
<i>Random parameters (means)</i>			
Travel time	-0.2069	**	-5.5398
Travel cost	0.2469		1.2957
Walking time to PT stop/ docking station	-0.1715	**	-3.1285
<i>Fixed parameters (service functionalities)</i>			
SF1 SB	0.0409		0.1197
SF2 SB	0.1950		0.7049
SF3 SB	-0.2693		-0.7603
SF4 SB	0.0051		0.0183
SF1 CS	0.0831		0.2074
SF2 CS	0.1426		0.3075
SF3 CS	0.0643		0.1393
SF4 CS	0.0881		0.2414
<i>Random parameters (standard deviations)</i>			
SD Travel time	0.2389	**	6.6337
SD Travel cost	1.0979	**	7.2658
SD Walking time to PT stop/ docking station	0.3030	**	4.6958

** significance at the 95% confidence level;

* significance at the 90% confidence level.

Socio-demographic interactions (Table 24) revealed that being employed negatively affected the utility of all modes except walking, particularly for public transport (-3.1348) and SEB (-1.6096), possibly reflecting preferences for flexibility or private mobility. A university education had a positive and significant influence on preferences for public transport (0.9827) and SEB (1.4866), which may lead to openness to sustainable modes among higher-educated users.

As for activity interactions, walking was significantly less preferred for grocery (-3.5147) and commerce (-3.3482) trips, while public transport and CS showed strong positive associations with health-related travel (6.3688, 7.8461 respectively). CS was negatively associated with commerce (-1.9073), which potentially explains that while valued for specific purposes like healthcare in this LL, it may be less suitable or convenient for everyday errands.

Table 23 Estimated effects of socio-demographics and trip purpose on mode utilities - Munich

Parameter	Estimates	Sig.	Rob.t.rat.
<i>Socio-demographic interactions</i>			
Walking x Employed	-1.5498		-1.3350
Walking x Income_med	1.8888	*	1.6475
Public transport x Employed	-3.1348	**	-3.5737
Public transport x Education_University	0.9827	*	1.8643
SB x Employed	-1.6096	*	-1.7393
SB x Education_University	1.4866	**	2.6140
CS x Employed	-1.5043		-1.4947
CS x Income_med	-0.9796		-1.3137
<i>Activity interactions</i>			
Walking x Grocery (eatable)	-3.5147	**	-3.1916
Walking x Commerce	-3.3482	**	-2.4736
Public transport x Commerce	-1.0083		-1.3139
Public transport x Health	6.3688	**	4.1926
Public transport x Education	3.2868	**	4.4759
SB x Health	6.0530	**	3.6545
SB x Education	1.8156	**	2.0681

CS x Commerce	-1.9073	*	-1.8145
CS x Health	7.8461	**	3.9223
CS x Leisure	-1.4769		-1.5905

** significance at the 95% confidence level;
* significance at the 90% confidence level.

4.4. Paris

Paris model also includes a set of transformed observed variables into binary (Table 24) to capture individual-specific characteristics that may influence mode choice behaviour.

Table 24 The transformed observed variables used in the model - Paris

Variable (z)	Definition
Age_18_34 (0/1)	1: if the participant's age is ≥ 18 and ≤ 34
Age_35_54 (0/1)	1: if the participant's age is ≥ 35 and ≤ 54
Unemployed (0/1)	1: if the participant stated unemployment but not being student or retired
Edu_uni (0/1)	1: if participant holds any university degree

A total of 1,194 choice observations were modelled. The adjusted Rho-square value of 0.3392 suggests a good fit (Table 25) relative to a model with equal choice probabilities, indicating that the included attributes significantly improve explanatory power. The log-likelihood at the starting point (-2307.13) and at convergence (-1234.83) show a substantial gain in likelihood, reflecting improved fit through estimation, while the AIC (2539.67) and BIC (2717.65) measure for model comparison, balancing goodness-of-fit with model complexity, and altogether it shows solid fit in this case.

Table 25 Model fit statistics - Paris

Metric	Value
Number of modelled outcomes	1194
Adj. Rho-square vs equal shares	0.3392
LL start (choice)	-2307.13
LL final (choice)	-1234.83
Akaike Information Criterion (AIC)	2539.67
Bayesian Information Criterion (BIC)	2717.65

The mixed logit (MXL) estimates for the Paris case (Table 26) shows how respondents value different transport alternatives and associated attributes. The alternative-specific constants (ASCs) are all large and statistically significant (at the 95% confidence level), suggesting strong inherent preferences for each mode over the opt-out base, with walking and public transport showing the highest ASCs. Among the random parameters, the negative and significant coefficients for travel time (-0.1940), travel cost (-0.5979), and walking time to access points (-0.1355) confirm that respondents generally prefer faster, cheaper, and more accessible options.

The fixed parameters associated with service functionalities demonstrate a consistent positive impact on utility. For shared electric bikes (SEB), SF1 (shared bike lanes at stations) and SF2 (dedicated and protected bike lanes with buffer zones) are both significant and positive, with SF2 (1.2760) having a stronger effect than SF1 (0.9125), indicating that infrastructure quality plays a crucial role in encouraging SEB use. SF3 (first 5 rides free) for SEB shows a positive statistically significant estimate (0.4632), while SF4 (first 10 rides free) has a stronger and more significant influence (0.5752), highlighting that the magnitude of the financial incentive matters. On another side, for shared electric scooters (SES), a similar pattern has been noticed. SF1 (bike lanes at stations) and SF2 (protected lanes) are both significant, with SF2 again having the largest impact (1.6533). Importantly, both SF3 (1.2860) and SF4 (1.1867) for SES are significant, indicating that promotional ride incentives are more effective for scooter users than bike users in this sample, which may reflect either higher novelty or price sensitivity associated with scooters. It should be noted that since the SFs were treated as fixed parameter, these results apply to the whole sample with the same intensity, the effect of more free rides concerns all ages and revenue classes.

The statistically significant standard deviations of the random parameters further confirm heterogeneity in preferences across the sample, especially in how respondents value travel cost (SD = 1.1343) and walking time (SD = 0.2808).

Table 26 MXL estimates for core choice attributes and random parameters - Paris

Parameter	Estimates	Sig.	Robust t-ratio
<i>Alternative-specific constants</i>			
ASC Walking	10.6307	**	8.6646
ASC Public transport	11.6529	**	11.9579
ASC Shared electric bike (SEB)	9.5811	**	9.2882
ASC Shared electric scooter (SES)	7.6400	**	5.7145
ASC Opt-out (base)	0	-	-
<i>Random parameters (means)</i>			
Travel time	-0.1940	**	-8.8442
Travel cost	-0.5979	**	-2.6061
Walking time to PT stop/ docking station	-0.1355	**	-4.1695
<i>Fixed parameters (service functionalities)</i>			
SF1 SEB	0.9125	**	4.0203
SF2 SEB	1.2760	**	5.2327
SF3 SEB	0.4632	*	1.7865
SF4 SEB	0.5752	**	2.6551
SF1 SES	0.8688	**	2.4082
SF2 SES	1.6533	**	3.9311
SF3 SES	1.2860	**	3.2716
SF4 SES	1.1867	**	3.3054
<i>Random parameters (standard deviations)</i>			
SD Travel time	0.1482	**	8.8823
SD Travel cost	1.1343	**	8.6559
SD Walking time to PT stop/ docking station	0.2808	**	6.5866
** significance at the 95% confidence level;			
* significance at the 90% confidence level.			

Table 27 presents the estimated effects of interaction terms between travel modes and both socio-demographic characteristics and activity-destination types. Among socio-demographic groups, individuals aged 35–54 are significantly more likely to choose all given modes with especially strong positive coefficients for SEB (5.4002) and SES (3.8857). Also, younger individuals (aged 18–34) also show significant positive interactions with SEB (0.7050) and SES (2.6247), indicating that younger users are key early adopters of micromobility.

In terms of trip purpose, negative interactions are found between walking and trips related to grocery shopping (-3.5136) and other commerce activities (-2.8830), likely due to the burden of carrying items or distance-related constraints. Similar negative effects are observed for SEB and SES when the primary trip purpose are activities from the commerce group. On the other hand, health-related trips show a positive association with SEB (0.8547) and public transport (1.2563).

