Occupant Behavior

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ENG-445 Energy and Comfort in Buildings

10 October 2024

Housekeeping

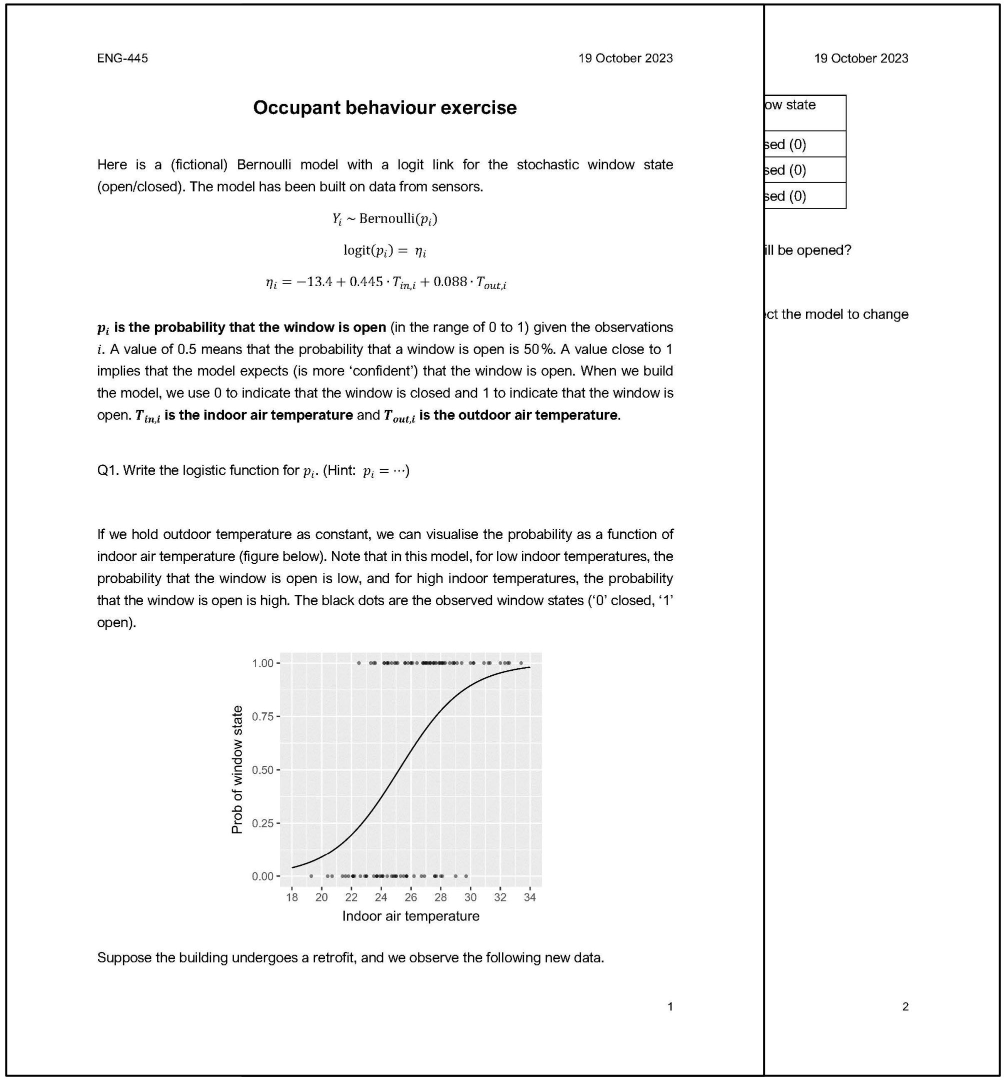
- Indicative feedback
  - It is very useful for us!
- Midterm Exam
  - 17 October 2024, at standard time 09:15 – 11:15h (2 hrs)
  - Please try to come a bit earlier if possible (~09:00h)
  - CE1106
  - See last week's lecture notes for more details

Today’s lines of inquiry

- Why do we care about occupant behavior (OB)?
- What is OB?
- How does OB impact building energy use?
- What are the types of OB?
- What drives OB?
- How to account for OB in energy simulation?
- How can we collect OB data?
- Can we change behaviour to make buildings more efficient?

Today's schedule

- 09:15-10:00 – Lecture (with questions)
- 10:15-11:00 – Lecture (with questions)
- 11:15-12:00 – Exercise



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Occupant behaviour exercise

Here is a (fictional) Bernoulli model with a logit link for the stochastic window state (open/closed). The model has been built on data from sensors.

$$Y_i \sim \text{Bernoulli}(p_i)$$

$$\text{logit}(p_i) = \eta_i$$

$$\eta_i = -13.4 + 0.445 \cdot T_{in,i} + 0.088 \cdot T_{out,i}$$

p_i is the probability that the window is open (in the range of 0 to 1) given the observations i. A value of 0.5 means that the probability that a window is open is 50%. A value close to 1 implies that the model expects (is more 'confident') that the window is open. When we build the model, we use 0 to indicate that the window is closed and 1 to indicate that the window is open. **$T_{in,i}$ is the indoor air temperature** and **$T_{out,i}$ is the outdoor air temperature.**

Q1. Write the logistic function for p_i. (Hint: $p_i = \cdots$)

If we hold outdoor temperature as constant, we can visualise the probability as a function of indoor air temperature (figure below). Note that in this model, for low indoor temperatures, the probability that the window is open is low, and for high indoor temperatures, the probability that the window is open is high. The black dots are the observed window states ('0' closed, '1' open).

Suppose the building undergoes a retrofit, and we observe the following new data.

1

19 October 2023

ow state

sed (0)

sed (0)

sed (0)

ill be opened?

ct the model to change

2

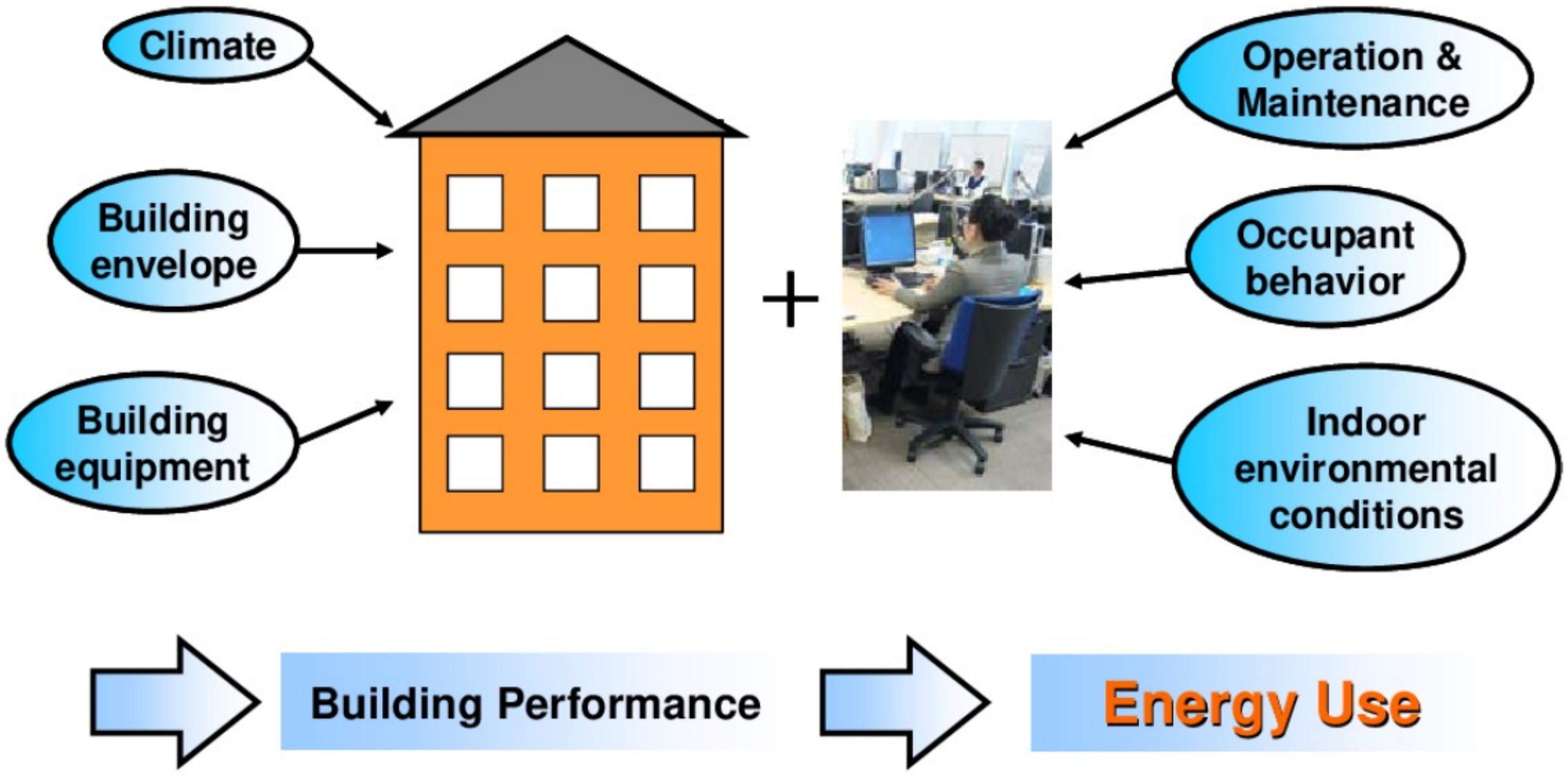
What's the biggest user of energy in buildings?

Response Counter

URL: **http://responseware.eu**
Session ID: **ethos**

Why do we care about occupant behavior?

Why do we care about OB?



(Source: IEA EBC Annex 53 Final Report)

A quick note on the research

IEA = International Energy Agency

EBC = Energy in Buildings and Communities Programme

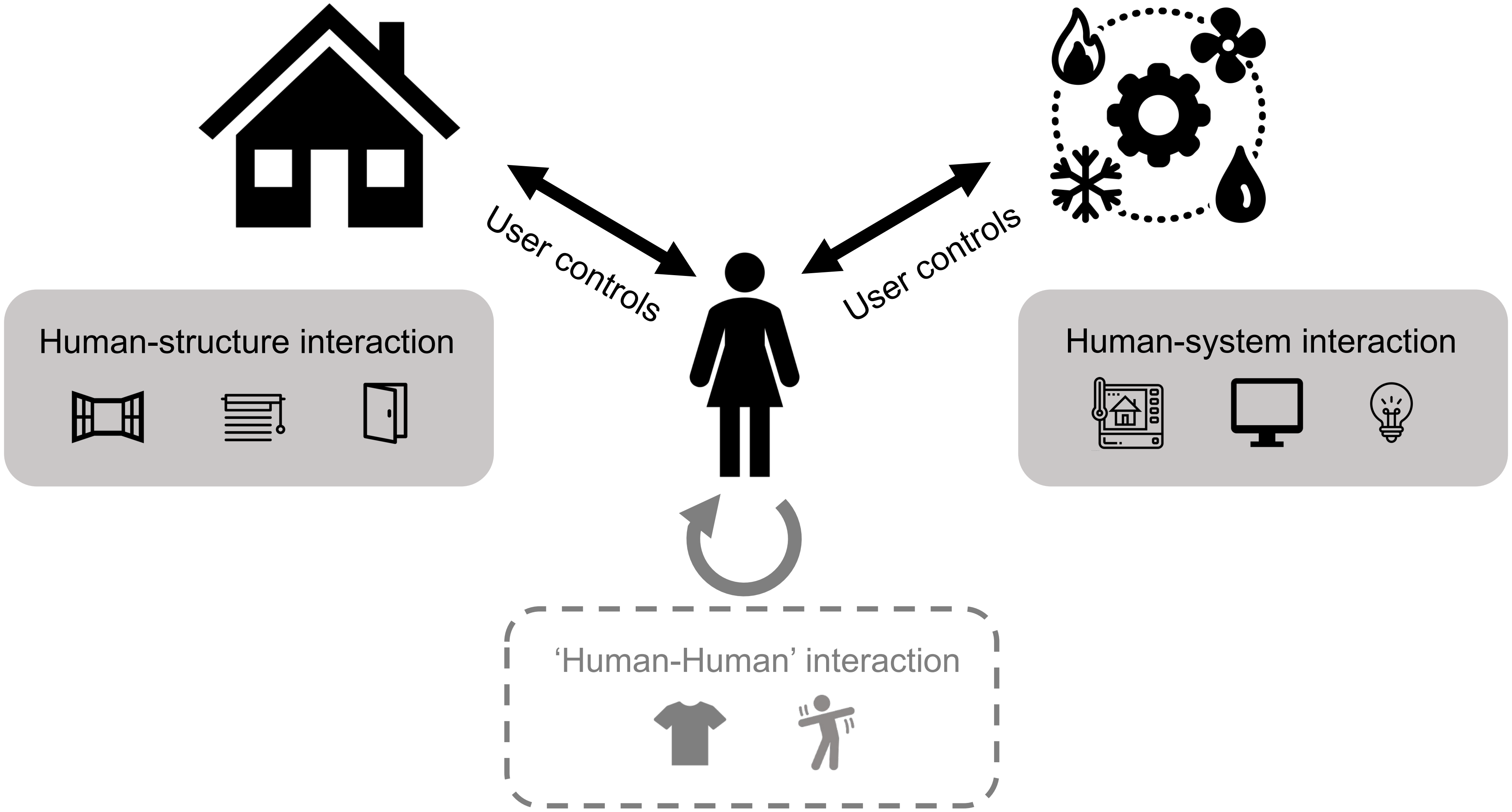
Annex = EBC research project
- Annex 79: Occupant-Centric Building Design and Operation (2018-2023)
- Annex 66: Definition and Simulation of Occupant Behaviour in Buildings (2013-2017)
- Annex 53: Total Energy Use in Buildings: Analysis & Evaluation Methods (2008-2013)

What is occupant behavior?

What is Occupant Behavior?

What is Occupant Behavior?

Modes of interaction

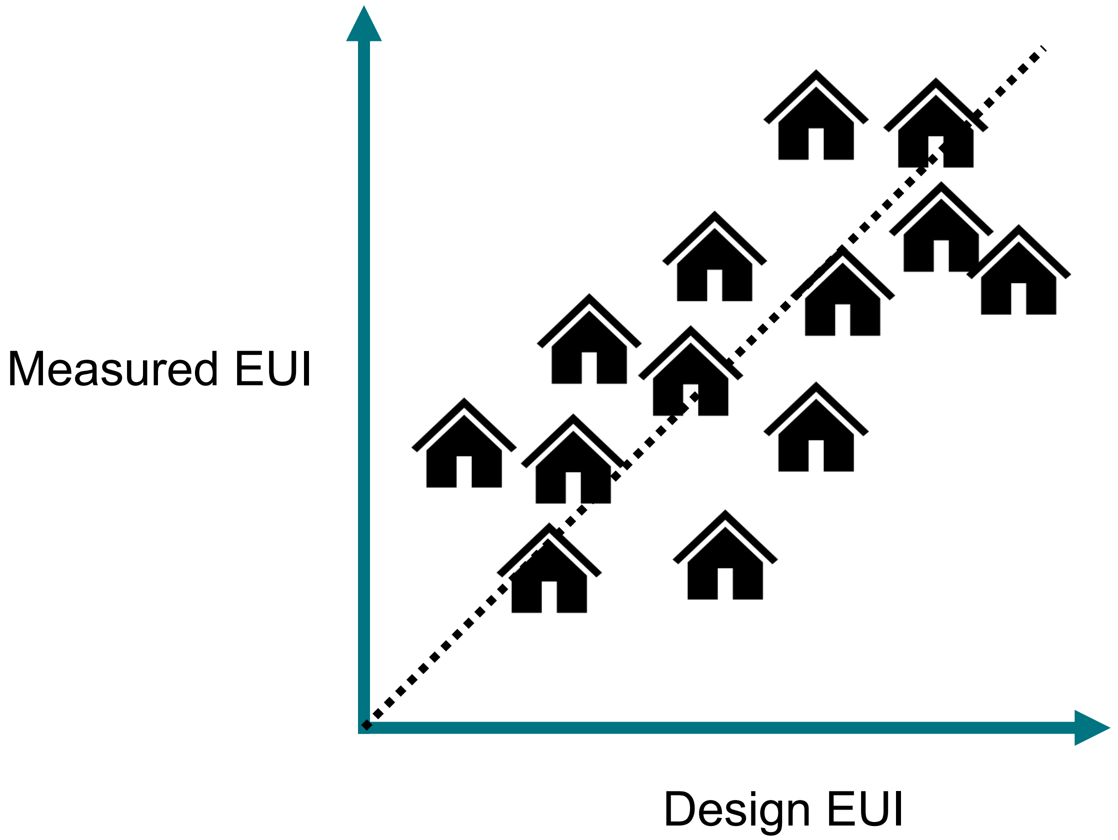


How does occupant behavior impact building energy use?

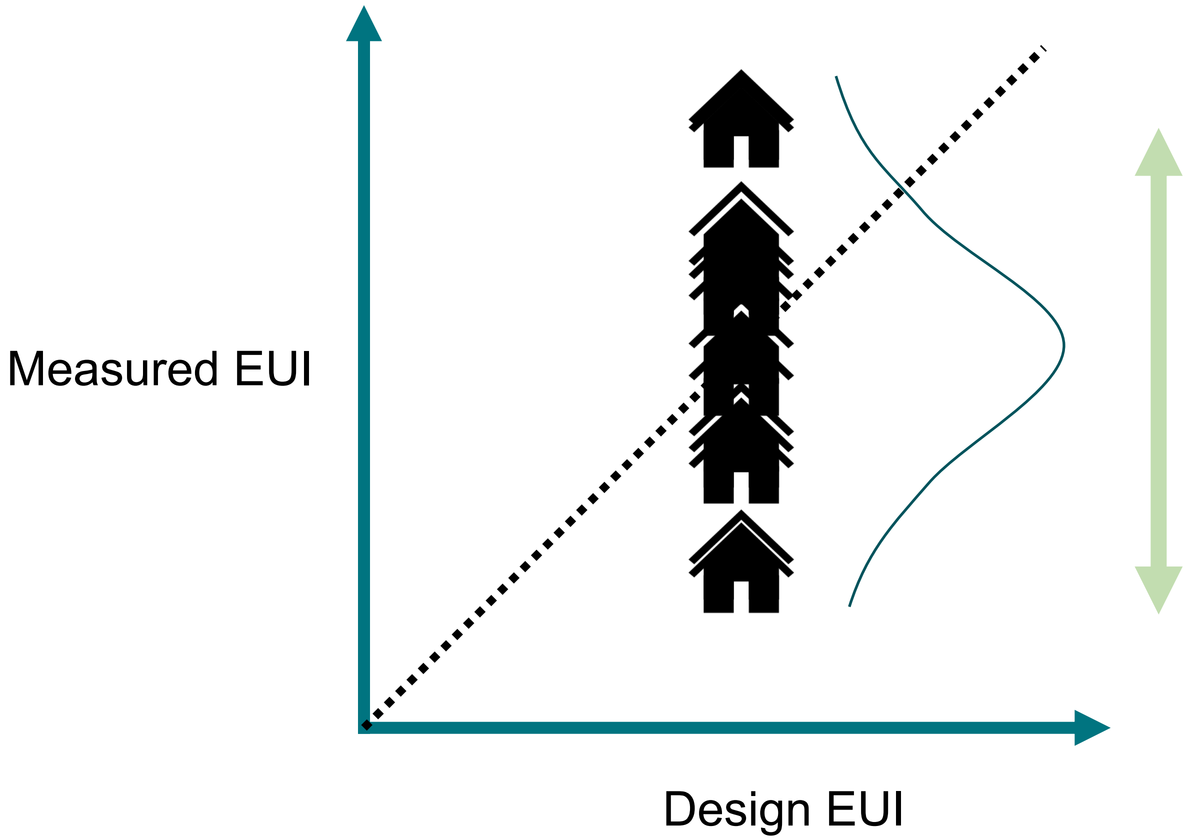
The energy performance gap

(Source: ArchDaily)

The energy performance gap



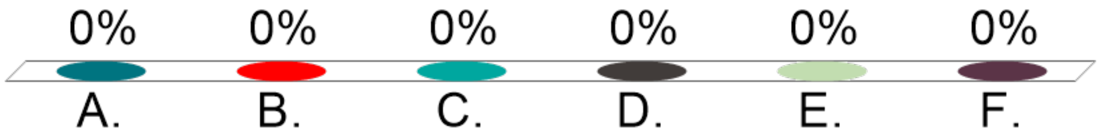
The energy performance gap



If buildings are completely identical, variation must be related to occupant behavior

In terms of percentage change of building energy use, how much can occupant behavior impact building energy use?

A. 1%
B. 10%
C. 50%
D. 100%
E. 150%
F. More



Response Counter

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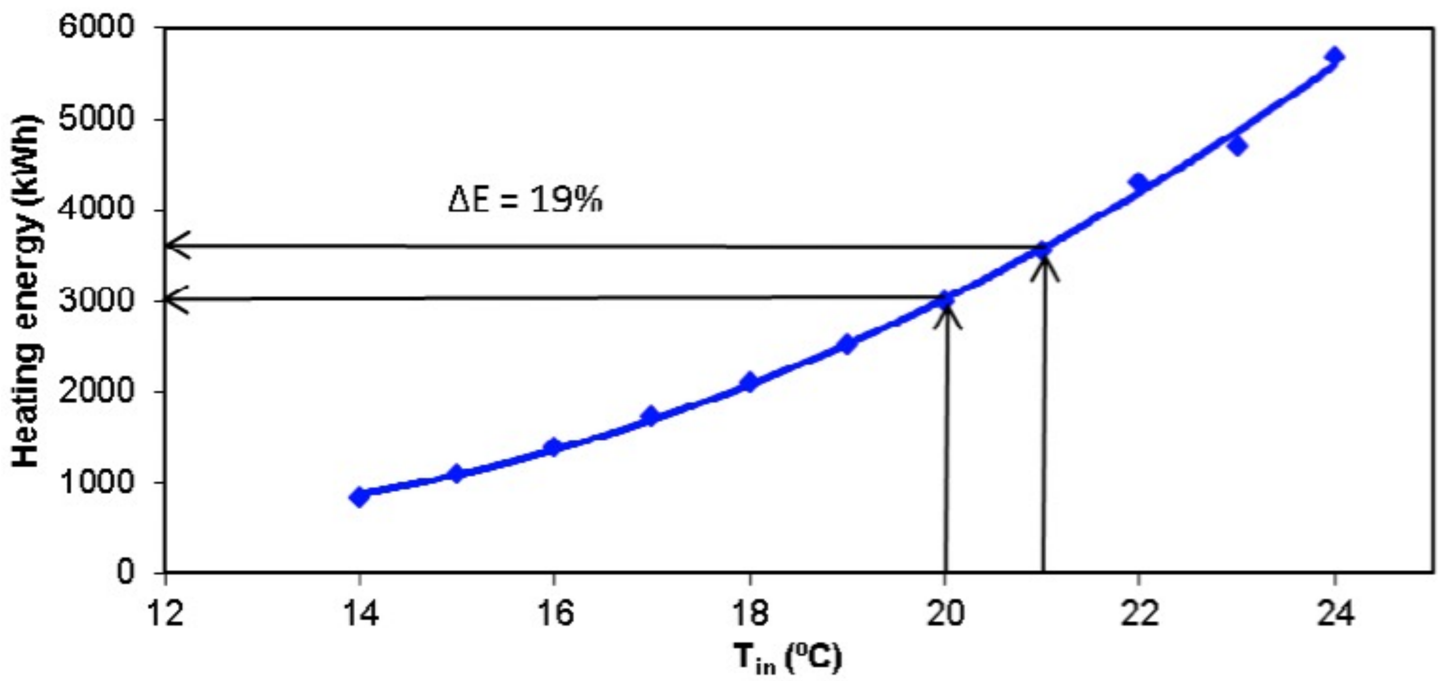
Heating energy sensitive to behaviour



- ➢ For a well insulated building, increasing set point from 20ºC to 21ºC results in a 19% increase in energy consumption

(Source: Annex 53 Final Report)

What behaviors matter?

