Assessing inhabitants' preference towards Energy Community participation: a preference learning approach

Cavana Giulio, Bottero Marta, Becchio Cristina, Fancello Giovanna and Tsoukias Alexis

Introduction_Renewable energy communities

REC means a legal entity based on voluntary participation of natural persons, SMEs or local authorities engaging in renewable energy projects. RECs are allowed to produce, consume, store and sell renewable energy, providing benefits for its members or for the areas where it operates.

environmental

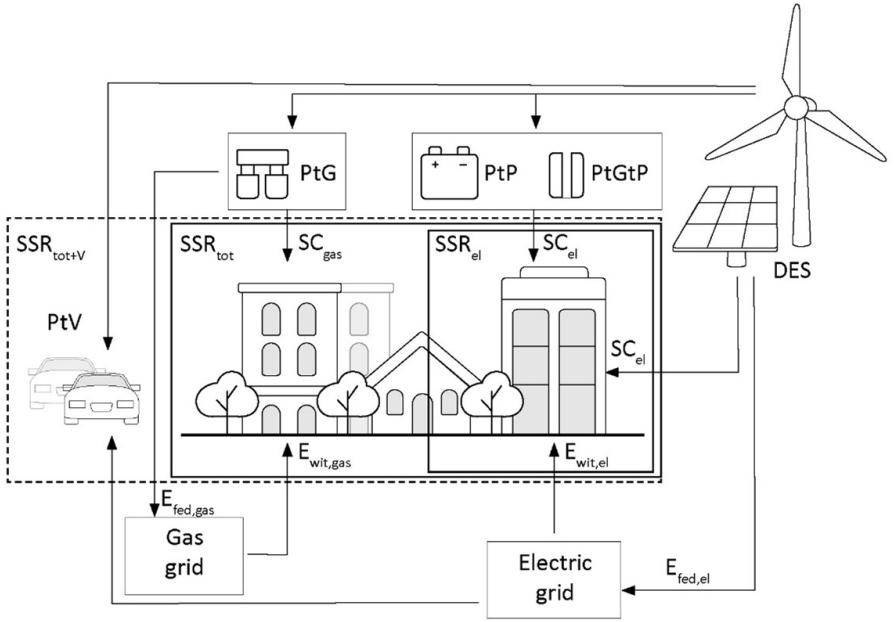
- promote RES generation
- increase energy security
- flexibility services to the grid
- promote energy efficiency
- decreasing energy consumption and emissions
- enhancing energy self-sufficiency

economic

- New jobs created
- market opportunities
- energy bills savings

social

- citizen participation
- combating energy poverty
- affordable energy tariffs
- split incentives issues



- Member States must establish an “enabling framework” to facilitate RECs formation
- economic and financial drivers that motivate consumers’ participation in RECs affecting their potential diffusion

Aim of the study

Analyze preferences for alternative solutions at the disposal of individuals

Support DM to define policies fostering REC formation maximizing desired impacts

Assessing inhabitants’ preference towards Energy Community participation: a preference learning approach_Cavana G., Bottero M., Becchio C., Fancello G., Tsoukias A.

Research questions

Q1 〉 *What are the **socio-demographic characteristics** of individuals and the **performance attributes** of potential alternatives that influence inhabitants' REC participation?*

Q2 〉 *What is the potential of **REC diffusion at the city scale and in different parts of the city,** and which are the most probable solutions to be implemented **based on the inhabitants' preference models**?*

Q3 〉 *What strategies could foster the **alignment of the private initiative** with the public perspective to **maximize the positive impacts of RECs implementation**?*

Presentation outline

1 | Literature review

2 | Method

3 | Application in Turin

4 | The “Public” option

5 | Conclusions

Literature Review

Cavana G, Becchio C, Bottero M. Feasibility and evolution studies on renewable energy communities in cities. Renewable and Sustainable Energy Reviews 2025;213:115477.

Literature Review

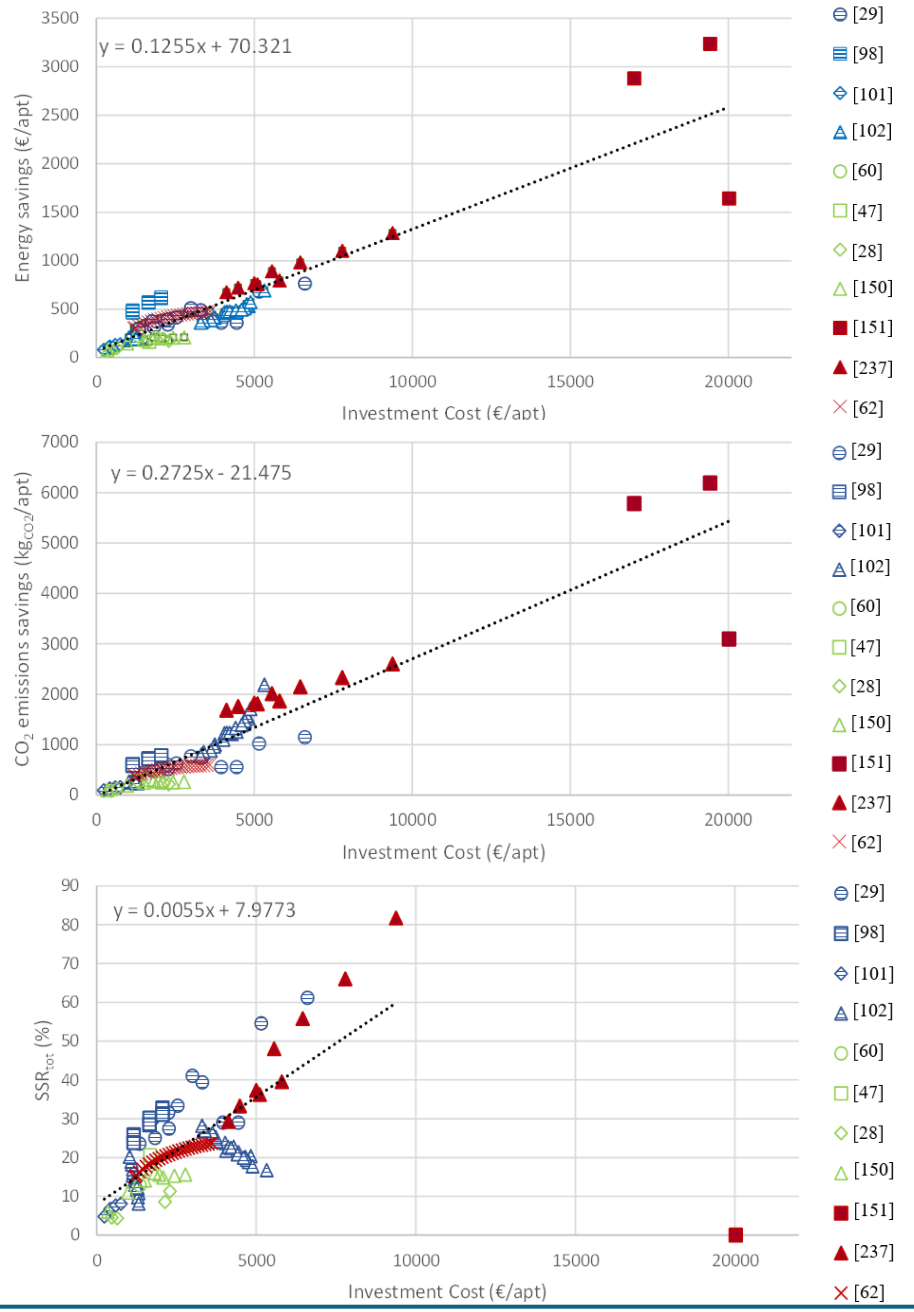
Objective:

- define a set of attributes commonly used to describe RECs (investment cost, energy savings, avoided CO_2 emissions, self-sufficiency.)
- define the range of performance of real-world alternatives

Participation in RECs is most often explained through the economic dimension.

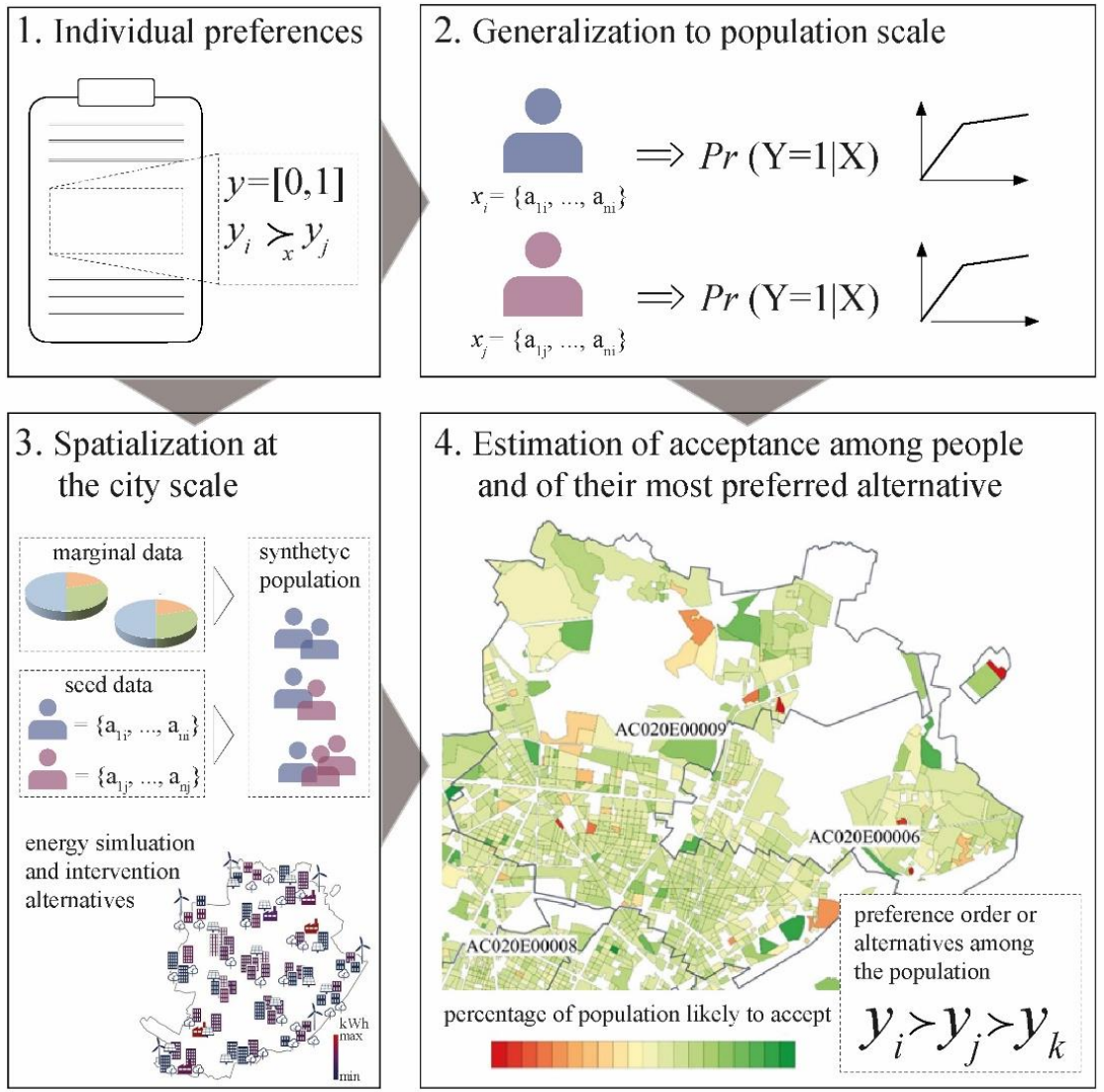
Several other dimensions that are taken into account by analysts and REC members.

Environmental concerns are among the most important reasons for participation, albeit secondary to cost savings, along with reasons for self-sufficiency and energy security.