Table 27 Estimated effects of socio-demographics and trip purpose on mode utilities - Paris

Parameter	Estimates	Sig.	Robust t-ratio
<i>Socio-demographic interactions</i>			
Walking – Age_35_54	3.8857	**	3.9431
Public transport – Age_35_54	3.4926	**	3.5117
SEB – Age_18_34	0.7050	*	1.6982
SEB – Age_35_54	3.7884	**	3.5098
SEB – Unemployed	-0.4067		-0.7482
SEB – Education_University	0.7140	**	1.9842
SES – Age_18_34	2.6247	**	2.7984
SES – Age_35_54	5.4002	**	2.7984

SES – Education_University	-1.0059	**	-2.4697
<i>Activity interactions</i>			
Walking – Grocery (eatable)	-3.5136	**	-3.0513
Walking - Commerce	-2.8830	**	-2.0583
Walking - Health	-0.1020		-0.1032
Public transport - Commerce	-2.0561	*	-1.8129
Public transport - Health	1.2563	**	2.3459
SEB - Commerce	-2.0543	**	-1.7873
SEB - Health	0.8547	*	1.6572
SES - Commerce	-2.2035	*	-1.8031

** significance at the 95% confidence level.
* Significance at the 90% confidence level.

4.5. Utrecht

Table 28 presents transformed socio-demographic characteristics transformed into binary variables and used in the model.

Table 28 The transformed observed variables used in the model - Utrecht

Variable (z)	Definition
Age_18_34 (0/1)	1: if the participant's age is ≥ 18 and ≤ 34
Employed (0/1)	1: if the participant stated that they are employed
Income: low (0/1)	1: if the participant's monthly income is < 1500 EUR

The model fit (Table 29) is strong, based on 1,368 observations. The adjusted Rho-square is 0.3327, which is among the highest across all living labs. The log-likelihood improved from -2030.42 to -1435.21, with corresponding AIC and BIC values of 2938.42 and 3115.94, respectively, supporting the model's explanatory power.

Table 29 Model fit statistics - Utrecht

Metric	Value
Number of modelled outcomes	1368
Adj. Rho-square vs equal shares	0.3327
LL start (choice)	-2030.42
LL final (choice)	-1435.21
Akaike Information Criterion (AIC)	2938.42
Bayesian Information Criterion (BIC)	3115.94

In case of Utrecht (*Table 30*), also all ASCs are positive and statistically significant, with public transport having the highest baseline utility (7.4120), followed by SEB (7.2449), walking (6.5391), and shared moped SM (5.8162), which again shows that all offered transport modes are preferred over the opt-out alternative, with public transport being the most attractive option overall. Among the core travel attributes, travel time (-0.1922) and walking time to access points (-0.1152) have statistically significant negative effects, confirming sensitivity to time-related burdens. In contrast, travel cost has a positive but not statistically significant coefficient (0.1993), which leads to the conclusion that cost does not play a decisive role in influencing choices of presented modes in the Utrecht sample.

Service functionality parameters are largely insignificant. For SEB, none of the service attributes are statistically significant, with coefficients remaining small and close to zero. For SM, only SF3 (park anywhere within a 1-minute walk) is positive and statistically significant (0.7374), suggesting that flexible parking options can enhance the attractiveness of this mode, with in general service features related to both docking and parking appear to have a limited impact on choice behaviour in this context.

The estimated standard deviations of the random parameters are all statistically significant. Travel cost (SD = 1.3854) shows the highest variation, followed by walking time to access points (SD = 0.2910) and travel time (SD = 0.1313), with important notion that although the average effect of cost is not significant, individuals differ considerably in their sensitivity to it.

Table 30 MXL estimates for core choice attributes and random parameters – Utrecht

Parameter	Estimates	Sig.	Robust t-ratio
<i>Alternative-specific constants</i>			
ASC Walking	6.5391	**	7.1053
ASC Public transport	7.4120	**	10.2078
ASC Shared electric bike (SEB)	7.2449	**	9.7973
ASC Shared moped (SM)	5.8162	**	8.3105
ASC Opt-out (base)	0	-	-
<i>Random parameters (means)</i>			
Travel time	-0.1922	**	-8.6556
Travel cost	0.1993		1.3239
Walking time to PT stop/ docking station	-0.1152	**	-2.9832
<i>Fixed parameters (service functionalities)</i>			
SF1 SEB	0.1685		0.6531
SF2 SEB	-0.1658		-0.6455
SF3 SEB	0.0037		0.0124
SF4 SEB	0.1889		0.7468
SF1 SM	-0.3104		-0.7182
SF2 SM	0.0796		0.1942
SF3 SM	0.7374	**	1.9356
SF4 SM	-0.4216		-0.9072
<i>Random parameters (standard deviations)</i>			
SD Travel time	0.1313	**	7.9834
SD Travel cost	1.3854	**	8.4450
SD Walking time to PT stop/ docking station	0.2910	**	5.7401

** significance at the 95% confidence level;

* significance at the 90% confidence level.

From the model's interactions with socio-demographic characteristics (Table 31) individuals with secondary education show a weakly significant positive association with walking (1.1378), indicating a slightly higher likelihood of choosing this mode. For SM, individuals aged 18–34 exhibit a strong and statistically significant positive interaction (1.8521), showing younger users' stronger preference towards this mode. In contrast, high-income individuals show a weakly significant negative association with SM (–0.6335). Other socio-demographic interactions, including those related to public transport and SEB, are not statistically significant.

Activity-based interactions reveal several notable effects. Walking is significantly negatively associated with commerce (–3.3845) and education (–2.5906), suggesting that it is less suitable for these types of trips. Its interaction with leisure is positive (1.1198), but not statistically significant. Public transport shows no statistically significant interactions with the considered activity types. For SEB, the interaction with education is positive (0.6960), although not statistically significant. Shared moped (SM), however, demonstrates a strong and statistically significant positive association with commerce-related trips (1.5835).

Table 31 Estimated effects of socio-demographics and trip purpose on mode utilities - Utrecht

Parameter	Estimates	Sig.	Robust t-ratio
<i>Socio-demographic interactions</i>			
Walking x Employed	-0.3074		-0.5201
Walking x Edu_second	1.1378	*	1.6726
Public transport x Age_18_34	1.0881		1.3667
Public transport x Edu_second	0.3576		0.5361
SEB x Age_18_34	0.8980		0.9525
SEB x Edu_second	0.0759		0.1018
SM x Age_18_34	1.8521	**	1.9090
SM x Income_high	-0.6335	*	-1.6471

SM x Edu_second	-0.3104		-0.4344
<i>Activity interactions</i>			
Walking x Commerce	-3.3845	**	-2.2770
Walking x Education	-2.5906	**	-2.1202
Walking x Leisure	1.1198		1.1387
Public transport x Grocery	-0.3678		-1.0340
SEB x Education	0.6960		1.2489
SM x Commerce	1.5835	**	3.3745
SM x Leisure	0.3067		0.4327

** significance at the 95% confidence level,
* significance at the 90% confidence level.

4.6. Vienna

Choice experiment 1

Table 32 presents transformed socio-demographic characteristics transformed into binary variables and used in the model.

Table 32 The transformed observed variables used in the CE1 model - Vienna

Variable (z)	Definition
Age_55 (0/1)	1: if the participant's age is ≥ 55
Unemployed (0/1)	1: if the participant stated that they are unemployed
Gender:_woman (0/1)	1: if the participant stated that they are woman

The model was estimated using a multinomial logit (MNL) specification. Model fit statistics (Table 33) support the robustness of the specification. With 3,798 modelled choices, the adjusted Rho-square is 0.1546, which is reasonable for a simple MNL. The log-likelihood improved from -4172.53 at initialization to -3514.64 at convergence. AIC (7055.28) and BIC (7136.43) values indicate a balance between model fit and parsimony.

Table 33 Model fit statistics CE1 - Vienna

Metric	Value
Number of modelled outcomes	3798
Adj. Rho-square vs equal shares	0.1546
LL start (choice)	-4172.53
LL final (choice)	-3514.64
Akaike Information Criterion (AIC)	7055.28
Bayesian Information Criterion (BIC)	7136.43

In the MNL model (Table 34), with IE treated as the base alternative, the alternative-specific constants (ASCs) show that CBE is preferred over IE (0.5299) while SC is less preferred (-0.2096), with a general tendency toward chain stores over independent or mall options, as shown in Table X.

All five fixed taste parameters are statistically significant. Larger size (0.1169) and greater variety of items (0.6152) increase utility, indicating clear preferences for more comprehensive retail offerings. Both price (-0.4774) and walking duration (-0.5291) have negative effects, confirming that higher-than-expected prices and longer travel times reduce destination attractiveness. In contrary, non-crowded environments increase utility (0.2290), supporting a preference for comfort and ease during shopping.