Which house is:

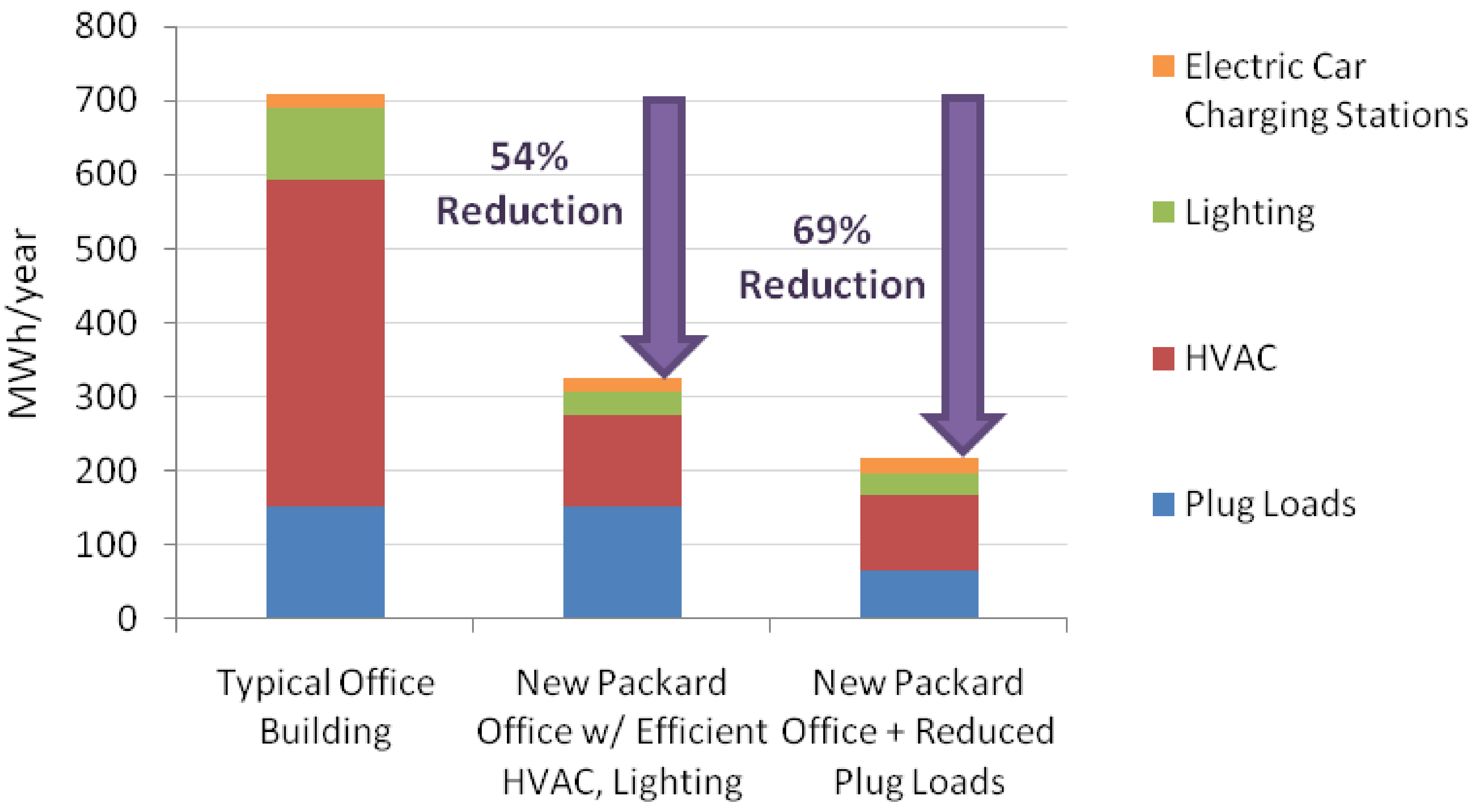
- More sensitive to variations in heating and cooling setpoints?

- More sensitive to variations in the use of electric equipment and lighting?

Low performing building

High performing building

Green buildings need green users



Estimated Building Annual Energy Use

(Source: Kaneda et al. 2010)

What are the types of OB?

OB categories (adjustments)

Physiological

Individual

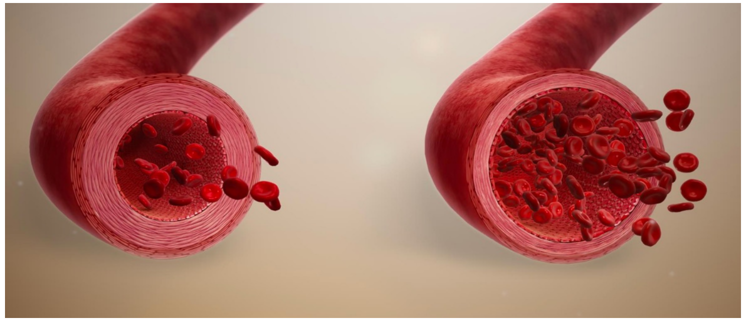
Spatial

Environmental

(Source: Exploring Occupant Behaviour in Buildings. Wagner, O’Brien, Dong. 2018.)

Physiological adjustments

- Sweating
- Blood vessel dilation/restriction
- Shivering
- “Goosebumps”
- Light reflex of pupils
- Ear sensitivity adjustment
- …



(Source: Exploring Occupant Behaviour in Buildings. Wagner, O’Brien, Dong. 2018.)

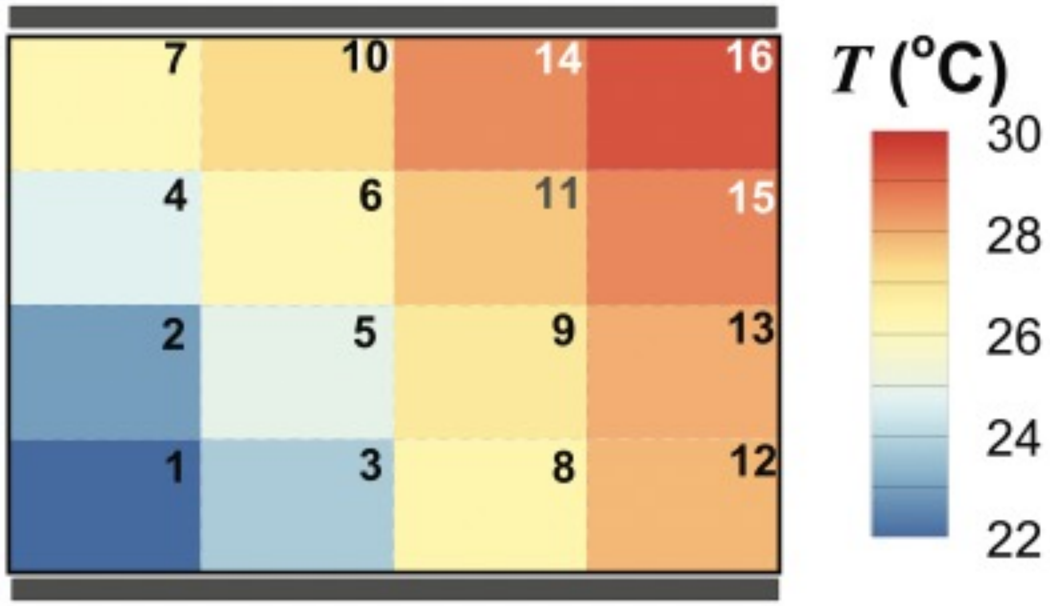
Individual adjustments

- Clothing adjustments
- Body posture adjustments
- Change of activity level
- Earplug/headphone use
- Drinking/eating hot or cold things
- …

(Source: Exploring Occupant Behaviour in Buildings. Wagner, O'Brien, Dong. 2018.)

Spatial adjustments

- Moving from one room to another
- Change of position or orientation in a room



Environmental adjustments

- Space heating/cooling use
  - Temperature set points
  - Number of heated rooms
  - Heating/cooling duration

Environmental adjustments

- Lighting and appliance use
    - Number of installed fixtures/appliances
    - Energy efficiency of devices
    - Usage frequency and duration

Environmental adjustments

- Domestic hot water use
  - Shower frequency and duration
  - Sink use frequency and duration
  - Washing machines
  - Dishwashers

Environmental adjustments

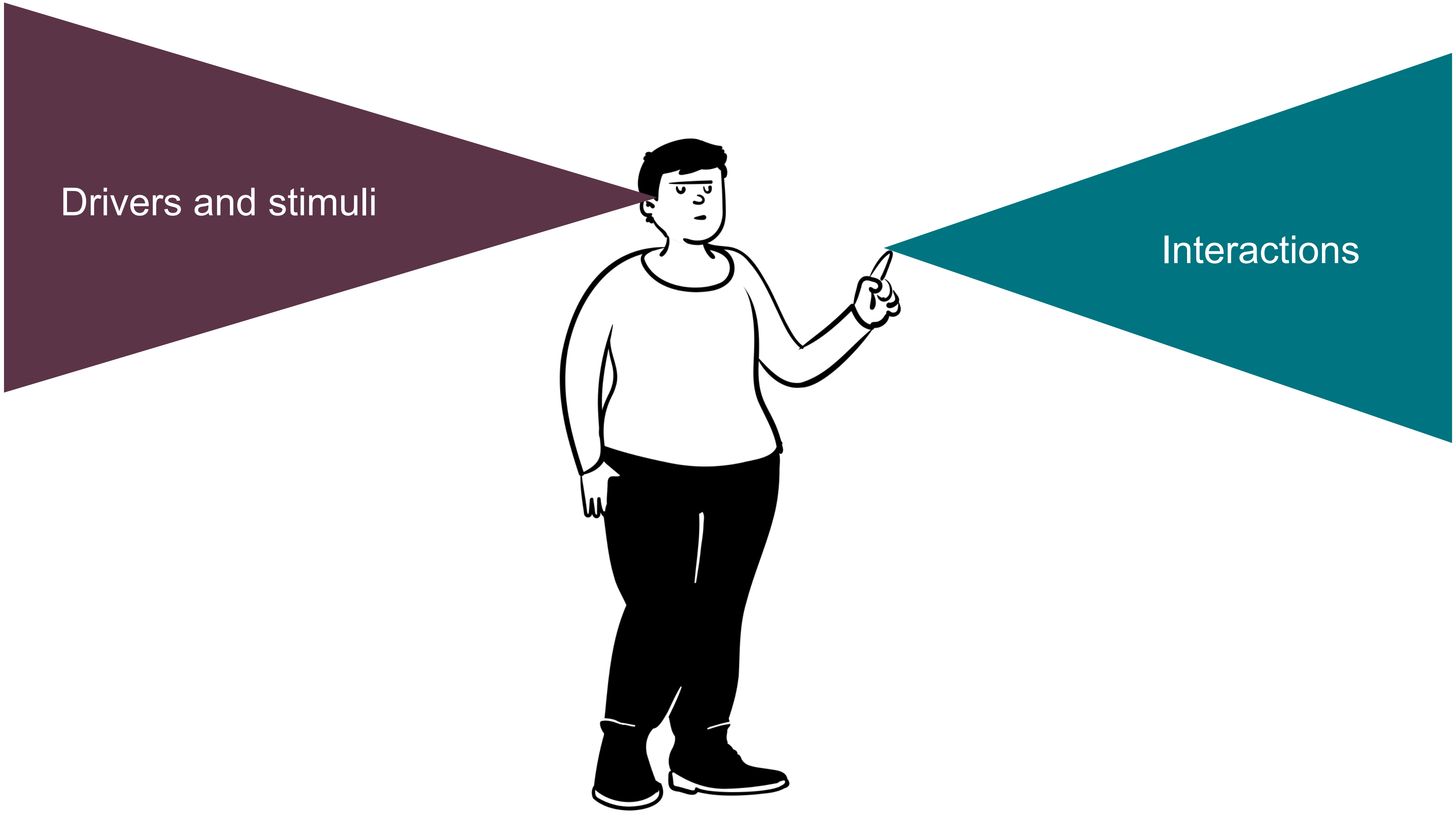
- Ventilation
  - Use of windows
  - Use of doors
  - Adjustments of mechanical ventilation system

Environmental adjustments

- Window blind behaviour
  - Lowering/raising blinds
  - Slat orientation
  - Addition of internal curtains
  - Frequency of use

What drives OB?

What causes us to interact with buildings?



Why would you open a window?

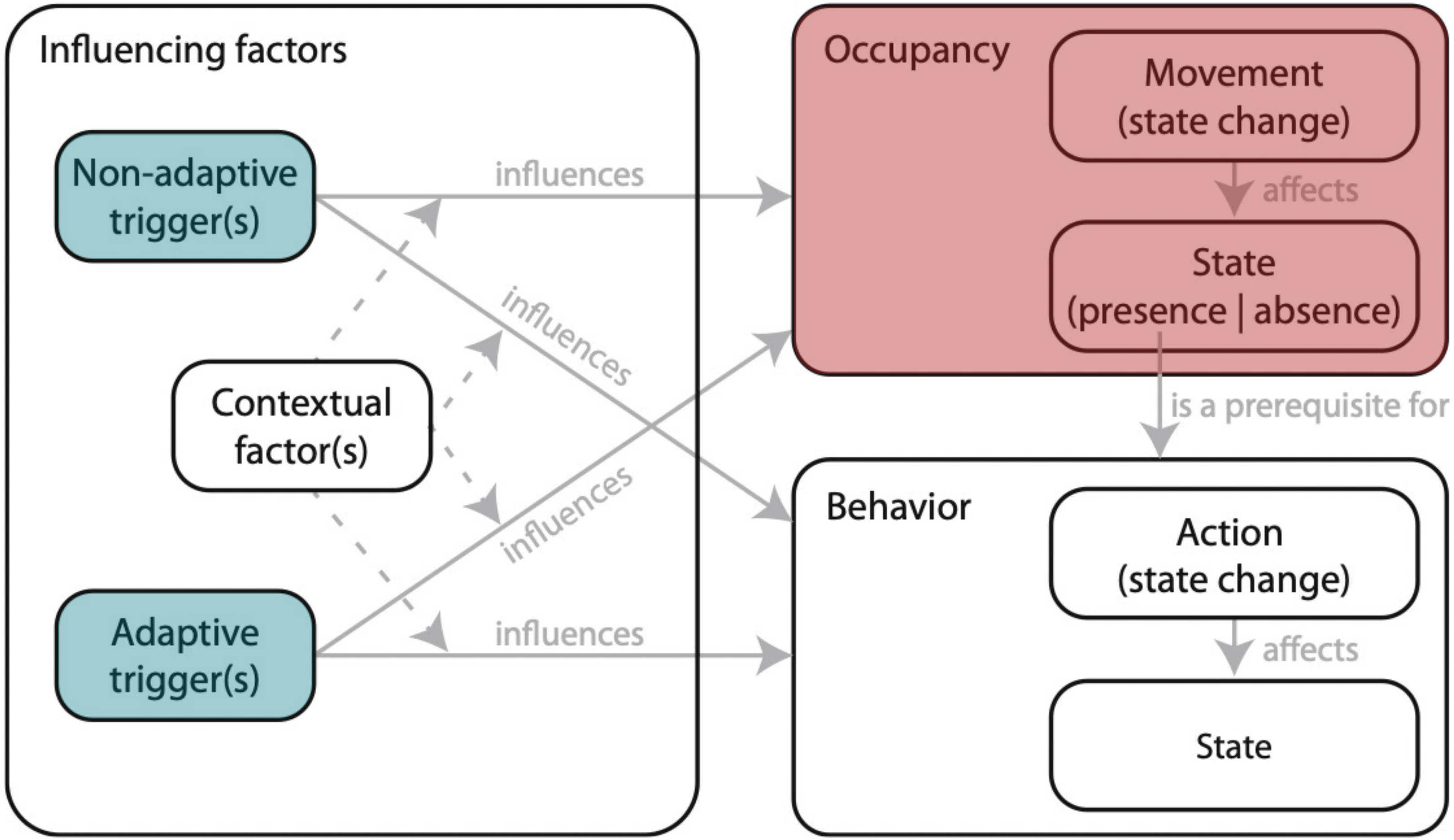
Response Counter

URL: **http://responseware.eu**
Session ID: **ethos**

Driving forces

Non-adaptive:
Part of occupant tasks (e.g. schedule)

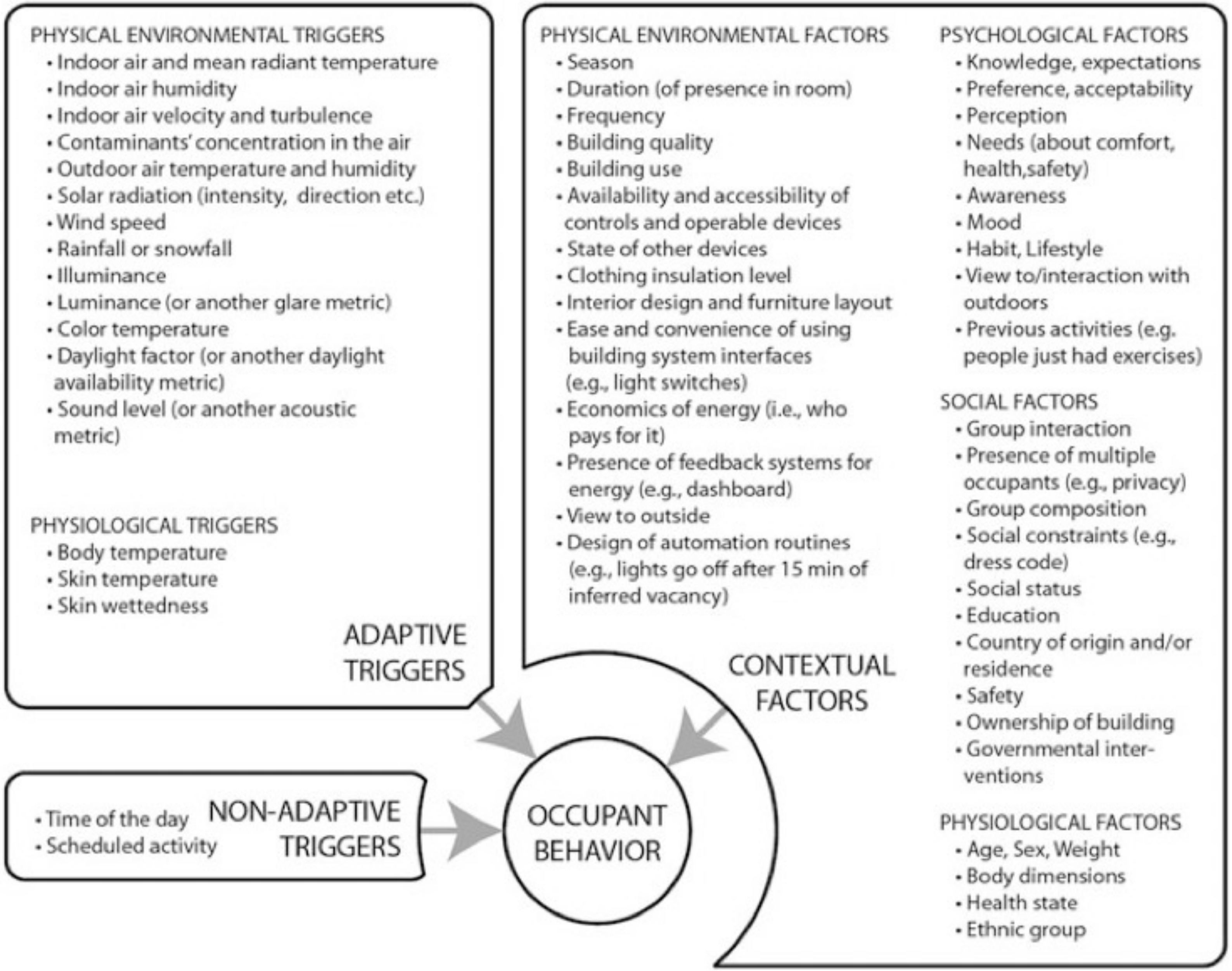
Adaptive:
Response to environment and comfort level



No occupancy, no action

(Source: Annex 66 final report)

Adaptive, non-adaptive, and contextual factors



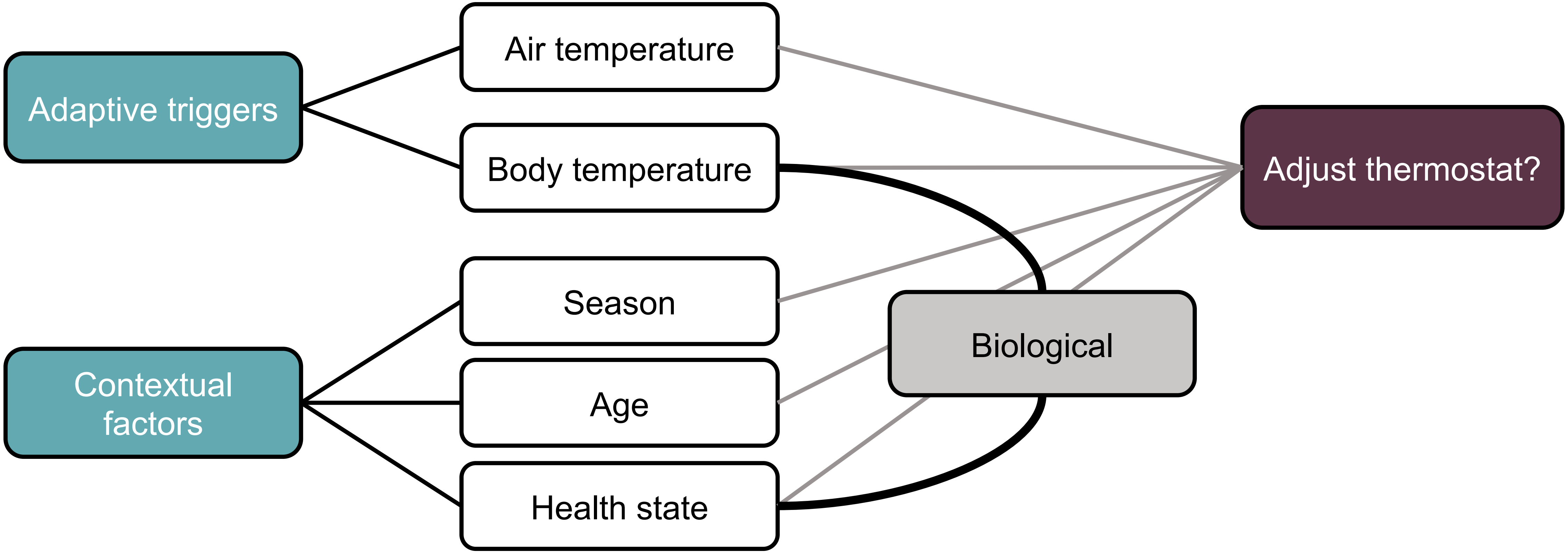
(Source: Annex 66 final report)

