The role of bounded rationality in travel choice behavior and implications for transport modeling

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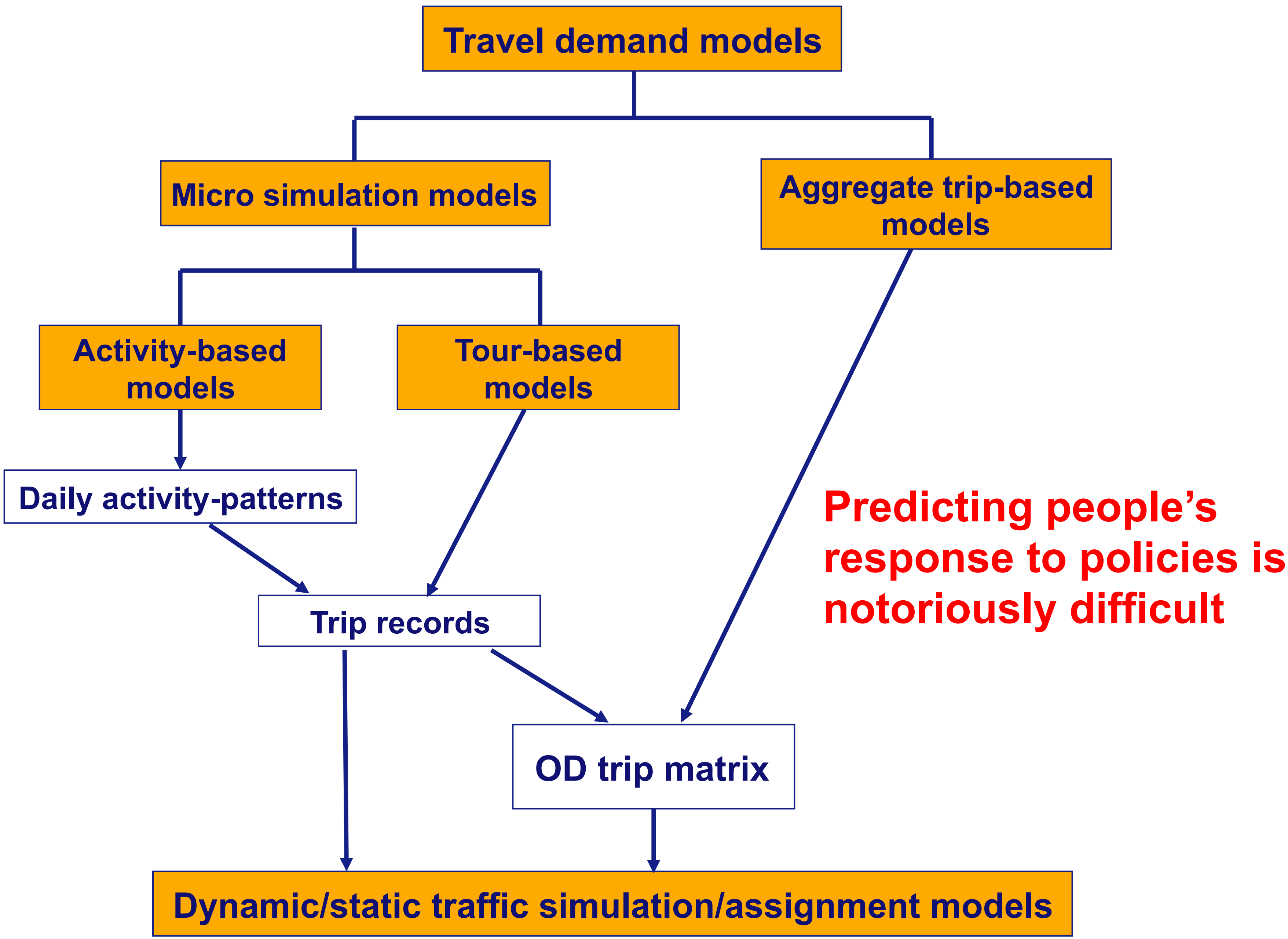
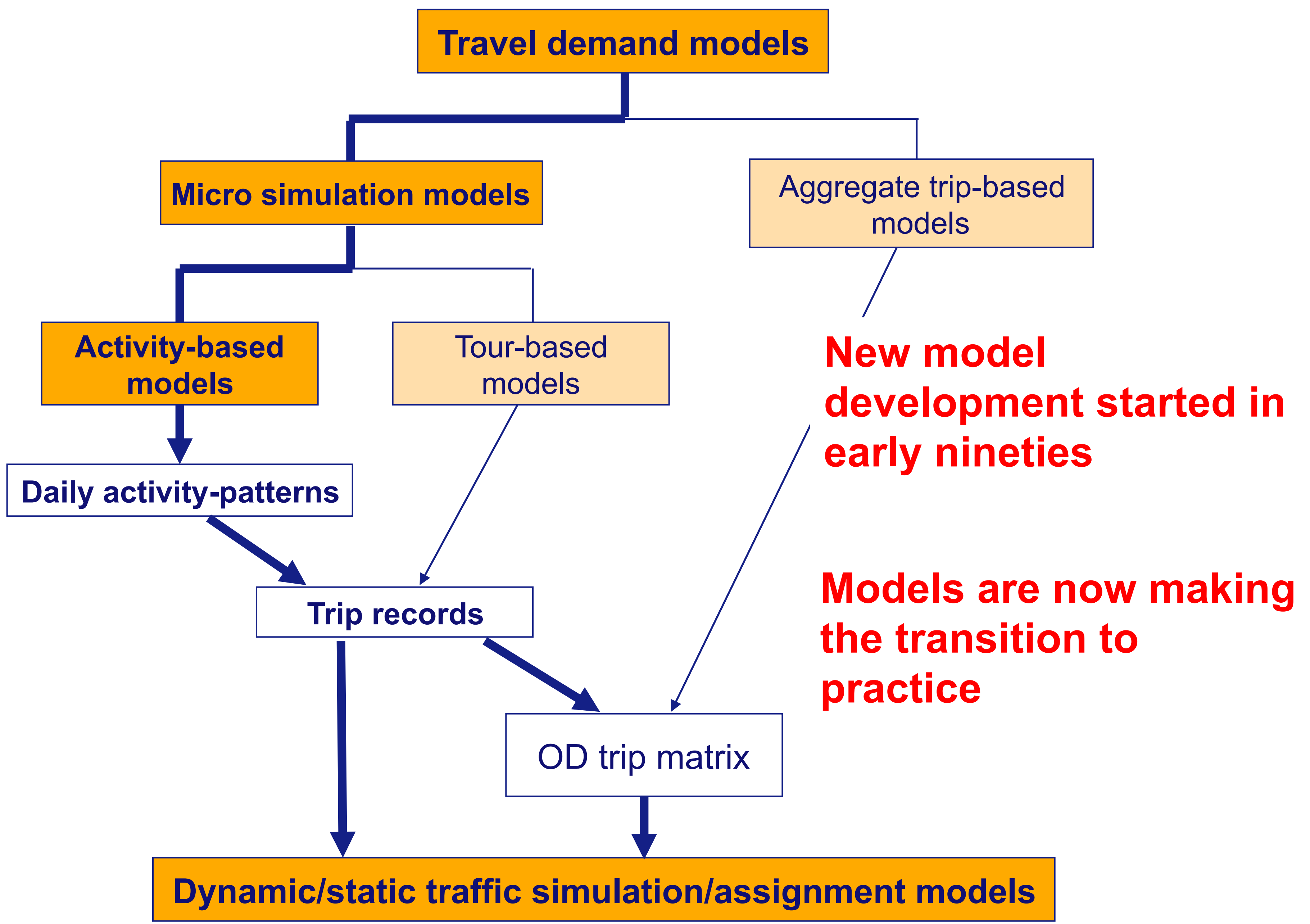