The model also includes socio-demographic interactions. Older participants (Aged 55 and older) are more likely to prefer chain-branded establishments (0.3283), while unemployed individuals are significantly less likely to choose CBE (-0.4954) or SC (-0.4910), which means stronger attachment to independent stores or perhaps greater sensitivity to cost or familiarity. Female respondents are less inclined to choose both CBE (-0.2272) and SC (-0.2632), showing a slight preference for independent establishments, potentially due to perceived authenticity or local value.

Table 34 MNL estimates CE1 - Vienna

Parameter	Estimates	Sig.	Robust t-ratio
<i>Alternative-specific constants</i>			
ASC Independent Establishment (IE)	0	-	-
ASC Chain Branded Establishment (CBE)	0.5299	**	5.3194
ASC Shopping Center (SC)	-0.2096	**	-1.9575
<i>Fixed taste parameters</i>			
Size	0.1169	**	4.7490
Variety of Items	0.6152	**	13.6604
Price	-0.4774	**	-15.9294
Walking duration	-0.5291	**	-16.1471
Quality	0.2290	**	4.9772
<i>Socio-demographic interactions</i>			
CBE x Gender_woman	-0.2272	*	-1.8222
CBE x Age_55	0.3283	**	2.5043
CBE x Unemployed	-0.4954	*	-1.6884
SC x Gender_woman	-0.2632	**	-1.9917
SC x Age_55	0.0555		0.3884
SC x Unemployed	-0.4910	*	-1.6495

** significance at the 95% confidence level;

* significance at the 90% confidence level.

Choice experiment 2

Table 35 presents transformed socio-demographic characteristics transformed into binary variables and used in the model.

Table 35 The transformed observed variables used in the CE2 model - Vienna

Variable (z)	Definition
Age_18_34 (0/1)	1: if the participant's age is ≥ 18 and ≤ 34
Income_med (0/1)	1: if the participant's monthly income is ≥ 1500 and ≤ 2990 EUR
Edu_compulsory (0/1)	1: if participant's highest education level is compulsory school

The model in Table 36 is based on 2,532 observations and shows a solid fit, with an adjusted Rho-square of 0.1735. The log-likelihood improved from -1755.05 to -1442.48, and the resulting AIC (2900.96) and BIC (2947.66) confirm the model's balance between parsimony and explanatory power.

Table 36 Model fit statistics for CE2 - Vienna

Metric	Value
Number of modelled outcomes	2532
Adj. Rho-square vs equal shares	0.1735
LL start (choice)	-1755.05
LL final (choice)	-1442.48
Akaike Information Criterion (AIC)	2900.96
Bayesian Information Criterion (BIC)	2947.66

The estimated multinomial logit model (Table 37) treats IE as the reference category. The alternative-specific constant for CBE is negative and highly significant (-0.7698), which means an overall lower preference for chain stores compared to independent establishments. Among the fixed taste parameters, larger store size (0.0845) and non-crowded environments (0.3778) positively influence utility, while both price (-0.7111) and travel duration (-0.3694) reduce it, which reinforce the importance of convenience, affordability, and comfort in shaping destination preferences.

Socio-demographic interactions highlight meaningful heterogeneity in responses. Young adults (aged 18-34) are more likely to prefer CBE (0.3943), as are individuals with only compulsory education (0.6051) and those with medium-level income (0.2345).

Table 37 MNL estimates for CE2 - Vienna

Parameter	Estimates	Sig.	Robust t-ratio
<i>Alternative-specific constants</i>			
ASC Independent Establishment (IE)	0	-	-
ASC Chain Branded Establishment (CBE)	-0.7698	**	-11.263
<i>Fixed taste parameters</i>			
Size	0.0845	**	2.014
Price	-0.7111	**	-13.066
Travel duration	-0.3694	**	-10.329
Quality	0.3778	**	5.487
<i>Socio-demographic interactions</i>			
CBE x Age_18_34	0.3943	**	3.382
CBE x Edu_compulsory	0.6051	**	2.227
CBE x Income_med	0.2345	**	2.007

** significance at the 95% confidence level;
* significance at the 90% confidence level.

4.7. Main finding from the choice experiments

The Brussels choice experiment shows that respondents continue to treat public transport as the default and most attractive option, followed by walking, while shared cargo bikes and car sharing remain more selective alternatives, with choices driven mainly by travel time and travel cost and with leisure trips increasing the attractiveness of walking and commerce-related trips increasing the utility of car sharing, suggesting that shared mobility effects are more context-specific than broadly substitutive for everyday mobility needs.

In Budapest, results indicate a strong baseline preference for public transport combined with evident sensitivity to monetary cost, while additional micromobility service functionalities contribute a little to utility, meaning that mode choice is shaped less by service design and more by trip purpose and personally perceived convenience, with public transport, shared bikes, and scooters becoming more attractive for service-related trips and bike- and scooter-based options losing appeal for health-related travel.

The Munich choice experiment suggests a comparatively broad acceptance of multiple transport options, as all offered modes start from positive baseline preferences, yet decisions are still structured by travel time and access time rather than price, while service functionalities do not significantly alter utility, indicating that the central issue is not openness to alternatives as such but whether a specific mode fits the practical purpose of the trip, especially given the weak performance of walking for grocery and commerce trips and the stronger role of public transport and car sharing in health-related travel.

Paris is the clearest case where the experiment captures the importance of the mobility environment itself, not just the mode. Public transport remains highly preferred, but unlike the other living labs, all tested service functionalities for shared micromobility have a positive effect, which means that in Paris, micromobility demand is not only present but can be actively strengthened when the service is embedded in a safe, visible, and easy-to-try system. The socio-demographic results also show that micromobility is especially promising among younger respondents.

In Utrecht, experiment confirms public transport as the strongest baseline option while also showing a relatively strong starting position for shared electric bikes, yet the most important result is that service improvements add little value whereas one concrete operational feature, like flexible parking, substantially increases the attractiveness of shared mopeds, especially among younger adults and for commerce-related trips.

The Vienna choice experiments show that respondents make their choices primarily on the basis of the core characteristics of the destination rather than abstract store labels alone, where larger size, greater

product variety, lower prices, shorter travel duration, and a less crowded environment all increase attractiveness, while chain-branded establishments are preferred over independent stores only under certain conditions.

5. CONCLUSIONS AND DISCUSSION

5.1. Importance of everyday services

Across all socio-demographic groups, the results show a clear and consistent prioritisation of daily and essential services, particularly grocery stores and basic healthcare (pharmacies and general practitioners). This finding reinforces existing evidence that proximity to food and health services constitutes the backbone of perceived neighbourhood accessibility. While leisure, cultural, and consumption-oriented amenities contribute to neighbourhood attractiveness, they are rarely perceived as critical when respondents are asked to prioritise what matters most.

The main conclusion of our analysis comprising mostly respondents from urban outskirts is that, in urban outskirts, the perceived success of a 15-minute neighbourhood is less dependent on the availability of a wide range of optional amenities and more on the reliable, walkable access to a small set of essential services that structure daily routines. From a planning perspective, residents appear to value reliable access to a limited set of essential amenities, complemented by acceptable access to a wider range of services beyond the immediate neighbourhood. Results indicate that acceptable walking distances for some amenities seems to extend beyond the 15-minute domain. This aligns with the DREAMS conceptualisation of the 15-minute neighbourhood as a flexible framework rather than a strict temporal threshold.

5.2. Perceived accessibility

Overall, respondents report high levels of perceived accessibility to most everyday services using their preferred mode of transport. Walking emerges as the dominant mode for accessing nearby daily amenities, indicating that, despite suburban and peri-urban characteristics, many urban-outskirts neighbourhoods already function as partially walkable environments. This finding nuances the often-binary depiction of outskirts as inherently car-dependent and highlights the relevance of fine-grained, neighbourhood-level accessibility conditions.

At the same time, the results reveal substantial variation across service domains. Commerce and leisure-related services display relatively consistent perceived access across cities, whereas healthcare and especially education-related services show much wider dispersion. These differences point to structural inequalities in how certain functions are spatially organised and serviced, suggesting that achieving a comprehensive 15-minute neighbourhood remains more challenging for services that depend on larger catchment areas, institutional planning, or sector-specific regulations.

These findings highlight the value of a domain-specific interpretation of the 15-minute concept, rather than treating accessibility as a uniform condition across all services. In urban outskirts, proximity thresholds that are realistic and meaningful for groceries or green spaces may not be directly transferable to education or specialised healthcare, calling for differentiated planning targets.

Reported accessibility barriers are mentioned by a relatively small share of respondents, with distance and transport connectivity emerging as the most common constraints. While this may suggest that most residents do not experience severe accessibility problems in their daily lives, it should not be interpreted as an absence of structural issues. Rather, the low prevalence of reported barriers likely reflects a combination of adaptation strategies, selective activity choices, and the normalisation of longer trips for certain services.

