

# Capability Sets as Decision-Aiding Tools for Policy Design

## A Case Study on Older Adults' Urban Mental Well-Being

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- 1 General Framework
- 2 Methodology
- 3 Case Study

Policy design requires a framework that **describes** the current situation, **anticipates** effects of inaction, and **compares** alternative interventions. When the objective is citizens' well-being, standard tools (cost-benefit analysis, GDP) fall short.

## Four difficulties that aggregated indicators cannot handle:

### 1. Multidimensional

Health, mobility, social life, safety. . . cannot be reduced to a single number.

### 2. Subjective

Citizens do not value actions and outcomes the same way.

### 3. Heterogeneous populations

The same policy affects different individuals differently.

### 4. Common goods

Shared infrastructure (transport, parks) generates *different* opportunities depending on who you are.

# The Capability Approach (Sen 1985)

Shift: from resources to real freedoms

What can each citizen actually *do* and *be*, given their resources, context, and constraints?

The operationalization gap

The CA is difficult to use in concrete policy contexts.

**We need** models that link data to actionable outputs:  
*which groups are constrained, and which constraints are binding.*

## A citizen

- Is endowed with private goods.
- Has access to common goods.
- Can undertake a number of actions.
- Which consume private goods and common goods.
- These actions are subjectively valued in several dimensions.

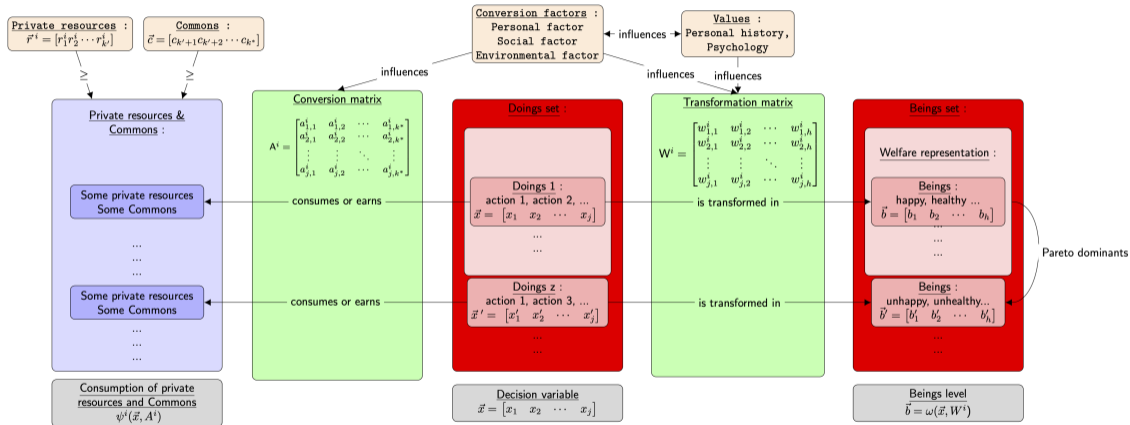
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## Well-being will be:

the Pareto frontier of the above multi-objective decision problem under the assumption that the citizen solves it.

# From Resources to Well-Being: The Framework



## Part 2

# Methodology

## Operationalising Capability Sets

## Decision-aiding question

Which constraints most limit mental health opportunities, and which policy relaxations would expand them?

### **HANC / MINDMAP study** (RECORD cohort)

216 Île-de-France residents aged  $\geq 60$ ,  
July 2019 to July 2021 (212 retained)

- **GPS traces** (1 week): geolocated leisure activities and transport modes
- **Psychological scores**: STAI (anxiety) and CES-D (depression), pre *and* post observation week
- **Questionnaire**: perceived safety, affordability, transport access → individual constraints

**End actions**  $a_j \in \mathbb{N}$ : weekly frequency

	Category	GPS labels
$a_1$	General shopping	Supermarket, grocery store
$a_2$	Spec. food shopping	Bakery, market, organic store, take-away. . .
$a_3$	Other shops/services	Bank, post office, hairdresser. . .
$a_4$	Medical	Doctor, dentist, pharmacy. . .
$a_5$	Green spaces	Green spaces
$a_6$	Sports facilities	Sports facilities
$a_7$	Cultural activities	Cinema, theatre, community. . .
$a_8$	Visiting people	Visiting, accompanying people
$a_9$	Restaurant	Restaurant, café, fast food. . .