Travel demand models
Micro simulation models
Aggregate trip-based models
Activity-based models
Tour-based models
Daily activity-patterns
Trip records
OD trip matrix
Dynamic/static traffic simulation/assignment models
Predicting people's response to policies is notoriously difficult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Trip records
OD trip matrix
Dynamic/static traffic simulation/assignment models
New model development started in early nineties
Models are now making the transition to practice

Outline of my presentation

- Brief review of activity-based modeling
  - objectives, approach and new developments
- Bounded rationality in travel behavior
  - human biases
  - towards dynamic models
- New modeling approaches
  - habitual behavior and spatial search
  - learning and wellbeing

Why activity-based modeling?

- **New demands from transport planning and policy making**
  - Switch in focus to travel demand measures
  - Importance of temporal factors (flexible work hours) and task combination
  - Integration of policies: land-use and transport planning
  - More comprehensive evaluation of policies

Activity-based versus trip-based approach

Trip-based	Activity-based
Focus is on trips	Focus is on activities
Unit is a trip	Unit is a day
Space-time constraints ignored	Space-time constraints taken into account
Low resolution time and place	High resolution time and place
Decision unit is individual	Decision unit is household
Predicts when, where, transport mode	Predicts which activities, when, where, for how long, trip-chaining and transport mode