Method

Method

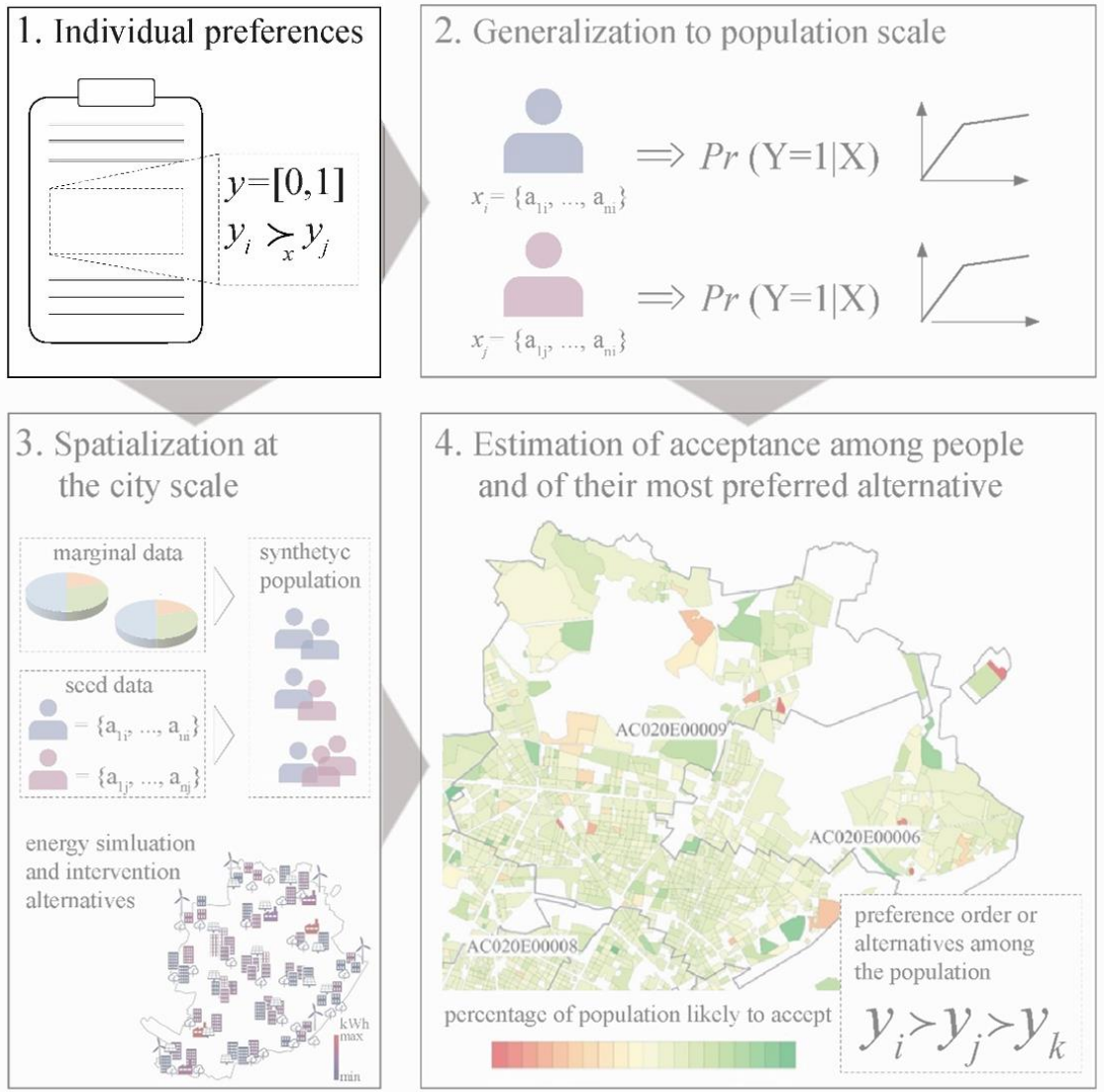

1. Individual preferences
$y=[0,1]$
$y_i \succ_x y_j$
2. Generalization to population scale
$x_i = \{a_{1i}, ..., a_{ni}\}$
$\Rightarrow Pr\,(Y=1|X)$
$x_j = \{a_{1j}, ..., a_{ni}\}$
$\Rightarrow Pr\,(Y=1|X)$
3. Spatialization at the city scale
marginal data
synthetyc population
seed data
$= \{a_{1i}, ..., a_{ni}\}$
$= \{a_{1j}, ..., a_{nj}\}$
energy simluation and intervention alternatives
kWh
max
min
4. Estimation of acceptance among people and of their most preferred alternative
AC020E00009
AC020E00006
AC020E00008
preference order or alternatives among the population
$y_i \succ y_j \succ y_k$
percentage of population likely to accept

Method

Individual preferences

1. **Questionnaire distributed to collect information** regarding willingness to participate to possible RECs alternatives (described with 4 attributes)
   - YES / NO
   - Ranking among alternative RECs

2. Two preference models are estimated:
   - Value function estimation applying **UTA method**
   - **Generalized linear mixed models** (GLMM) to estimate the likelihood to accept the REC alternative



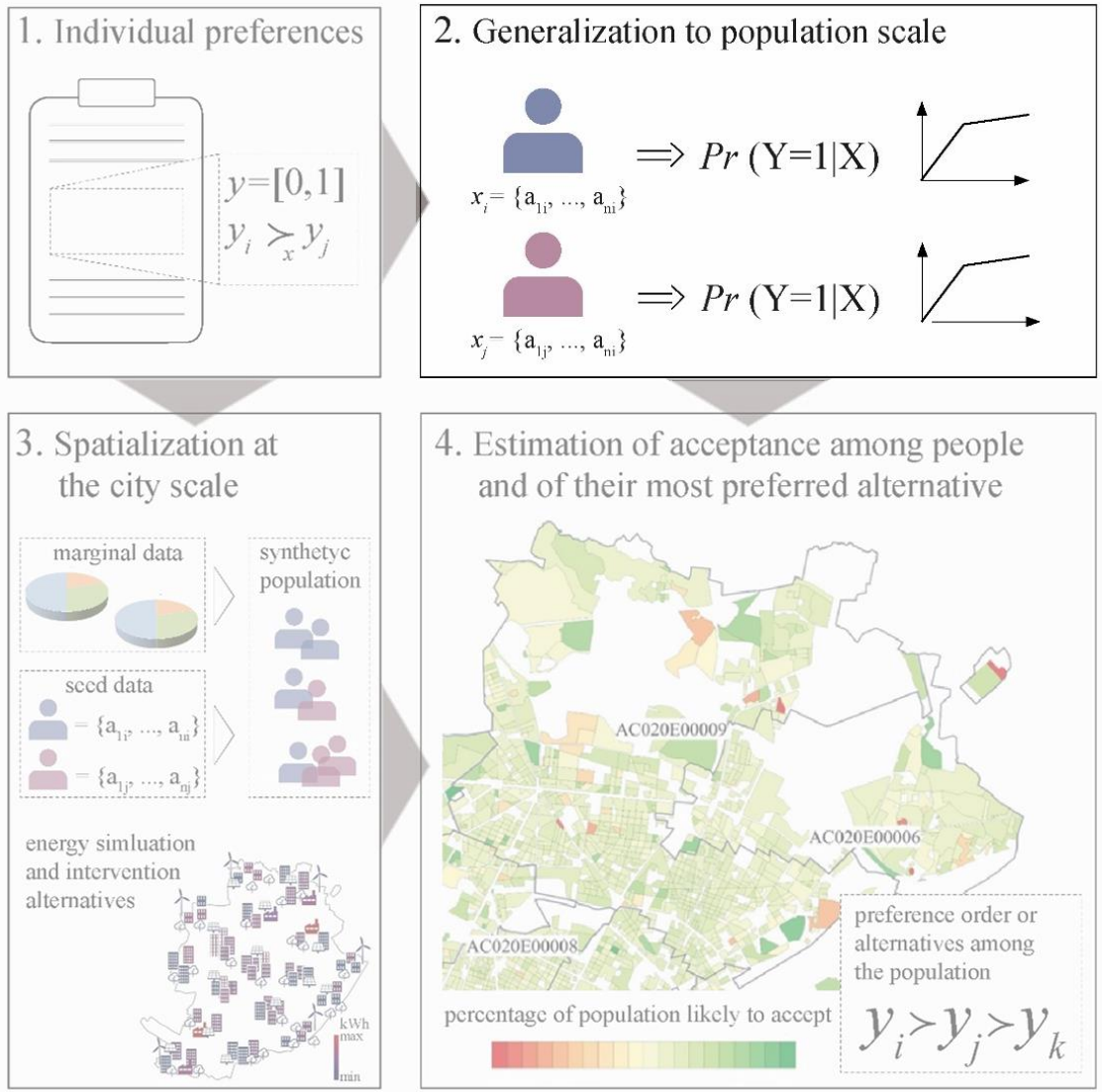
Method

Generalization to population scale

1. **types of individuals** are defined by **vector of socio-demographic attributes** based on the results of GLMM and using Linear mixed models to test association between socio-demographic characteristics and value functions shape

2. **Individuals' value functions are clustered** using an unsupervised algorithm and one **characteristic value function** is extracted for each cluster

3. supervised classification algorithm is used to **assign value functions to the different types of individuals** with a probabilistic approach.