Example: Too Cold

Adaptive triggers

Contextual factors

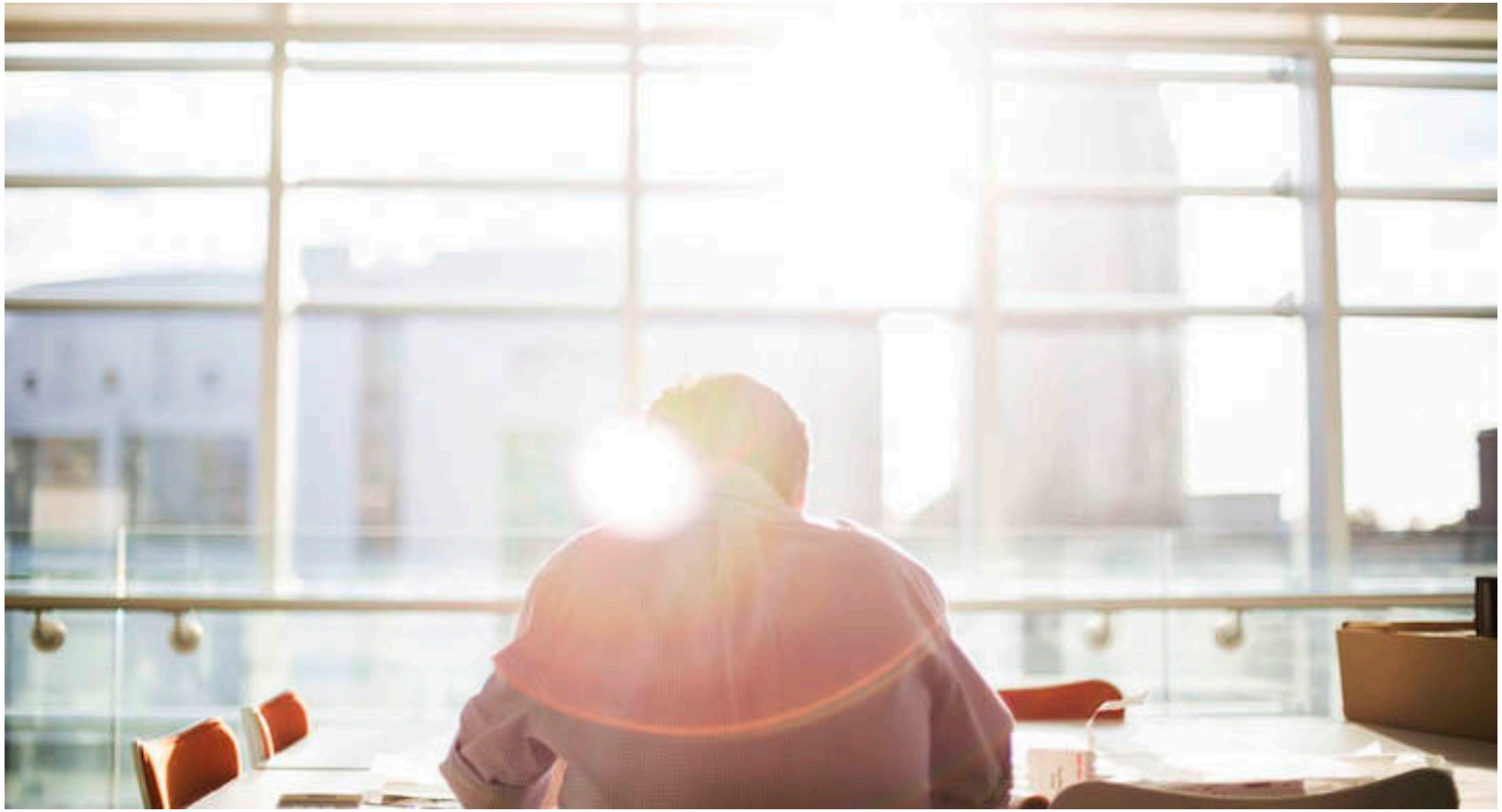
Example: Too Cold



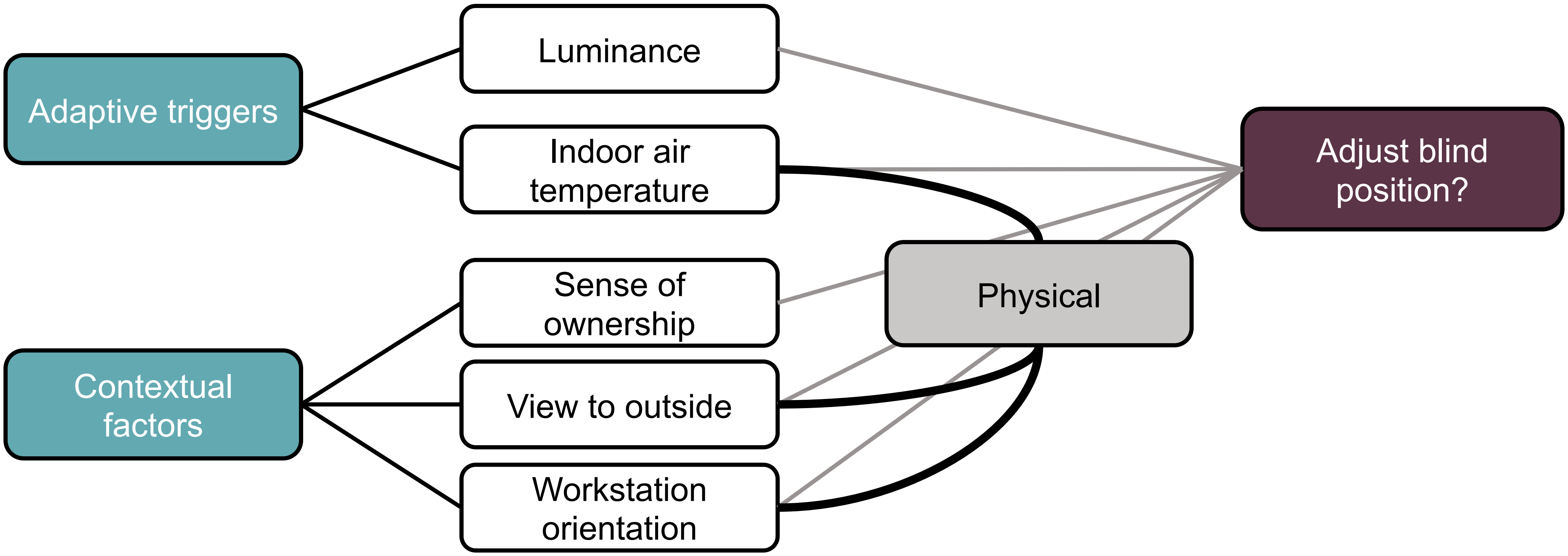
Another example: Experiencing glare

Adaptive triggers

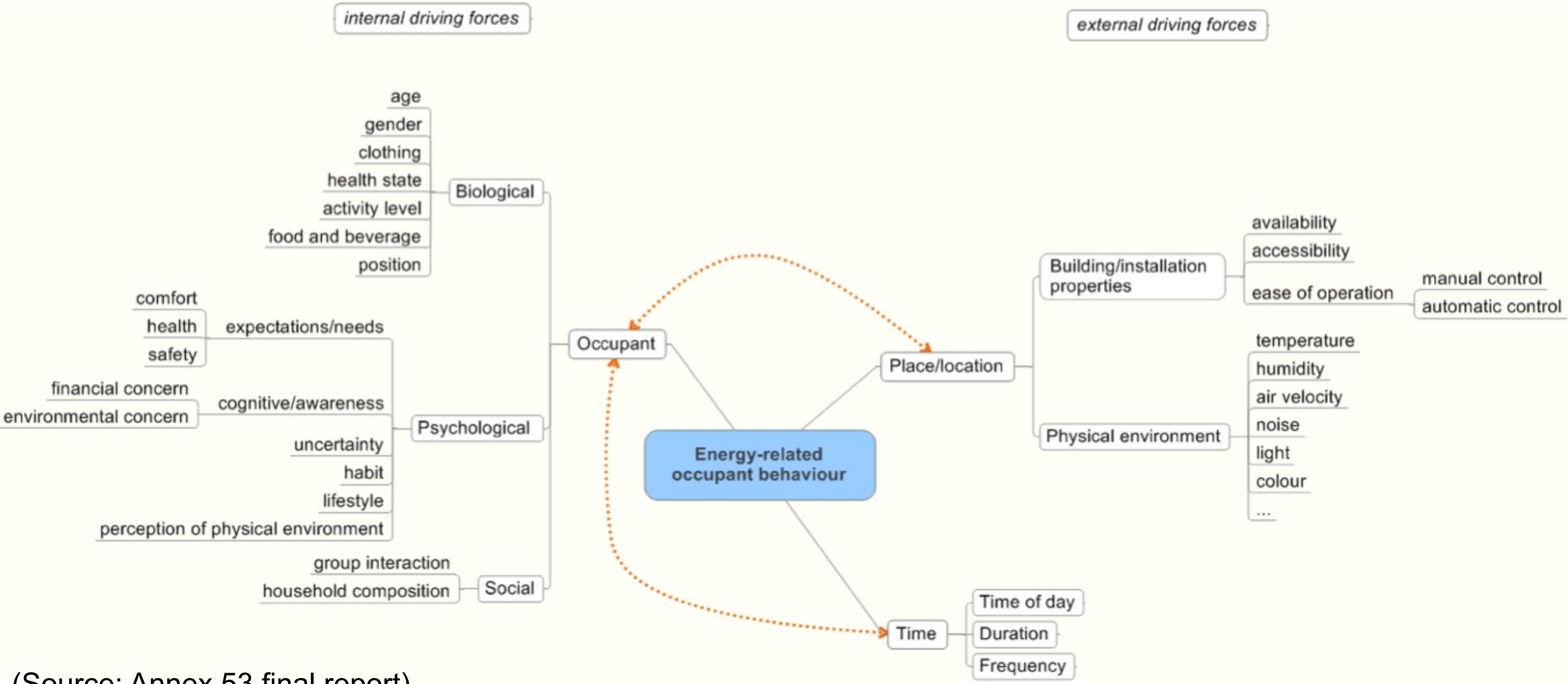
Contextual factors



Example: Glare



Another way to categorize driving forces



(Source: Annex 53 final report)

Drive forces for space heating

BEHAVIOUR	BIOLOGICAL/ PHYSIOLOGICAL	PSYCHOLOGICAL	SOCIAL (CONTEXTUAL)	TIME (NON-ADAPTIVE TRIGGER)	PHYSICAL ENVIRONMENT (ADAPTIVE TRIGGER)	BUILDING/EQUIPMENT PROPERTIES (CONTEXTUAL)
Temperature set point adjustment	▪ Gender ▪ **Clothing**	▪ Expectations ▪ **Interaction frequency with heathing controls** ▪ Window opening	▪ **Ownership**	▪ Time of day	▪ **Outdoor air temperature** ▪ **Outdoor relative humidity** ▪ Indoor relative humidity ▪ Wind speed	▪ **Building insulation level** ▪ Ventilation type ▪ Type of metering
Heating duration	▪ Clothing	▪ Knowledge of control ▪ Window opening	▪ Ownership ▪ (Government interventions)		▪ **Outdoor air temperature** ▪ **Outdoor air humidity** ▪ Wind speed	▪ **Building insulation level** ▪ **Heating system type** ▪ **Level of control**
Number of heated rooms		▪ Interaction frequency with heathing controls				▪ **Level of control** ▪ Type of metering
Which rooms are heated	▪ Gender					▪ **Level of control**

Bold = most significant; Red = not significant (Source: Annex 53 final report)

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Number of heated rooms		▪ Interaction frequency with heathing controls				▪ **Level of control** ▪ Type of metering
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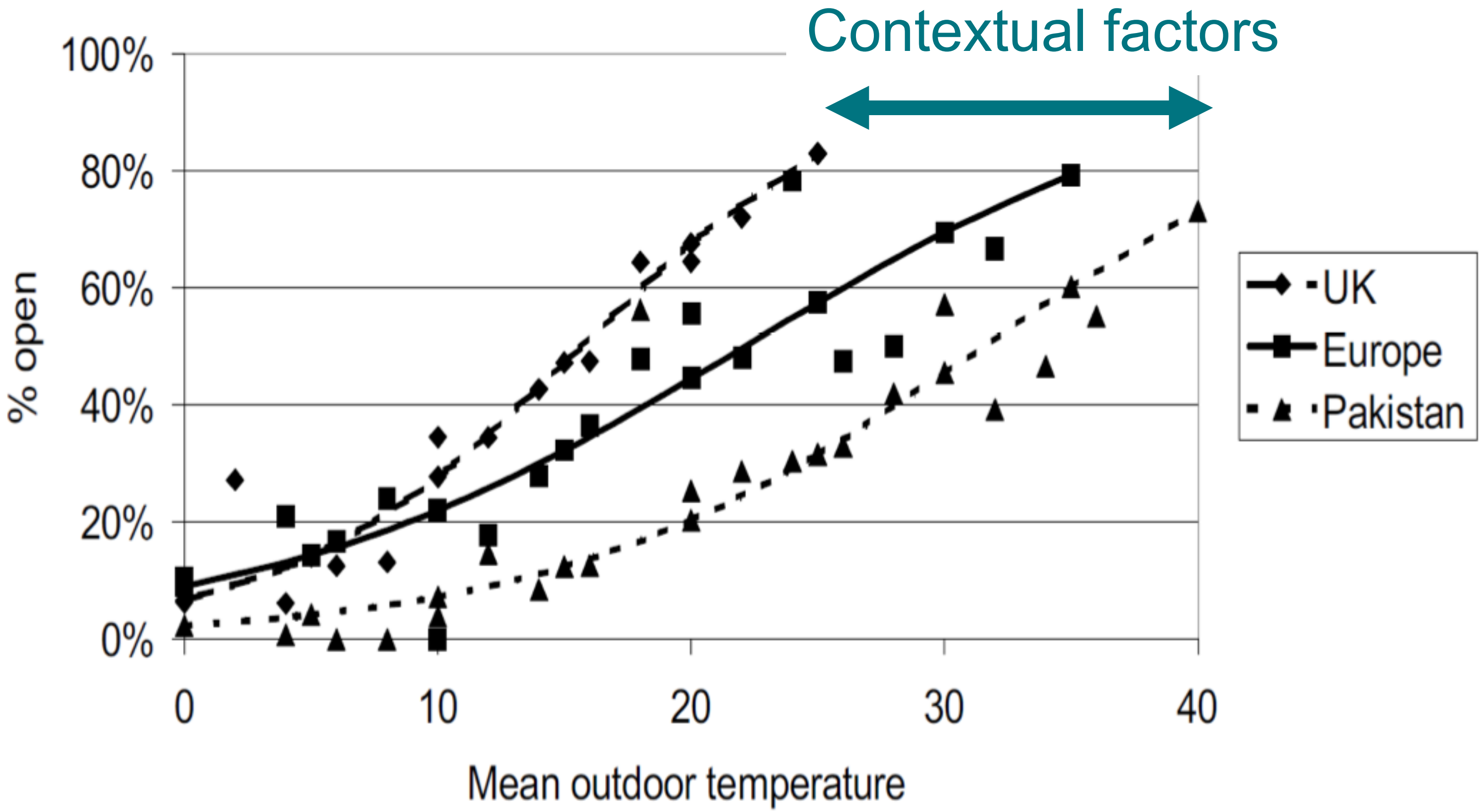
Bold = most significant; Red = not significant

(Source: Annex 53 final report)

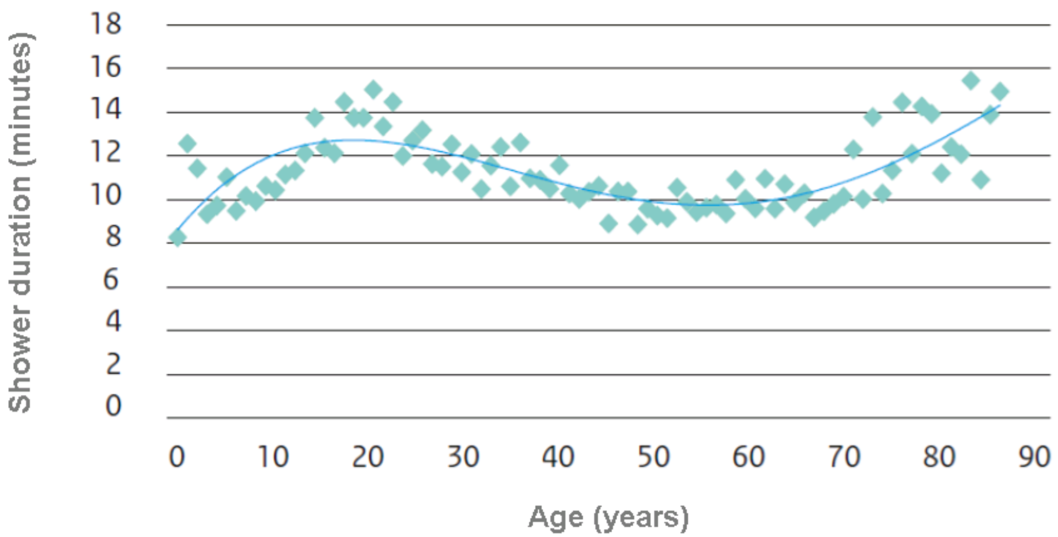
Window use as function of outdoor temperature



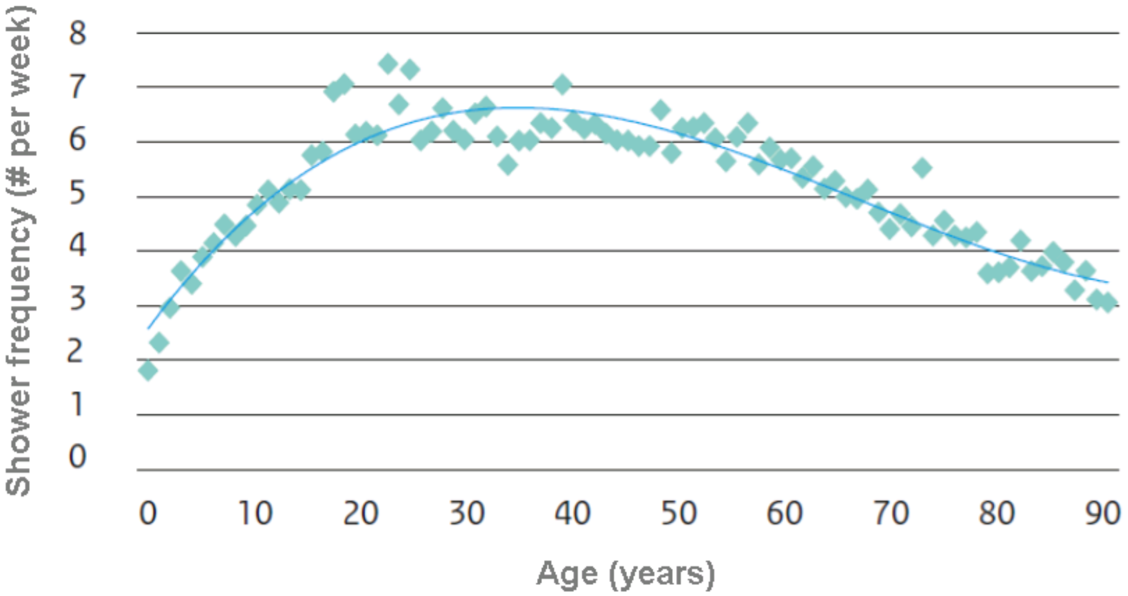
(Source: Annex 53 final report)

More contextual factors

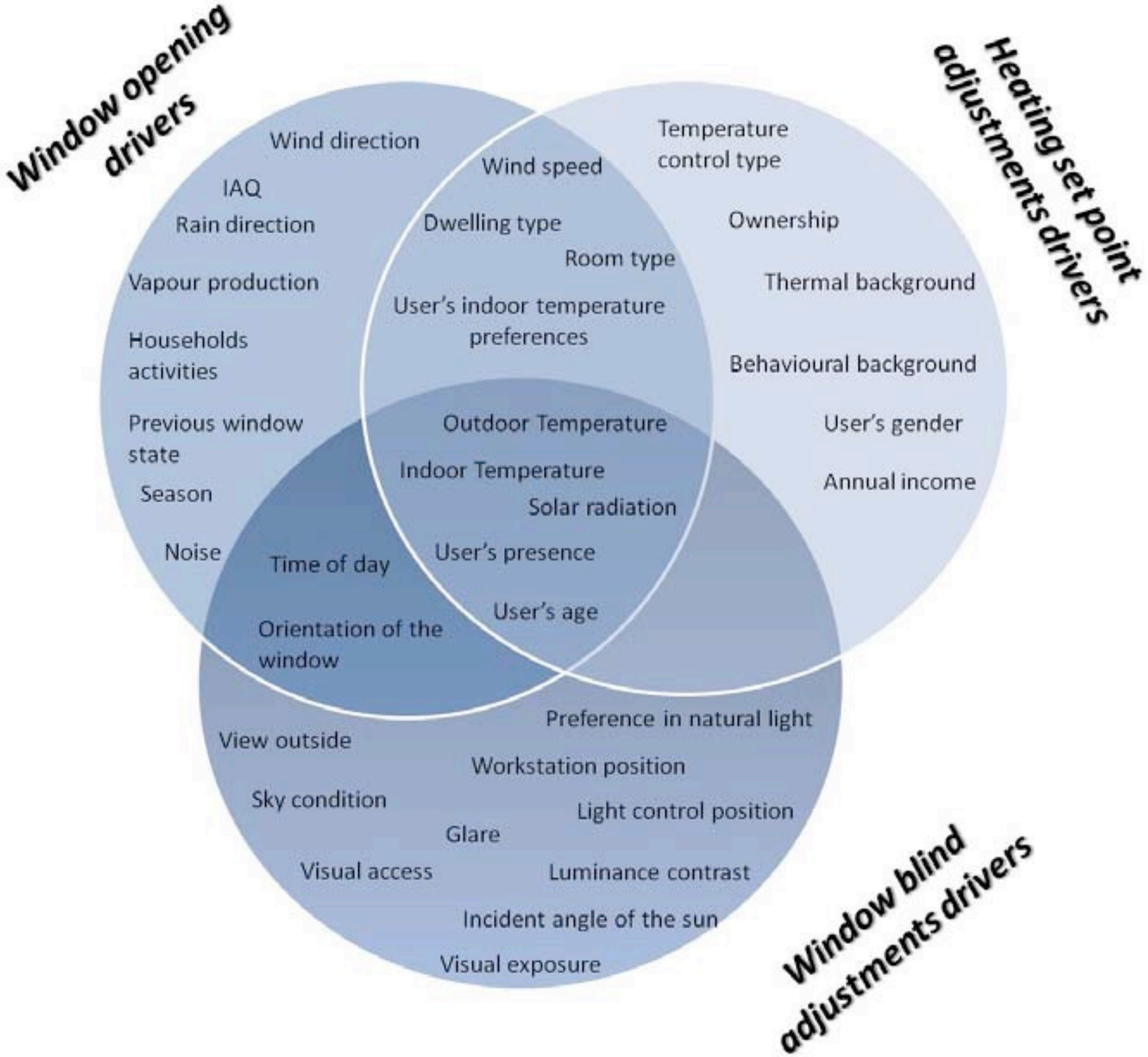
Shower duration



Shower frequency



(Source: Annex 53 final report)



(Source: Fabi et al. 2011)

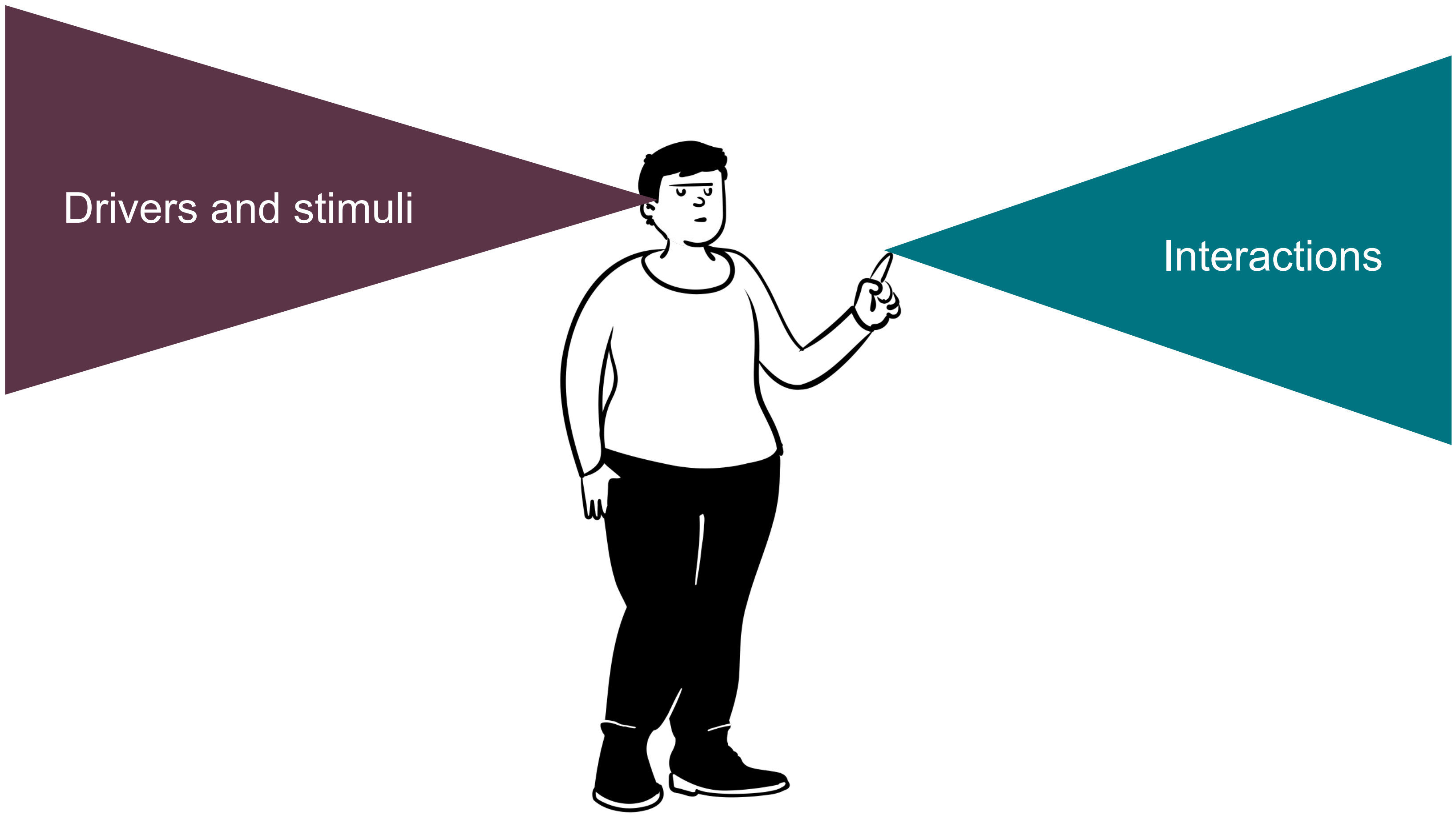
Mapping drivers to three behaviors

Feasible to capture all this information?