Despite few reported barriers, model results revealed some drivers of perceived accessibility in the survey sample. For policy makers results suggest improving access to transport modes does not necessarily improve perceived accessibility. The strongest effects on perceived accessibility come from equity issues such as income, mobility issues and gender. Hence, results suggest the most effective measure to improve people's perceived accessibility is to focus on proximity to services disadvantaged population groups find important rather than improving transport options.

5.3. Service bundles and the relevance of personas

A central contribution of this analysis lies in demonstrating that perceived accessibility is best understood through bundles of services rather than individual amenities. The identification of five global service-preference personas shows that residents' accessibility needs follow distinct logics, ranging from health- and care-oriented and family- and child-oriented profiles to daily convenience, leisure-oriented, and urban social and consumption-oriented patterns.

The persona analysis reveals an important duality. On the one hand, some service-preference profiles are closely aligned with identifiable life situations, such as ageing in place or households with children, confirming the relevance of life-course perspectives in accessibility planning. On the other hand, several personas cut across socio-demographic boundaries, indicating that certain accessibility logics—particularly those centred on daily convenience or social consumption—are not confined to specific population groups. These findings challenge overly deterministic assumptions that link accessibility needs directly to age, income, or household type. For planning and policy, this suggests that proximity-based interventions should not rely solely on socio-demographic targeting but should also account for diverse lifestyle-driven accessibility needs that coexist within the same neighbourhoods.

5.4. Behavioural validation through discrete choice modelling

The stated preference experiments and discrete choice models provide behavioural validation of the perceived accessibility patterns identified in the first part of the study. Across all five living labs focused on mode choice, public transport remains the most stable and attractive baseline option, while shared and micromobility services operate mainly as complementary modes rather than universal substitutes. Their usefulness depends strongly on the purpose of the trip, the characteristics of the user, and the local mobility environment.

Results consistently show strong sensitivity to travel time and travel cost, confirming that efficiency and affordability remain central drivers of mode choice in urban outskirts. Importantly, the significant random parameters across all cities reveal substantial heterogeneity in preferences, particularly in cost sensitivity. This indicates that while average effects are stable and predictable, individuals differ considerably in how they evaluate trade-offs between time, cost, and access conditions. Such heterogeneity aligns with the persona-based findings, suggesting that accessibility needs and behavioural responses are not uniform even within the same neighbourhood context.

Service-related incentives focussed on micromobility services produce differentiated and strongly context-dependent behavioural effects across the living labs. Infrastructure-based service incentives improvements tend to generate clearer and more robust utility gains than financial incentives. In Paris, protected bike lanes substantially increase the attractiveness of shared micromobility, indicating that perceived safety and dedicated space are decisive for behavioural uptake. In Utrecht, flexible parking conditions for shared mopeds significantly improve utility, which may affect reducing last-mile friction and enhancing spatial convenience directly influence choice. These interventions modify the structural conditions of access rather than simply adjusting prices. By contrast, purely monetary incentives such as bundled subscription discounts, bonus credits, or free-ride promotions often show weak or statistically insignificant effects in Munich, Budapest, and several Brussels specifications. Even where financial bundles reach significance, the magnitude of the effects remains modest relative to core attributes such as travel time and cost. This suggests that short-term price signals may not fundamentally reshape behaviour when underlying spatial or infrastructural constraints remain unchanged.

Together the behavioural evidence indicates that residents respond more strongly to improvements that increase reliability, safety, and ease of access than to temporary or conditional financial rewards. In urban outskirts, where daily routines are tightly structured and time-

sensitive, reducing friction in the physical environment appears more influential than marginal price adjustments. From a planning perspective, this supports prioritizing durable, infrastructure-based interventions that enhance everyday accessibility conditions. Pricing mechanisms can complement such strategies. These results align with the idea that infrastructure intervention alone is not sufficient to support the significant development of active transport modes, and that a truly systemic approach is required (Moinse, 2025). In this context, complimenting infrastructures with soft measures including pricing services can play a significant role

In Vienna, where retail destination choice experiments were estimated using MNL, the results confirm similar structural preferences in a different domain. Larger store size, greater variety, lower prices, shorter travel duration, and non-crowded environments significantly increase utility. While the MNL framework assumes homogeneous preferences, socio-demographic interactions still reveal differentiated patterns across age, income, and education groups. Together, the Vienna results extend the 15-minute neighbourhood discussion beyond mobility, showing that retail accessibility is shaped by the same fundamental trade-offs between proximity, cost, and experiential quality.

5.5. Limitations

Despite the overall robustness of the survey design, several limitations should be acknowledged. Considering the survey design, the grouping strategy, consisting of five general categories and 30 specific amenities, was sometimes perceived as inadequate by respondents and partners, particularly in relation to the commerce-related categories and the placement of grocery shops. Although the grouping was grounded in existing literature, it may not represent the most intuitive or context-sensitive classification, and additional categories such as indoor leisure or blue waterlines amenities could be considered in future work. Second, in the section on reachability, it remains unclear what respondents had in mind when answering the question “can you always reach...?”, even after refining the wording. A more precise formulation referring to specific destination types would strengthen the validity of this measure. Furthermore, the survey was notably long, as it was two surveys combined, and the absence of a progress bar may have contributed to respondent burden. While the intention was to translate the instrument into multiple migrant-relevant languages across the living labs, practical constraints meant that only English and the native languages of each city were ultimately implemented. Finally, although our target of at least 300 complete responses for each choice experiment was achieved in four of the six living labs, Paris and Munich fell short of this threshold.

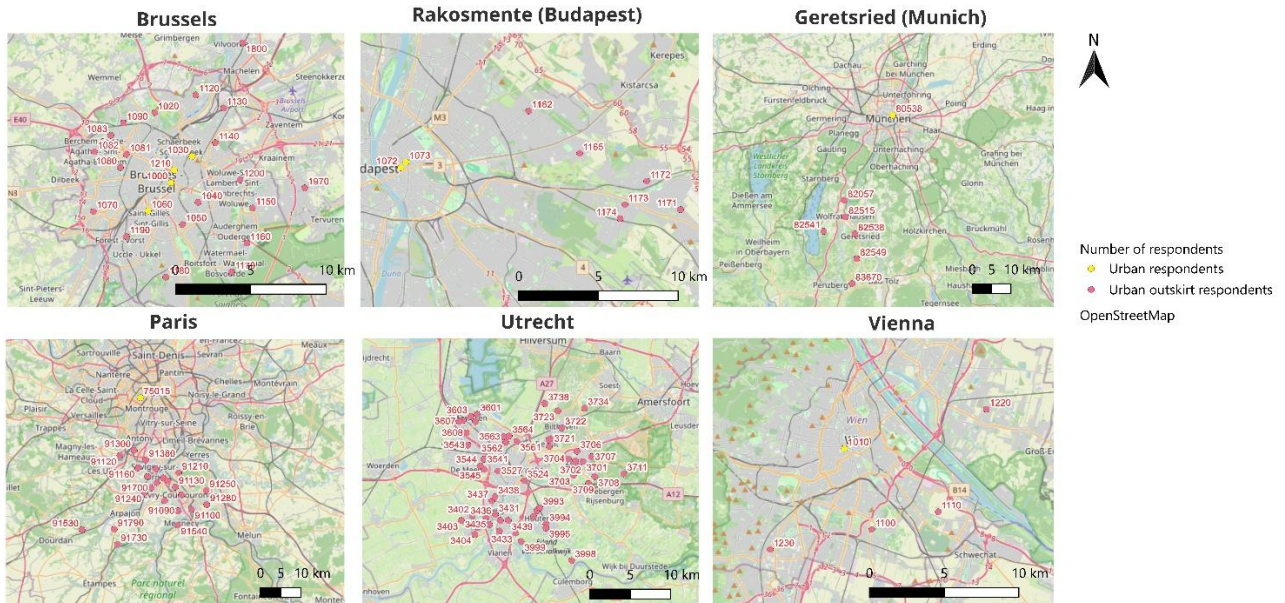
6. REFERENCES

1. Hess, S., & Palma, D. (2019). Apollo: A flexible, powerful and customisable freeware package for choice model estimation and application. *Journal of Choice Modelling*, 32, Article 100170. <https://doi.org/10.1016/J.JOCM.2019.100170>
2. Hess, S., Train, K. E., & Polak, J. W. (2006). On the use of a Modified Latin Hypercube Sampling (MLHS) method in the estimation of a Mixed Logit Model for vehicle choice. *Transportation Research Part B: Methodological*, 40(2). <https://doi.org/10.1016/j.trb.2004.10.005>
3. McFadden, D. (1974). The measurement of urban travel demand. *Journal of public economics*, 3(4), 303-328. [https://doi.org/10.1016/0047-2727\(74\)90003-6](https://doi.org/10.1016/0047-2727(74)90003-6)
4. McFadden, D., & Train, K. (2000). Mixed MNL models for discrete response. *Journal of Applied Econometrics*, 15(5), 447-470. [https://doi.org/10.1002/1099-1255\(200009/10\)15:5<447::aid-jae570>3.0.co;2-1](https://doi.org/10.1002/1099-1255(200009/10)15:5<447::aid-jae570>3.0.co;2-1)