Albatross example of an activity-based model

- Rule-based
- Continuous time scale
- Within household-interaction
- Space-time constraints
- National level
- Computation time
  - 10 % of population – 2.1 million agents
  - More than 4000 postcode areas
  - Around 8 hours computation time on a standard PC

Albatross example of an activity-based model

Albatross abroad

- Feathers – Belgium
- Under development
  - Seoul
  - Indonesie

Model is static – time span is one day

New developments in activity-based modeling

- From static to dynamic models
  - expand time frame from one day to multiple days
  - include life trajectories and long-term mobility decisions
- Include social networks and social interactions
  - social influence in decision making
  - group decision making – negotiation
- New survey methods and data sources
  - tracking of movements with GPS or mobile phone positioning
  - social media – big data

Incorporating bounded rationality in models of travel demand

Time is ripe

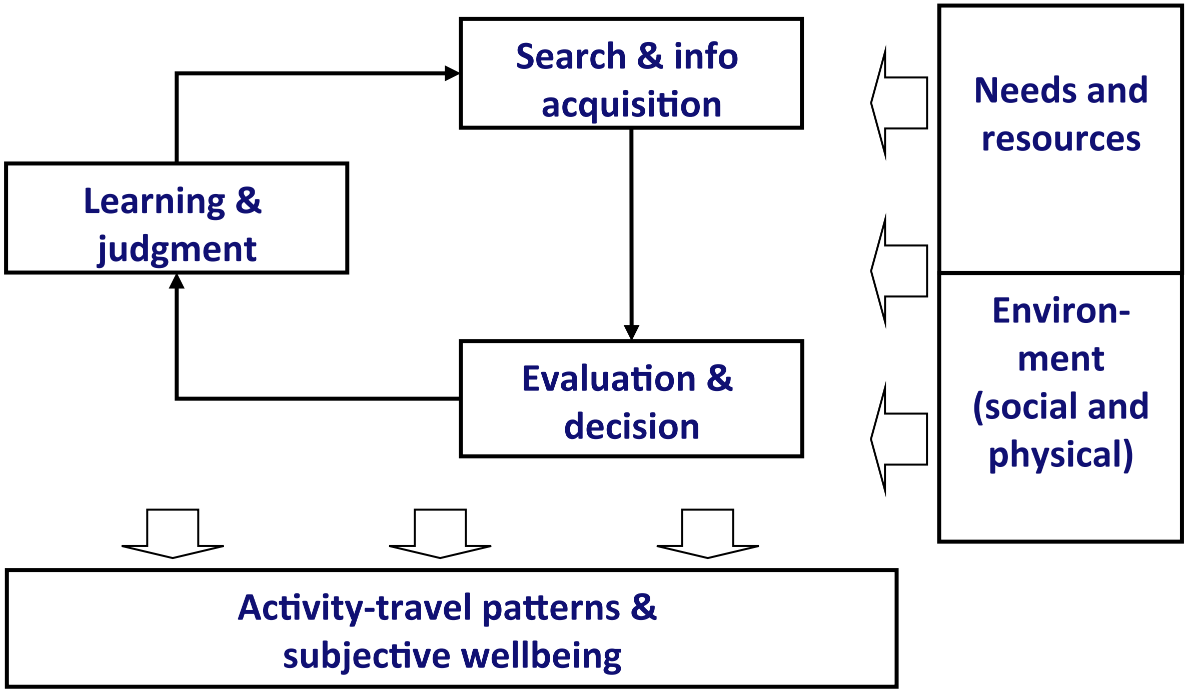
- **Cumulative evidence from psychology and behavioral economics**
  - **See recent book of Daniel Kahneman (2011) – Thinking, Fast and Slow**

- **Human biases are well documented and tools for data collection and modeling available**

- **Modern survey technologies facilitate a move from one-day to multiple days data collection**