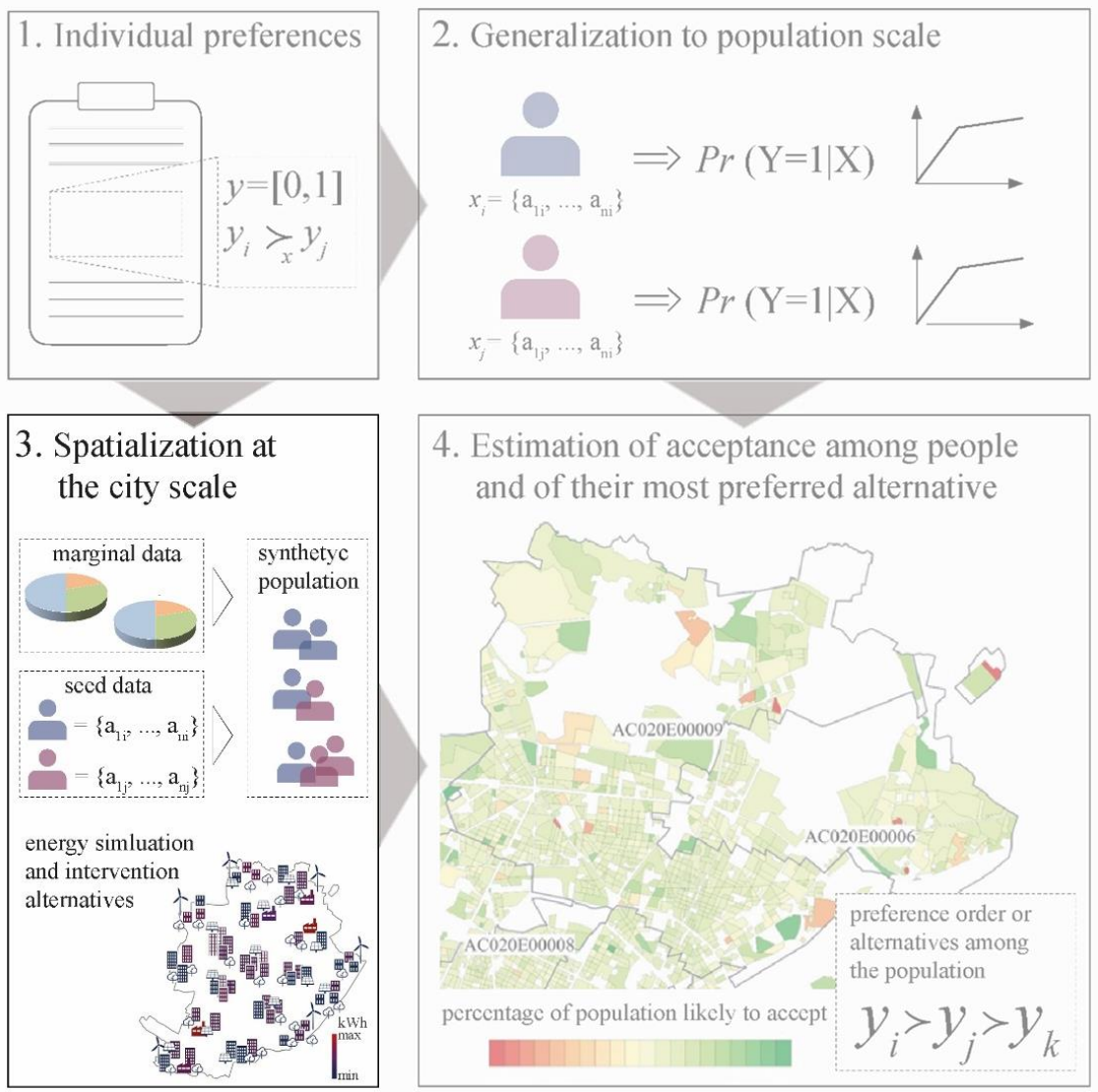


Method

Spatialization at the city scale

1. Generation of a **synthetic population** clustered into the types of individuals

2. Definition of **performance levels of the possible RECs alternative** configurations



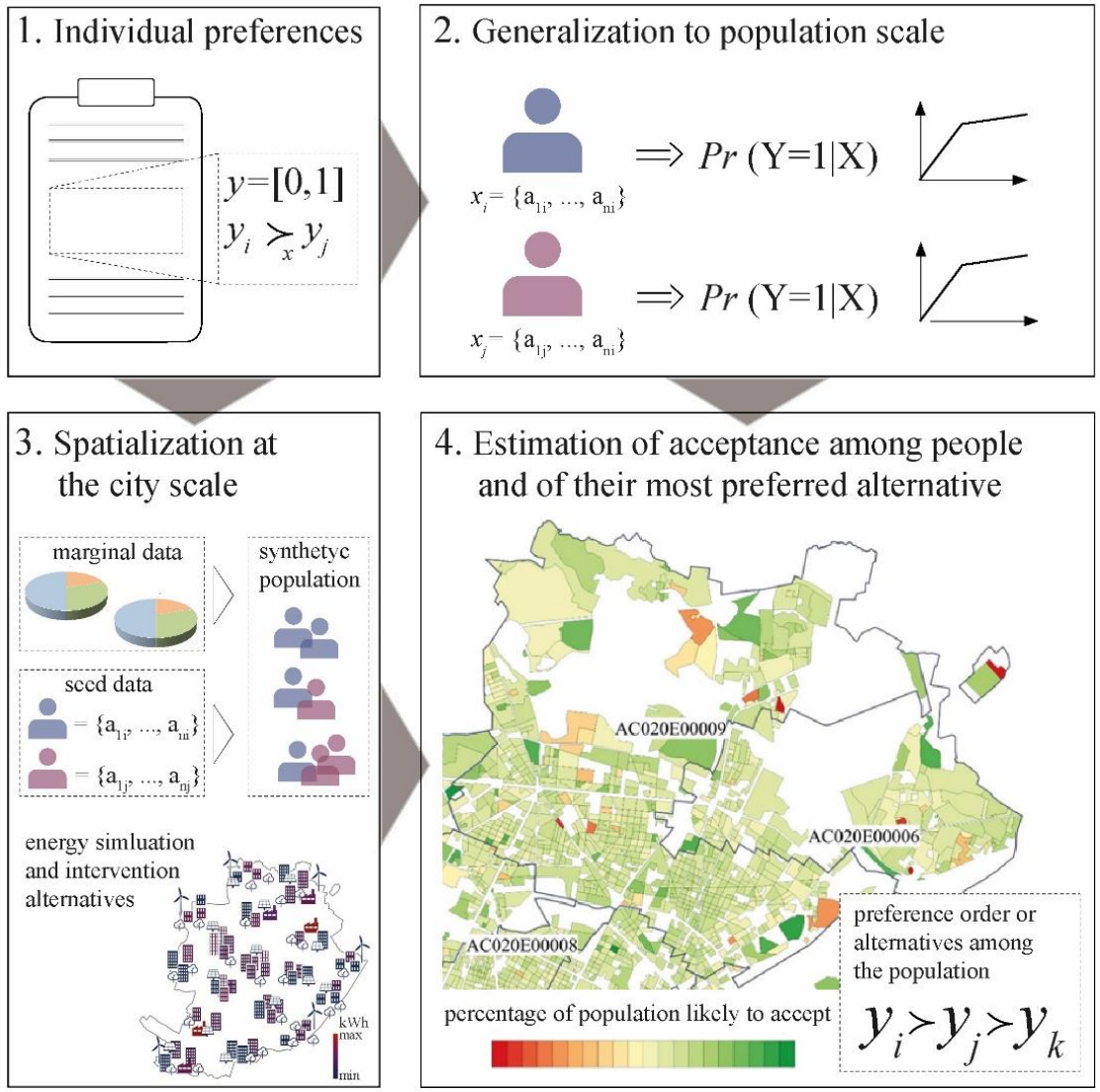
Method

Estimation of acceptance among population

The previously defined models are used to:

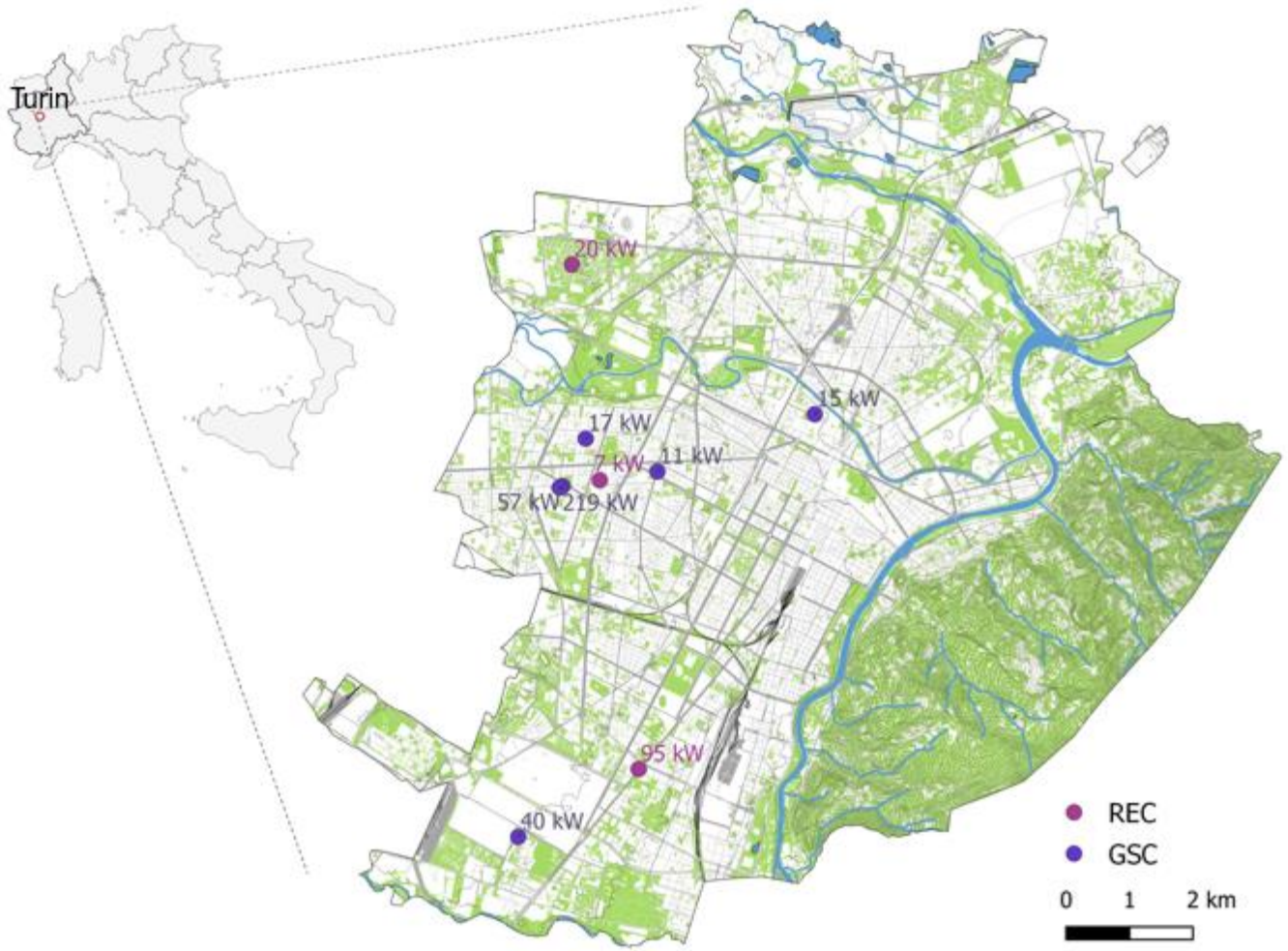
- **estimate the likelihood of the urban population to accept a possible REC** configuration

- **estimate the preferred alternative** among the available set of possible configuration at the disposal of the individuals.

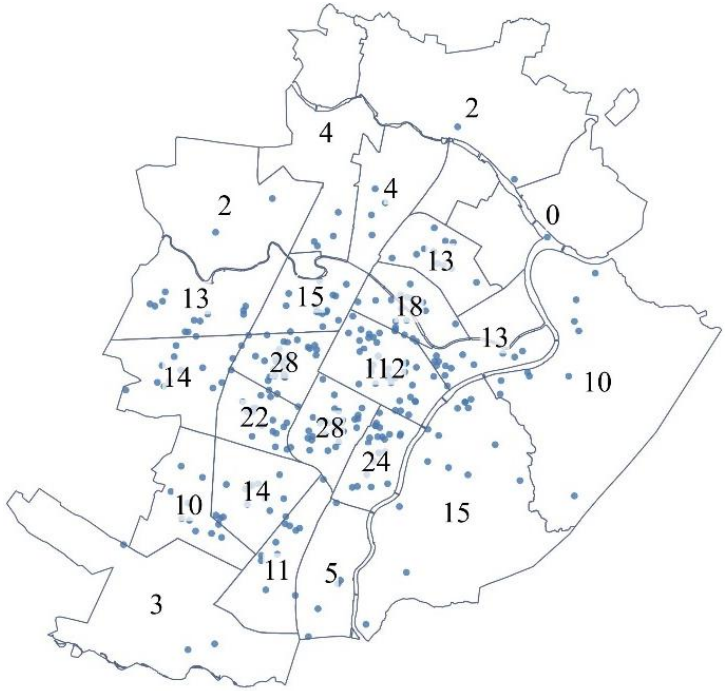


Application

Step 1_Data collection



The questionnaire was distributed from October 2024 to June 2025 using a convenience sampling technique.



1479 questionnaire collected
637 valid ones

349 used

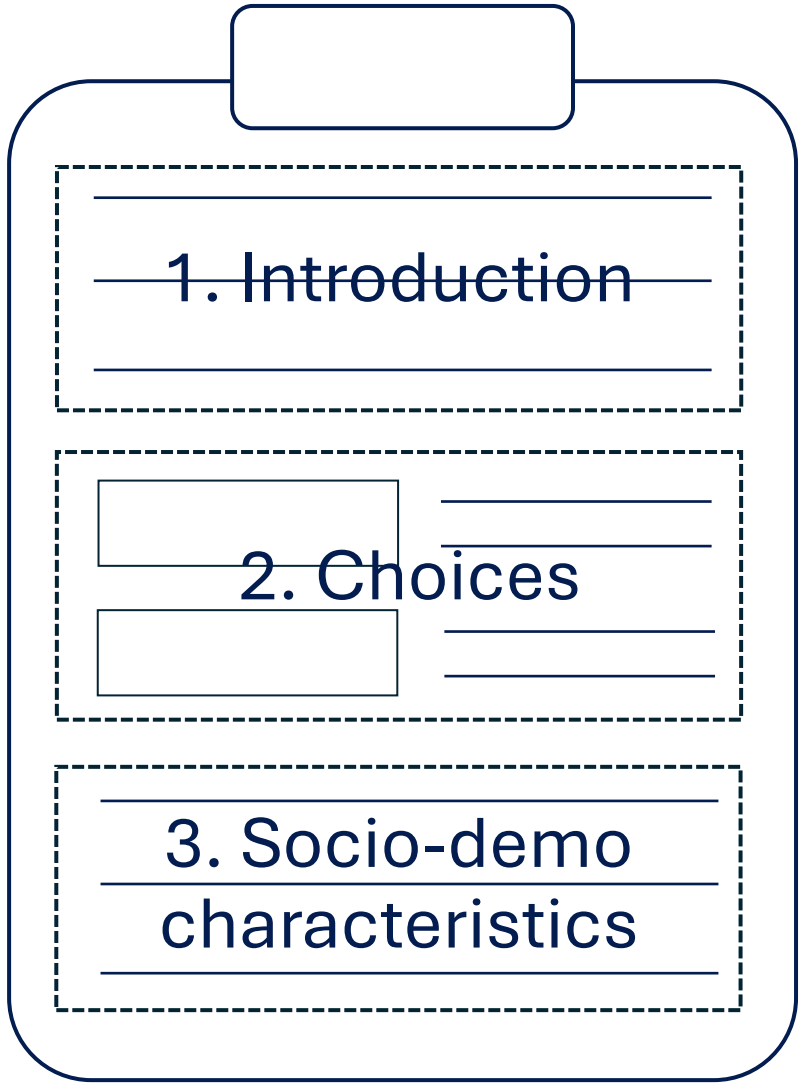
Step 1_Questionnaire

1. Introduction:
4-point Likert scale questions to gather respondents' inclination toward RECs and their possible economic, environmental, and social benefits

2. Choice:
- if they would accept-maybe accept-not accept to participate in REC alternatives.
- to rank the alternatives they defined as acceptable and maybe acceptable

3. Socio-demographic characteristics:

Sex
Age group
Educational level
Profession
Citizenship
Household size
Property regime of the household
Annual income of the household
Household location



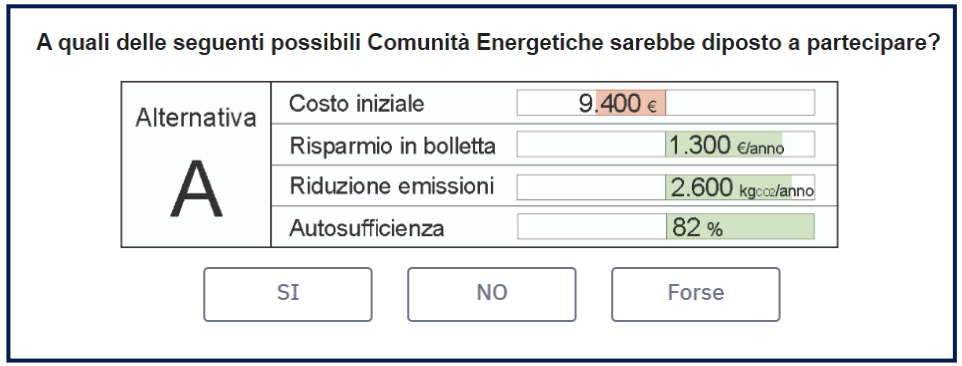
Step 1_Questionnaire

The set of alternatives Y for which the respondents had to express their acceptability and preference was extracted from the case studies reconstructed in the literature review on RECs.