5. Train, K. E. (2009). Discrete choice methods with simulation, second edition. In, vol.9780521766555. Discrete choice methods with simulation, second edition. <https://doi.org/10.1017/CB09780511805271>
6. Vij, A., & Walker, J. L. (2016). How, when and why integrated choice and latent variable models are latently useful. *Transportation Research Part B: Methodological*, 90. <https://doi.org/10.1016/j.trb.2016.04.021>
7. European Union - GISCO. (2024). *Postal codes*. Retrieved from Eurostat: <https://ec.europa.eu/eurostat/web/gisco/geodata/administrative-units/postal-codes>
8. Ikotun, A. M., Ezugwu, A. E., Abualigah, L., Abuhaija, B., & Heming, J. (2023). K-means clustering algorithms: A comprehensive review, variants analysis, and advances in the era of big data. *Information Sciences*, 178-210. doi:10.1016/j.ins.2022.11.139
9. Moïnse, D. (2025). Exploring the relationship between perceived bikeability and gender-inclusive micromobility usage: A study across 53 French cities. *Transportation Research Part A: Policy and Practice*, 193. doi:10.1016/j.tra.2025.104379
10. Williams, R. A., & Quiroz, C. (2020). *Ordinal Regression Models*. SAGE Research Methods. doi:10.4135/9781526421036885901

7. APPENDICES

Appendix 1 Urban and non-urban survey respondents

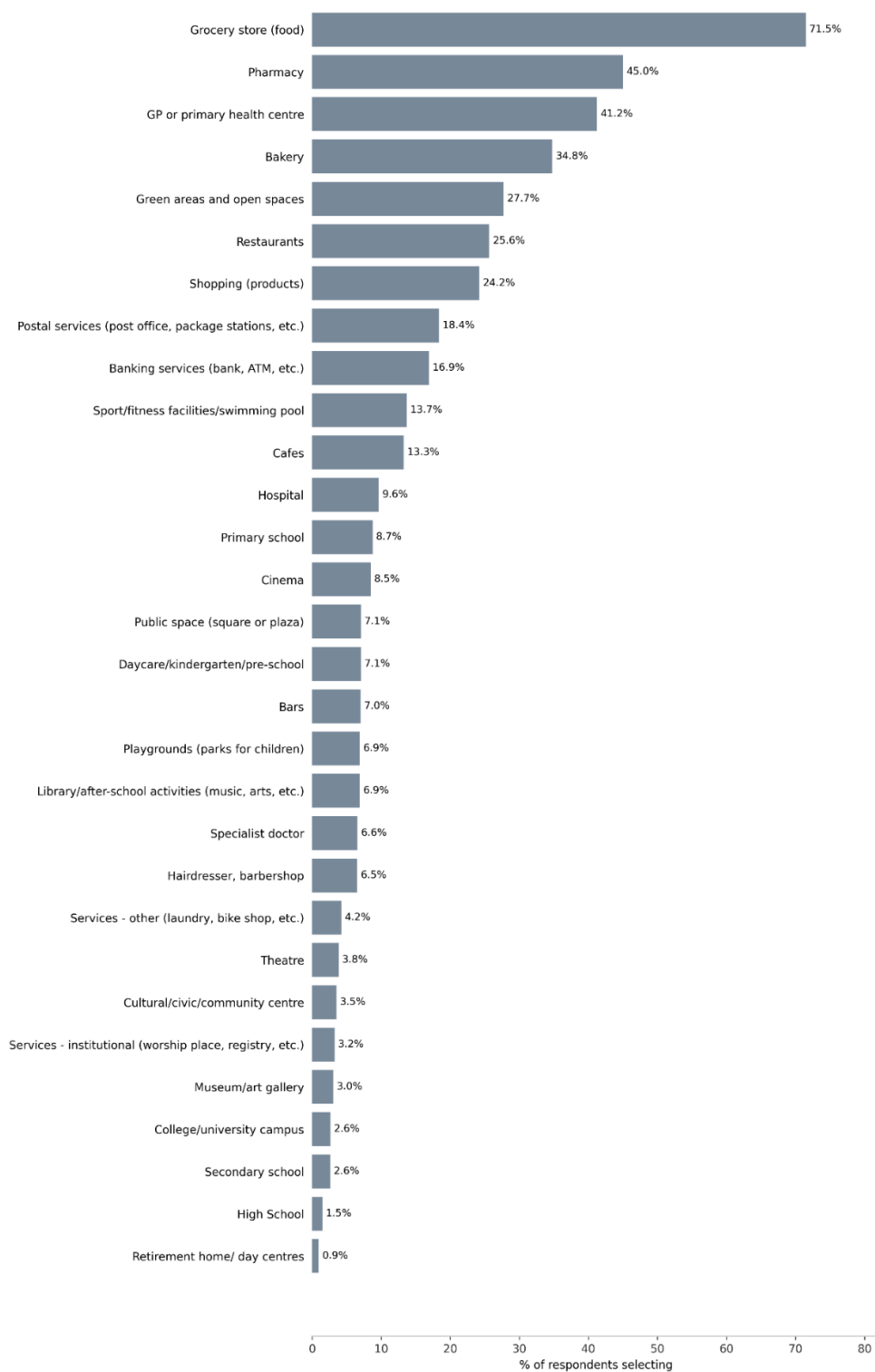


note: additional postcodes were filtered for Vienna, but do not show up on map due to Eurostat data being incomplete: 1020, 1030, 1040, 1050, 1060, 1080, 1090

Respondents removed per city:

- Brussels: 160
- Budapest: 8
- Munich: 1
- Paris: 1
- Utrecht: 0
- Vienna: 191

Appendix 2 Full set of amenities and their importance for DREAMS survey respondents



Appendix 3 DREAMS survey questions

Question

Question	Answer option
Choose your country of residenceC2:C2:C511	The Netherlands Austria Belgium France Germany Hungary
What is the postal code of the place where you live?	The Netherlands Austria Belgium Germany France Hungary
EDU	<25 25-45 45-65 65+
Gender, how do you identify?	Other Woman Man Non-binary/Third gender Prefer not to say
For how long have you lived in The Netherlands?	I was born in The Netherlands More than 10 years 6-10 years 1-5 years Less than 1 year Prefer not to say
For how long have you lived in Austria?	I was born in The Austria More than 10 years 6-10 years 1-5 years Less than 1 year Prefer not to say
For how long have you lived in Belgium?	I was born in Belgium More than 10 years 6-10 years 1-5 years Less than 1 year Prefer not to say
For how long have you lived in France?	I was born in France More than 10 years 6-10 years 1-5 years

	<p>Less than 1 year</p> <p>Prefer not to say</p>
For how long have you lived in Germany?	<p>I was born in Germany</p> <p>More than 10 years</p> <p>6-10 years</p> <p>1-5 years</p> <p>Less than 1 year</p> <p>Prefer not to say</p>
What is the highest level of education you have completed? Hungary	<p>Primary education</p> <p>Secondary education</p> <p>Bachelor</p> <p>Master</p> <p>Doctorate</p>
What is the highest level of education you have completed? Austria	<p>Compulsory school</p> <p>Apprenticeship with vocational school</p> <p>Technical or commercial school</p> <p>Matura</p> <p>Degree from a university or college</p> <p>Other qualification after the Matura</p>
What is the highest level of education you have completed? Belgium	<p>None</p> <p>Primary school</p> <p>Secondary school</p> <p>Bachelor</p> <p>Master</p> <p>PhD</p> <p>Prefer not to say</p>
What is the highest level of education you have completed? Germany	<p>Elementary school (Kindergarten, Tageseltern, Kinderkrippe)</p> <p>Primary school (Grundschule)</p> <p>Secondary school (Hauptschule, Realschule, Berufsschule, Fachoberschule, Gesamtschule, Gymnasium)</p> <p>Vocational Education (Berufsschule, Fachschule, Ausbildung)</p> <p>Tertiary Education (University - bachelor, masters, PhD)</p>
What is the highest level of education you have completed? France	<p>Primary education</p> <p>Lower secondary education</p> <p>Upper secondary education</p> <p>Post-secondary non-tertiary education</p> <p>Short-cycle tertiary education</p>