- **Wide use of smart phones allows new *in-situ* data collection methods**

Aspects of bounded rationality

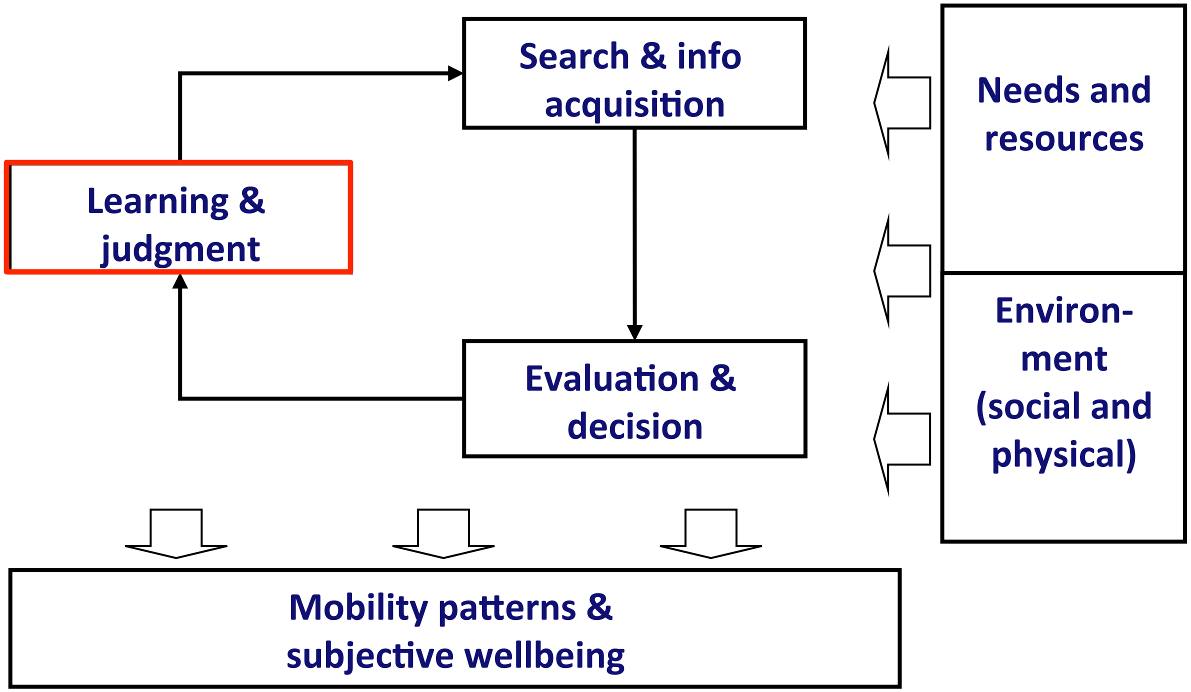


Biases are well-documented

- Sensitivity to losses
- Over responding to peak experiences
- Sticking with habits
- Impact of emotion
- Memory distortions
- Limited search and effort
- …….

Accounting for biases requires a change from static to dynamic modeling and involves all 4 areas

A model with bounded rationality

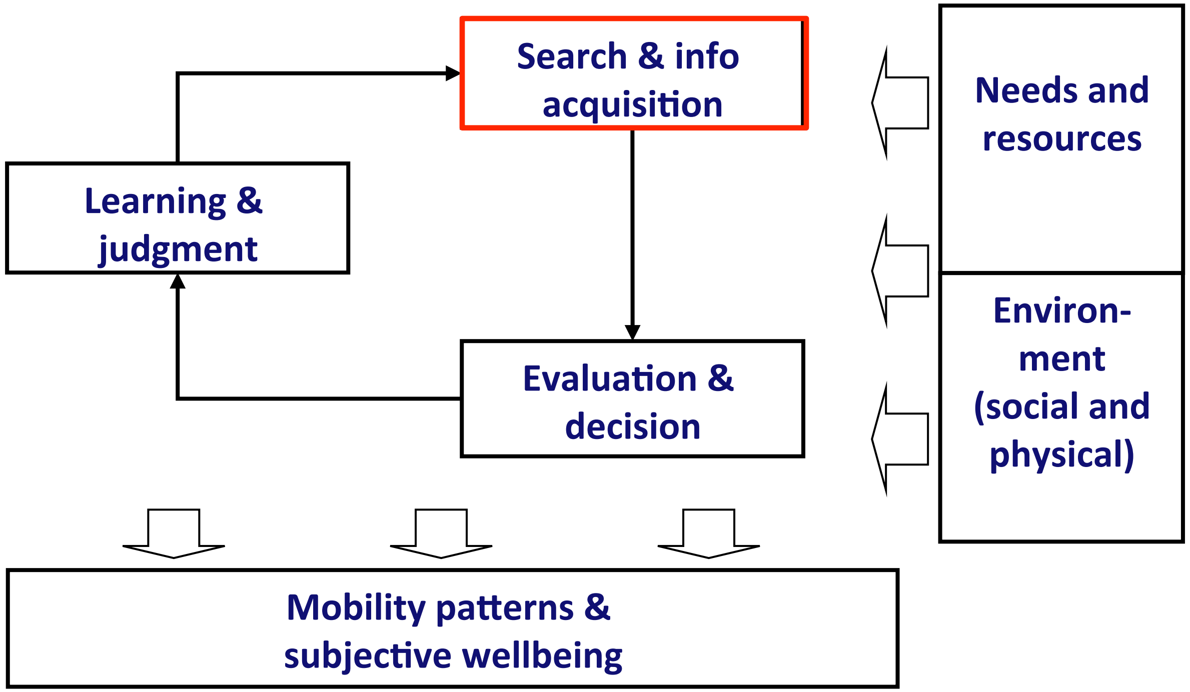


Memory biases

Heuristics

Learning & judgment model predicts how an individual learns and makes judgments about risks based on experiences