Is it possible to generalise?

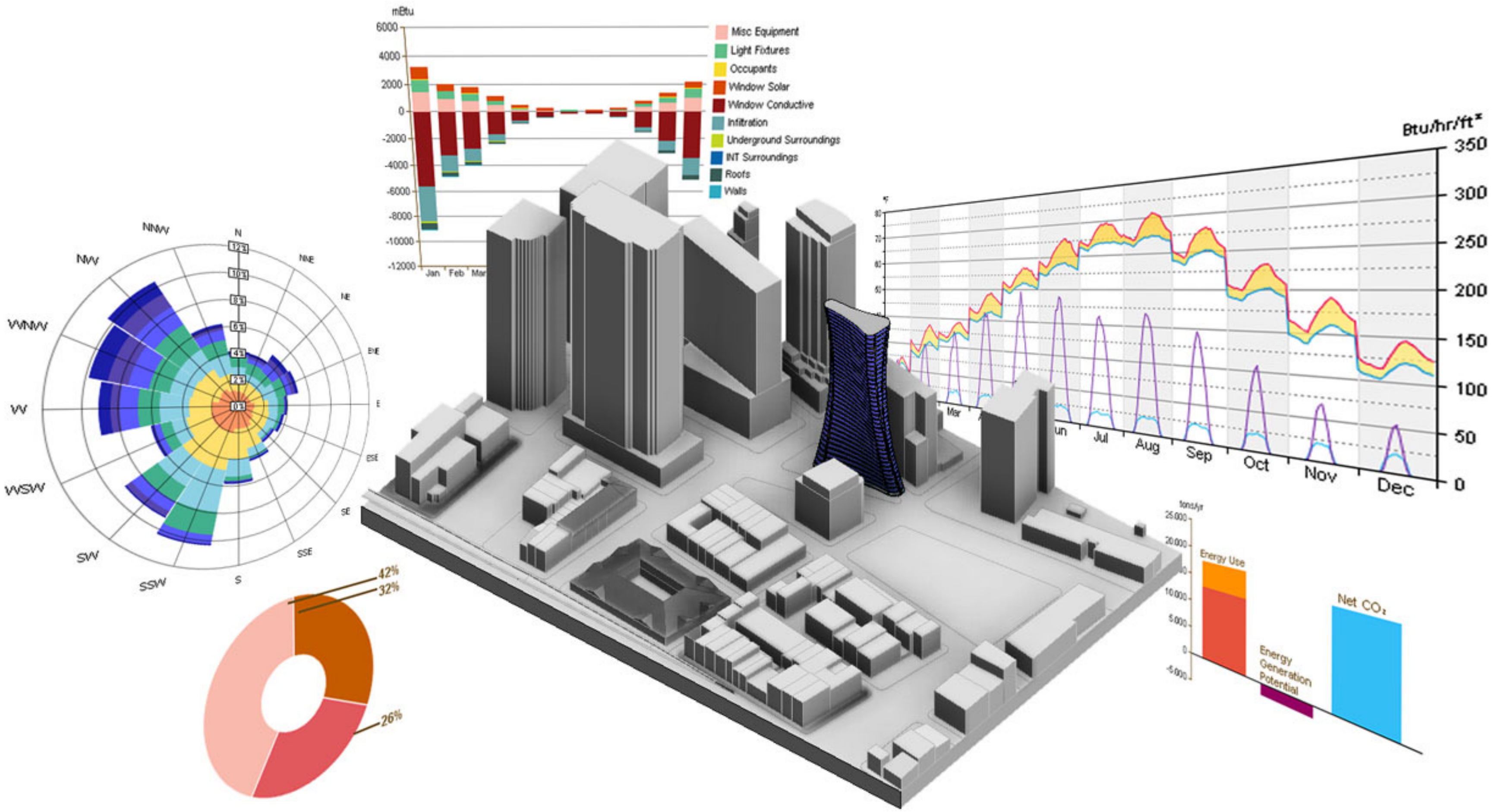
What are the real impacts of behavior?

Can we capture these relationships numerically?



How to account for OB in simulation?

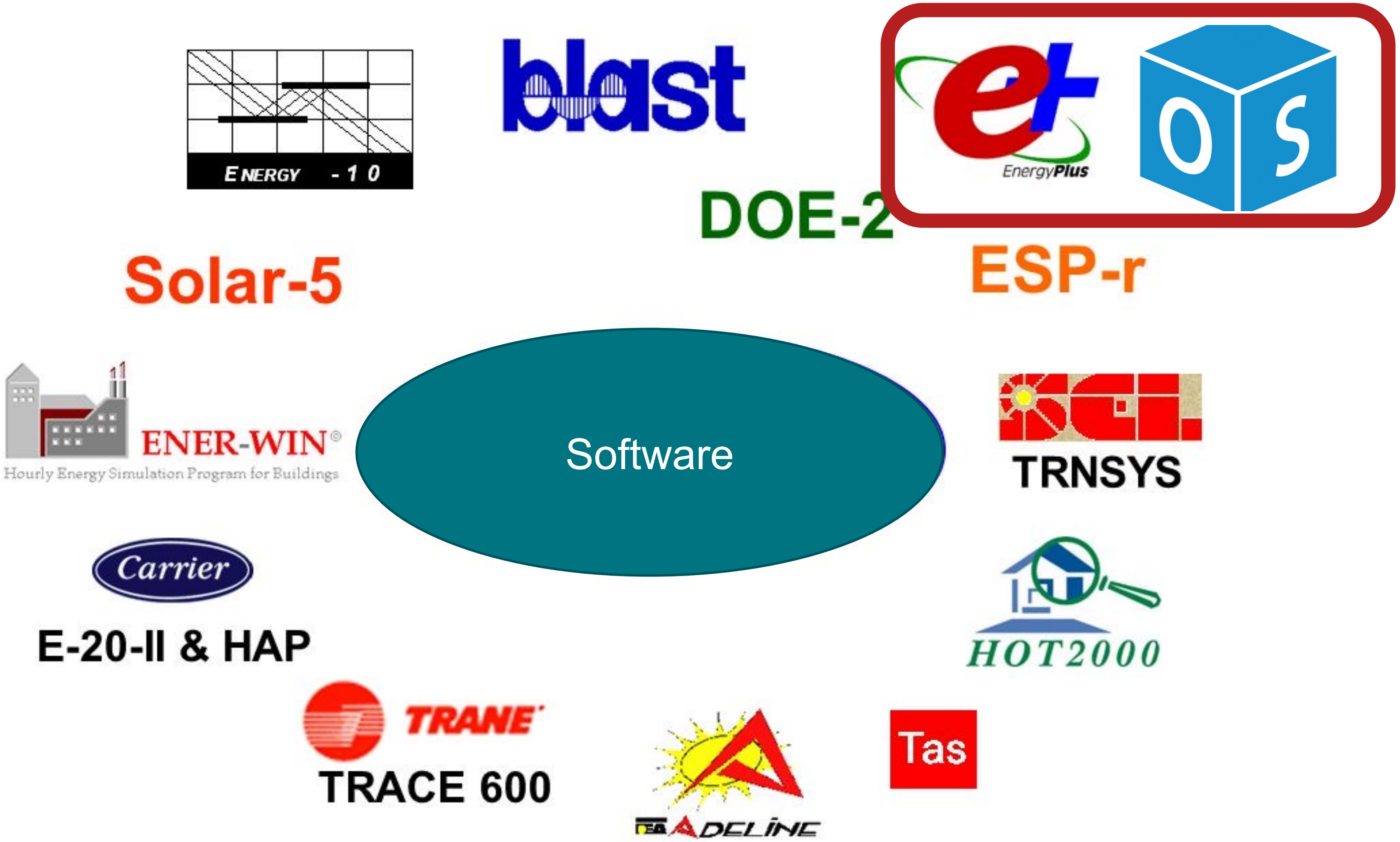
Why simulate?



Starting points:
- Building design
- Existing building

How much energy is needed
- Heating
- Cooling
- Ventilation
- Lighting
- Equipment
- …

Tools



EnergyPlus
OpenStudio

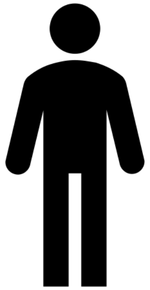
In practice, occupant behaviour is rarely considered effectively in building energy simulation

OB in simulation

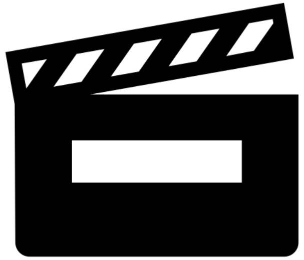
OB models are commonly divided into:

- Presence models
- Actions models
    - Window control
    - Blind control
    - Thermostat settings
    - Light switch use
    - …

Note: We can combine models



Presence



Action!

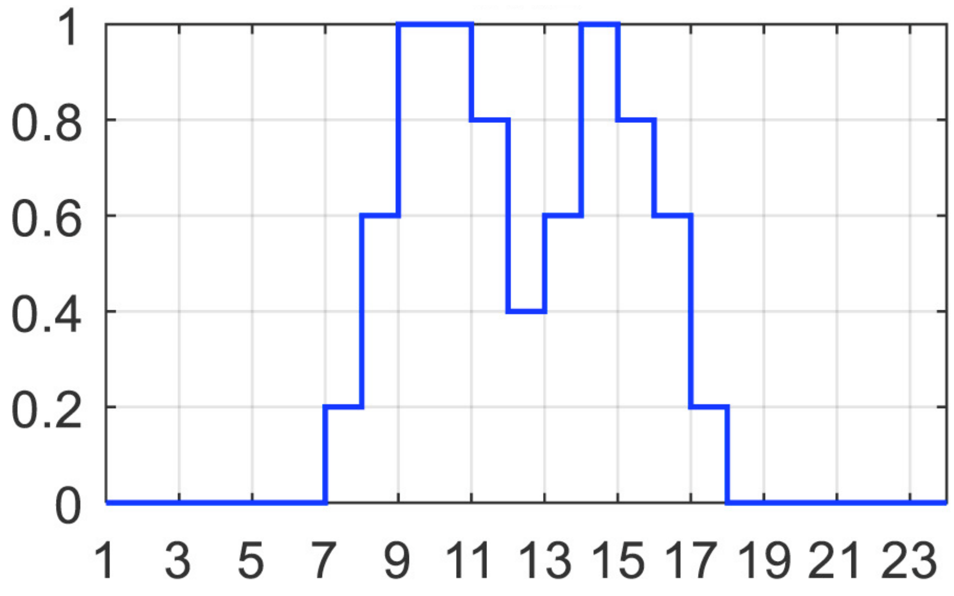
Incorporating OB in simulation

Models can be classified according to their ability to capture information as well as their complexity

Simulation framework	Type of model	Size	Resolution	Complexity
Conventional	Schedules	●	●	●
	Deterministic	●	↑	↑
	Non-probabilistic	●	↑	↑
	Probabilistic/stochastic	●	↑↑↑	↑↑↑
Agent-based	Agent-based stochastic	↑↑↑	↑↑↑	↑↑↑↑↑↑↑↑↑

(Source: Gaetani 2016)

Most common model: schedules



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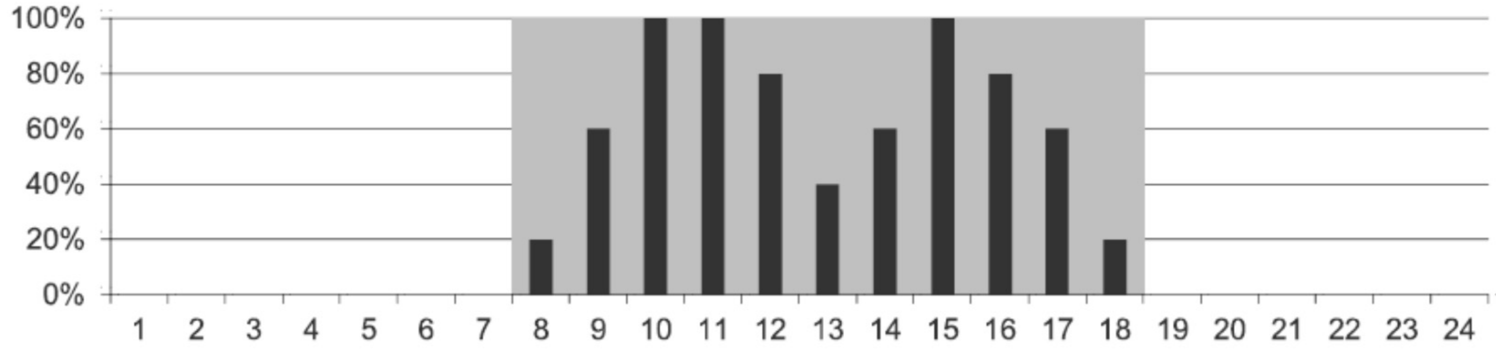
	Probabilistic/stochastic	●	↑↑↑	↑↑↑
Agent-based	Agent-based stochastic	↑↑↑	↑↑↑	↑↑↑↑↑↑↑↑↑

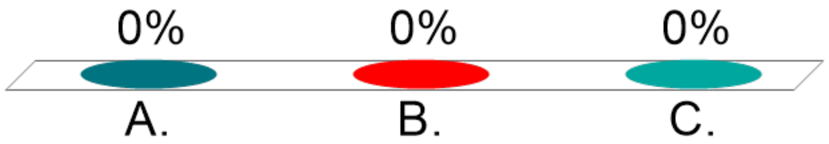
- A priori schedules represent the lowest level of complexity but are **commonly implemented** in energy simulation software
- Schedules are fractions from 0 to 1 that are used to multiply maximum quantities
  - People
  - Lighting loads
  - Equipment loads
- Schedules are usually **derived from standards** but can be derived from data

(Source: Gaetani 2016)

What kind of schedule is this?

A. Lighting schedule for residential buildings
B. Equipment use schedule in schools
C. Occupancy schedule in office

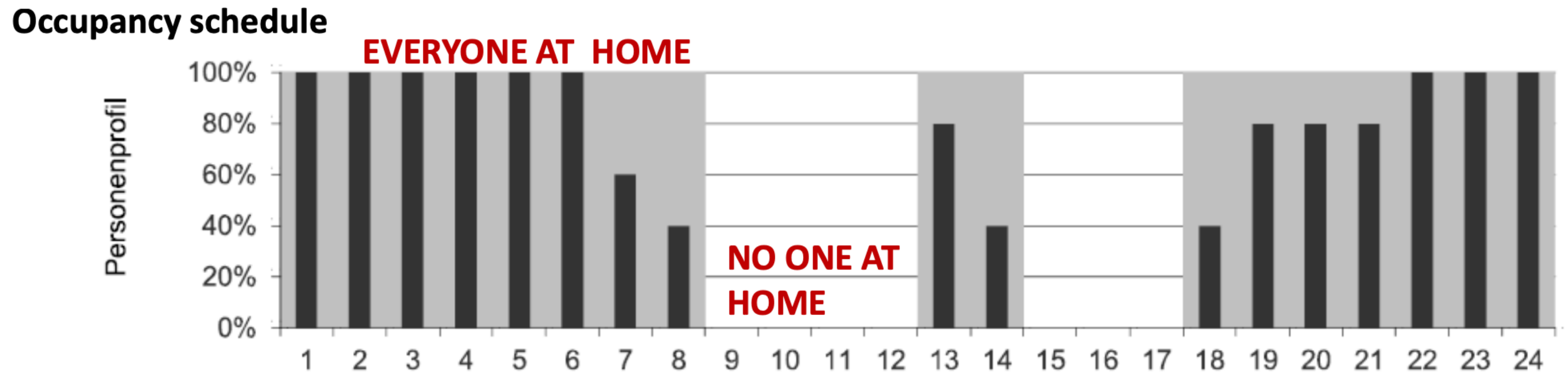


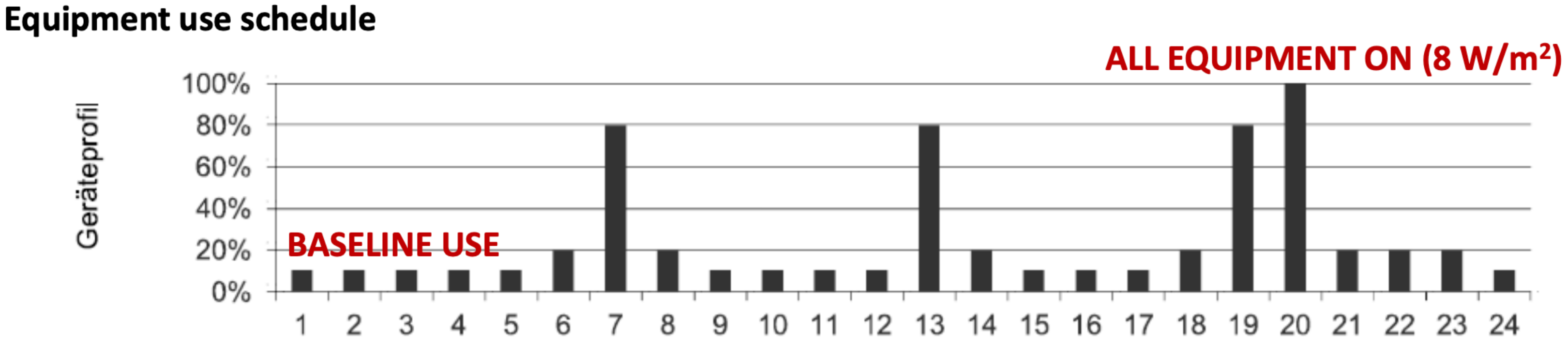


Response Counter

URL: **http://responseware.eu**
Session ID: **ETHOSMF**

Schedules: Multifamily buildings



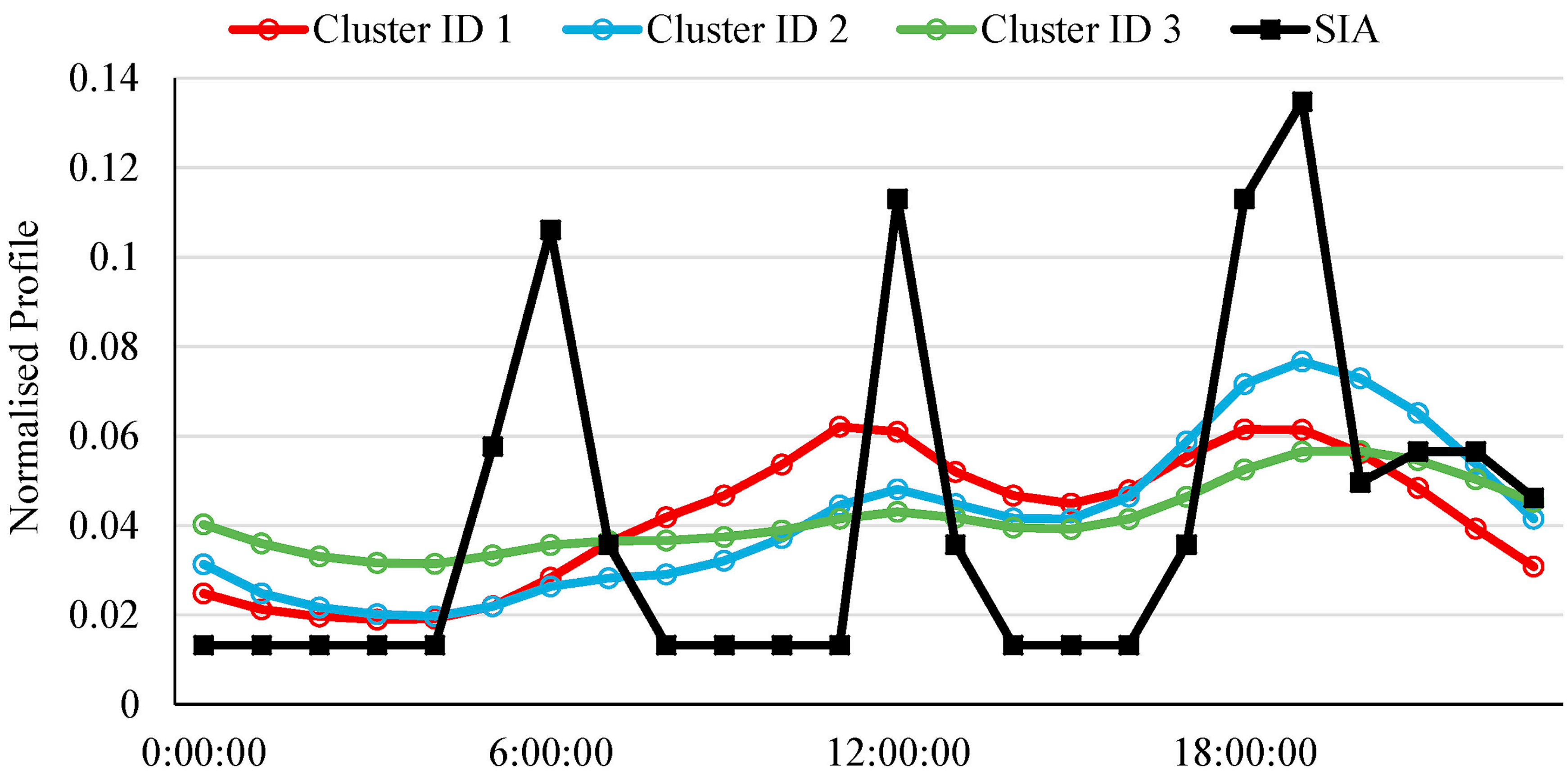


Lights: No schedule!