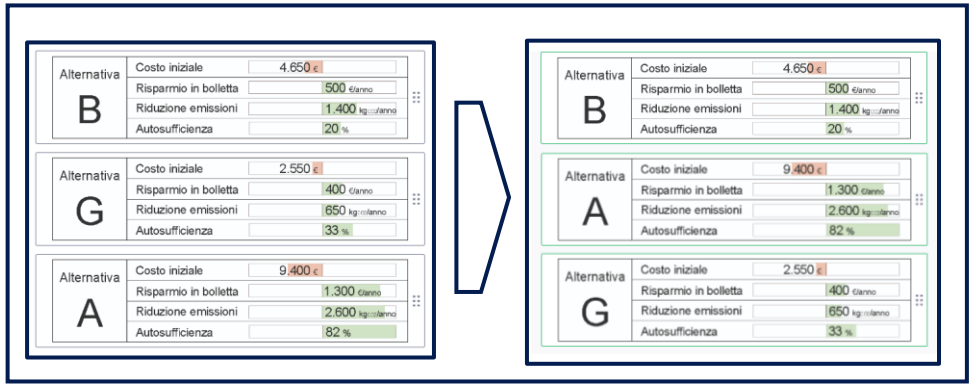
4 attribute to describe the alternative RECs:

- investment cost,
- energy savings,
- avoided CO_2 emissions,
- self-sufficiency.

8 Alternatives



$Y_x^{(i)} = \text{Yes}$ $Y_x^{(j)} = Maybe$ $Y_x^{(k)} = No$



$$\tau_x\left(Y_x^{(i)}\right) = (\tau_1^{(i)} \succ \tau_n^{(i)})$$

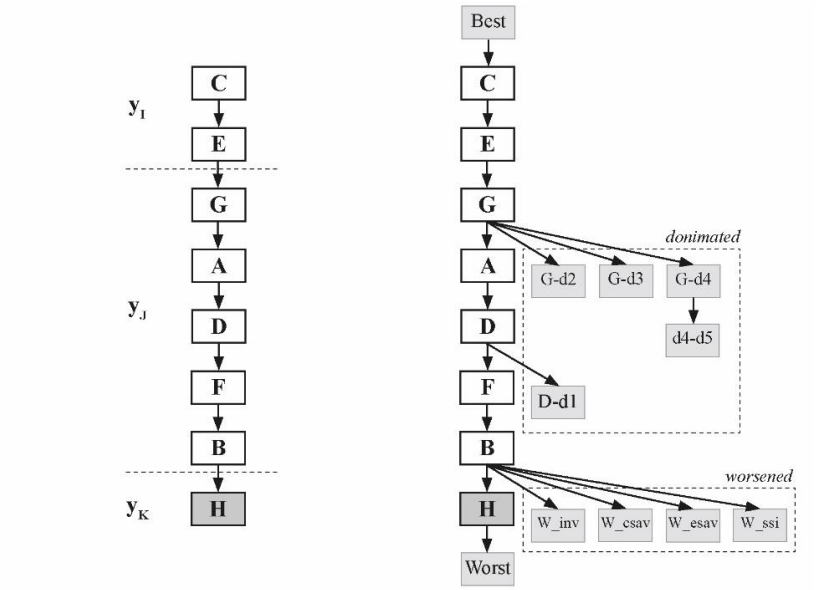
$$\tau_x\left(Y_x^{(j)}\right) = \tau_1^{(j)} \succ \tau_m^{(j)}$$

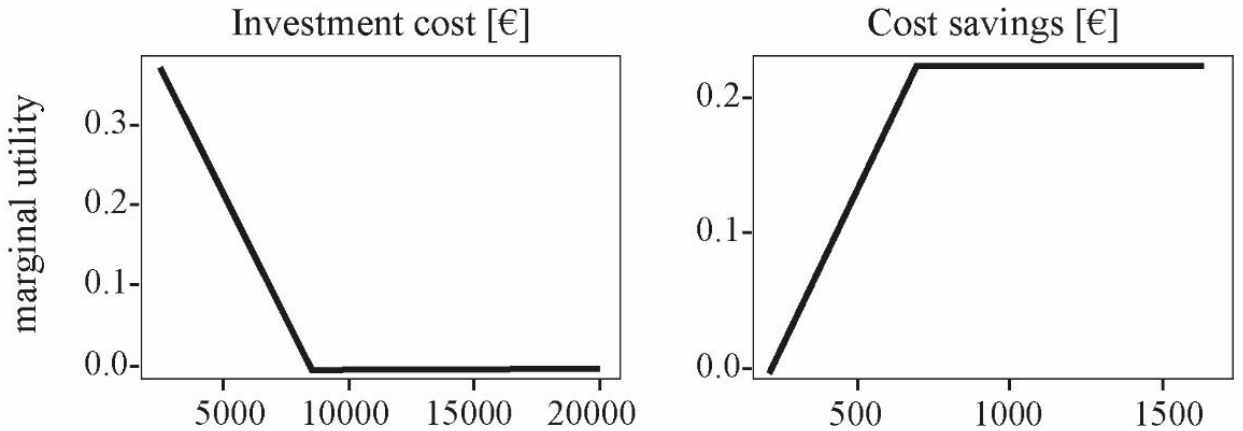
Step 1_ Value function estimation

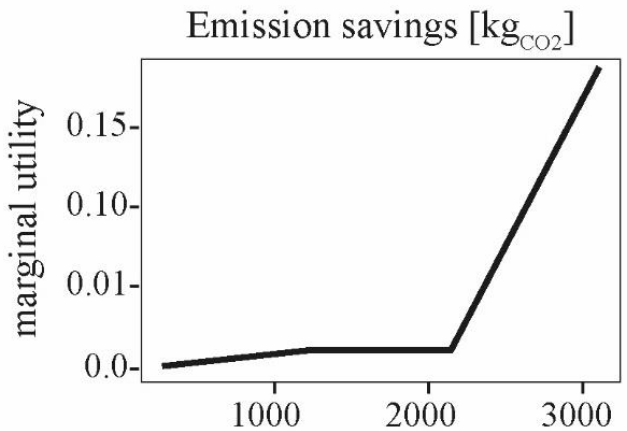
UTA methods use linear programming to infer a set of piece-wise linear value functions that match a learning set.
One pair of ordered alternatives on which to train the algorithm set as the minimum.
Additional dummy alternatives were introduced to expand the learning set provided by each respondent.

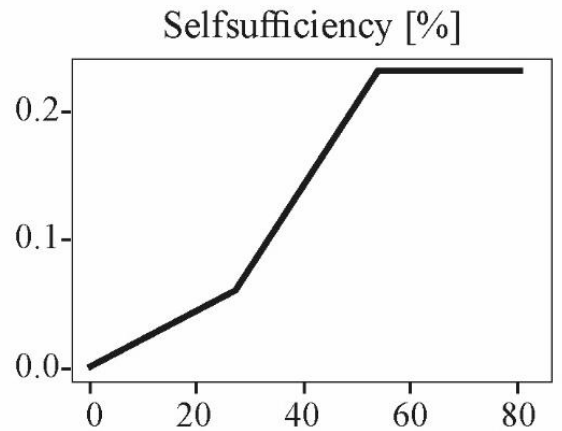
$$\tau_x\left(Y_x^{(i)}\right) + \tau_x\left(Y_x^{(j)}\right) + Y_x^{(k)} =$$

$$(\tau_1^{(i)} \succ \tau_n^{(i)} \succ \tau_1^{(j)} \succ \tau_m^{(j)} \succ y_1^{(k)} \sim y_q^{(k)})$$









Step 1_ Probability to participate

GLMM are used to estimate the likelihood of respondents to participate in a REC.

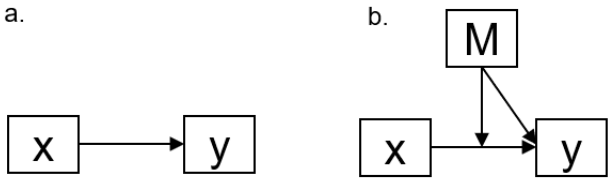
$$Pr_x(Y = 1) = f(A_x, P_{REC})$$

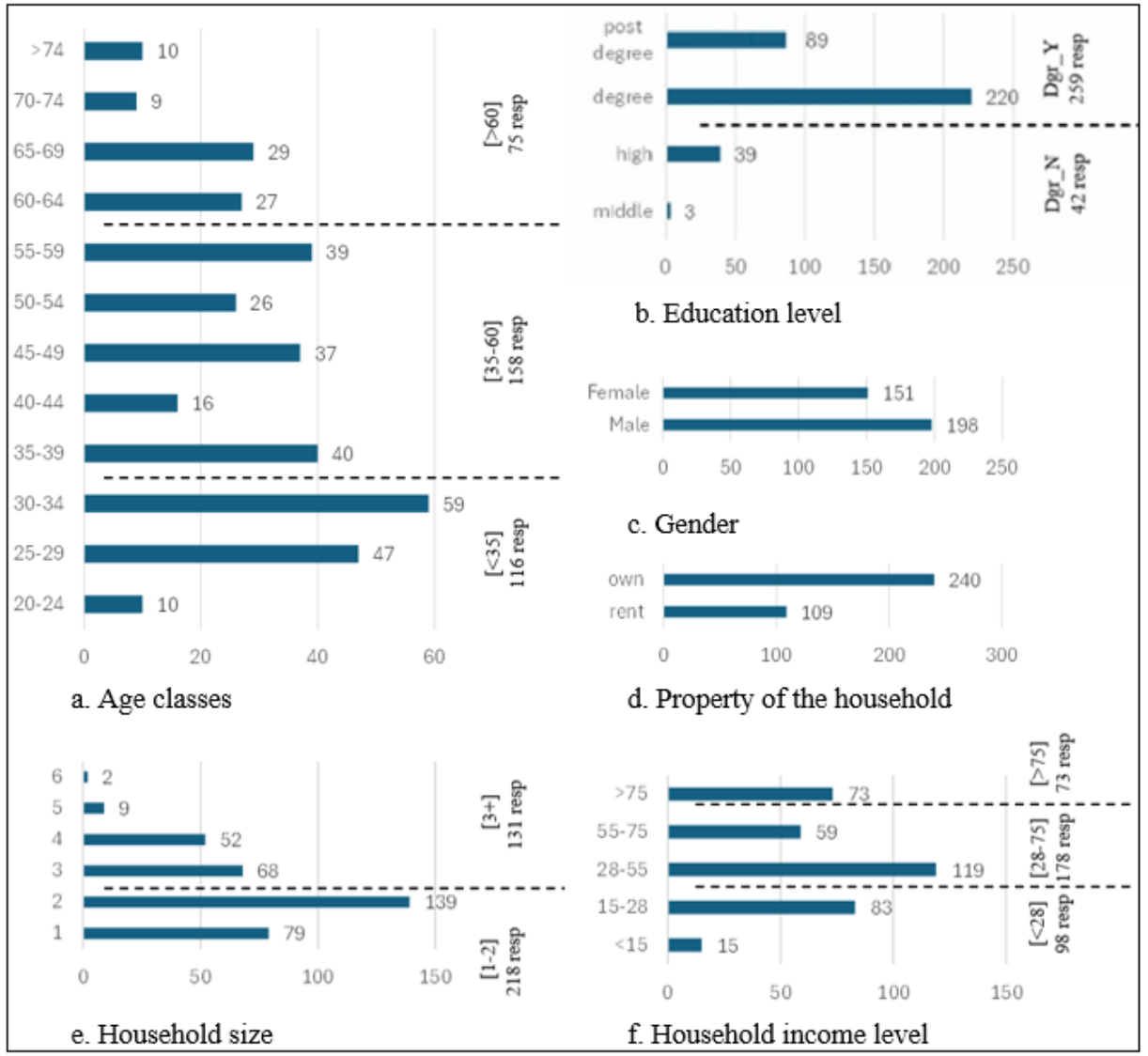
$$Y \sim \beta_0 + \beta_n P + \beta_n A + \beta_m P * A + (1|seed)$$

Fixed effect: determinant used to explain a specific output variable under study.

- *P* = vector of performance of REC attributes
- *A* = vector of socio-demographic characteristics of the respondent

Moderating effect of socio-demographic characteristics on the association between REC performance and participation



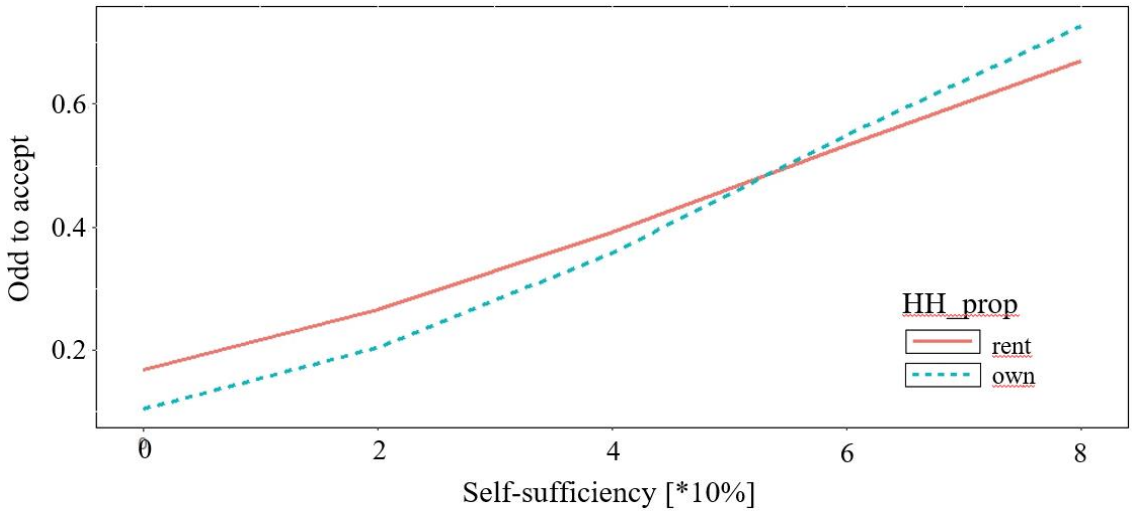


Step 1_ Probability to participate

$$Y \sim Inv_{cost} + Cost_{sav} + Cost_{sav} + Emis_{sav} + SSuff + Cost_{sav} * Gender + Cost_{sav} * HH_{num} + SSuff *_{prop} + SSuff *_{num} + (1|seed)$$

Interactions have a counterbalancing effect compared to the association between socio-demographic variables and participation.