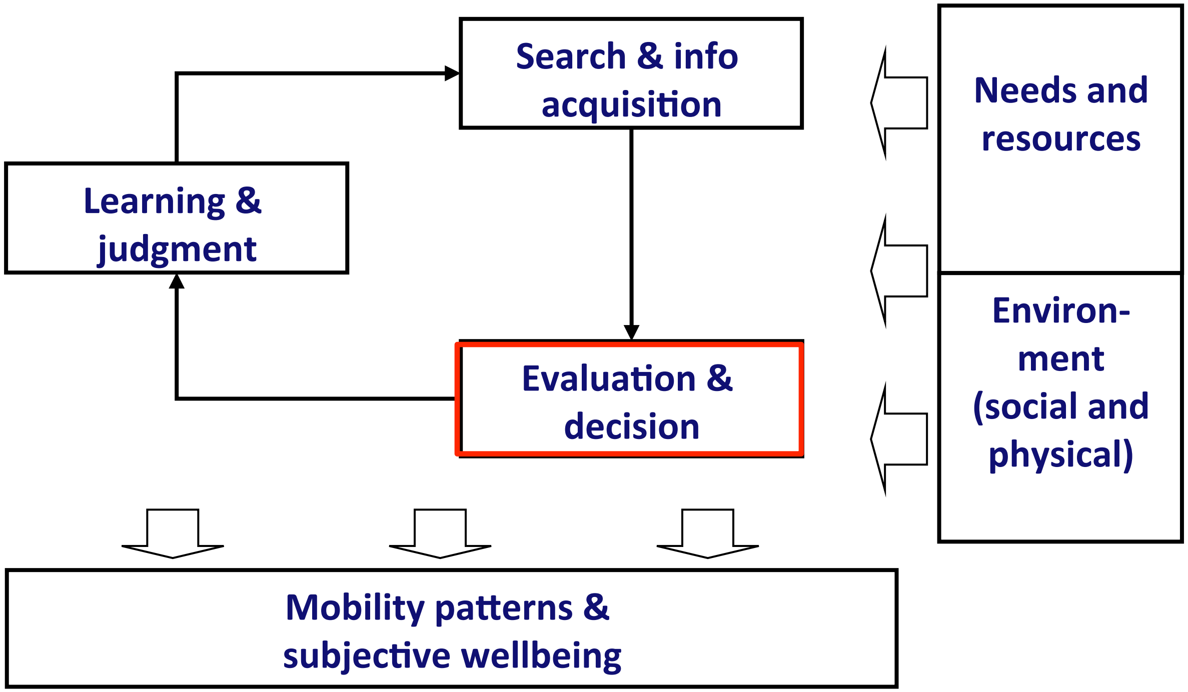
A model with bounded rationality



Limited search

Search-and-information-acquisition model predicts the search for alternatives and formation of choice-sets