Standard indicates power density (2.7 W/m^2) and hours of usage:

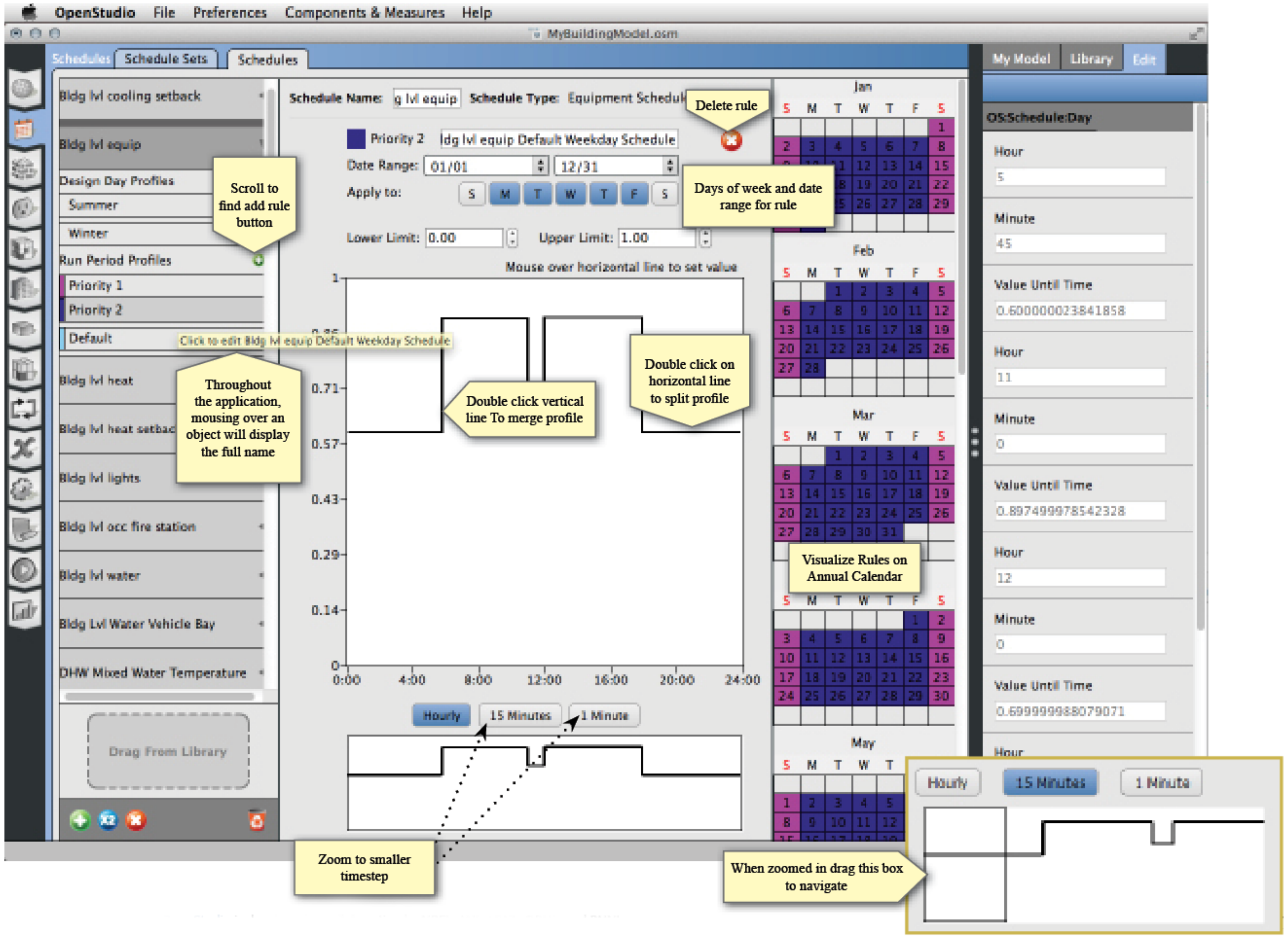
- Day time: 4 hours
- Night time: 3 hours

Standards vs reality: electricity use

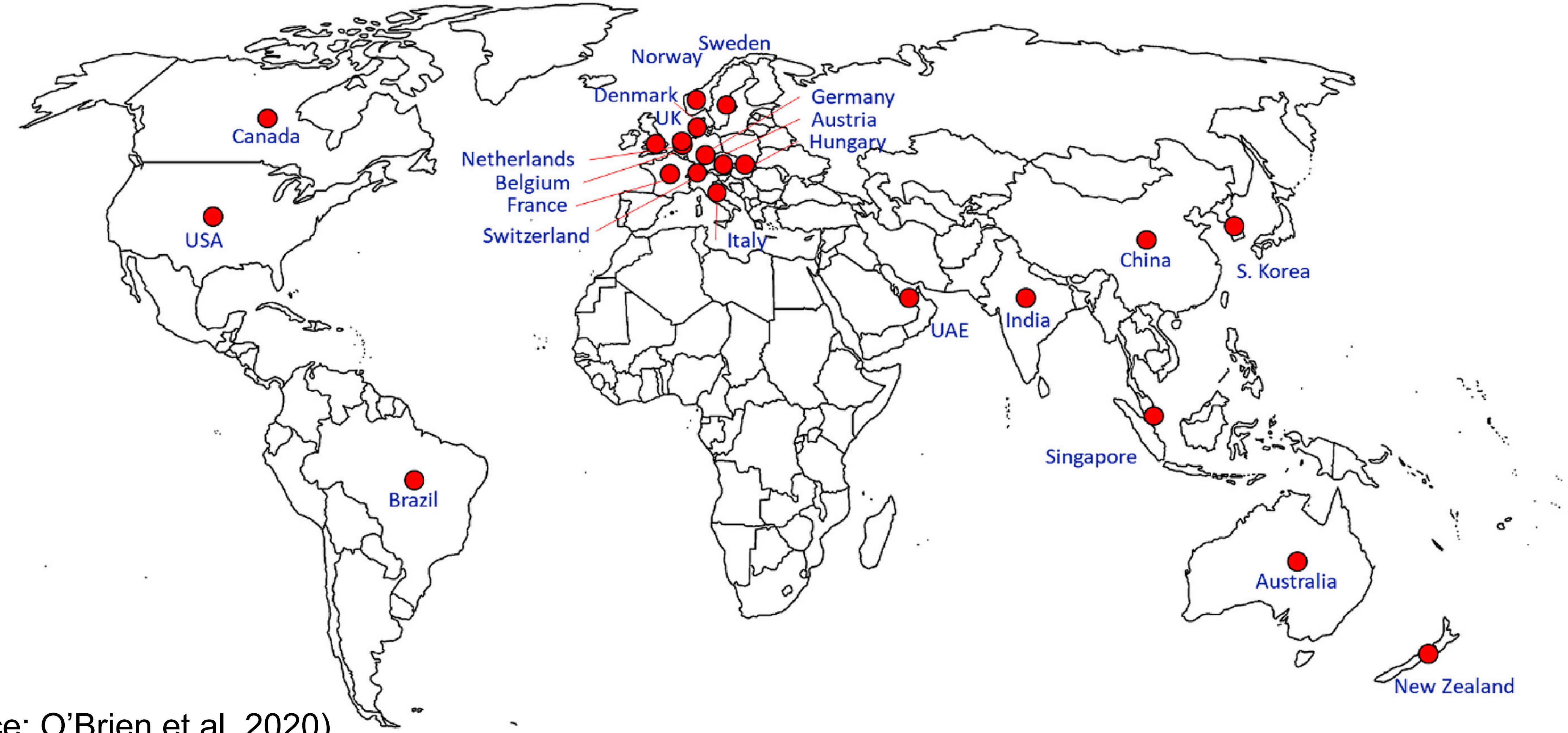


(Source: Yilmaz et al. 2018)

Example of working with schedules



Is there agreement on schedules?

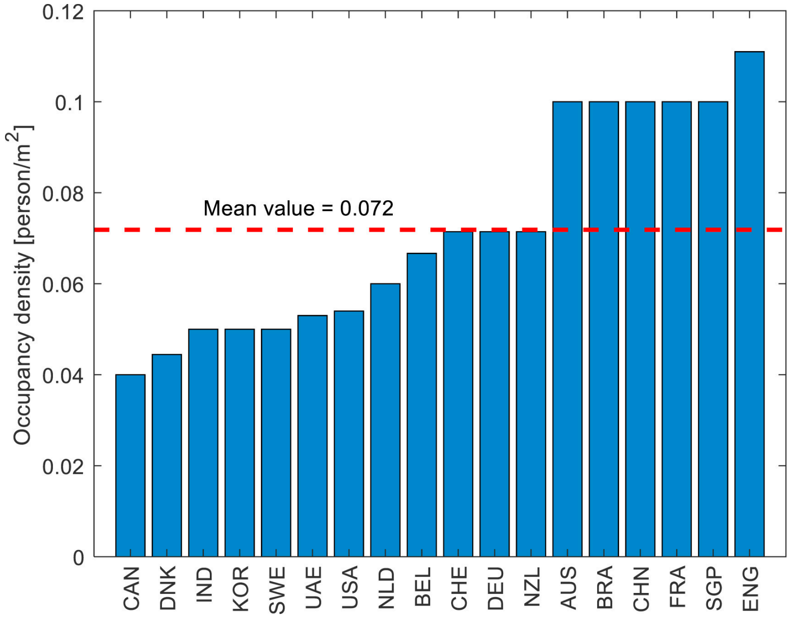


(Source: O'Brien et al. 2020)

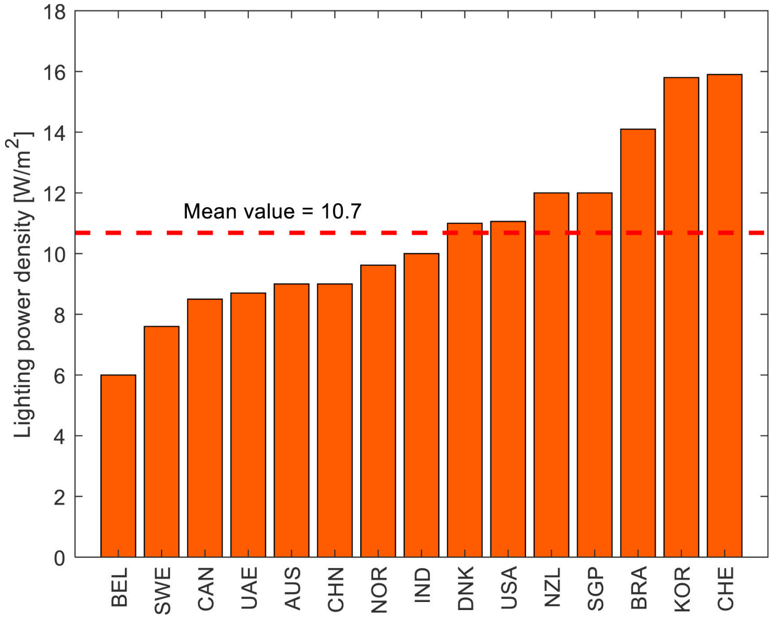
Is there agreement? Not really!

For offices:

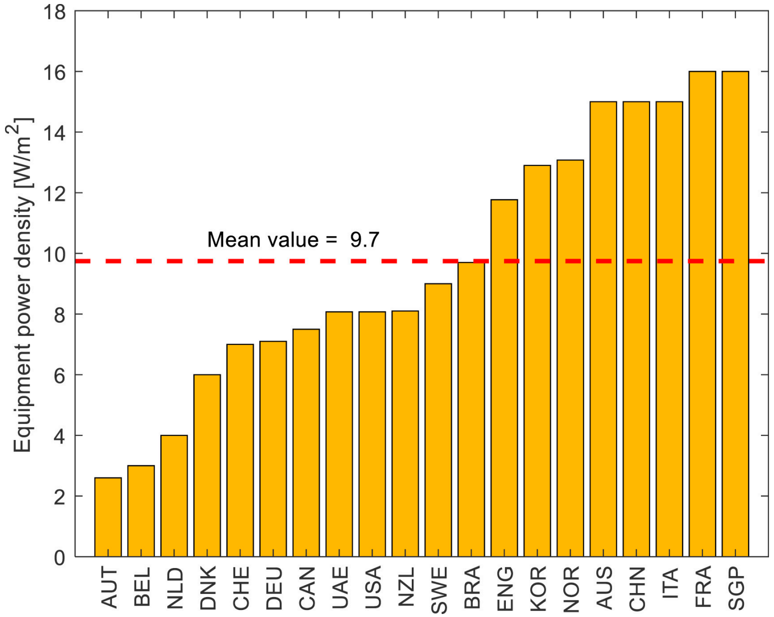
Occupancy density



Lighting power density

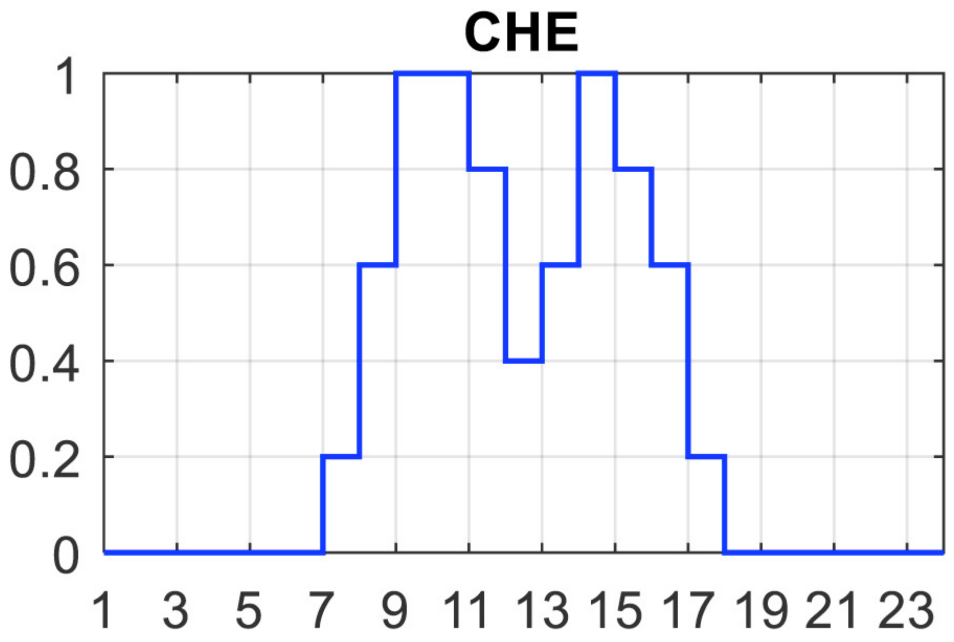


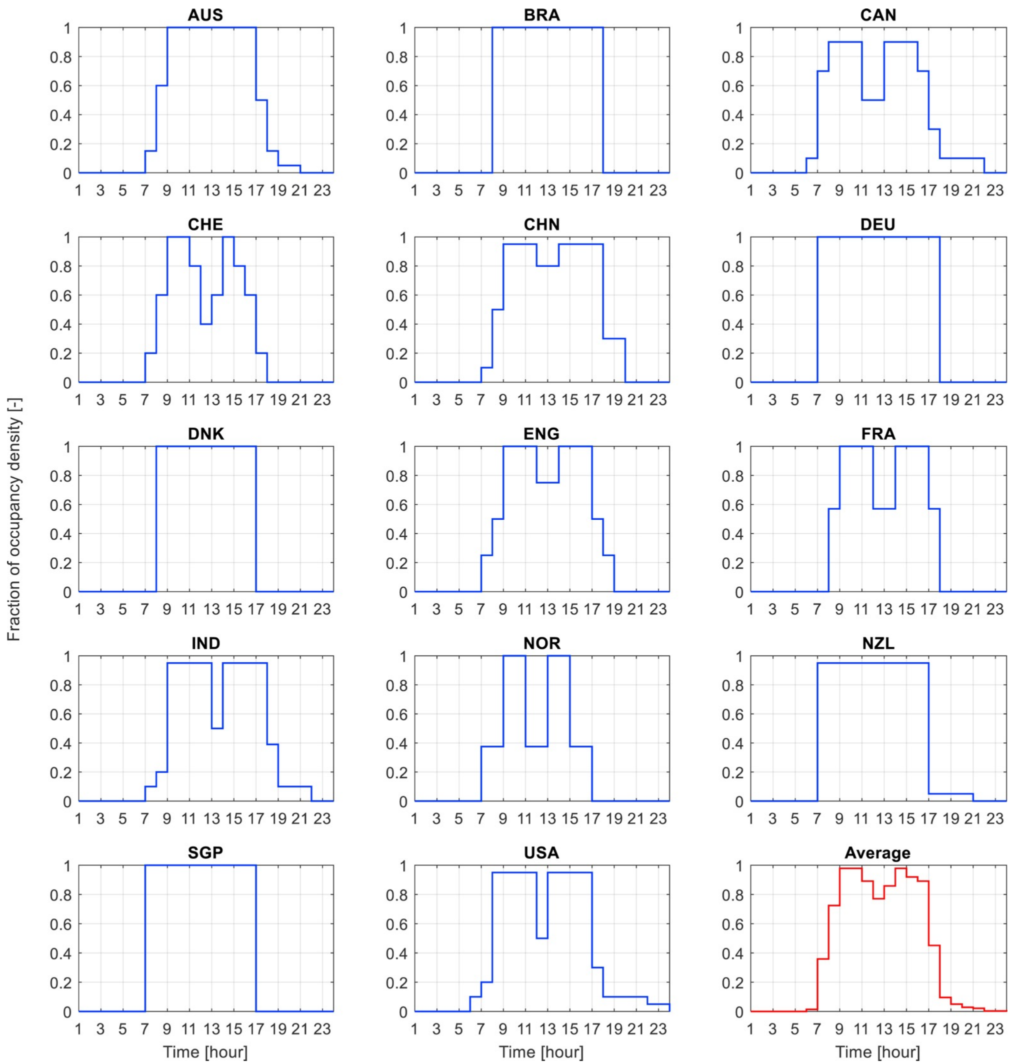
Equipment power density



(Source: O’Brien et al. 2020)

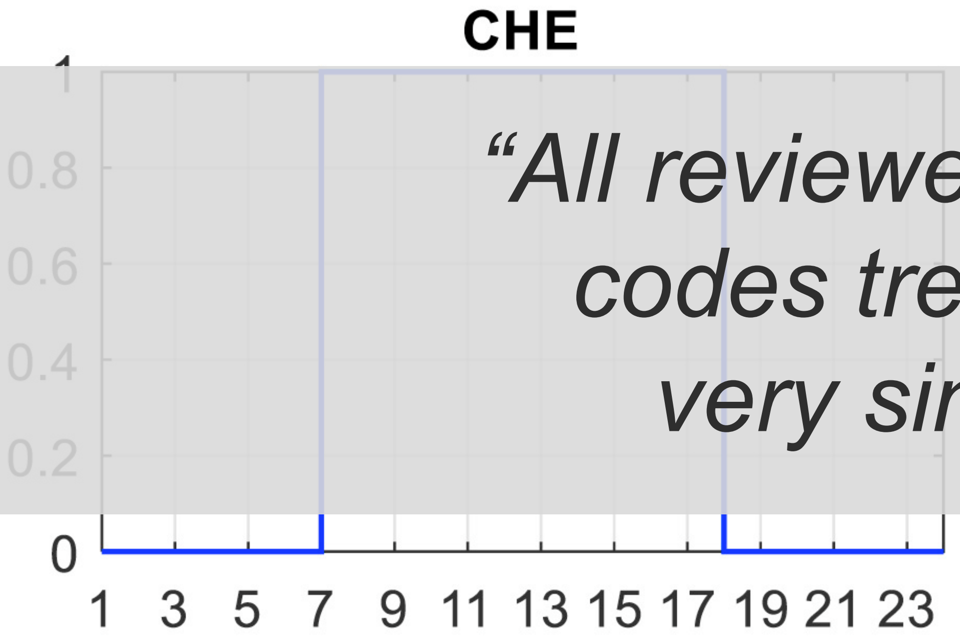
Office occupancy comparison

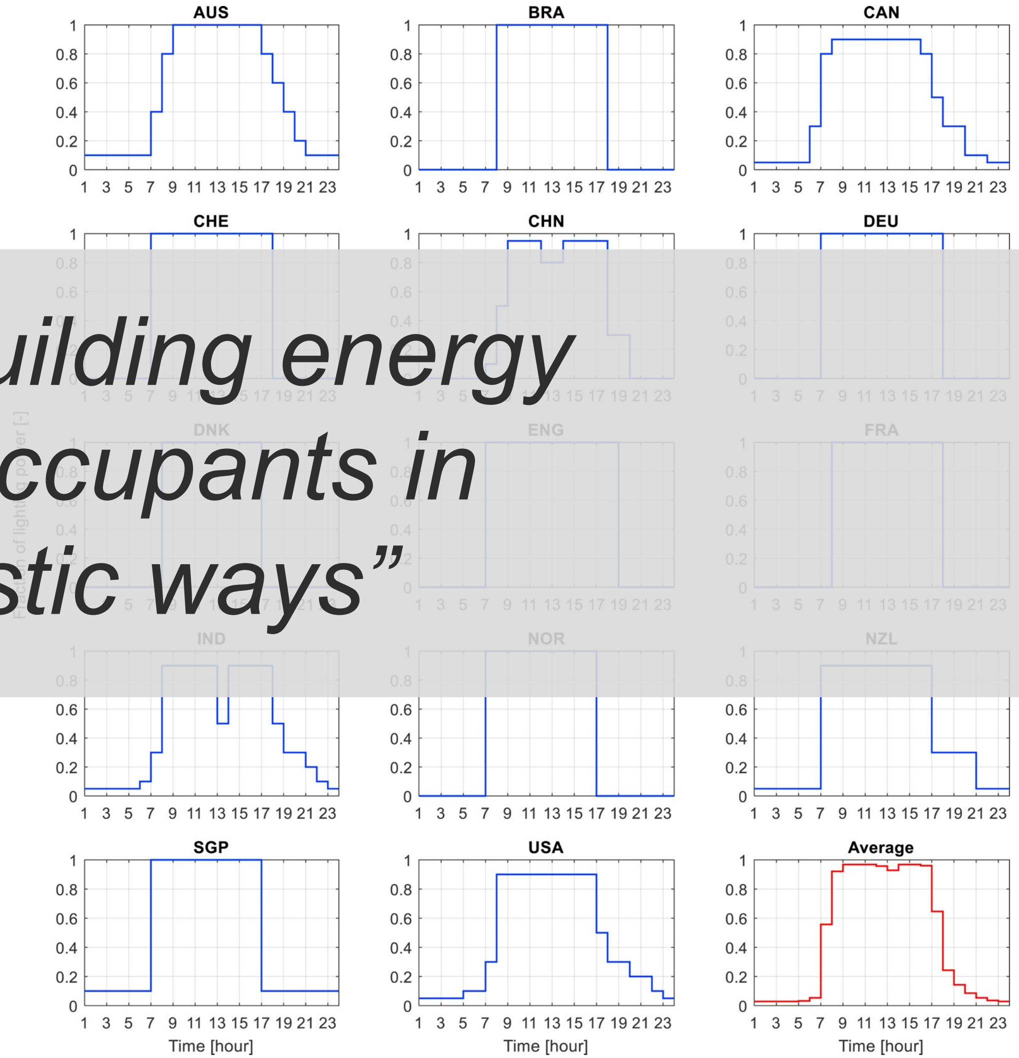




(Source: O'Brien et al. 2020)

Office lighting schedule comparison

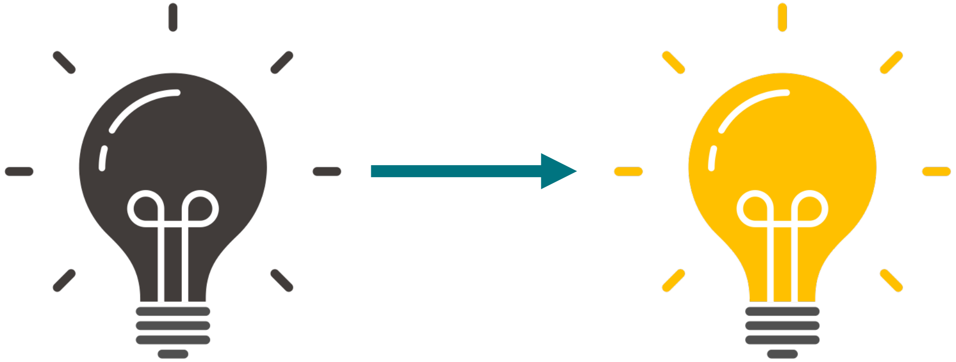




"All reviewed building energy codes treat occupants in very simplistic ways"

(Source: O'Brien et al. 2020)

Deterministic models



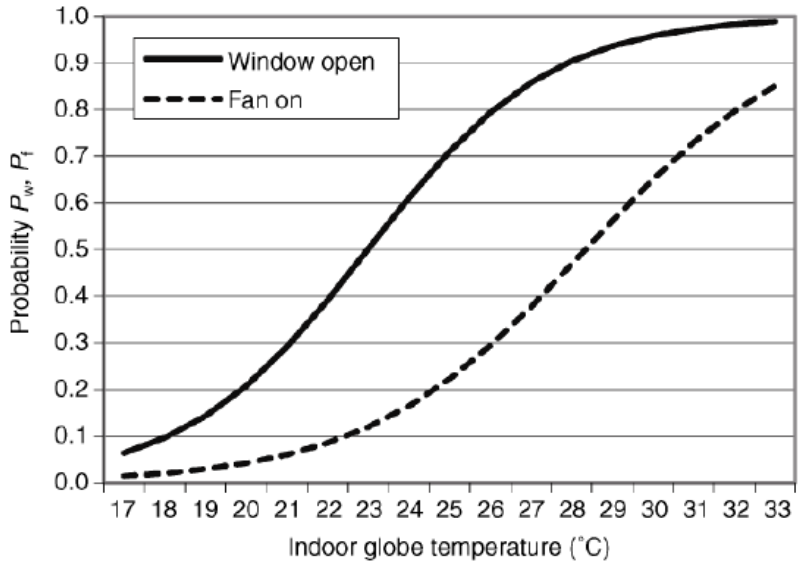
Example:
If indoor illuminance falls below 150 lux, lights are turned on