For instance, HH_prop[own] reduces the propensity to participate. However, HH_prop[own] moderates self-sufficiency performance, increasing the likelihood of acceptance of the alternative



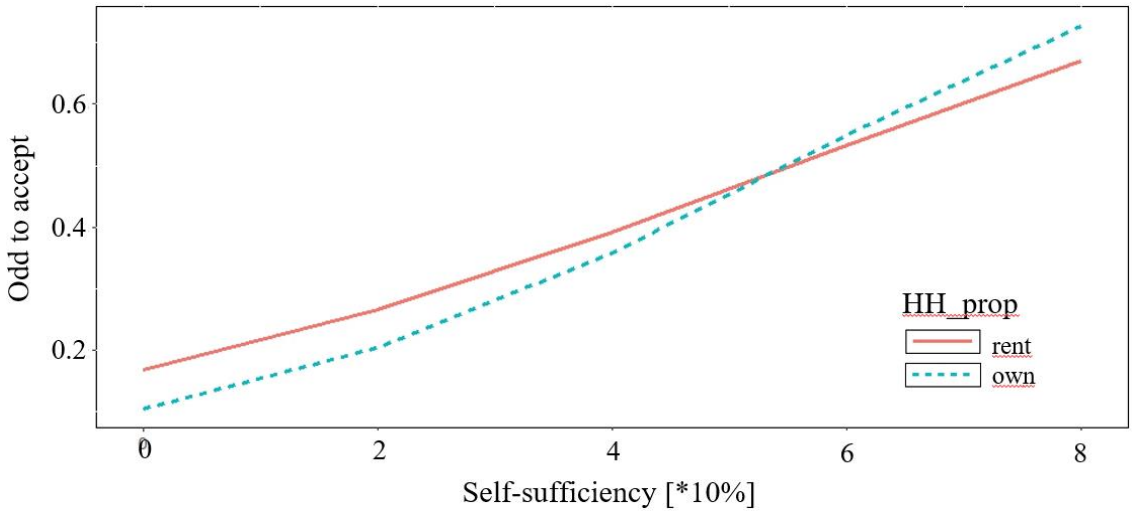
	Model_7			Model_8b		
Predictors	OR	CI 95%	p	OR	CI 95%	p
Numerical						
Intercept	0.65	0.37-1.12	0.122	1.25	0.68-2.28	0.473
Inv_cost (k€)	**0.75**	0.73-0.76	<0.001	**0.75**	0.73-0.76	<0.001
Cost_sav (k€)	**4.57**	3.20-6.52	<0.001	**2.60**	1.64-4.10	<0.001
Emis_sav(tCO_2)	**1.66**	1.47-1.89	<0.001	**1.68**	1.48-1.90	<0.001
SSuff(%)	**1.42**	1.38-1.47	<0.001	**1.29**	1.22-1.37	<0.001
Categorical						
Age [< 35]	ref.					
Age [35-60]	**0.62**	0.43-0.90	0.012	**0.63**	0.43-0.91	0.014
Age [60+]	**0.38**	0.24-0.60	<0.001	**0.38**	0.24-0.60	<0.001
HH_num [>3]	ref.					
HH_num [3+]	**0.69**	0.50-0.95	0.022	**0.35**	0.22-0.55	<0.001
HH_inc [<28k]	ref.					
HH_inc [28-75k]	1.27	0.90-1.80	0.178	1.27	0.89-1.81	0.180
HH_inc [75k+]	**1.65**	1.04-2.62	0.034	**1.66**	1.04-2.64	0.034
Edu_lev [Dgr_N]	ref.					
Edu_lev [Dgr_Y]	0.80	0.51-1.25	0.332	0.80	0.51-1.26	0.330
Gender [Fem]	ref.					
Gender [Mal]	0.82	0.62-1.10	0.191	**0.60**	0.41-0.89	0.010
HH_prop [rent]	ref.					
HH_prop [own]	0.82	0.58-1.16	0.256	**0.57**	0.38-0.87	0.009
Interactions						
Cost_sav (k€) *Gender [Mal]				**1.71**	1.11-2.62	0.014
Cost_sav (k€) *HH_num [3+]				**1.96**	1.25-3.06	0.003
SSuff (%) *HH_prop [own]				**1.11**	1.04-1.18	0.002
SSuff (%) *HH_num [3+]				**1.08**	1.01-1.16	0.020
Evaluation metrics						
AIC	6079			6053		
BIC	6174			6175		
Marginal R^2 / Conditional R^2	0.590 / 0.713			0.593 / 0.717		

Step 1_ Probability to participate

$$Y \sim Inv_{cost} + Cost_{sav} + Cost_{sav} + Emis_{sav} + SSuff + Cost_{sav} * Gender + Cost_{sav} * HH_{num} + SSuff *_{prop} + SSuff *_{num} + (1|seed)$$

Interactions have a counterbalancing effect compared to the association between socio-demographic variables and participation.

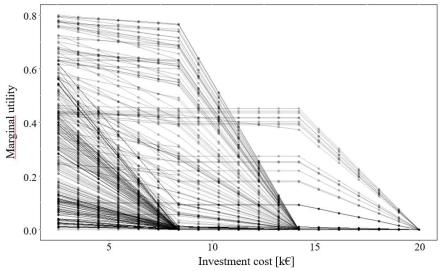
For instance, HH_prop[own] reduces the propensity to participate. However, HH_prop[own] moderates self-sufficiency performance, increasing the likelihood of acceptance of the alternative



	Model_7			Model_8b		
Predictors	OR	CI 95%	p	OR	CI 95%	p
Numerical						
Intercept	0.65	0.37-1.12	0.122	1.25	0.68-2.28	0.473
Inv_cost (k€)	**0.75**	0.73-0.76	<0.001	**0.75**	0.73-0.76	<0.001
Cost_sav (k€)	**4.57**	3.20-6.52	<0.001	**2.60**	1.64-4.10	<0.001
Emis_sav(tCO_2)	**1.66**	1.47-1.89	<0.001	**1.68**	1.48-1.90	<0.001
SSuff(%)	**1.42**	1.38-1.47	<0.001	**1.29**	1.22-1.37	<0.001
Categorical						
Age [< 35]	ref.					
Age [35-60]	**0.62**	0.43-0.90	0.012	**0.63**	0.43-0.91	0.014
Age [60+]	**0.38**	0.24-0.60	<0.001	**0.38**	0.24-0.60	<0.001
HH_num [>3]	ref.					
HH_num [3+]	**0.69**	0.50-0.95	0.022	**0.35**	0.22-0.55	<0.001
HH_inc [<28k]	ref.					
HH_inc [28-75k]	1.27	0.90-1.80	0.178	1.27	0.89-1.81	0.180
HH_inc [75k+]	**1.65**	1.04-2.62	0.034	**1.66**	1.04-2.64	0.034
Edu_lev [Dgr_N]	ref.					
Edu_lev [Dgr_Y]	0.80	0.51-1.25	0.332	0.80	0.51-1.26	0.330
Gender [Fem]	ref.					
Gender [Mal]	0.82	0.62-1.10	0.191	**0.60**	0.41-0.89	0.010
HH_prop [rent]	ref.					
HH_prop [own]	0.82	0.58-1.16	0.256	**0.57**	0.38-0.87	0.009
Interactions						
Cost_sav (k€) *Gender [Mal]				**1.71**	1.11-2.62	0.014
Cost_sav (k€) *HH_num [3+]				**1.96**	1.25-3.06	0.003
SSuff (%) *HH_prop [own]				**1.11**	1.04-1.18	0.002
SSuff (%) *HH_num [3+]				**1.08**	1.01-1.16	0.020
Evaluation metrics						
AIC	6079			6053		
BIC	6174			6175		
Marginal R^2 / Conditional R^2	0.590 / 0.713			0.593 / 0.717		

End of Step 1

Individual value functions



One set of value function for each respondent of the questionnaire

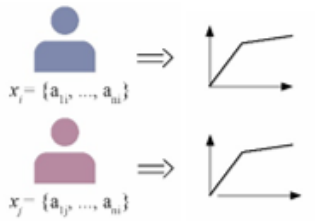
Logistic model to assess YES/NO participation

$$Pr(y=1) = logit^{-1} * \; (-0.288 * \mathrm{Inv_{cost}} + 0.955 * \mathrm{Cost_{sav}} + 0.519 * \mathrm{Emis_{sav}} + 0.255 * \mathrm{Ssuff}) +$$

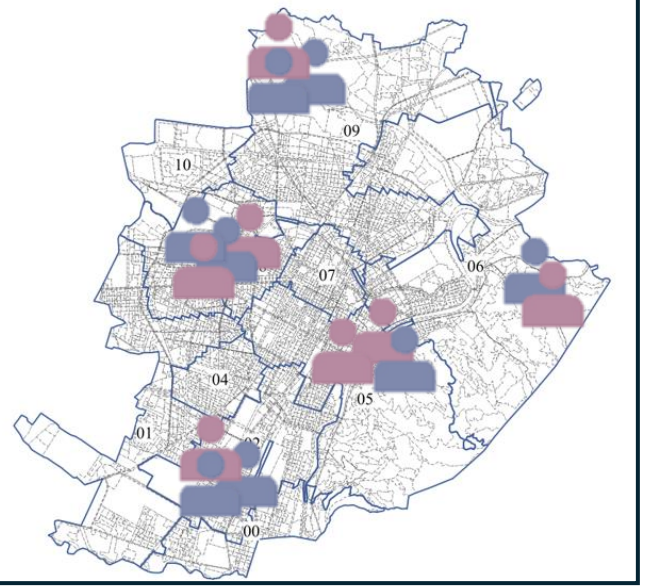
$$(-0.462 * \mathrm{Age}^{[35-60]} - 0.968 * \mathrm{Age}^{[60+]} - 1.050 * \mathrm{HH_{num}}^{[3+]} + 0.507 * \mathrm{HH_{inc}}^{[75k+]} - 0.511 * \mathrm{Gender}^{[Mal]} - 0.562 * \mathrm{HH_{prop}}^{[own]}) +$$

$$(+0.536 * \mathrm{Cost\_sav} * \mathrm{Gender}^{[Mal]} + 0.673 * \mathrm{Cost\_sav} * \mathrm{HH_{num}}^{[3+]} + 0.104 * \mathrm{SSuff} * \mathrm{HH_{prop}}^{[own]} + 0.077 * \mathrm{SSuff} * \mathrm{HH_{num}}^{[3+]})$$

Assign one set of value functions to each type of individual based on socio-demographic vectors



Population distribution

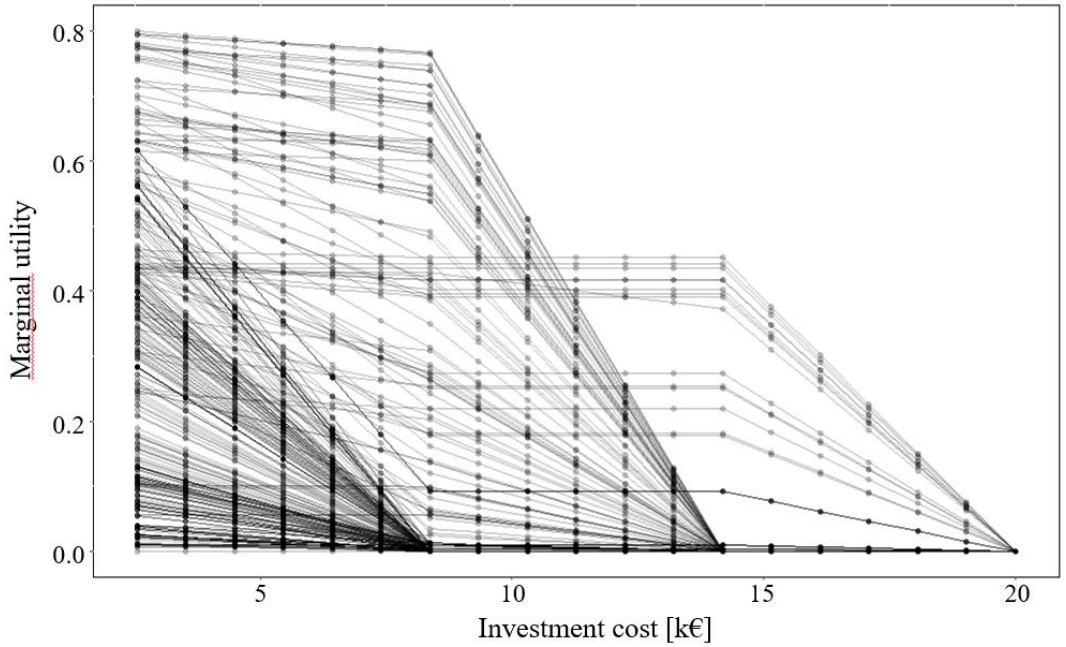


Step 2_ Types of individuals

LMM have been used to test the association between the socio-demographic characteristics and the respondents' decision models (value function shapes).

$$U_a \sim \beta_0 + \beta_1 a + \beta_n X + \beta_m a * X + (1|seed)$$

U_a: marginal utility for each performance attribute of REC,
a: performance attributes of the alternative REC,
X: vector of socio-demographic attributes of the respondent



Investment cost value functions of the 349 respondents. 248 are the unique value functions.