	Bachelor Master Doctorate
What is the highest level of education you have completed? The Netherlands	No education or primary education Secondary education (LBO, VBO, VMBO, MAVO, HAVO, VWO) Secondary vocational education (MBO) HBO/WO Bachelor's degree MSc/MA/PhD or other comparable level PhD Other
Which category best describes your occupation/employment status?	Other Employed (full time) Employed (part time) Self-employed (full time) Self-employed (part time) Student Working in household or other unpaid activity Retired/Pensioner Unemployed Unable to work
On average, how often do you work/study from home?	Never Less than once per month 1 to 3 days per month 1 to 2 days per week 3 to 4 days per week Nearly every day I always work/study remotely
When you travel for work purposes...How long does it typically take? consider door-to-door travel time in minutes Austria	0-5 minutes 6-10 minutes 11-15 minutes 16-20 minutes 21-30 minutes 31-45 minutes More than 45 minutes
When you travel for work purposes...Which mode do you usually use? Austria	Walking Cycling Public transport Taxi Private car

When you travel for study purposes...How long does it typically take? consider door-to-door travel time in minutes Austria	<p>Shared mobility (car-sharing, bike-sharing, etc.)</p> <hr/> <p>0-5 minutes</p> <p>6-10 minutes</p> <p>11-15 minutes</p> <p>16-20 minutes</p> <p>21-30 minutes</p> <p>31-45 minutes</p> <p>More than 45 minutes</p>
When you travel for study purposes...Which mode do you usually use? Austria	<hr/> <p>Walking</p> <p>Cycling</p> <p>Public transport</p> <p>Taxi</p> <p>Private car</p> <p>Shared mobility (car-sharing, bike-sharing, etc.)</p>
Which category best describes your current living situation?	<hr/> <p>Other</p> <p>Single household</p> <p>Couple</p> <p>Single with a child/children</p> <p>Couple with a child/children</p> <p>Shared with others (Multi-person households without being related)</p> <p>Households with only senior citizens (pensioner) and senior couples</p> <p>Households with senior citizens (pensioner) and younger people</p>
	<hr/> <p>Less than 1.000 €/month</p> <p>1.000 - 1499 €/month</p> <p>1.500 - 1.999 €/month</p> <p>2.000 - 2.999 €/month</p> <p>3.000 - 3.999 €/month</p> <p>4.000 - 4.999 €/month</p> <p>More than 5.000 €/month</p> <p>Prefer not to answer</p>
Which of the following tasks are you able to do using your smartphone?	<hr/> <p>Looking up information like opening hours, available services, etc.</p> <p>Using a journey planner for travelling with your own vehicle (such as car, bike or moped) (e.g. Google Maps).</p> <p>Using a journey planner to plan a trip by public transport.</p> <p>Using an app for purchasing public transport tickets/App to transfer money.</p>

Using an app to reserve/book shared mobility services (car-sharing, bike-sharing, etc.) (e.g. DOTT, Uber) .

I don't have a smartphone/ I have a smartphone but is not connected to the internet.

I have a smartphone, but I can't do any of the above tasks.

I go less often to the supermarket because I shop for groceries online.	Strongly disagree Disagree Neither agree nor disagree Agree Strongly agree
I go less often to the doctor's office because I use online health consultations.	Strongly disagree Disagree Neither agree nor disagree Agree Strongly agree
I go less often to the bank because I do my banking online.	Strongly disagree Disagree Neither agree nor disagree Agree Strongly agree
I go less often to government offices because I do administrative tasks online.	Strongly disagree Disagree Neither agree nor disagree Agree Strongly agree
I go less often to shops because I buy clothes, electronics, and other products online.	Strongly disagree Disagree Neither agree nor disagree Agree Strongly agree
I go less often to the pharmacy because I order my medicine online.	Strongly disagree Disagree Neither agree nor disagree Agree Strongly agree
I go less often to restaurants or takeout places because I order meals online (e.g., Uber Eats). SQ-7	Strongly disagree Disagree Neither agree nor disagree

	Agree Strongly agree
Which of the following do you currently have access to or use at home?	Bike/cargo-bike. Electric bike/cargo-bike. Scooter. Motorcycle/moped. Public Transport pass/subscription. Shared mobility subscription. Car driving license (s). Car, indicate how many you own/have access to:
Do you have difficulties walking or cycling (more than 200 metres)?	Yes, I have difficulty walking. Yes, I have difficulty cycling. Yes, I have difficulty walking and cycling. Yes, I don't know how to ride a bike. No, I don't have any difficulties.
Do you know how to ride a bike? Austria	Yes No
I like cycling.	Strongly disagree Disagree Neutral Agree Strongly agree
I think cycling is a safe way to travel.	Strongly disagree Disagree Neutral Agree Strongly agree
I cycle only when my usual mode of transport is not available.	Strongly disagree Disagree Neutral Agree Strongly agree
I cycle only when the weather is nice (not raining/cold).	Strongly disagree Disagree Neutral Agree Strongly agree
I can afford to buy a bike.	Strongly disagree Disagree Neutral Agree Strongly agree
I can afford to pay for maintenance of a bike.	Strongly disagree Disagree Neutral

	Agree Strongly agree
I would use a shared cargo-bike service if it was available.	Strongly disagree Disagree Neutral Agree Strongly agree
Most of my trips are too long do on a bike.	Strongly disagree Disagree Neutral Agree Strongly agree
I would use a shared car-sharing service if it was available.	Strongly disagree Disagree Neutral Agree Strongly agree
Based on your current living situation, select your top most important amenities or services that you travel to and would like to have close to your home, within walking/cycling distance?	Bars Cafes Restaurants Shopping (non-edible products) Grocery store (edible products) Bakery Daycare/kindergarten/pre-school Primary school Secondary school High School College/university campus Library/after-school activities (music, arts, etc.) GP or primary health centre Pharmacy Specialist doctor Hospital Retirement home/ day centres Green areas and open spaces Playgrounds (parks for children) Public space (square or plaza) Sport/fitness facilities/swimming pool Cinema Museum/art gallery Theatre Services - other (laundry, bike shop, etc.) Services - institutional (workshop place, registry, etc.) Cultural/civic/community centre

	Hairdresser, barbershop Postal services (post office, package stations, etc.) Banking services (bank, ATM, etc.)
When you travel to your selected services...How do you typically travel to this service?	Walking Bike/ e-bike Car driver Car passenger Bus Tram/Metro/Train Shared e-bike/ cargo-bike / scooter / moped Shared car Taxi
When you travel to your selected services...How frequently do you go there?	Daily 4-5 times per week 2-3 times per week Weekly 2-3 times per month Monthly Less than monthly
When you travel to your selected services...How long does it usually take you to get there?	0-5 minutes 6-10 minutes 11-15 minutes 16-20 minutes 21-30 minutes 31-45 minutes More than 45 minutes
When you travel to your selected services...What is the maximum walking time you would spend getting there? (Max. acceptable travel time)	0-5 minutes 6-10 minutes 11-15 minutes 16-20 minutes 21-30 minutes 31-45 minutes More than 45 minutes
How many locations of your selected services...Do you usually visit throughout the year?	1 2 3 or more
How many locations of your selected services...Would you like to have at walking/cycling distance?	I do not need more I would like +1 I would like +2 I would like +3 or more
How often do you shop for groceries? Physical	Daily

	4-5 times per week 2-3 times per week Weekly Monthly Less than monthly
How often do you shop for groceries? Online	Daily 4-5 times per week 2-3 times per week Weekly Monthly Less than monthly Never
Why do you shop so often?	I prefer to shop in smaller quantities to avoid carrying heavy bags. I want to buy fresh products everyday I usually combine grocery shopping with other daily tasks (accompany kids to school/going to work/going to the gym) Shopping is part of my daily routine. I rely on public transport, which makes it easier to shop frequently. Other
What days of the week do you usually go for shopping?	Weekdays Weekends
At what time of the day do you usually visit the shopping location?	In the morning, before work In the evening, after work In the morning, on days when I don't work or I'm working from home In the evening, on days when I don't work or I'm working from home
When you go for shopping...How long does it take you to get there?	0-5 minutes 6-10 minutes 11-15 minutes 16-20 minutes 21-30 minutes 31-45 minutes More than 45 minutes
When you go for shopping...How do you get there?	Walking Bike/e-bike Car driver Car passenger Bus Tram/Metro/Train Shared bike/e-bike Shared cargo-bike

	Shared scooter Shared moped Shared car Taxi
How much time do you spend, on average, in the grocery store of your choice?	0-10 minutes 11-30 minutes 31-60 minutes More than an hour
How are grocery shopping duties shared in your household?	I do all, others do none (also applies to single households) I do none, others do all I do most of it, other members do some I do some, others do most
Do you typically use any of your top selected services...but further away from your regular walking/cycling distance (outside your neighbourhood)?	Yes, all/most are outside of my neighbourhood No, all/most are within my neighbourhood Yes, but not my top services... I go outside for this other(s) service(s):
Why do you choose to access these services outside your neighbourhood?	Because the service is not available at my neighbourhood. Higher quality. Better safety in that area. More affordable service. More accessible (e.g., better public transport, easier to reach). Better suited to my needs. More variety or choice. Social or community reasons (e.g., friends/family nearby). Work or school location is closer to service. Habit or personal preference. Other
Are any of your selected most relevant services located outside of the Brussels Region?	No I don't know Yes, I usually access this service outside Brussels Region
Why do you choose to go outside of the region?	Higher quality. Language reasons. Better safety in that area. More affordable service. More accessible (e.g., better public transport, easier to reach). Better suited to my needs.