Simulation framework	Type of model	Size	Resolution	Complexity
Conventional	Schedules	●	●	●
	Deterministic	●	↑	↑
	Non-probabilistic	●	↑	↑
	Probabilistic/stochastic	●	↑↑↑	↑↑↑
Agent-based	Agent-based stochastic	↑↑↑	↑↑↑	↑↑↑↑↑↑↑↑↑

- Actions are modeled based on deterministic rules
- Direct consequence of one or more drivers
- They represent environments where modeled behavior is always **fully foreseeable and repeatable**

(Source: Gaetani 2016)

Probabilistic/stochastic models



Example: Probability of window opening and fan use as function of indoor temperature

Simulation framework	Type of model	Size	Resolution	Complexity
Conventional	Schedules	●	●	●
	Deterministic	●	↑	↑
	Non-probabilistic	●	↑	↑
	Probabilistic/stochastic	●	↑↑↑	↑↑↑
Agent-based	Agent-based stochastic	↑↑↑	↑↑↑	↑↑↑↑↑↑↑↑↑

- More recent
- Take into account the variability of human behavior
  - At certain conditions, some occupants will perform actions but not all
- More computationally expensive
  - Need to simulate multiple times
- Still difficult to implement in building energy simulation tools

(Source: Gaetani 2016)

Probabilistic models: Generalized Linear Models

0/1 outcome

probability of event

$$Y_i \sim \text{Bernoulli}(p_i)$$

$$f(p_i) = \underline{\alpha + \beta_X X_i}$$

$f(\,)$ maps probability scale to linear model scale

can take any real value

Expected value is some function of an additive ('linear') combination of parameters

f is the link function

Links parameters of distribution to linear model

f^{-1} is the inverse link function

$$Y_i \sim \text{Bernoulli}(p_i)$$

$$f(p_i) = \alpha + \beta_X X_i$$

$$p_i = f^{-1}(\alpha + \beta_X X_i)$$

Probabilistic models: Logistic regression

Bernoulli models most often use logit link

$$\text{logit}(p_i) = \log \boxed{\frac{p_i}{1 - p_i}}$$

'log odds'   odds

$$Y_i \sim \text{Bernoulli}(p_i)$$

$$\text{logit}(p_i) = \alpha + \beta_X X_i$$

$$p_i = \text{logit}^{-1}(\alpha + \beta_X X_i)$$

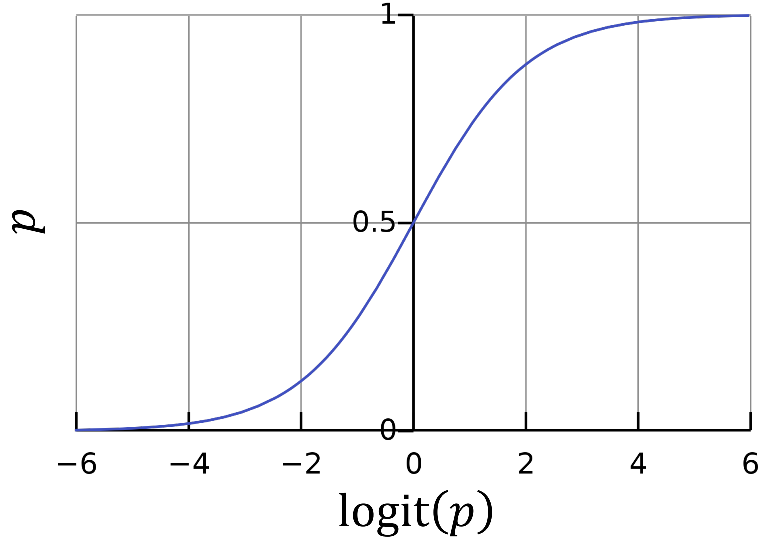
'logistic'

For calculation: $\eta_i = \alpha + \beta_X X_i$

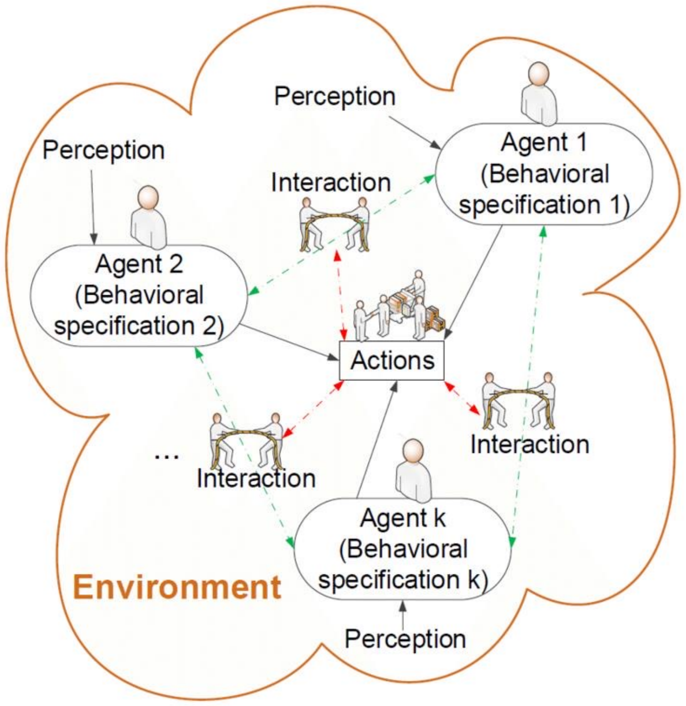
logit^{-1} or logistic

$$\text{logit}(p_i) = \eta_i \rightarrow \log\frac{p_i}{1 - p_i} = \eta_i \rightarrow p_i = \boxed{\frac{e^{(\eta_i)}}{1 + e^{(\eta_i)}}}$$

or $p_i = \dfrac{1}{1 + e^{-(\eta_i)}}$



Agent-based models



Simulation framework	Type of model	Size	Resolution	Complexity
Conventional	Schedules	●	●	●
	Deterministic	●	↑	↑
	Non-probabilistic	●	↑	↑
	Probabilistic/stochastic	●	↑↑↑	↑↑↑
Agent-based	Agent-based stochastic	↑↑↑	↑↑↑	↑↑↑↑↑↑↑↑↑

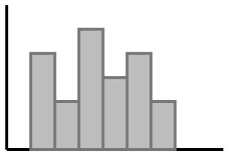
- Models the individual, not the group
- Very computationally expensive!
- Requires a lot of up-front information

(Source: Gaetani 2016)

OB in energy simulation

ACCURACY

STANDARD SCHEDULES



All the occupants interact with building devices according to **deterministic and static rules**

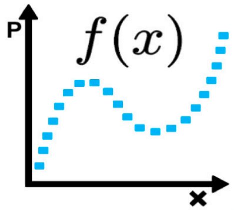
Example:
Windows are open only if indoor temperature is higher than both a fixed limit value and outdoor temperature.

USER TYPES
(active - medium - passive)
&
BEHAVIOUR STYLES
(conscious - normal - waster)

Interaction with devices and building systems is modelled according to different **frequencies of interactivity** and environmental (i.e. thermal and visual) preferences

Example:
Heating set-point is set at 18 °C for the energy saver, at 20 °C for the normal and at 22 °C for the waster.

BEHAVIOURAL MODELS



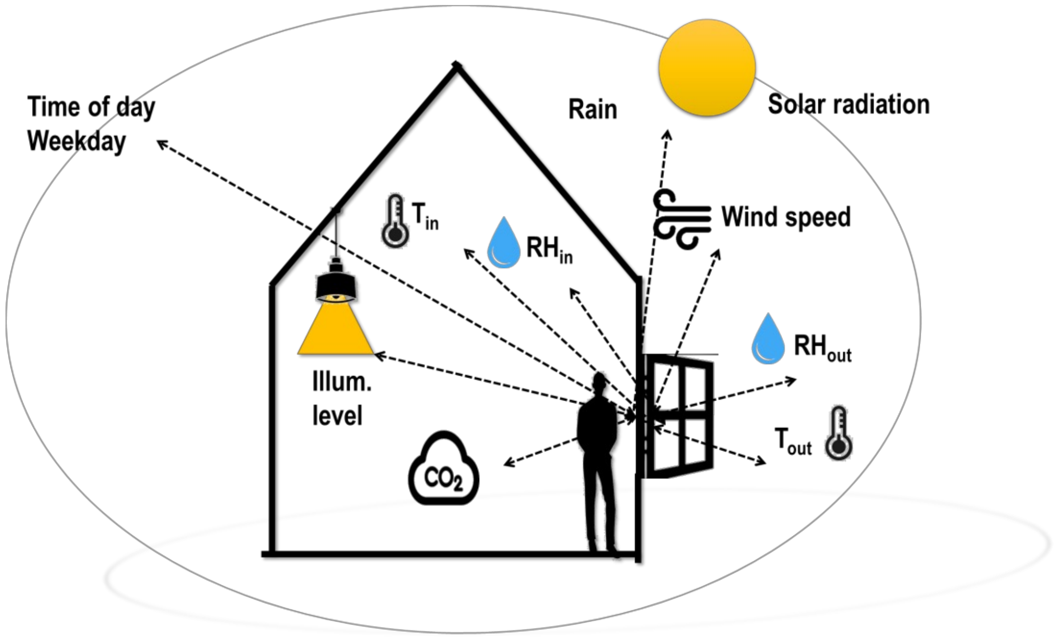
Models, developed using data from the real life, that predict the **occurrence probability** (p) of an action in relation to one or more predictors (x_1...x_n) (e.g. environmental, time-related)

Example:
Light-switching probability is calculated in function of illuminance levels; then whether the probability is higher than a random number generated from a uniform distribution, the action occurs

(Source: Naspi et al. 2018)

OB models – why?

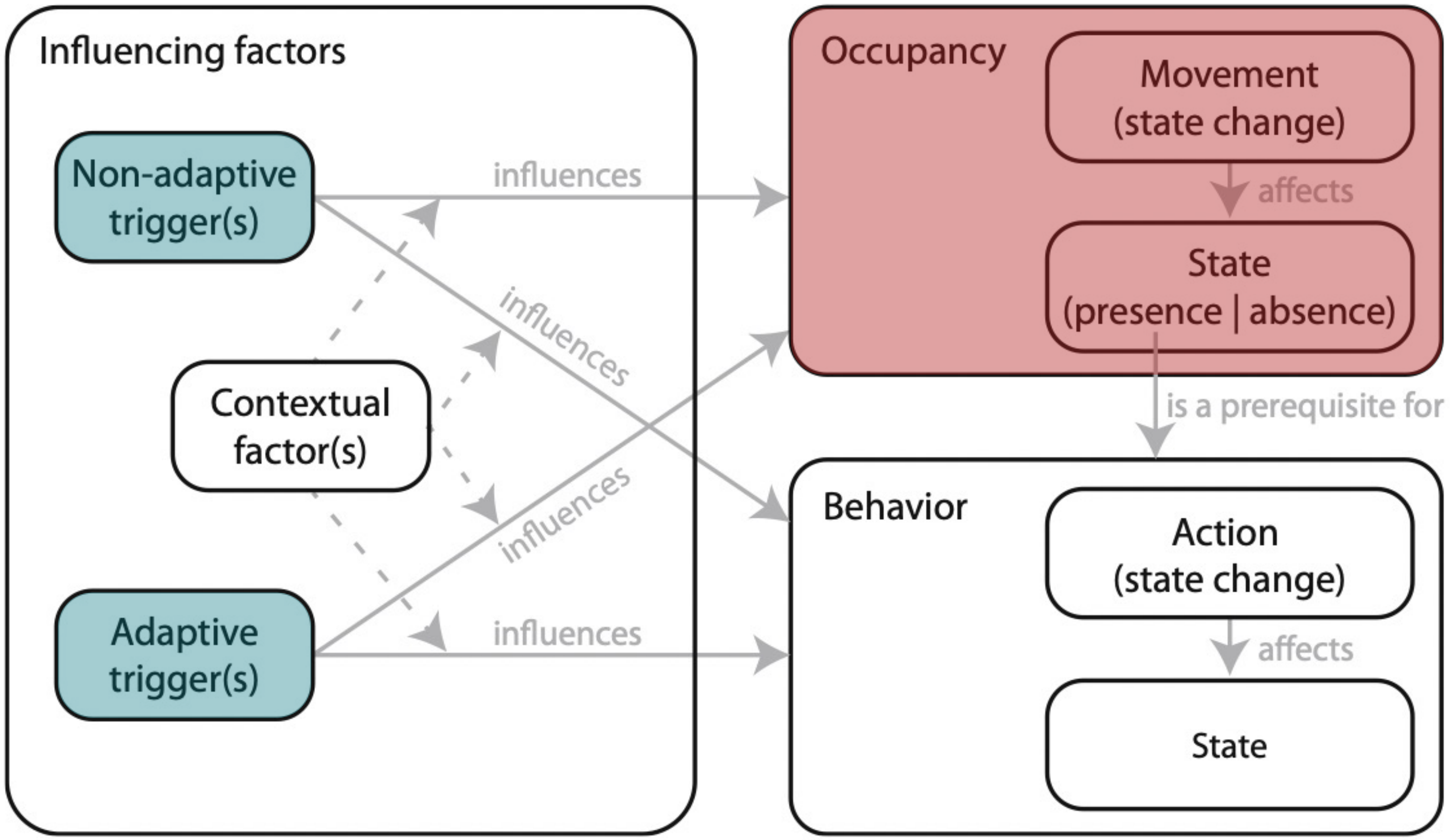
- Understand driving forces for behavior itself
- Understand link between behavior and energy consumption
- Move toward occupant-centric building design and operation



To build a good model, we need <u>good</u> data!!

How can we collect OB data?

Two challenges



- No occupancy, no action
- Need data on occupancy

- Actions involve building features and environmental conditions
- Need environmental and operation data

(Source: Annex 66 final report)

How to collect data?

In situ

Laboratory

Survey

Virtual reality

(Source: Annex 66 final report)

In situ studies

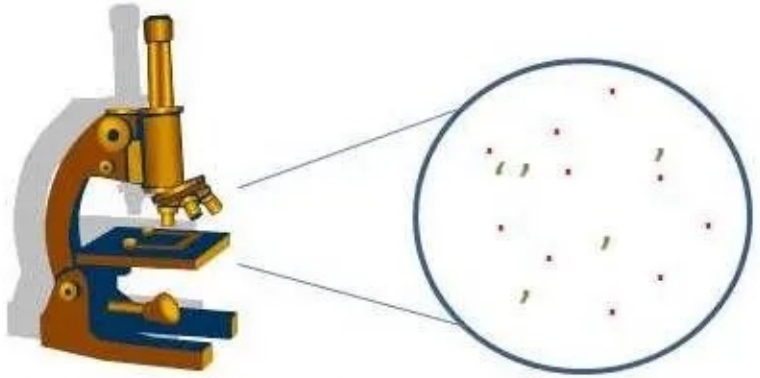
- In situ – literally “on site” in Latin
- Involves monitoring occupants in their natural environment
- Data acquired through sensors

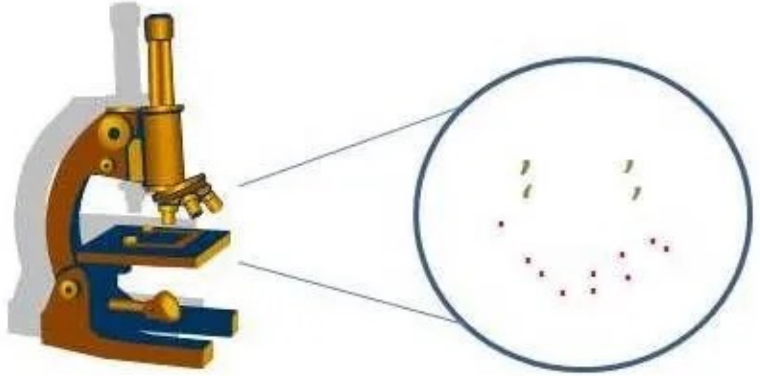
+ Use existing conditions
+ Reduce Hawthorne effect (next slide)
– Lack of flexibility / experimentation
– Ethical issues

Hawthorne effect

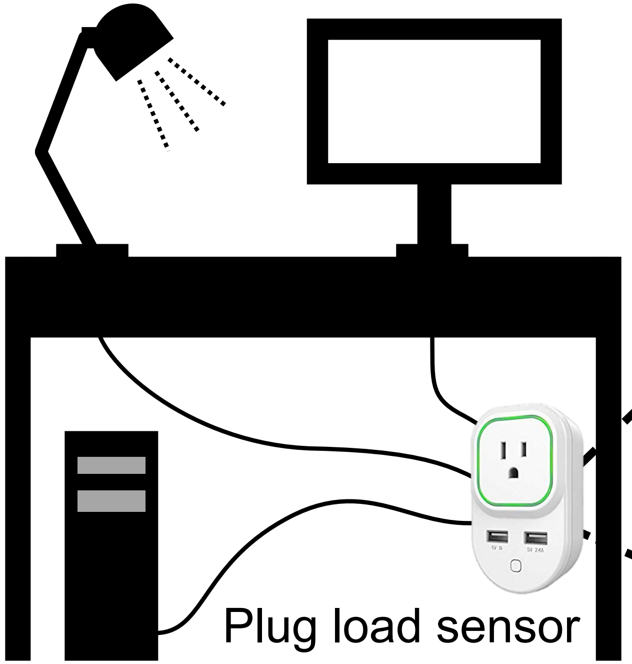
- People act differently when they know they are being observed

- Thought to be unavoidable but reduceable

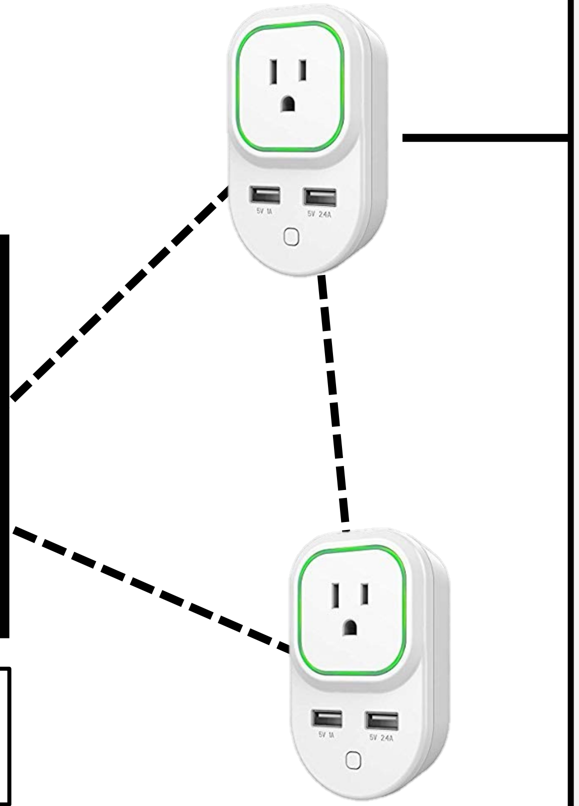


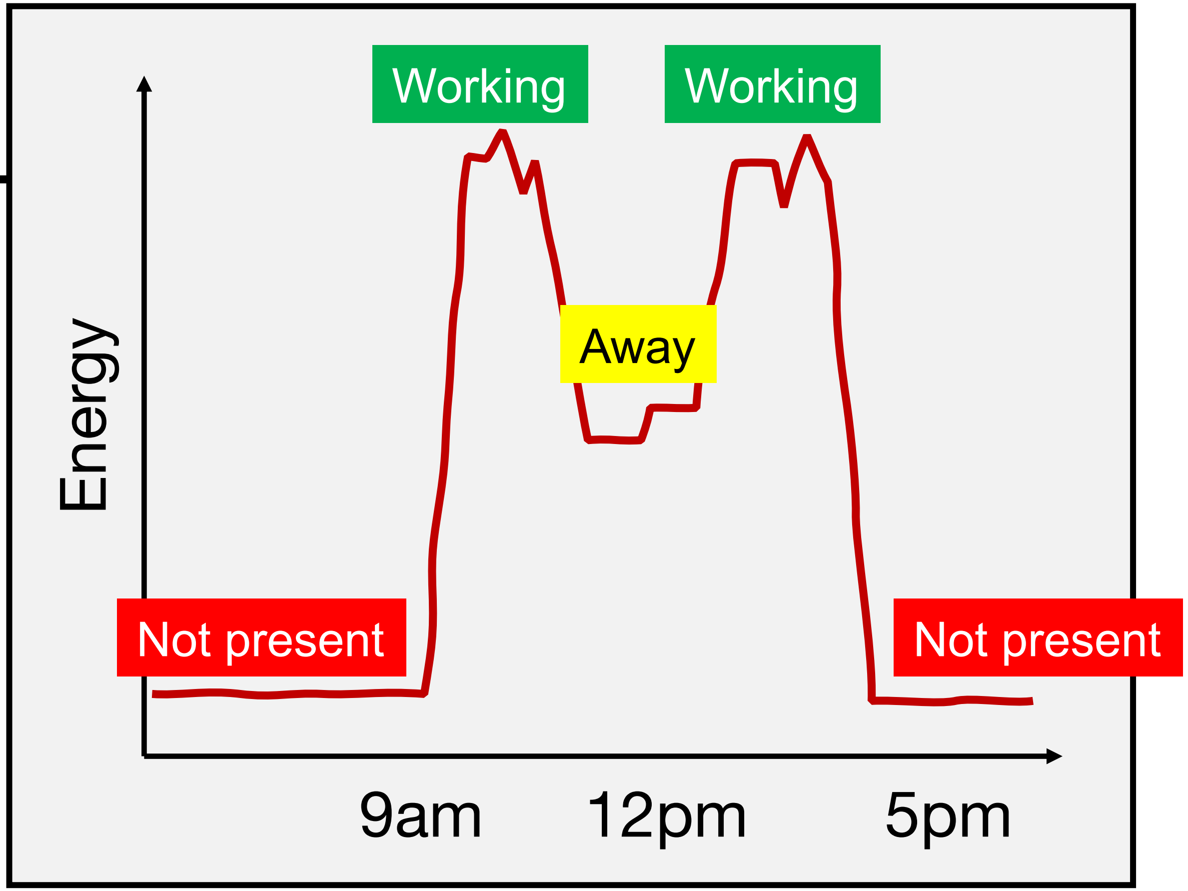


Example from my research

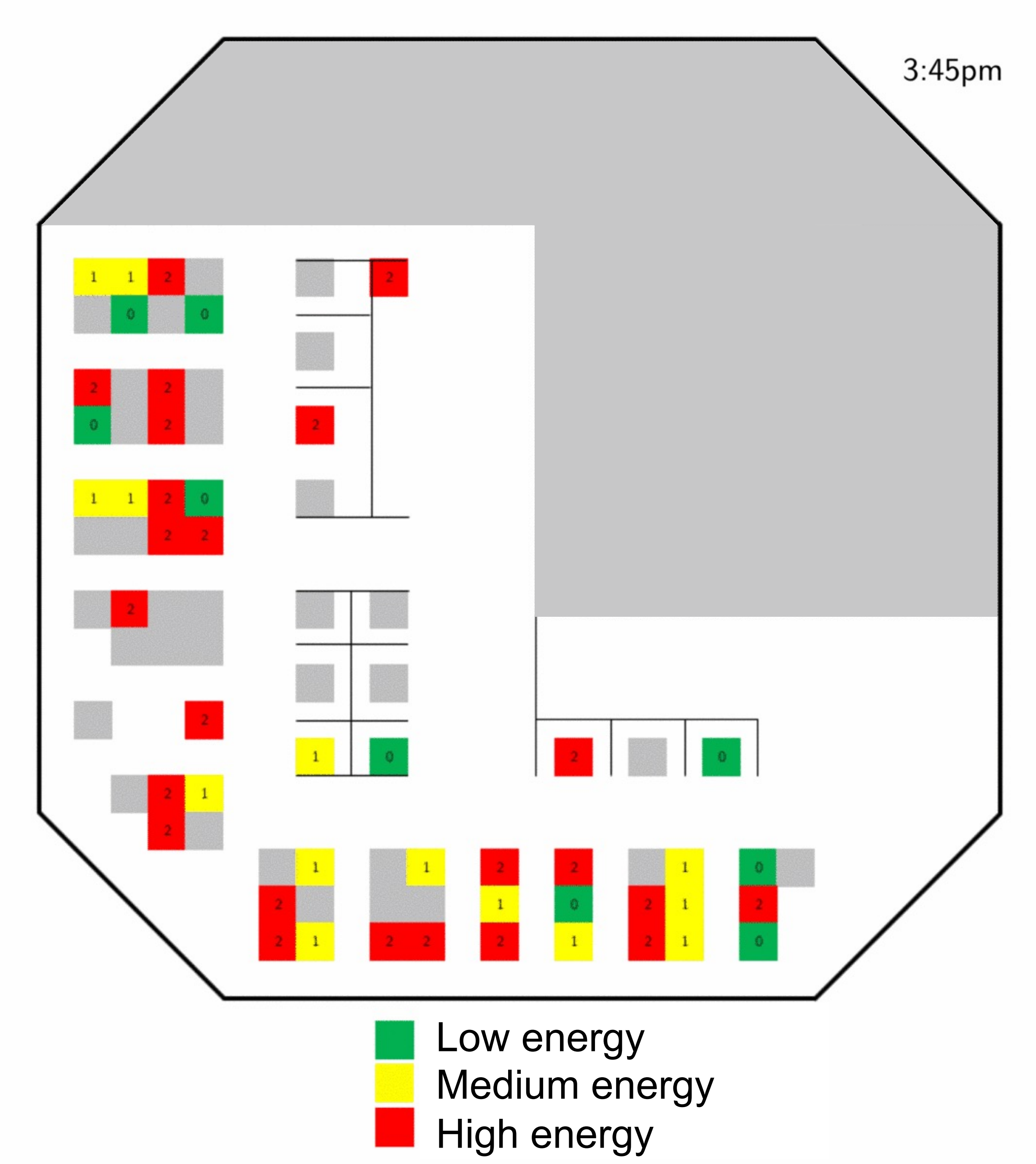


- Stored on device
- Wireless transmission





Activity States Visualized
(Real office in San Francisco)