**Transport actions**  $t_{m,j} \in \mathbb{N}$ :  
trips by mode  $m$  to destination  $j$

$t_1$	Walking
$t_2$	Cycling
$t_3$	Private transport
$t_4$	Surface public transport
$t_5$	Underground

## Step 2 — Objectives: Transformation Matrix

$$\max_{\mathbf{a}, \mathbf{t}} \left\{ \underbrace{\sum_{j=1}^9 a_j w_{j,h}}_{\text{activities}} + \underbrace{\sum_{j=1}^9 \sum_{m=1}^5 t_{m,j} w'_{m,h}}_{\text{transport}} \right\}_{h \in \{\text{STAI}, \text{CES-D}\}}$$

$w_{j,h}$  activity weights

Marginal contribution of activity  $a_j$   
to well-being dimension  $h$

$w'_{m,h}$  transport weights

Marginal contribution of mode  $t_m$   
to well-being dimension  $h$

Together: the **transformation matrix**  $W$  — linking actions to well-being outcomes.

But how to estimate  $W$ ?

# Estimating $W$ — The Data Situation

	Before observation week		Observation week	
Well-being scores	$S_{h,\text{pre}}^i$	✓ questionnaire	$S_{h,\text{post}}^i$	✓ questionnaire
Activity counts	$x_{j,\text{pre}}^i$	✗ <b>unobserved</b>	$x_{j,\text{post}}^i$	✓ GPS traces

Goal: regress  $\Delta S_h^i$  on  $\Delta x_j^i$

We want: score change =  $\sum_j w_{j,h} \cdot \Delta x_j^i + \dots$

We have  $\Delta S = S_{\text{pre}} - S_{\text{post}}$  from questionnaires and  $x_{\text{post}}$  from GPS.

Missing piece:  $x_{j,\text{pre}}^i$  must be **reconstructed**.

## Reconstruction principle

If a participant's score *improved* ( $S_{\text{pre}} > S_{\text{post}}$ ), we assume they were *more active* the week before — and vice versa. Two independent reconstructions were run to assess sensitivity.

- 1 **Linear:** score changes are linear in activity-frequency changes

$$\Delta S_h^i = \sum_j w_{j,h} \Delta x_j^i + \sum_{m,j} w'_{m,h} \Delta t_{m,j}^i$$

- 2 **Homogeneous:** one common matrix  $W$  for all 212 individuals — no individual-specific slopes
- 3 **Association, not causation:** the regression captures co-variation only. Depression may *reduce* activity rather than activity improving mental health — causal direction is ambiguous.

## Step 3 — Constraints: Feasibility (1/2)

### Time budget

$$\sum_j a_j \tilde{t}(a_j) + \sum_{j,m} t_{m,j} \tilde{t}(t_{m,j}) \leq 1482 \text{ min/week}$$

$\tilde{t}(a_j)$ : **median observed duration** of activity  $j$

1482: Q3 of weekly leisure time

### Frequency bounds

$$a_j \leq M(a_j) \quad \sum_j t_{m,j} \leq M(t_m)$$

$M(a_j), M(t_m)$ : **observed maxima** from the one-week GPS traces

### Transport–action consistency

$$\sum_{m=1}^5 t_{m,j} = a_j \quad \forall j$$

Each end-action occurrence requires exactly one trip by some mode.

## Step 4 — Constraints: Individual

### Mode unavailability (from questionnaire)

If individual  $i$  does not meet the requirements for mode  $m$  (affordability, perceived safety, physical ability, vehicle access...):

$$t_{m,j} = 0 \quad \forall j$$

### Walkability (from questionnaire)

If walking to destination  $j$  is reported as infeasible for individual  $i$ :

$$t_{1,j} = 0$$

## Bi-objective MILP (one per individual / constraint profile)

$$\max_{\mathbf{a}, \mathbf{t}} \left\{ \sum_{j=1}^9 a_j w_{j,h} + \sum_{j=1}^9 \sum_{m=1}^5 t_{m,j} w'_{m,h} \right\}_{h \in \{\text{STAI, CES-D}\}}$$

s.t.  $\sum_j a_j \tilde{t}(a_j) + \sum_{j,m} t_{m,j} \tilde{t}(t_{m,j}) \leq 1482$  (time)

$a_j \leq M(a_j), \quad \sum_j t_{m,j} \leq M(t_m)$  (bounds)

$\sum_m t_{m,j} = a_j \quad \forall j$  (consistency)

$t_{m,j} = 0$  if mode  $m$  unavailable;  $t_{1,j} = 0$  if not walkable (individual)