A model with bounded rationality



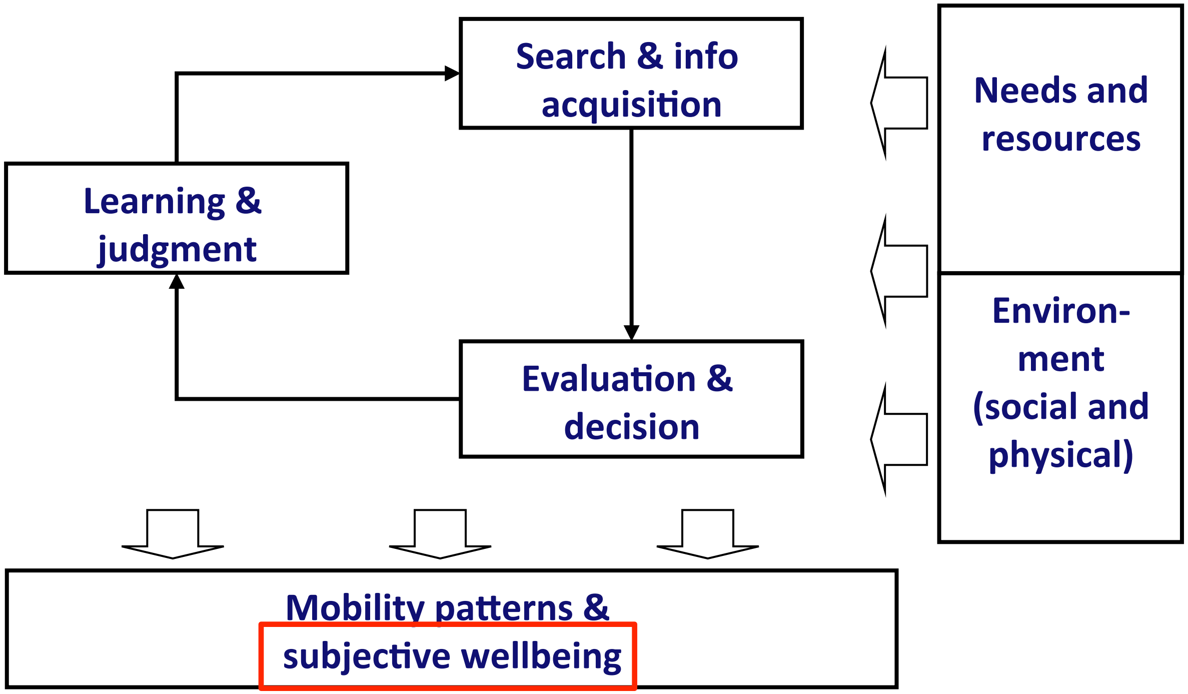
Reluctance to change

Framing

Emotional weighting

The evaluation-and-decision making model, given the choice-sets and judgments of risks, predicts an individual's choices

A model with bounded rationality



Memory biases

Emotional weighting

The model of subjective-wellbeing predicts an individual's satisfaction with the (transport and location) options he has

New modeling approaches (1)

Habitual behavior and spatial search

Habitual behavior

- Over time individuals develop particular routines for implementing their activities
- A routine has the form of a script that defines
  - departure time
  - location (destination)
  - duration
  - where from (origin – trip chaining)
  - main transport mode
  - route
- For each activity there may be multiple scripts - alternative ways of implementing an activity
- In habitual mode, individuals select the scripts that best fit the current needs and constraints

Habitual behavior

Example of an agent’s set of scripts

Activity	Start time	Location	Duration	Where from	Mode	Route
work	7 am	TUe	8 hours	Home	Walk - Train	local train
work	8 am	TUe	8 hours	Home	Car	highway
work	7.45 am	TUe	8 hours	Home	Car	local route
groceries	morning	Aldi	20 min.	Home	Car	shortest
groceries	lunch-break	AH	10 min.	Work place	Walk	shortest
groceries	early afternoon	Market	30 min.	Home	Walk	shortest
……						
…..						
touring -walk	7 am	Neighborh.	20	Home	Walk	-
touring -walk	afternoon	Wood 1	2 hours	Home	Car	via Reusel
touring -walk	afternoon	Wood 2	1 hour	Home	Car	via Oisterwijk

Alternative ways to implement the work activity – referred to as Scripts

Habitual behavior

Utility of a script

Activity component — Travel component

$$U_i(d,t,m,l,T) = \boxed{v_i(d,t,l)\cdot f_i(T)} + \boxed{U^R(d,t,m,l)}$$

Decision rule

– consider the scripts that meet the following condition

$$U_i(S) > c_d \cdot T(S)$$

Threshold constr.

– choose the script that maximize *U*

Adaptation rule

Increase threshold if time budget is exceeded

Decrease threshold if time budget is not fully used

Spatial search

- **If dissatisfied with current set of scripts then the agent starts exploration**