	<p>More variety or choice.</p> <p>Social or community reasons (e.g., friends/family nearby).</p> <p>Work or school location is closer to those amenities.</p> <p>Habit or personal preference.</p> <p>Other</p>
<p>Are there any caregiving duties (e.g., for children, older adults, or others) that make it more difficult for you to access your relevant services?</p>	<p>No</p> <p>Yes, I have care responsibilities that affect my access to</p>
<p>You selected: services In general, how often can you reach(access) these services using your preferred mode of transportation?</p>	<p>Always</p> <p>Often</p> <p>Sometimes</p> <p>Rarely</p> <p>Never</p>
<p>What do you consider to be barriers for reaching your services?</p>	<p>It's too far from where I live.</p> <p>It's hard to get there by bike, bus, train, or other transport.</p> <p>Getting there doesn't feel safe.</p> <p>I don't feel safe when I'm there.</p> <p>It's not easy to use /access if you have limited mobility or health condition.</p> <p>It's too expensive for me.</p> <p>There aren't enough options/ it is not suited for families, kids, or people needing care.</p> <p>They're not open when I need them.</p> <p>It doesn't feel welcoming for people of all gender identities or communities.</p> <p>I can't get/travel there in a sustainable way.</p> <p>The staff doesn't speak my preferred language.</p> <p>Traffic is too busy to get there.</p> <p>Other</p>
<p>Which of the following transport facilities will increase your ability to reach these services?</p>	<p>A bus stop near the location.</p> <p>A tram/metro/train stop near the location.</p> <p>A shared e-bike/cargo-bike in my neighbourhood.</p> <p>A shared scooter/moped in my neighbourhood.</p> <p>A shared car in my neighbourhood.</p>

None of the above.

If you had to choose only one, which of the selected services would be the most important to have within a walking/cycling distance from home?

Bars
Cafes
Restaurants
Shopping (non-edible products)
Grocery store (edible products)
Bakery
Daycare/kindergarten/pre-school
Primary school
Secondary school
High School
College/university campus
Library/after-school activities (music, arts, etc.)
GP or primary health centre
Specialist doctor
Hospital
Pharmacy
Retirement home/ day centres
Green areas and open spaces
Playgrounds (parks for children)
Public space (square or plaza)
Sport/fitness facilities/swimming pool
Cinema
Museum/art gallery
Theatre
Cultural/civic/community centre
Hairdresser, barbershop
Postal services (post office, package stations, etc.)
Banking services (bank, ATM, etc.)
Services - institutional (workshop place, registry, etc.)
Services - other (laundry, bike shop, etc.)

You selected: {top 1 service}... as your most important service to have within a walking/cycling distance from home. When choosing a particular location of this service to visit...what do you consider?

The service location is within a walking/cycling distance from my home.

Is cheaper to travel to this service location.

The high quality of the products is attractive / They offer sustainable options.

I can always find parking.

I feel safe to travel to this service location/ I feel safe at the service location.

My preferred language is spoken.

I know the people working there.

Easy to combine with other activities.

Closest location to work/On the way from work to home.

Easy to get to this service location by public transport.

Accessible for people with mobility issues/care givers.

Affordable prices at this service location.

Open when I need it.

Is there any other service you wish was closer to your home - one that is not currently within walking/cycling distance right now?

Bars

Cafes

Restaurants

Shopping (non-edible products)

Grocery store (edible-products)

Bakery

Daycare/Kindergarten/pre-school

Primary school

Secondary school

High School

College/University campus

Library

GP or Primary health centre

Specialist doctor

Hospital

Pharmacy

Retirement home/ day centres

Green areas and open spaces

Playgrounds (parks for children)

Public space (square or plaza)

Sport/fitness facilities/swimming pool

Cinema

Museum/art gallery

Theatre

Cultural/civic/community centre

Hairdresser, Barbershop

Postal services (post office, package stations, etc.)

Banking services (bank, ATM, etc.)

Services - Institutional (workshop place, registry, etc.)

Services - other (laundry, bike shop, etc.)

No, all the services are nearby

You selected: {PA17.shown} Why do you wish to have more of this service nearby?

The service is not available within a walking/cycling distance from home.

Limited or inconvenient public transport options make it hard to reach this service.

Concerns about personal safety (e.g., crime, poor lighting) when traveling to this service.

Lack of infrastructure for people with disabilities or limited mobility.

High cost prevents me from using similar services elsewhere.

Lack of child-friendly or caregiver-supportive services.

Existing options are outdated, poorly maintained, or of low quality.

Current services do not align with my lifestyle or preferences.

Services are not open during the times I need them.

There are no services that are inclusive of diverse gender identities or communities.

I prefer sustainable or eco-friendly services that are currently lacking.

Staff does not speak my preferred language.

How would you rate your neighbourhoods' overall accessibility to services by walking/cycling?

Poor - Very difficult to access essential services; most are far or inconveniently located.

Fair - Somewhat accessible, but many key services are not easily reachable.

Good - Most services are reasonably accessible, though some may require moderate effort (more than 15 minute walking/cycling travel time).

Very Good - Key services are easily accessible with minimal effort (within 15 minute walking/cycling travel time)

Excellent - All key services are readily and conveniently accessible.

How would you rate your neighbourhoods' overall accessibility to services by walking?

Poor - Very difficult to access essential services; most are far or inconveniently located.

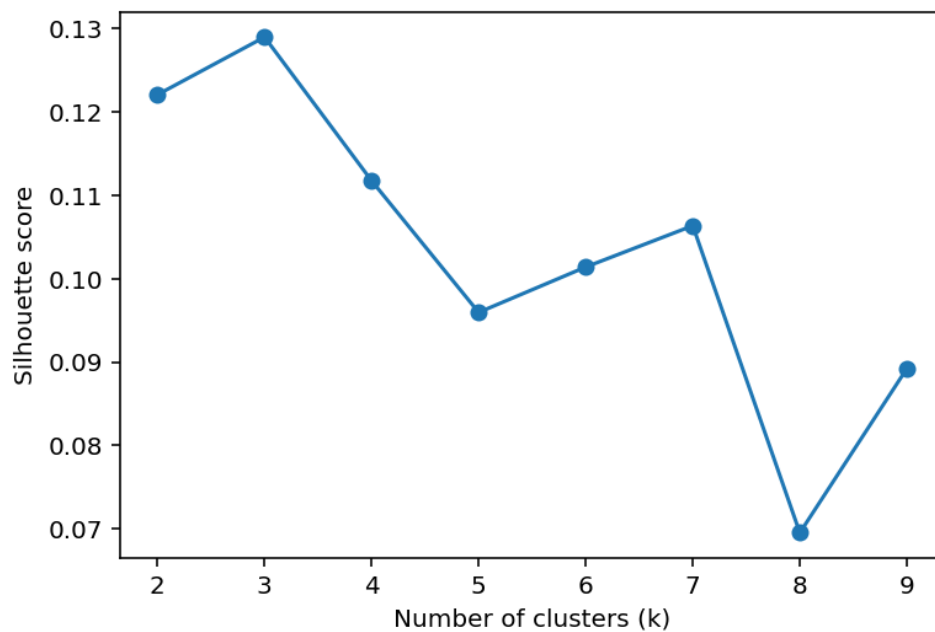
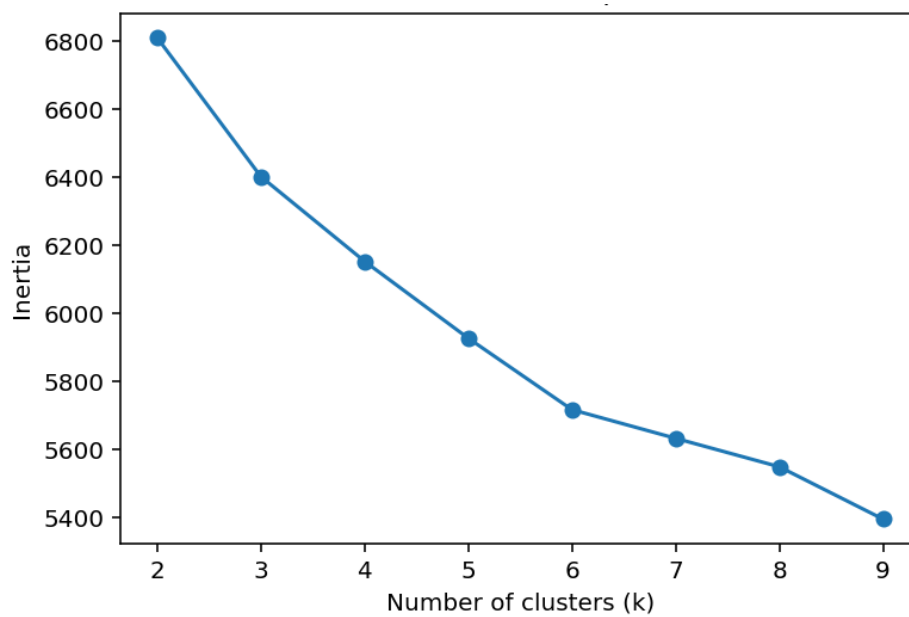
Fair - Somewhat accessible, but many key services are not easily reachable.