	Age (3 cls)	Gender (2 cls)	HH_num (2 cls)	HH_inc (3 cls)	HH_prop (2 cls)	Edu_lev (2 cls)
Inv_cost	X	X	X	X	X	-
Cost_sav	-	X	X	X	X	-
Emis_sav	-	-	X	X	X	X
SSuff	-	X	X	X	X	-

Number of types = $2^4 * 3^2$ =
144 types of individuals

Step 2_ Assignment to types of individuals

Value function clustering

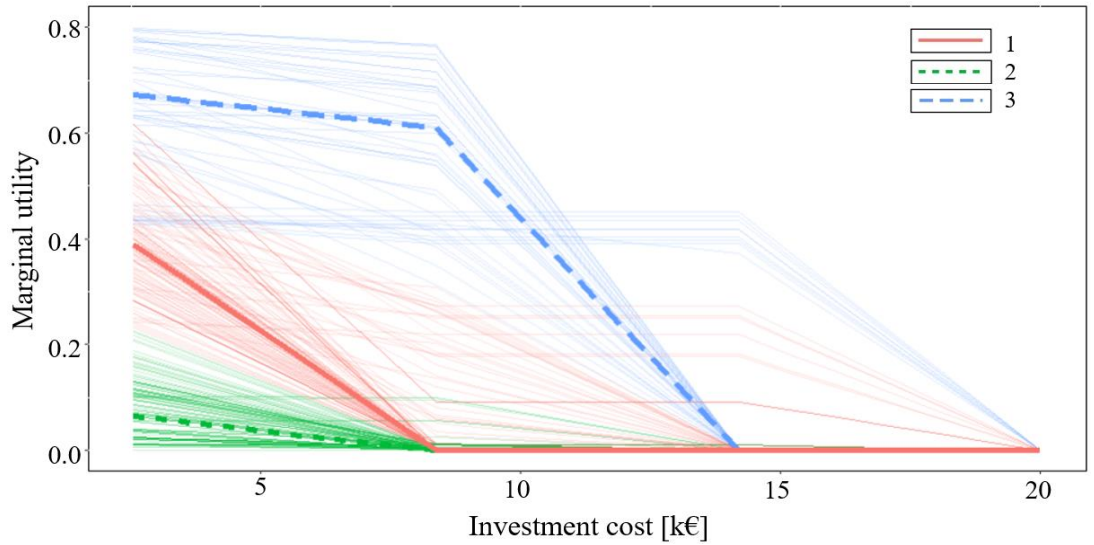
unsupervised classification algorithm: K-medoids (PAM)

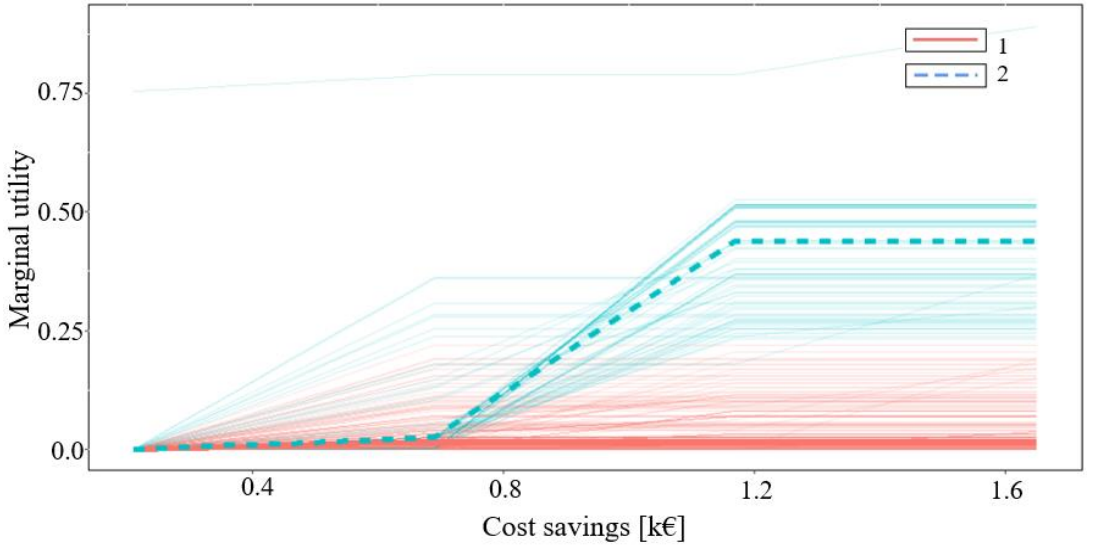
The partition was based on the marginal utility value of the four discontinuity points of each of the piece-wise value functions.
The estimation of the most suitable number of clusters was based on the silhouette metric.

3 clusters for investment cost, energy savings, and self-sufficiency
2 clusters for cost savings

A sensitivity test was conducted to evaluate the detriment in the ranking accuracy by applying the characteristic value functions to the learning sets

87.1% accuracy across all the pairwise comparisons





Step 2_ Assignment to types of individuals

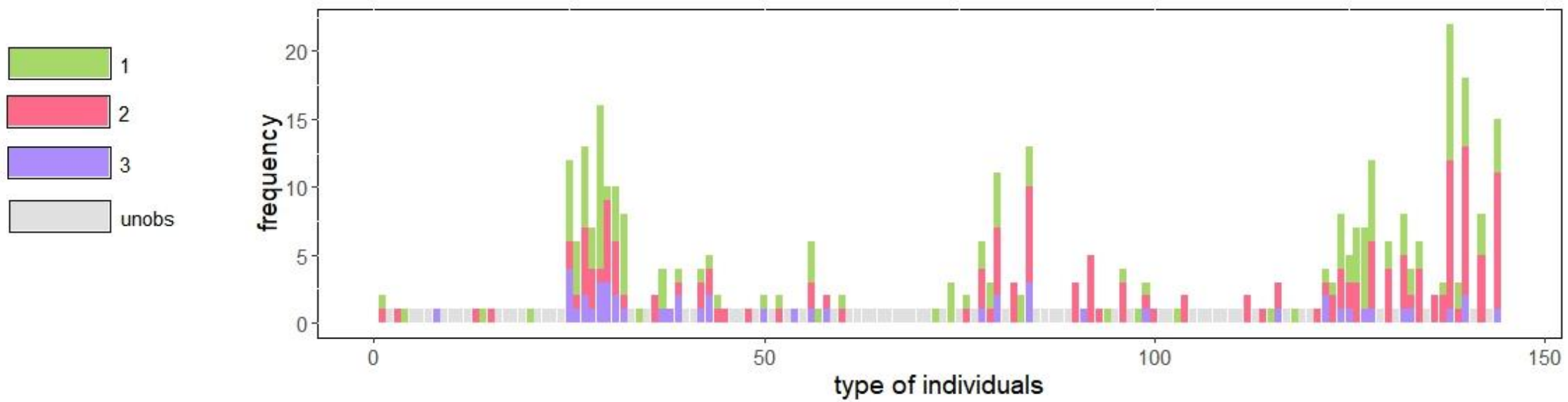
Assignment of value functions to types of individuals

Supervised classification algorithms to calculate the probability of different types of individuals to belong to one cluster or another.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Weighted\ F-1\ score = \sum_{i=1}^{n} w_i * F-1score_i$$

Algorithm	Tuning params	
Naive Bayes	3	
Support Vector Machine (linear)	3	
Support Vector Machine (Poly)	3	
~~Rule-Based Classifier (JRip)~~	~~3~~	
Rule-Based Classifier (PART)	2	.532
C5.0	3	
Single5.0Tree	-	
C4.5-like Trees J48	2	
Penalized Multinomial Regression	1	



Step 2_ Assignment to types of individuals

Type	Age, Edu_lev, HH_size, HH_inc	Gender	HH_prop	Inv cost		Cost sav		Emis sav		SSuff	
				Class	%	Class	%	Class	%	Class	%
113*	Age = 35-60, Edu_lev = Dgr_Y, HH_size = 3+, HH_inc = 28-75k€	fem	rent	**1**	**56.2**	**1**	**86.7**	1	27.9	**1**	**70.6**
				2	37.5	2	13.3	**2**	**48.8**	2	23.5
				3	6.2	-		3	23.2	3	5.9
114		fem	own	1	32.0	**1**	**80.0**	1	24.5	**1**	**40.9**
				2	**61.5**	2	20.0	2	15.7	2	27.2
				3	6.5	-		**3**	**59.8**	3	31.8
115		mal	rent	**1**	**56.2**	**1**	**86.7**	1	27.9	**1**	**70.6**
				2	37.5	2	13.3	**2**	**48.8**	2	23.5
				3	6.2	-		3	23.2	3	5.9
116		mal	own	1	32.0	**1**	**65.8**	1	24.5	**1**	**40.9**
				2	**61.5**	2	34.2	2	15.7	2	27.2
				3	6.5	-		**3**	**59.8**	3	31.8

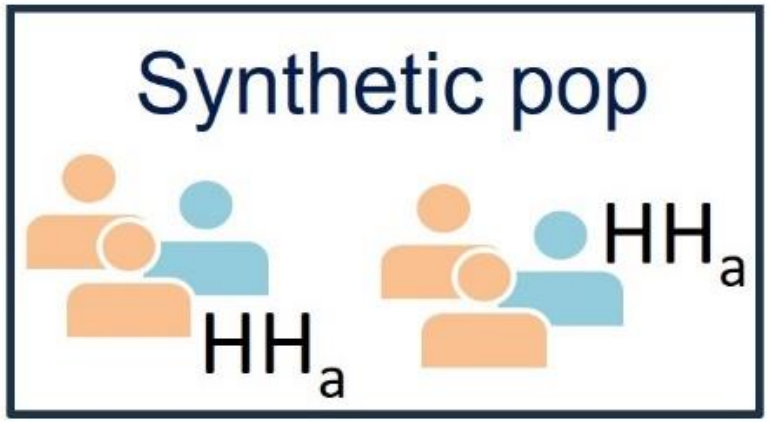
*unobserved type

Step 3_ Population synthesis

Population synthesis refers to the process of creating a simplified microscopic representation of an actual population that matches the aggregated statistical measures of the actual population

Marginal distribution data are usually provided with a coarser aggregation at a higher spatial resolution.
Disaggregated data at the individual level are usually provided at the regional or national scale.

Synthetic population is generated expanding the disaggregated dataset (Seeds) to match the marginal distribution of socio-demographic characteristics in the area thus reconstructing the individual vectors of socio-demographic characteristics of a population.



Source of datasets: ISTAT
Seed dataset: “Aspect of daily life”
Marginal data: National Census

Step 3_ Population synthesis

SEZ21_ID = 12720000001

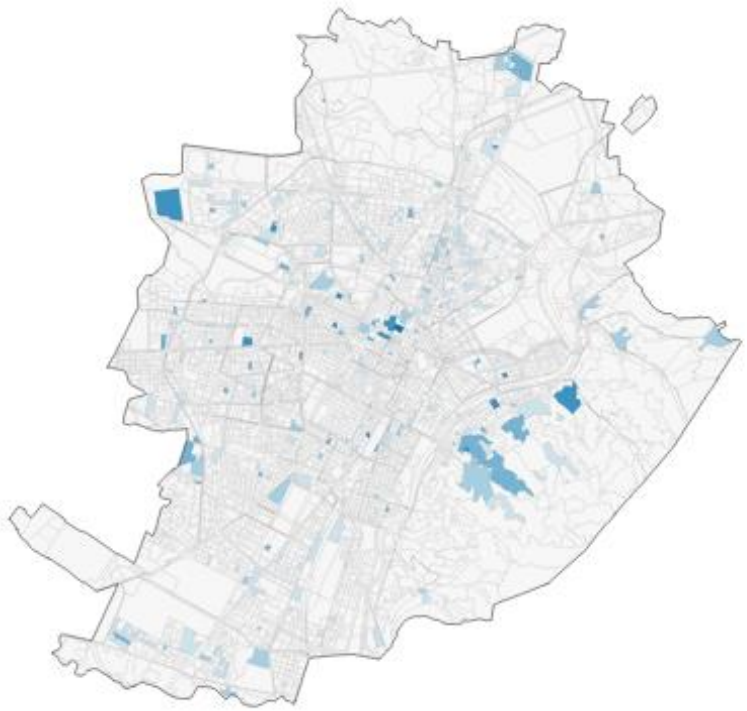
HH_ID	Person number	Age (y.o.)	Gender	Education level	Employed	Income source	HH-property
1	1	30-34	Male	High school	Yes	Employee	Owned
1	2	25-29	Female	High school	No	Allowance	Owned
2	1	50-54	Male	Secondary	No	Pension	Owned
3	1	55-59	Female	Primary	No	Allowance	Owned
4	1	30-34	Female	High school	Yes	Self-empl	Owned
5	1	35-39	Male	Degree/+	Yes	Employee	Owned
5	2	35-39	Female	Degree/+	Yes	Self-empl	Owned
5	3	11-13	Male	Primary	N.A.	N.A.	Owned
...							