The probability that a location *i* is discovered is specified as

$$P(i|K) = \frac{\exp(U_i(K)/\tau)}{\sum_{j \in J} \exp(U_j(K)/\tau)}$$

The Boltzman model

Attributes considered

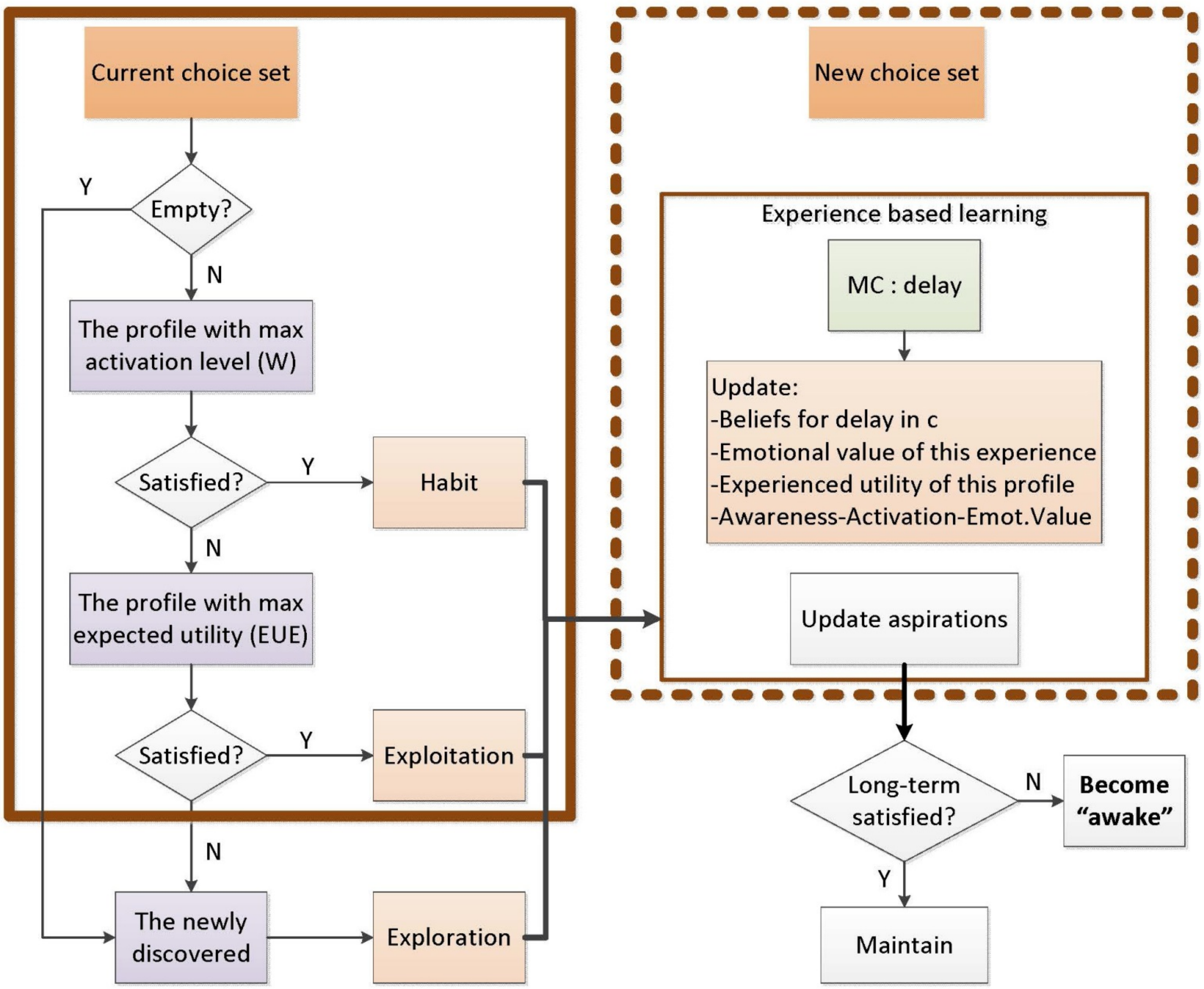
Universal choice set

Hidden utility for the agent

Lack of information
- Limited effort
- Limited access to info sources

Limited search can be modeled by means of τ

An implementation



New modeling approaches (2)

Effect of memory and emotion on learning and satisfaction

How do travelers judge the likelihood of a risky event?

How do travelers judge degree of satisfaction with choice alternatives?

How do travelers judge the likelihood of a risky event?

Arentze, T.A. (2013) Incorporating human memory biases in travel-behavior models of judgment and learning: availability and fluency heuristics. Paper presented at the HKSTS Annual Conference, December 2013, Hong Kong.

- **This is a relevant question**
  - **knowing how travelers make likelihood judgements is important for understanding their choice behavior**

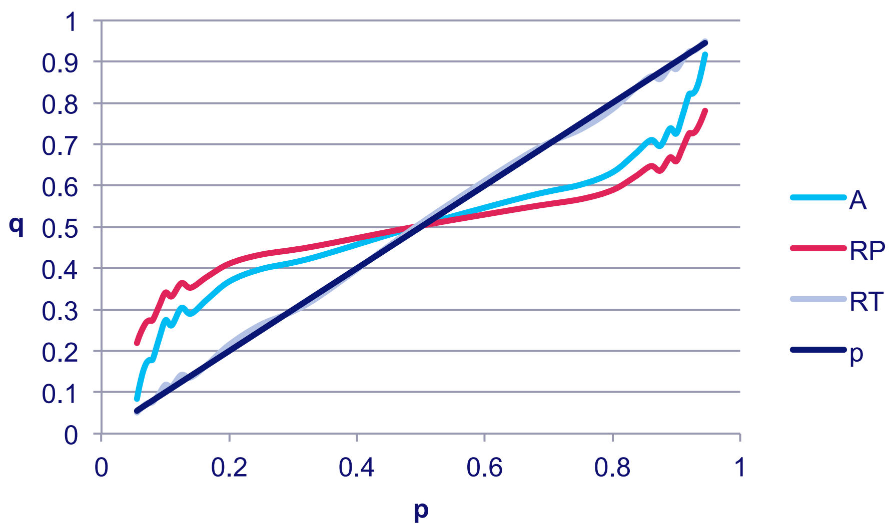
- **Naïve model**
  - **people count occurences and store frequency data in memory – their judgments are unbiased**