Key benefits:

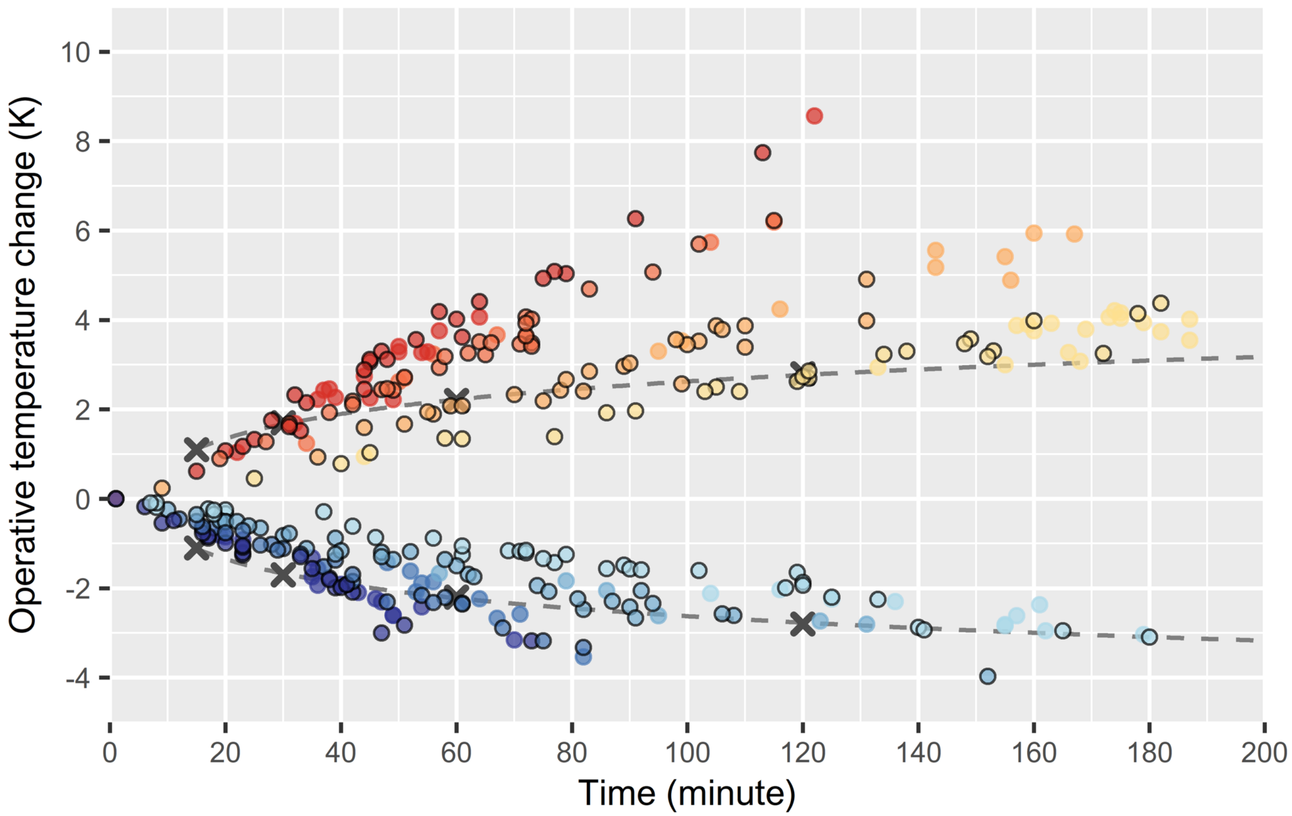
- Real-time (15-min)
- Spatial granularity
- Provides additional information beyond presence/ absence

Laboratory studies

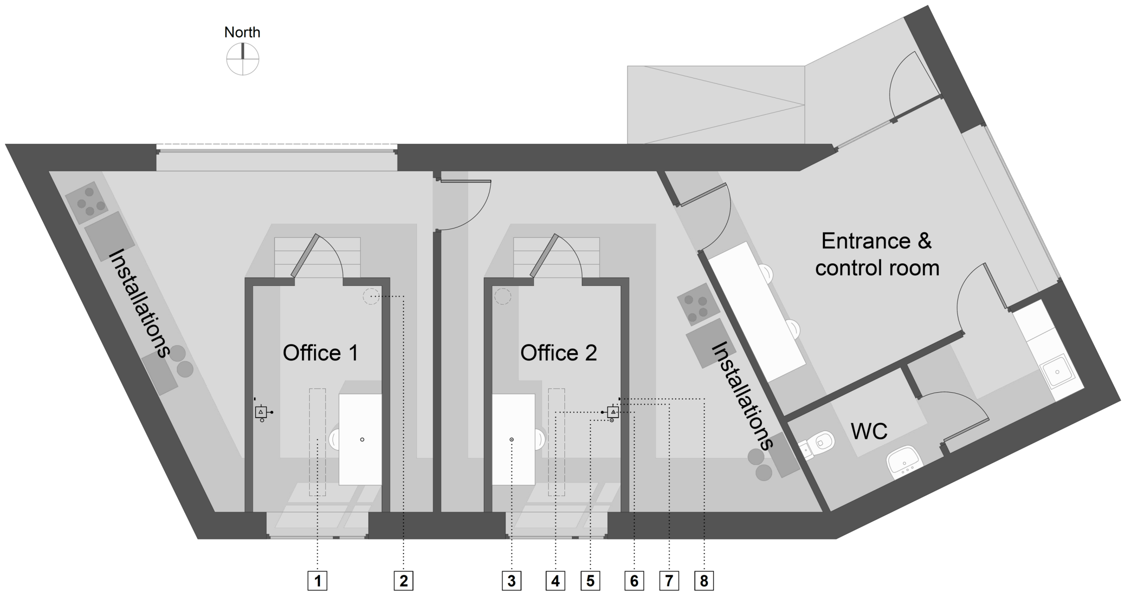
- Occupants interact with fabricated environment designed specifically for studies
- Look like real environments but heavily equipped with sensors/controls

+ High control
+ Flexibility in recruiting participants
– Costly
– More subject to Hawthorne effect

Example from Matteo's research



Thermal discomfort event



1 Air supply diffuser
2 Air extraction duct
3 Horizontal illuminance
4 Globe temperature
5 Vertical illuminance
6 Air temperature
7 Airspeed
8 CO_2 and relative humidity

Floor plan of the facility

Surveys

- Occupants self-report behaviour
- Can involve questionnaires, interviews, or focus groups

\+ Can measure things sensors can't

\+ Cost-effective

– Hawthorne effect / social desirability effect (conscious or unconscious)

– Hard to get frequent input

Survey innovation

Paper-based

Interview

Less-intrusive applications:
- Mobile apps
- Smart watches

Virtual reality

- Occupants immersed in virtual environments

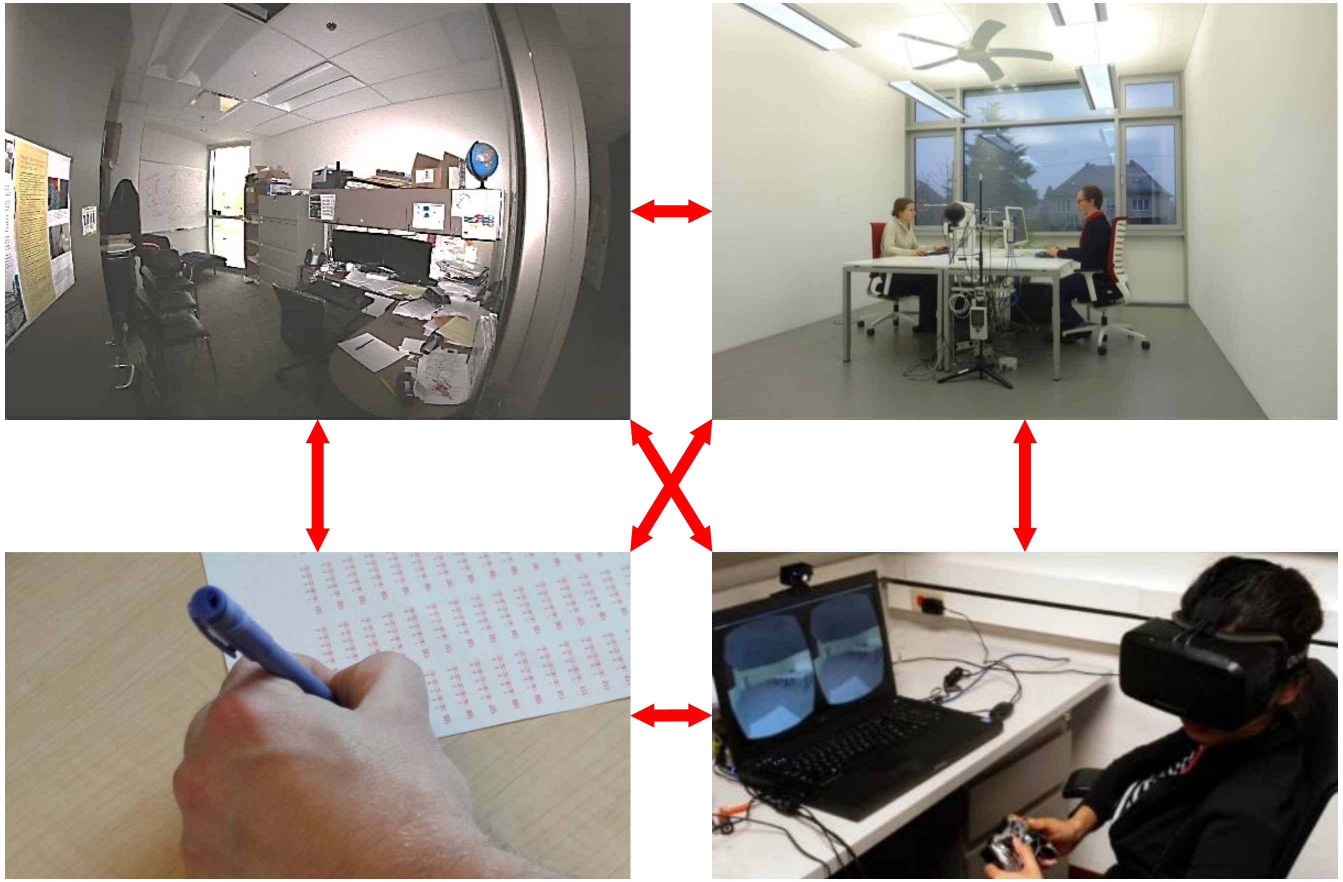
+ Can test different settings without actually building new things

+ Useful for building prototypes

– It's not real

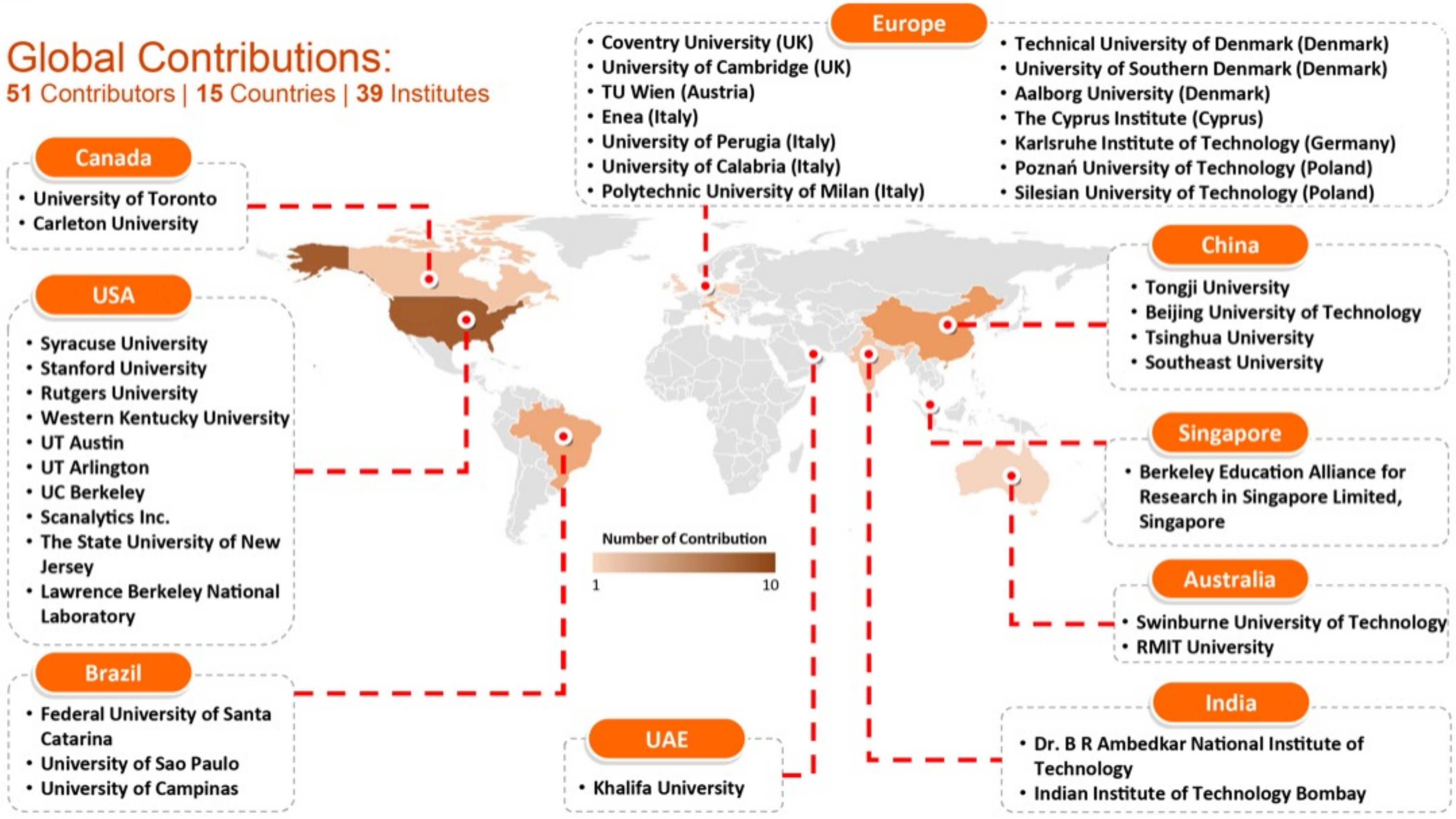
– Can't be used to study indoor environmental quality

Can always combine (Mixed methods)



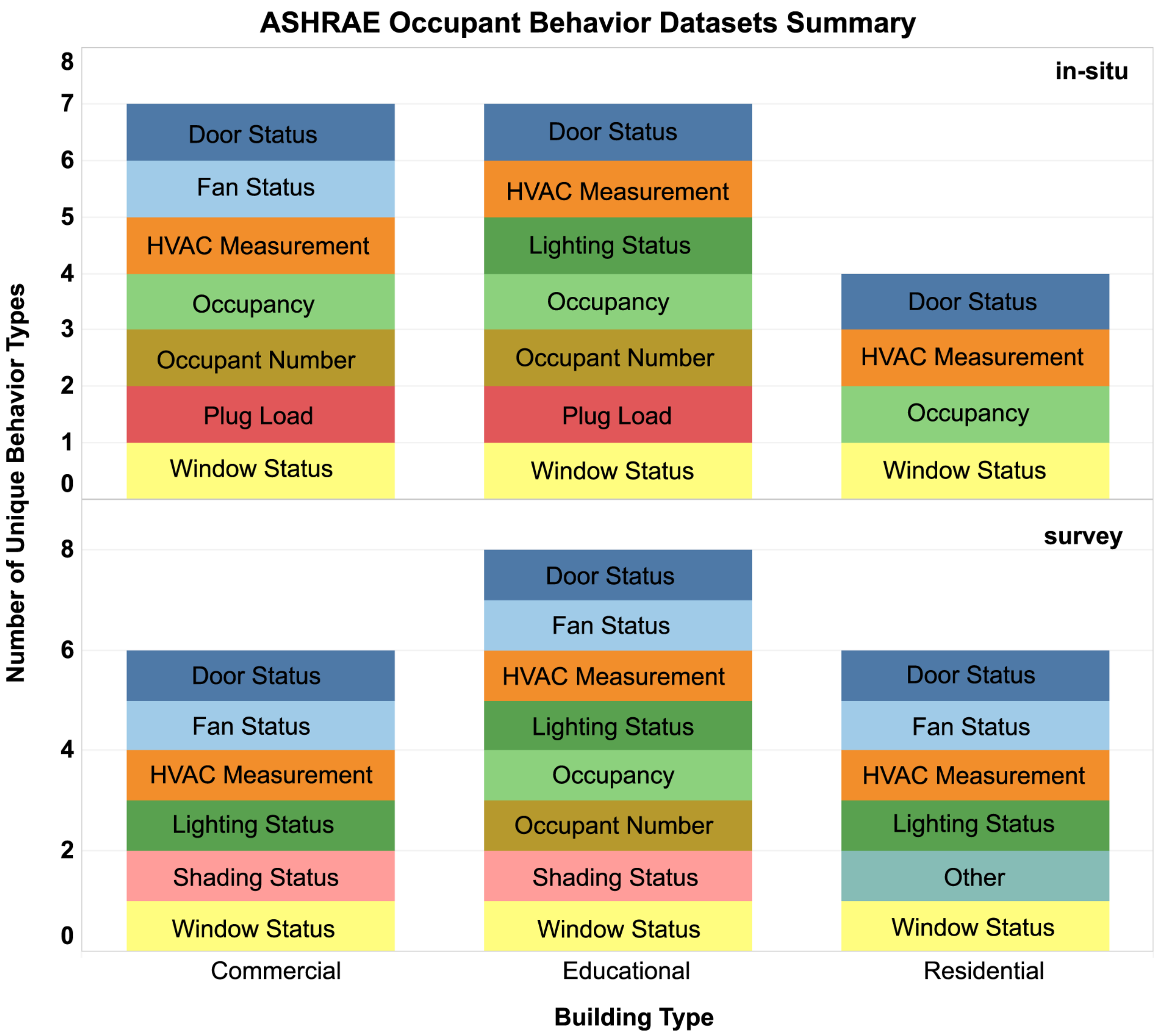
(Source: Annex 66 final report)

ASHRAE Global OB Database



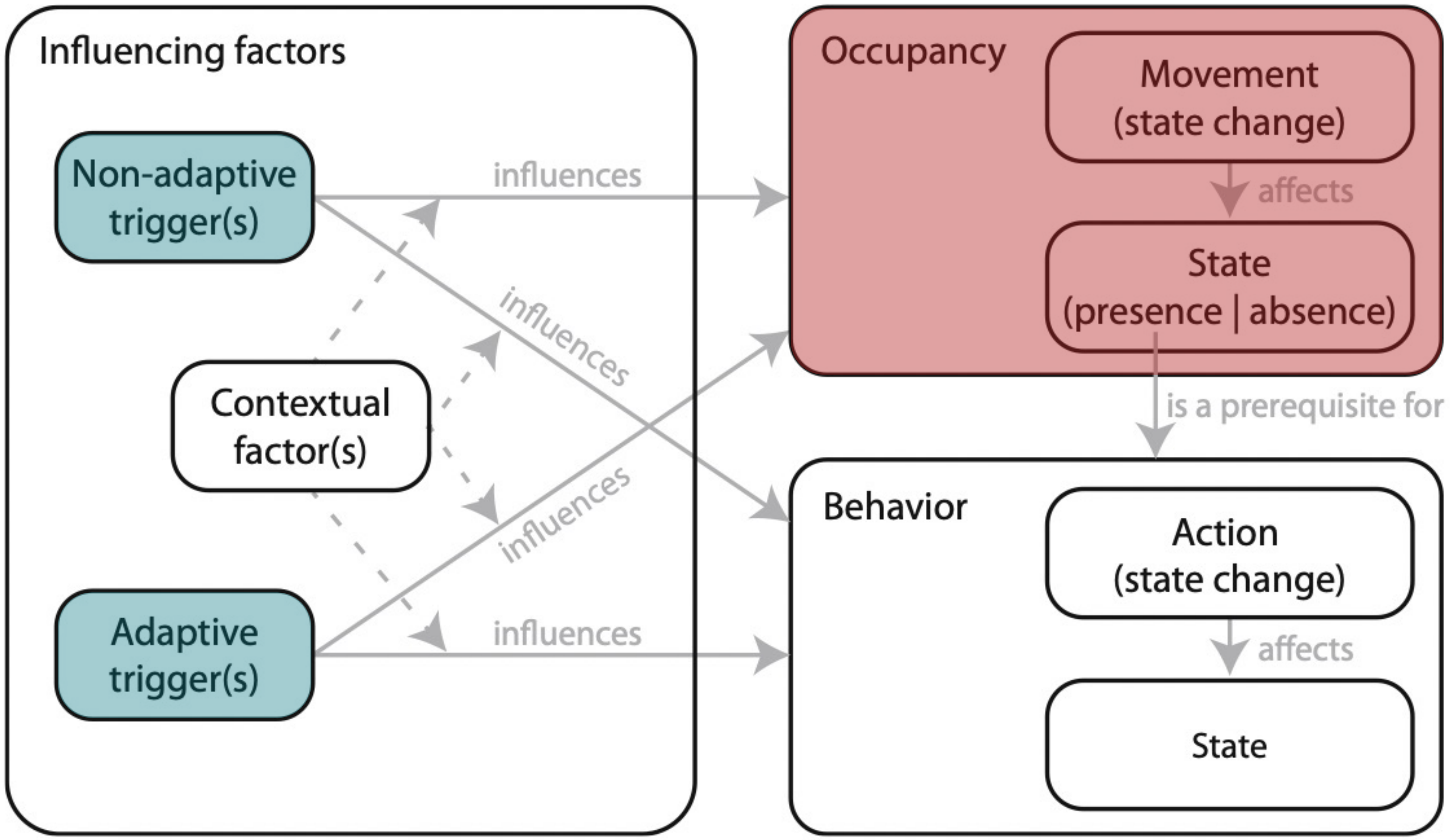
(https://ashraeobdatabase.com)