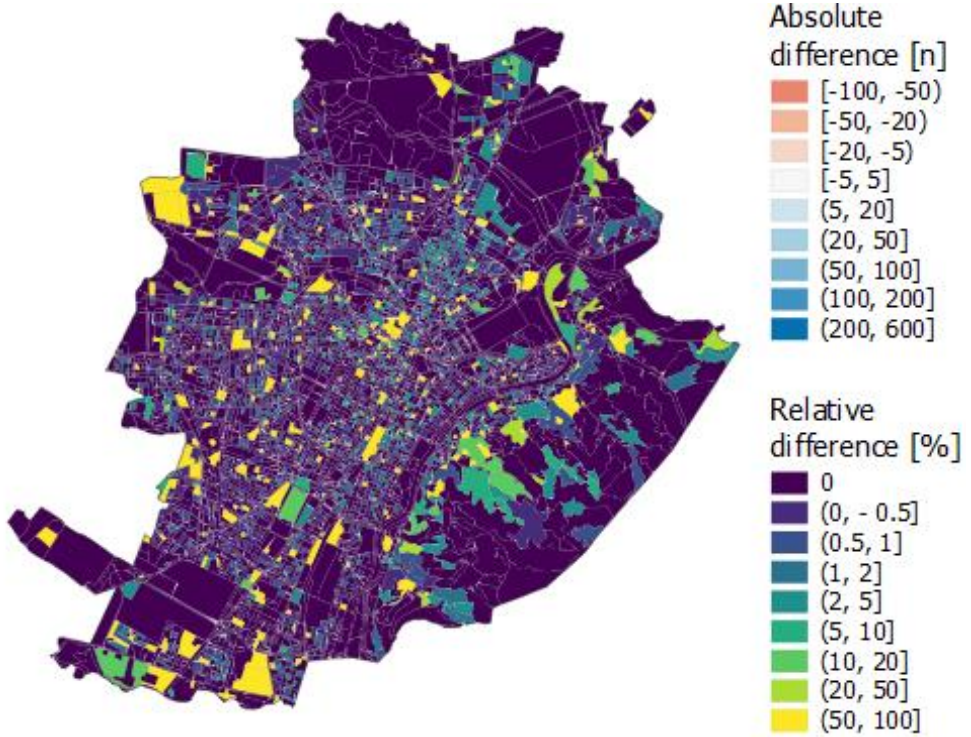
SEZ21_ID = 12728888888

HH_ID	Person number	Age (y.o.)	Gender	Education level	Employed	Income source	HH-property
...							
433469	1	25-29	Female	High school	Yes	Support	Owner
433469	2	3-5	Male	N.A.	N.A.	N.A.	Owner

837,559 individuals
433,469 households

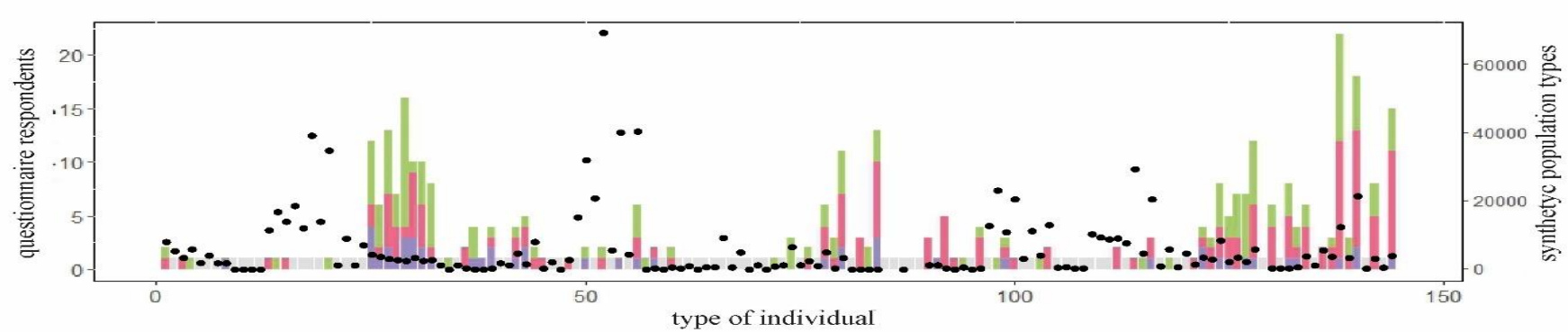
Step 3_ Population synthesis





Number of inhabitants:

difference between census data and synthetic population generated.



Distribution of types

Comparison between distribution of types of individuals in the synthetic population and in the data from questionnaire

Step 4_Estimation of acceptance

Once the distribution of types of individuals is estimated, the two decision models have been spatialized pivoting on socio-demographic characteristics.

Percentage of population likely to accept a REC solution:

$$P_i(Y = 1) = \frac{\sum_{x=1}^{n} Pr_{x,i}}{n}$$

P_i = percentage of population likely to accept alternative *i*,
$Pr_{x,i}$ = probability of an individual *x* to accept alternative *i*.

Preferred alternative based on total utility for different types of individuals:

$$U_{tot,i,x} = \sum Pr_{c,a,x} * U_{m,c,a,i}$$

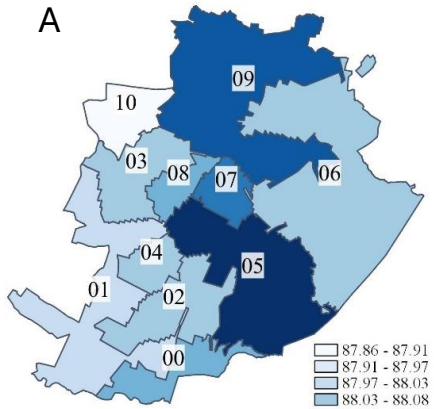
$U_{tot,i}$ = total utility of alternative *i* for an individual *x*,

$Pr_{c,a,x}$ = probability for the individual to be assigned one of the characteristic value function *c*, relative to attribute *a*

$U_{m,c,a,i}$ = marginal utility for attribute *a* of alternative *i*, calculated using value function *c*.

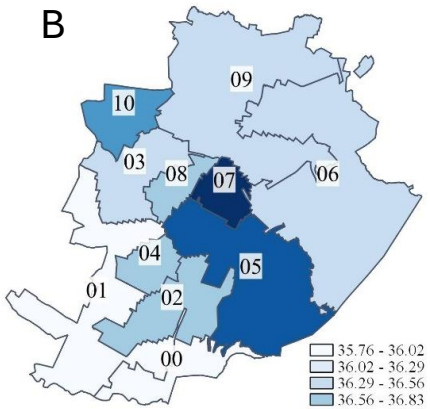
Step 4_Estimation of acceptance

A



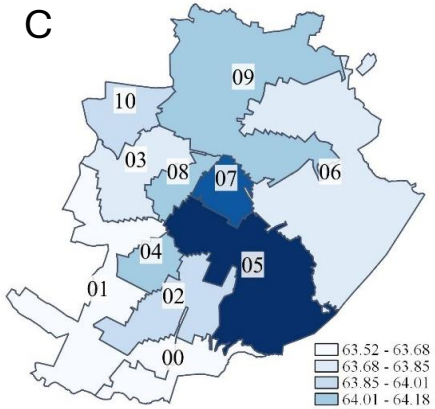
Min 87.86
Max 88.37
Ave 88.14

B



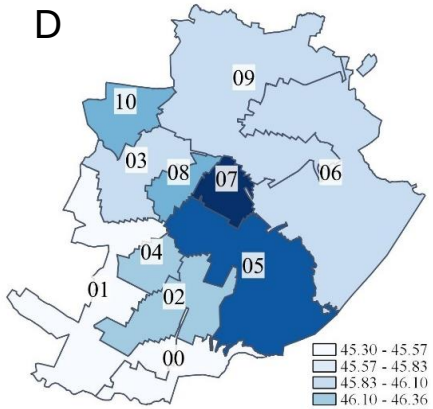
Min 36.31
Max 38.16
Ave 36.59

C



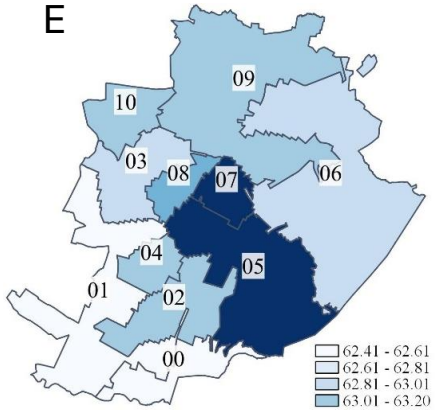
Min 63.52
Max 64.99
Ave 64.03

D



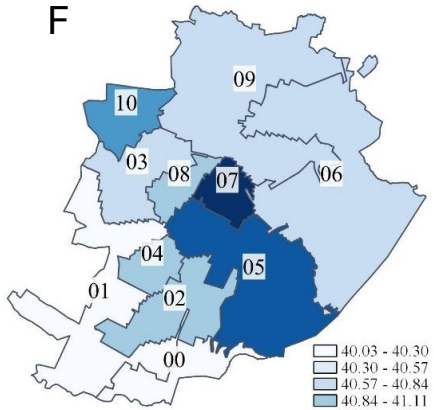
Min 45.30
Max 47.69
Ave 46.16

E



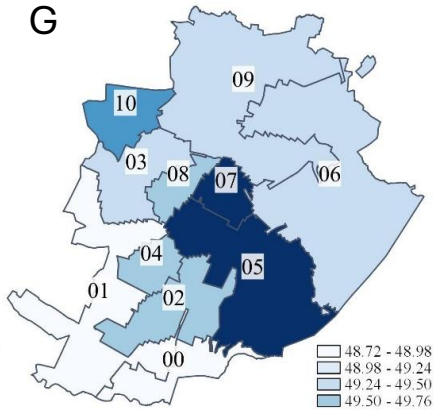
Min 62.41
Max 64.19
Ave 63.08

F



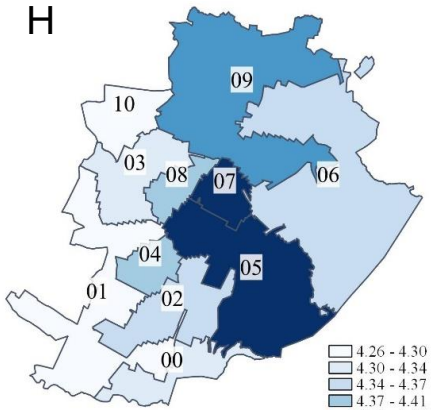
Min 40.03
Max 42.46
Ave 40.87

G



Min 48.72
Max 51.05
Ave 49.53

H

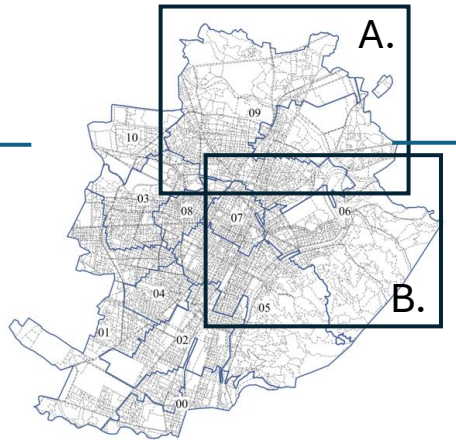


Min 4.26
Max 4.60
Ave 4.40

Difference of less than 3% in acceptability of the same alternative across HV/MV sub-stations

Higher percentage of population likely to accept any alternative RECs in the central and south-eastern part of the city (HV/MV substations 05 and 07) . This percentage radially decreases moving toward the outskirts of the city, with an exception represented by alternative A and H due to effect of socio-demographic moderators.