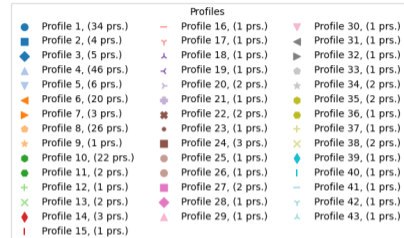
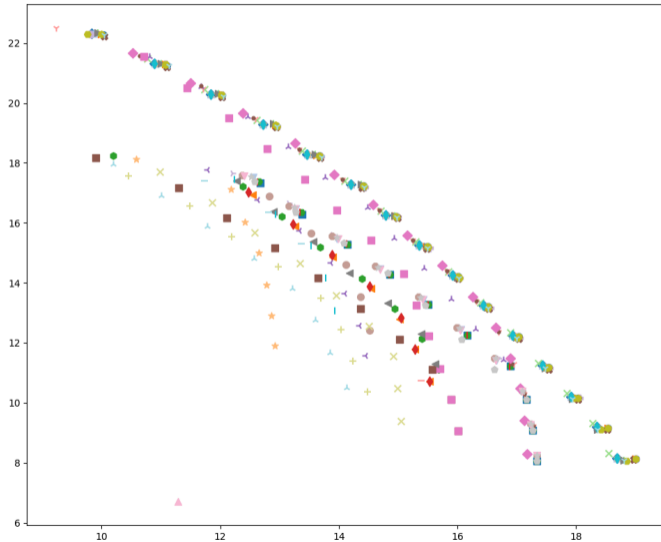
$a_j, t_{m,j} \in \mathbb{N}$

## **Part 3**

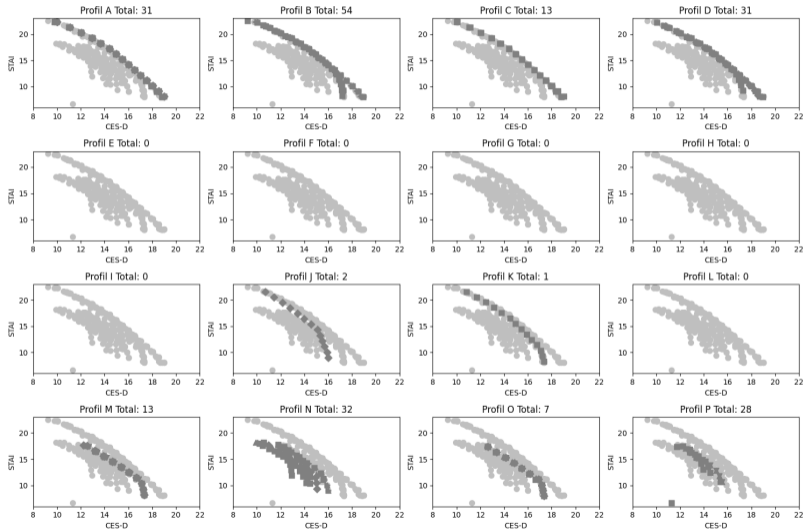
# Case Study

Mental Health of Older Adults in Paris

# Case Study: Capability Sets for 212 Participants

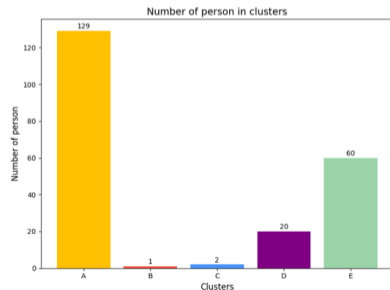
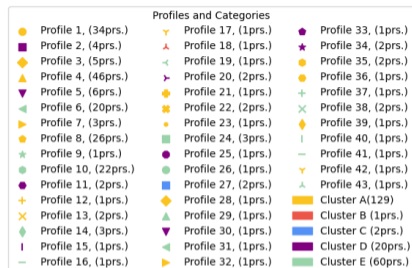
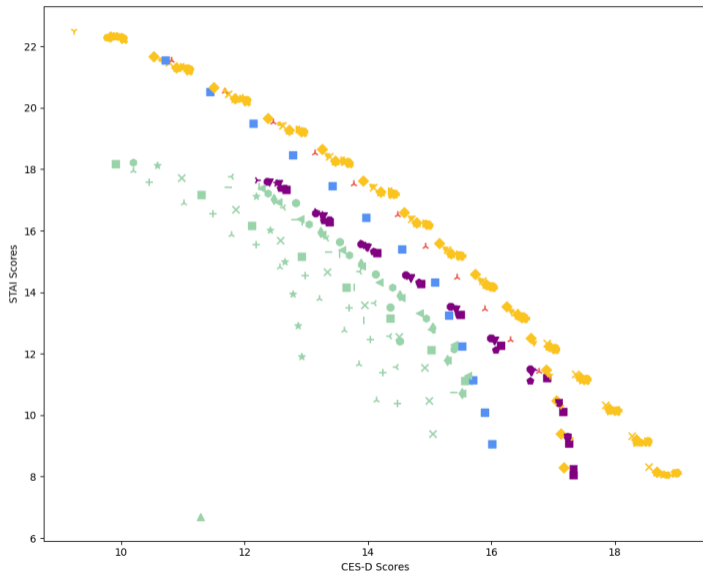