ASHRAE Global OB Database



(https://ashraeobdatabase.com)

Two challenges



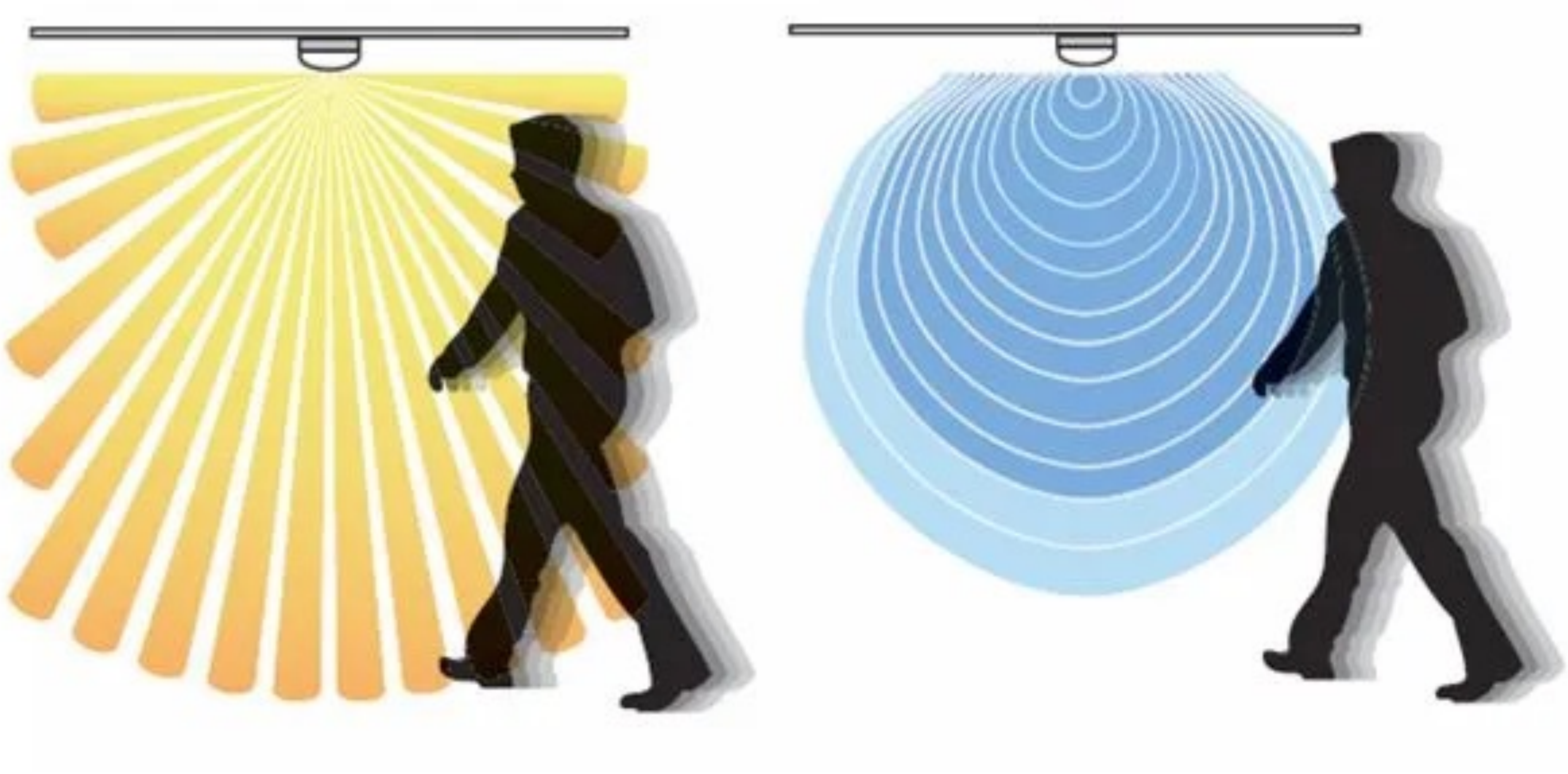
- No occupancy, no action
- Need data on occupancy

- Actions involve building features and environmental conditions
- Need environmental and operation data

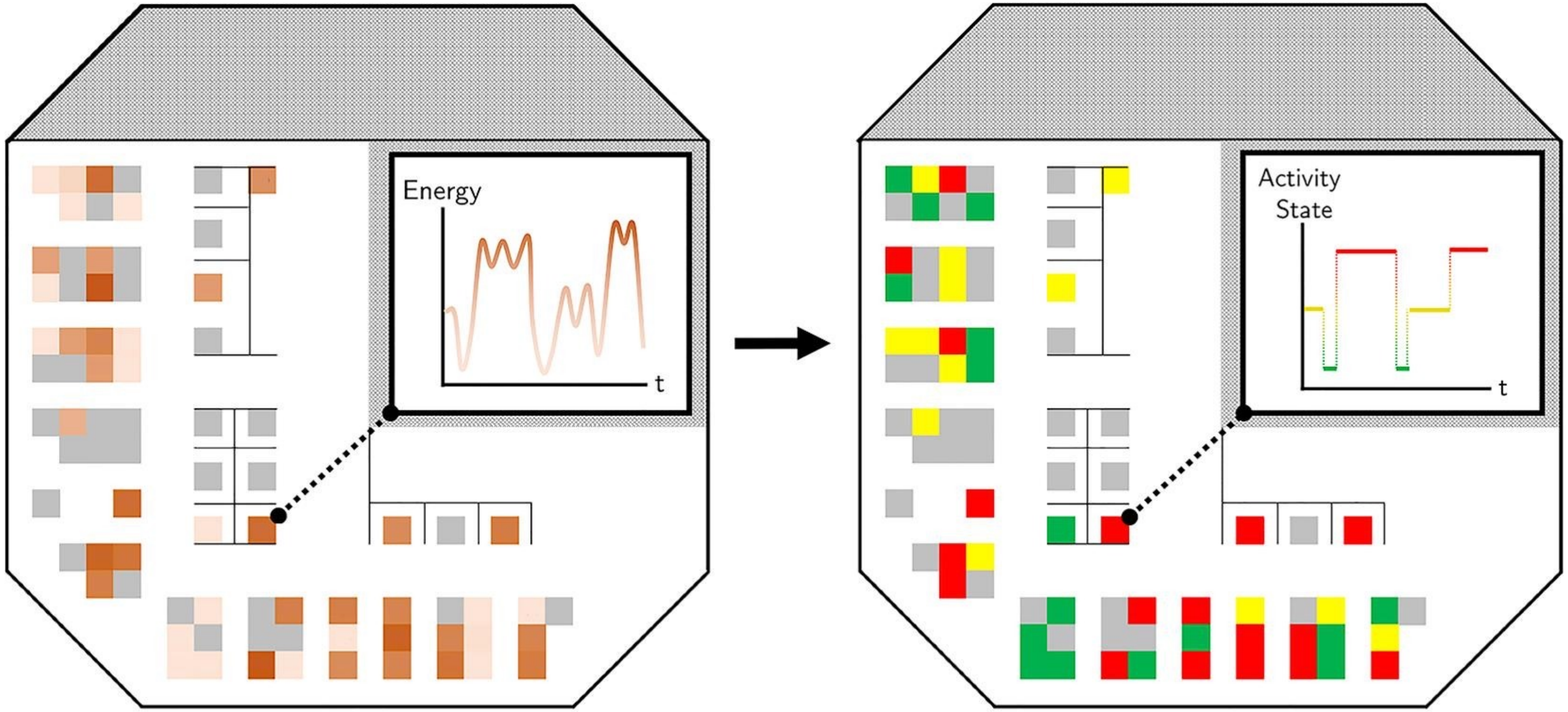
(Source: Annex 66 final report)

Occupant presence monitoring: PIR

Passive infrared (PIR) sensor (motion detection)



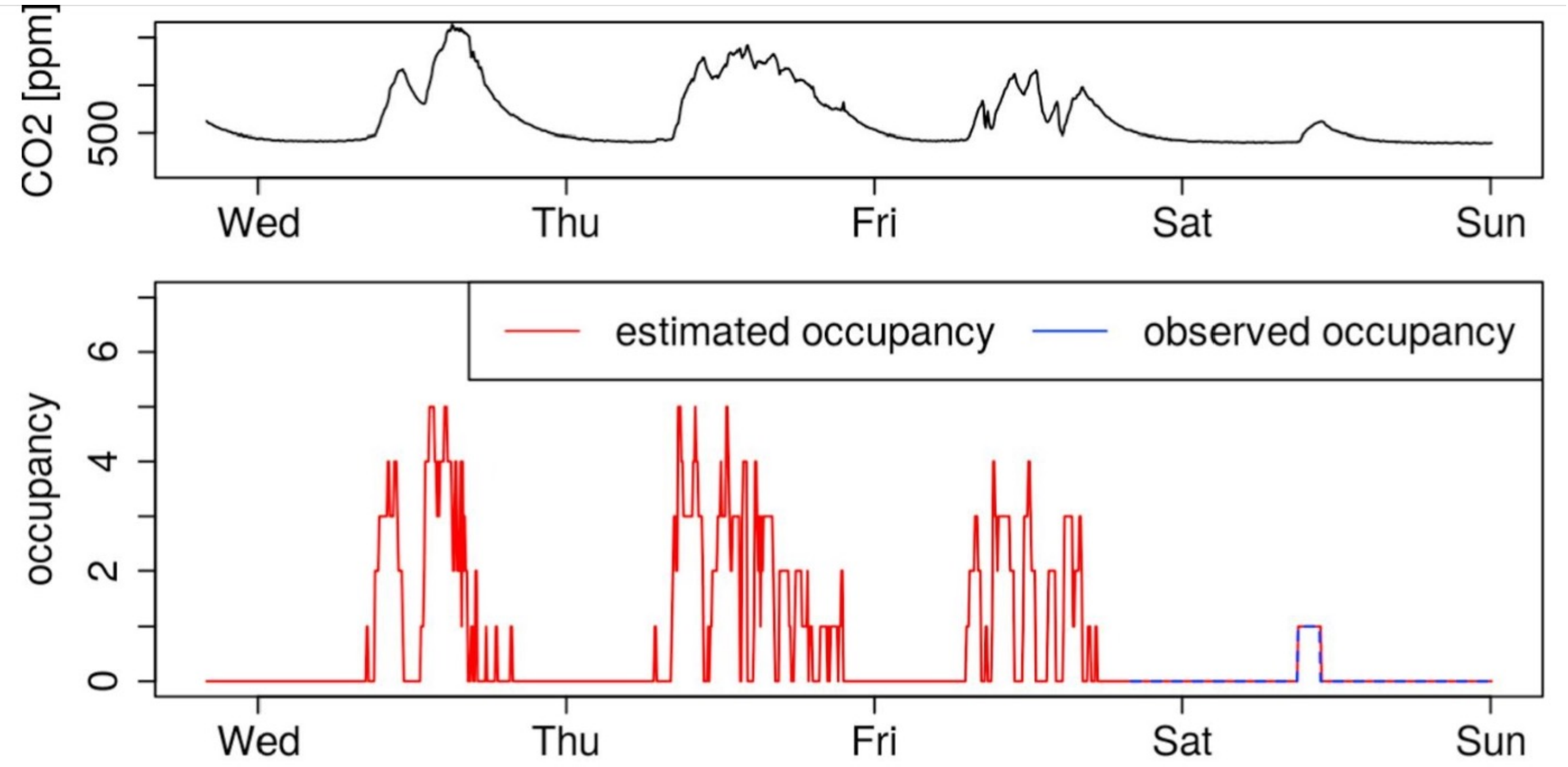
Occupant presence monitoring: Plug loads



Plug load energy consumption at occupants' workstations

Occupant activity state classification

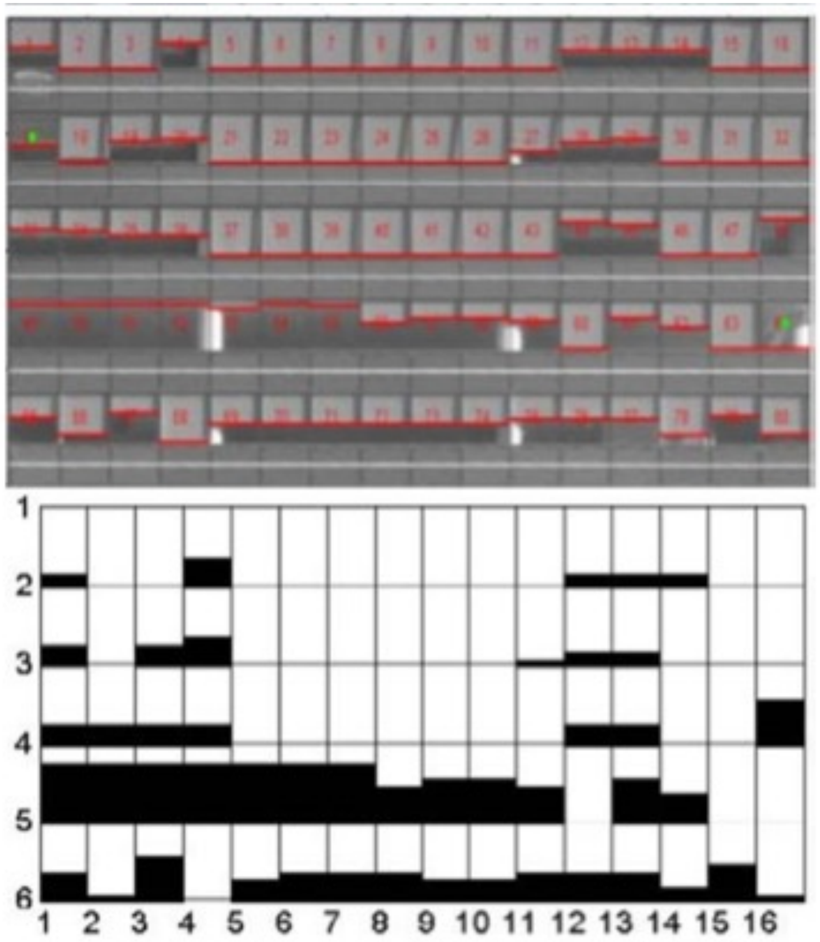
Occupant presence monitoring: CO_2



(Source: Wolf et al. 2019)

Window sensors

Tracking blind control with time-lapse cameras



(Source: Kapsis et al. 2013)

Plug loads

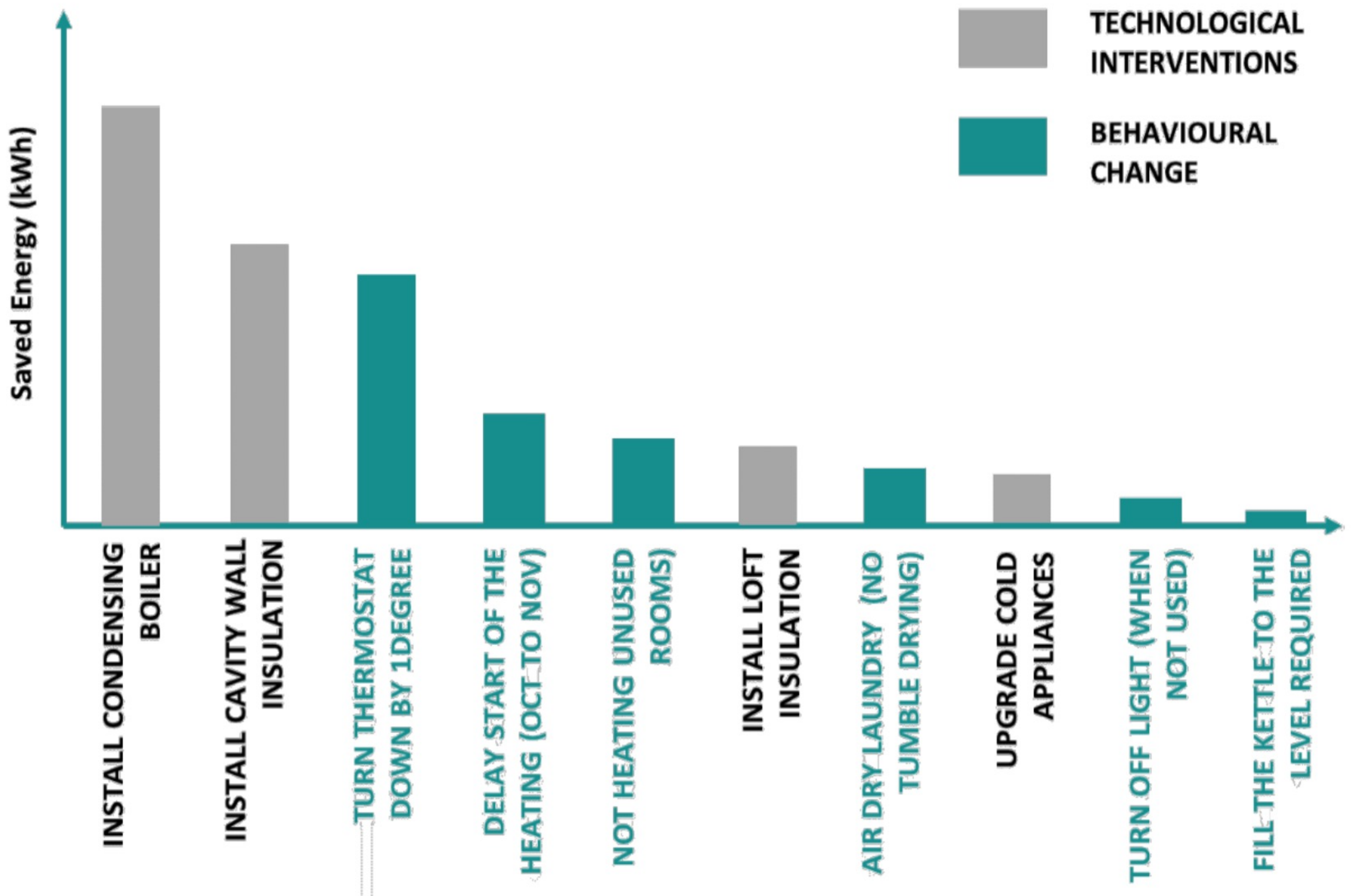
Illuminance sensor for lighting

Smart thermostats

Smart water flow meters

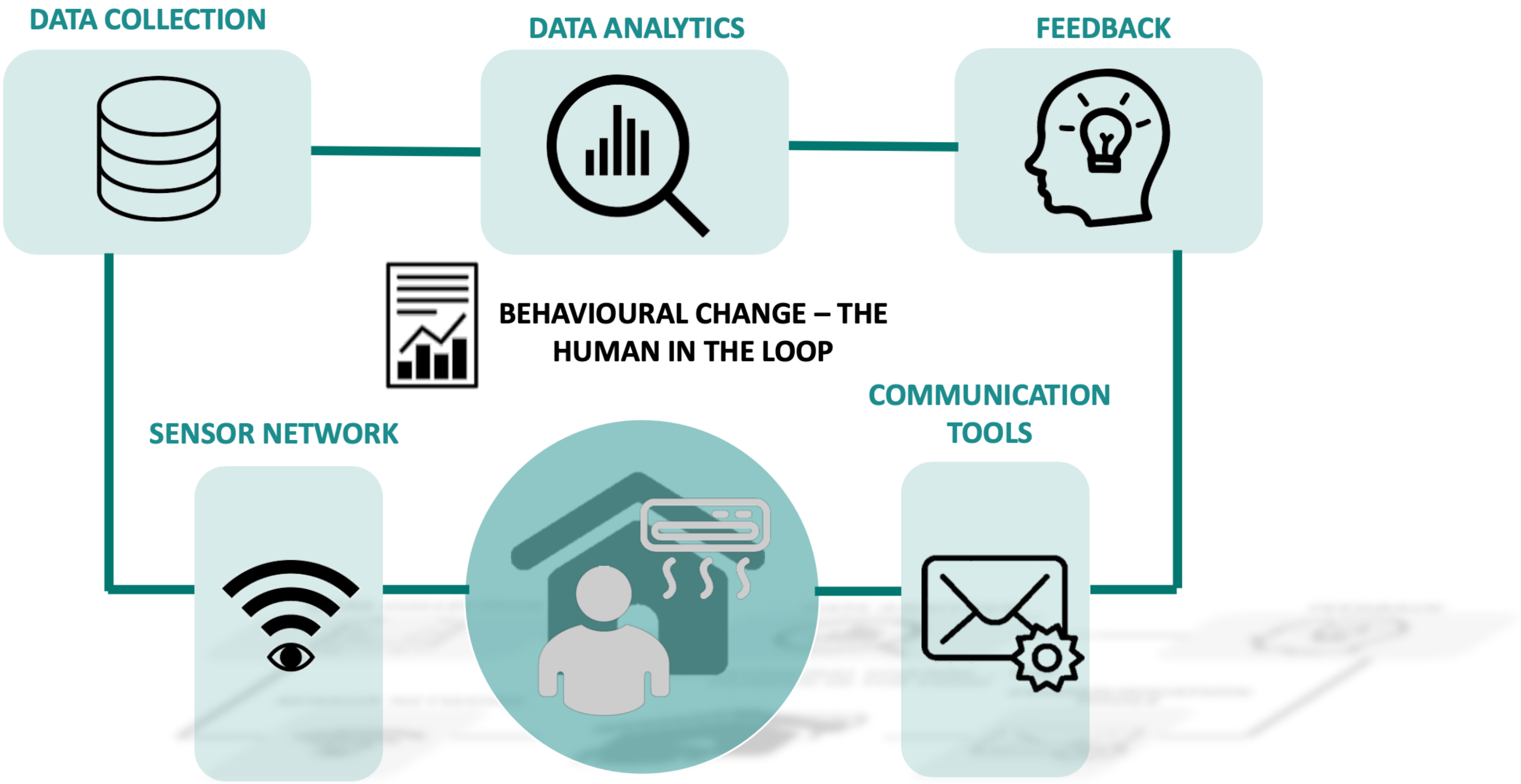
Can we change behavior to make buildings more efficient?

Technology and behaviour



(Source: Clarity Sustainability 2015)

Bringing the human in the loop

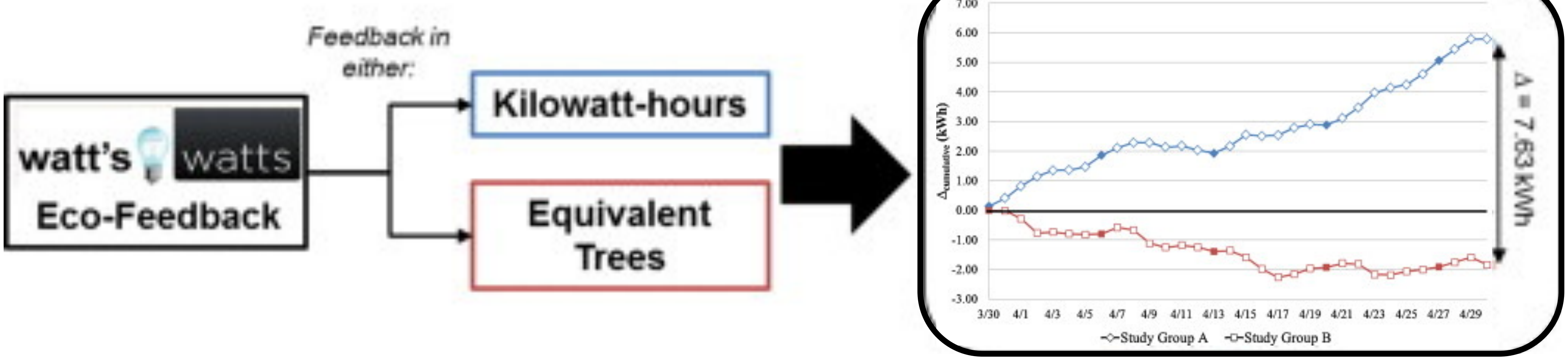


(Source: Barthelmes et al. 2019)

Eco-feedback

(Source: Jain et al. 2012)

Eco-feedback



(Source: Jain et al. 2013)

Smart building sensors

Occupant behaviour

Organizational modeling

Opportunities for energy efficiency

Integrated design and management