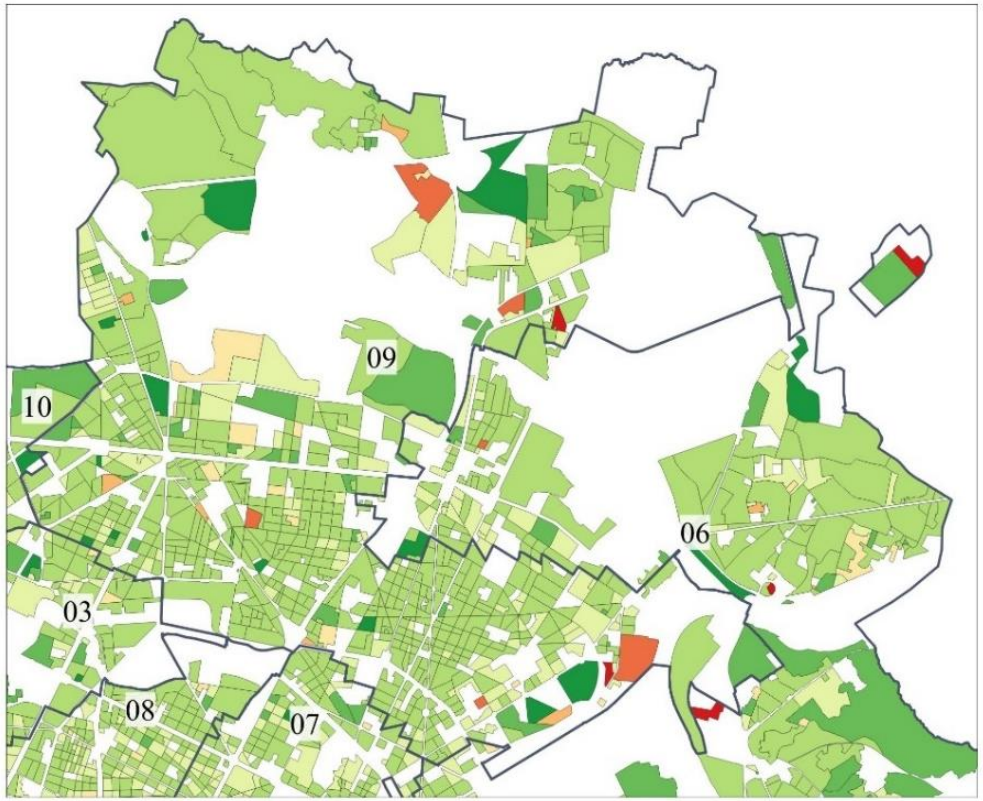
Step 4_Estimation of acceptance



Focus on the percentage of simulated population likely to accept Alternative A at the census track scale for the city of Turin.

It is possible to notice a fair increase in the variation of percentage of population likely to accept the alternative across the different census tracks clustered in the same HV/MV substation.

A.



B.

The “Public” option

Public-oriented alternatives

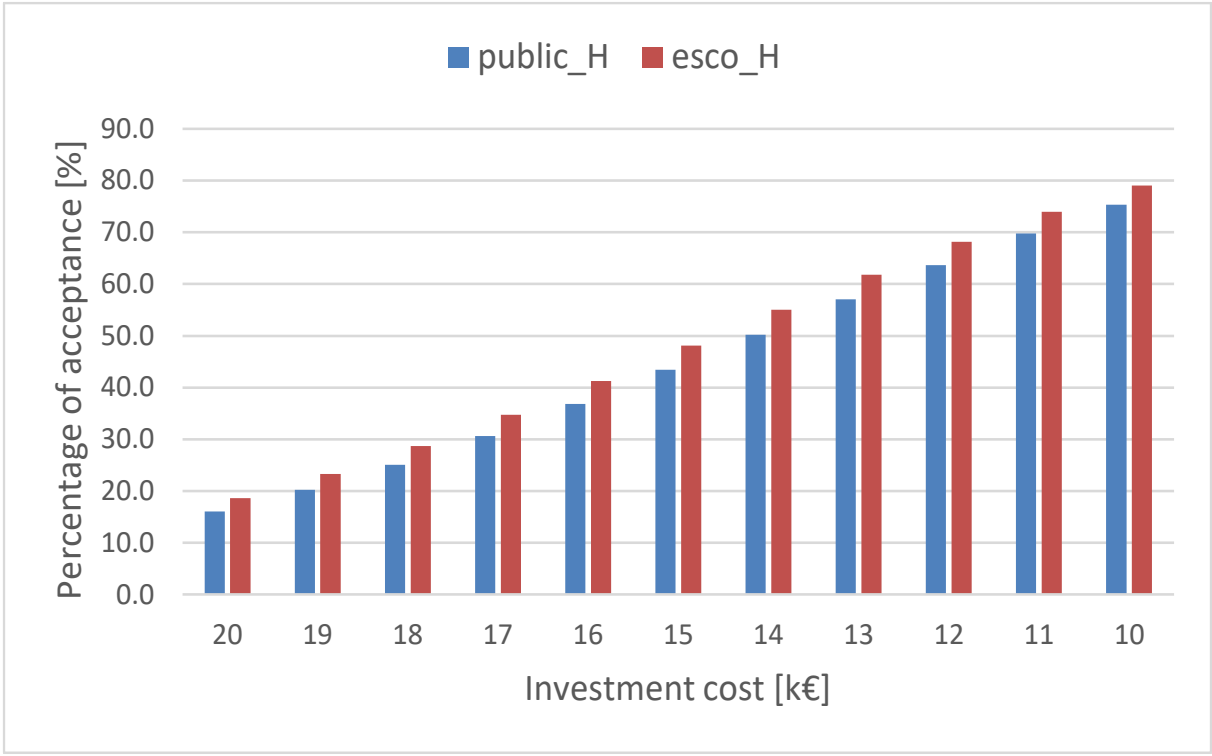
Final analysis combines the two approaches used to evaluate the percentage of population likely to accept to participate in a REC, and to assess the most probably preferred alternative across the population of the city. The goal is to identify the trade-offs between the performance of a potentially widely accepted alternative and those of a “public oriented” one.

Analysis of the performance changes of the alternative maximizing CO_2 emission reduction to increase its desirability

Alternative	Investment Cost [€]	Cost Savings [€]	Emission Savings [kg_{CO_2}]	Selfsufficiency [%]
A	9400	1300	2600	82
public_H	20000	1650	3100	40
Esco_H	20000	1300	3100	60

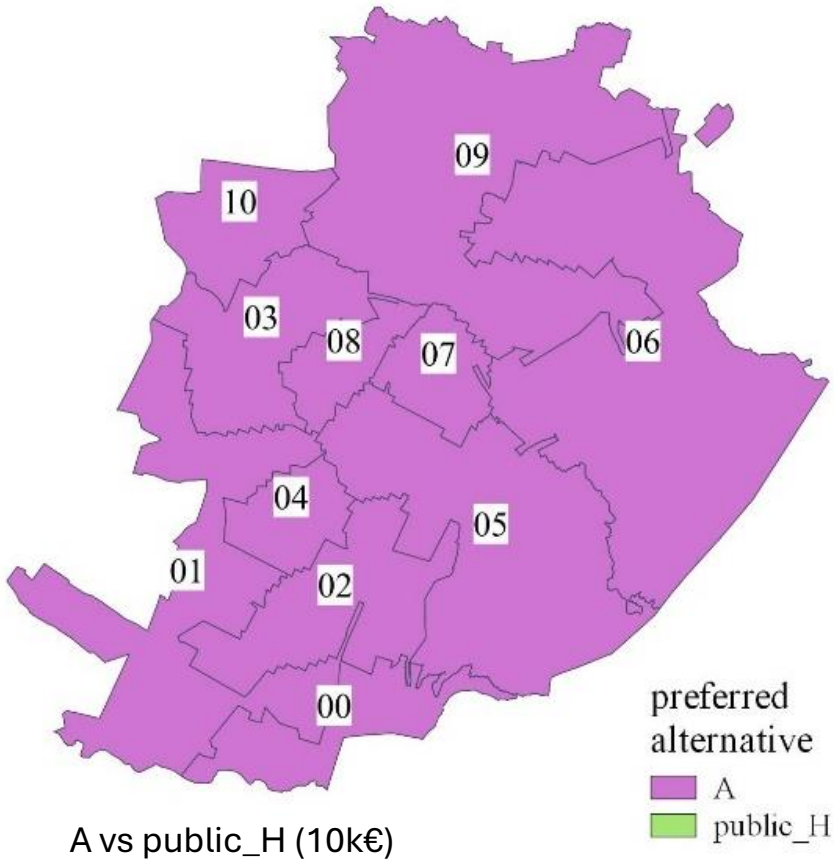
public H → increases the self-sufficiency performance of the original alternative H to the average of the alternatives.

esco_H → further increases self-sufficiency performance while reducing the cost savings to tests for external investor (ESCO) impact

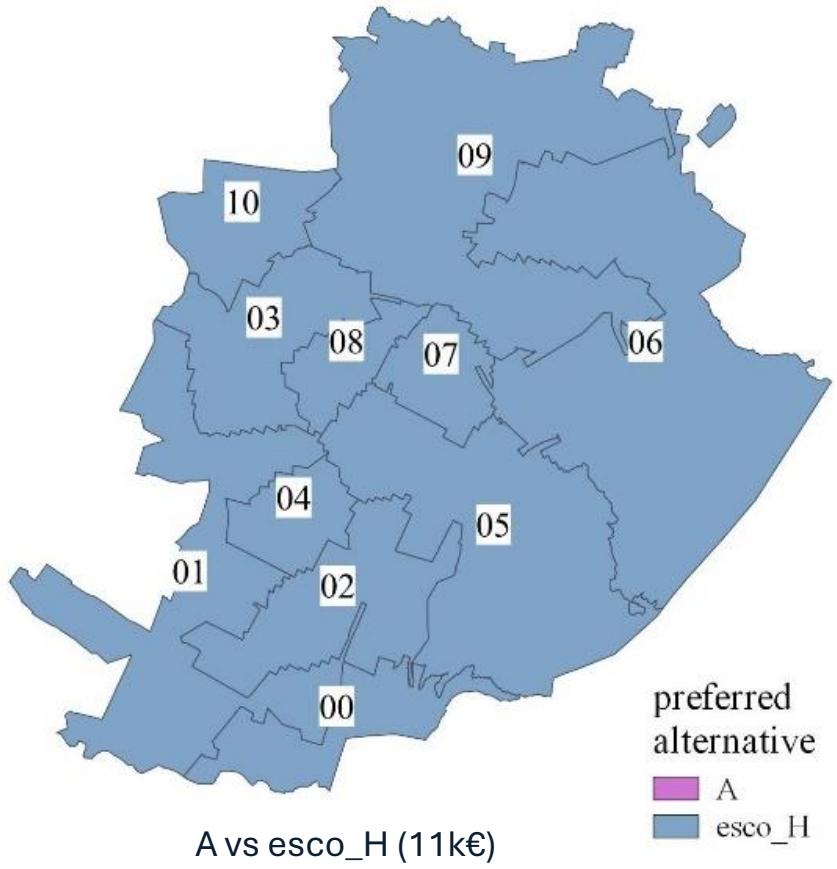


Preference evaluation

Value function determination refined in 5-segment piecewise curves.



A vs public_H (10k€)



A vs esco_H (11k€)

- preference for higher level of self-sufficiency over additional increase in cost savings.
- total financial support from third-party to guarantee that alternative esco_H becomes the preferred one is 3,901,221,000€ (9000€/apartments*433,469 apartments)

Conclusions

Limitations and improvements

Data collection

dataset size & population sampling technique	• responses retrieved from the survey cannot be considered as explanatory of the actual population
alternatives construction	• construction of location specific alternatives to better define the performance range of the alternatives • uneven distribution of performance determined a lack of discriminatory information in the modeling

Modellization

value functions estimation	• several sets of possible value functions could have been identified (especially for small learning sets)
clustering of the individual value functions	• the definition of the characteristic value function might be performed by minimizing the observed ranking errors
unbalanced distribution of the collected questionnaire	• impossibility to test for variation in acceptability and preferences specifically related to the residency location of the respondents (random effect in GLMM)

The analysis is based on stated preferences

Conclusions

Q1 〉 *What are the **socio-demographic characteristics** of individuals and the **performance attributes** of potential alternatives that influence inhabitants' REC participation?*

- 144 types of individuals individuated by combining socio-demographic attributes (age, gender, size, income level, property, education level).

Q2 〉 *What is the potential of **REC diffusion at the city scale and in different parts of the city**, and which are the most probable solutions to be implemented **based on the inhabitants' preference models**?*

- individuals show interest for self-sufficiency (alternative A with 88% estimated acceptance);
- lower acceptance for alternatives maximizing GHG emission reductions and cost savings but with high investment cost (alternative H with 4.4% estimated acceptance).
- higher variation at the census track scale (around 20%).

Q3 〉 *What strategies could foster the **alignment of the private initiative** with the public perspective to **maximize the positive impacts of RECs implementation**?*

- total financial support from third-party to guarantee that alternative esco_H becomes the preferred one is 3,901,221,000€

Conclusions

- It should be stressed that the present application represents a proof of concept for the applicability of the proposed method. Even if the method could be replicated in other urban areas, the results of this specific application could not be directly generalized.

- Results could assist the Decision-makers in tailoring and fine-tuning the enabling framework to promote the acceptance of renewable energy communities and participation in such schemes.

- It is possible to consider the method as a predictive tool to forecast decision outcomes in different scenarios of implementation of a REC, supporting the Decision-maker in estimating the possible realization of one or the other of the possible scenario at the disposal of the individuals.

- Extension of the study could be to analyze trade-offs between REC attributes for different groups of individuals to propose customized participatory models in order to optimize the economic resources involved while maximizing the probability of participation.

Thank you for your attention

Assessing inhabitants' preference towards Energy Community participation: a preference learning approach

Cavana Giulio, Bottero Marta, Becchio Cristina, Fancello Giovanna and Tsoukias Alexis

giulio.cavana@polito.it