# Dominance-Based Clustering (1/2)

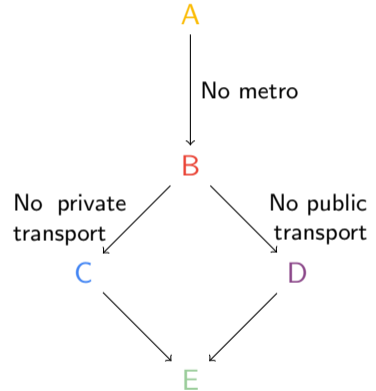
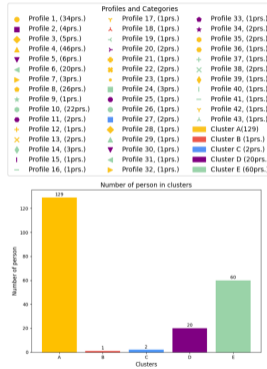
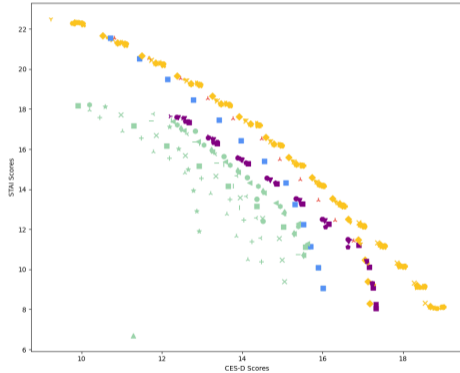


	U	S	B	C
A	✓	✓	✓	✓
B	✓	✓	✓	✗
C	✓	✓	✗	✓
D	✓	✓	✗	✗
E	✓	✗	✓	✓
F	✓	✗	✓	✗
G	✓	✗	✗	✓
H	✓	✗	✗	✗
I	✗	✓	✓	✓
J	✗	✓	✓	✗
K	✗	✓	✗	✓
L	✗	✓	✗	✗
M	✗	✗	✓	✓
N	✗	✗	✓	✗
O	✗	✗	✗	✓
P	✗	✗	✗	✗

# Dominance-Based Clustering (2/2)



# Case Study: Explanatory Graph



## Quasi-dominance order:

- A (129)  $\succ$  B (1): losing underground
- B  $\succ$  C (2): additionally no private transport
- B  $\succ$  D (20): additionally no public transport
- C, D  $\succ$  E (60): most constrained group

## Decision-aiding output

The partial order tells us *who* is worse off and *which constraint* is responsible, directly actionable for policy design.

## Free underground (affordability constraint removed):

- 16 persons (27% of E): E → A

- 2 persons (10% of D): D → A

⇒ **18 persons gain** (8.5% of cohort)

## Improved perceived safety (safety constraint removed):

- 26 persons (43% of E): E → A

- 1 person: E → B

- 10 persons (50% of D): D → A

⇒ **37 persons gain** (17.5% of cohort)

## Reading the graph as a policy map

Each edge in the explanatory graph is a potential intervention. The simulations quantify the *capability gain* per policy lever.

## Contributions:

- Operationalise a capability-theory framework as a **bi-objective MILP** linking mobility data, questionnaire constraints, and mental health outcomes.
- Use **Pareto frontiers** as individualized capability-set proxies; compare groups via dominance.
- **Explanatory clustering graphs** make binding constraints legible for policy discussion.

## Open problems:

- **Heterogeneous preference learning**: learn action-to-outcome mappings per individual, not a common matrix.
- **Similarity measures for capability sets**: enable reproducible, automated clustering.

- **[This paper]** Fayard, N., Chaix, B., Fancello, G. (2026). “Implementing Capability Theory Inspired Tools for Policy Design: A Case Study on Older Adults’ Urban Mental Well-Being”, *DA2PL Workshop*.
- Fayard, N., Mazri, C., & Tsoukiàs, A. (2022). “Capability theory inspired tools for aiding policy design”, *EURO Journal on Decision Processes*, 10, 100024.
- Fayard, N., Insua, D.R., & Tsoukiàs, A. (2024). “A framework for expected capability sets”, *Cahier du LAMSADE 407*.
- Fayard, N. (2025). “Compromising over capability sets”, *Cahier du LAMSADE*.
- Sen, A. (1985). *Commodities and Capabilities*. North-Holland.
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<b>Action</b>	$\tilde{t}(a_j)$ (min)	$M(a_j)$
$a_1$ General shopping	16	13
$a_2$ Food shopping	5	9
$a_3$ Other shops/services	10	22
$a_4$ Medical	22	9
$a_5$ Green spaces	14	9
$a_6$ Sports facilities	75	7
$a_7$ Cultural activity	95	10
$a_8$ Visiting people	40	15
$a_9$ Restaurant	59	9

$\tilde{t}(a_j)$ : median observed duration       $M(a_j)$ : observed maximum weekly frequency