Good - Most services are reasonably accessible, though some may require moderate effort (more than 15 minute walking/cycling travel time).

Very Good - Key services are easily accessible with minimal effort (within 15 minute walking/cycling travel time)

Excellent - All key services are readily and conveniently accessible.

Appendix 3: Cluster diagnostics



Appendix 4: Persona reports

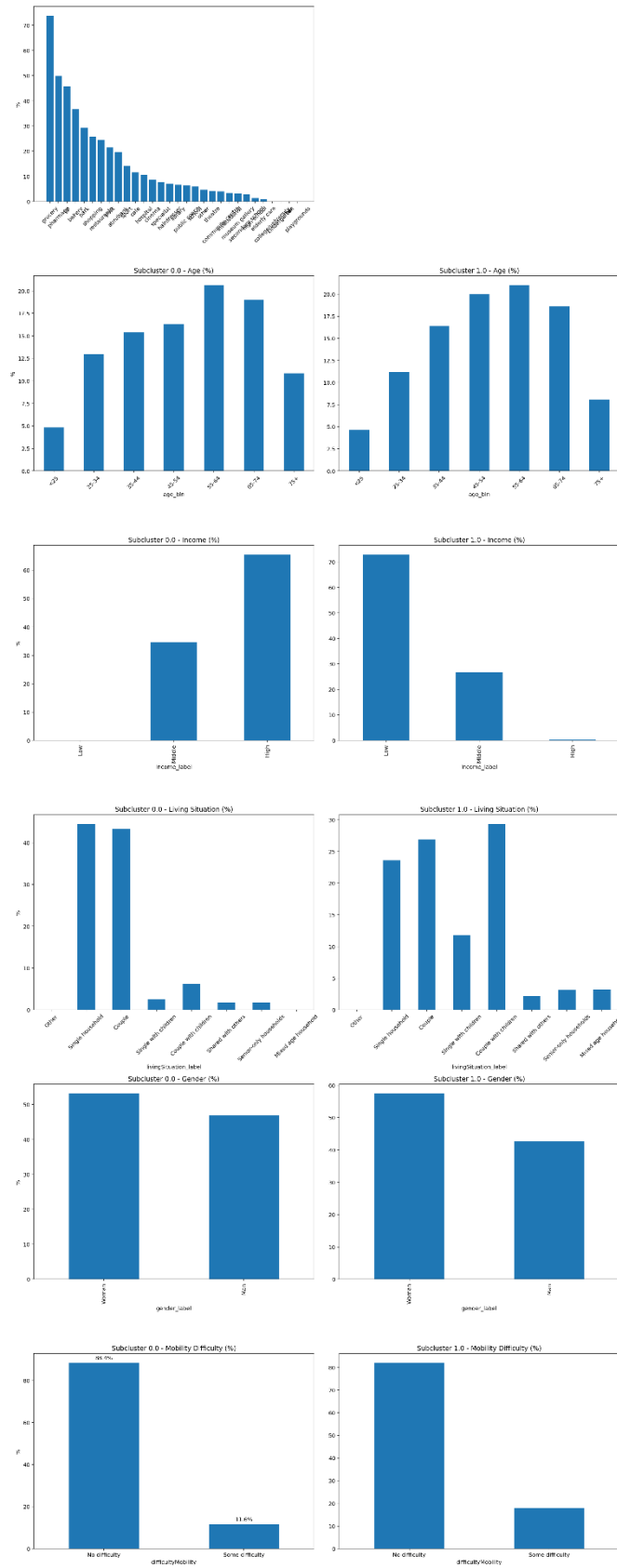


Figure 37: Persona reports for cluster 1: Essential needs-oriented persona

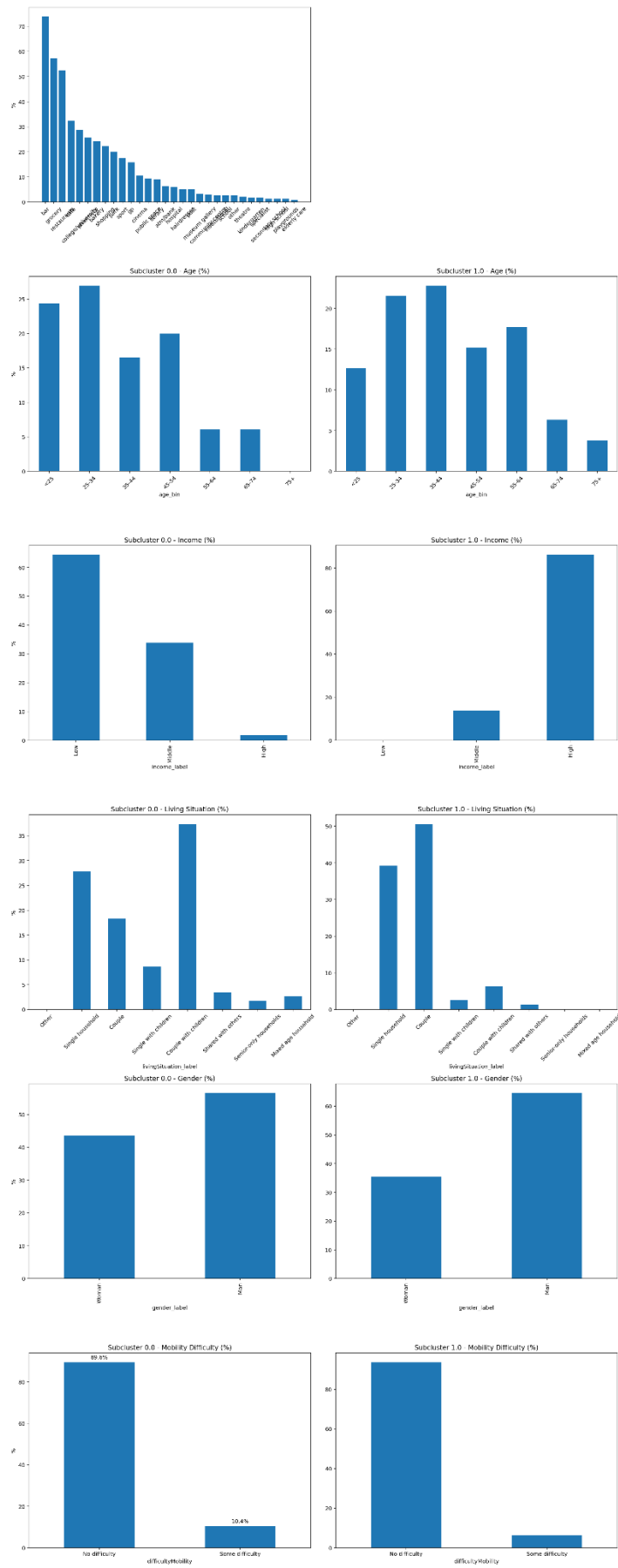


Figure 39: Persona reports for cluster 3: Social oriented persona