- **However, this is not in line with evidence. Two fundamental biases in human likelihood judgements are well-known (Lichtenstein et al., 1978)**

Evidence

Primary bias

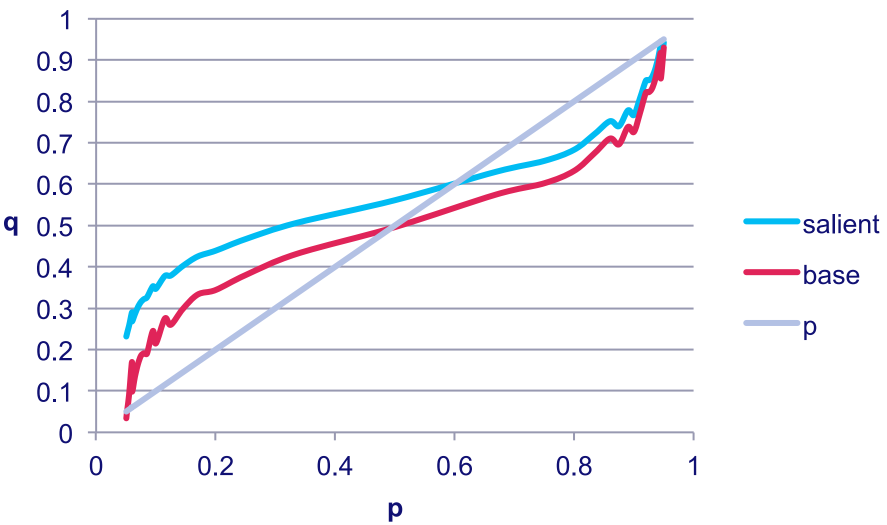
- small probabilities are overestimated and large probabilities are underestimated
- this eplains why rare events may have a large impact



Evidence

Secondary bias

- **events that are more vividly imagined are overestimated**
- **this explains why a salient event such as a plane crash tends to have much more impact than a more common event**



Theory

- **Availability / fluency heuristic**
  - **first formulated by Tversky and Kahneman (1973)**
  - **supported by numerous empirical studies**
- **Tversky and Kahneman (1973)**
  - **people use a byproduct of memory processes to judge the likelihood of some event**
  - **that is, the ease with which examples of the event can be retrieved from memory is used as criterion**
  - **the easier examples come to mind the more likely the event is judged to be**
- **This heuristic explains the primary and secondary biases (Hertwig et al. 2005)**

Memory model

- **ACT-R cognitive architecture provides a model of memory encoding and retrieval processes (Anderson et al. 2004)**

$$A_{ik} = \ln\left(\sum_{j \in k} (t_{ij})^{d}\right)$$

$$Q_{ik} = \frac{A_{ik}}{\sum_{j} A_{ij}}$$

- **This model explains the primary bias**

Memory model

- **Extension of the ACT-R memory model to account for effect of arousal on memory**

$$A_{ik} = \ln\left(\sum_{j\in k} (t_{ij})^{d(S)}\right)$$

$$Q_{ik} = \frac{A_{ik}}{\sum_{j} A_{ij}}$$

- **This extended model also explains the secondary bias**

How do travelers judge degree of satisfaction with choice alternatives?

Wielens, N.J. and T.A. Arentze (2014) The role of affective experiences in travelers' assessments of risks and subjective wellbeing: an experience sampling approach. Paper prepared for the HKSTS Annual Conference, December 2014, Hong Kong.

- **This is a relevant question**
  - **knowing how travelers arrive at satisfaction judgements is important for understanding subjective wellbeing and habitual behavior**
- **Naïve model**
  - **decision utility is the same as experienced utility**
  - ➢ **utilities can be derived from choice behavior**
- **However, Kahneman (2000) points to known biases:**
  - **neglect of duration of episodes**
  - **dominance of end outcome of episodes**
  - **disproportional impact of peak experiences**

Model

- **Again, the memory model of ACT-R offers a way to describe this process**

$$A_{ij} = \ln\left((t_{ij})^{d(S)}\right)$$

$$U_i = \sum_j A_{ij} \cdot U_{ij}$$

- **This model explains the disproportional impact of extreme events on satisfaction**

Data collection

$$A_{ij} = \ln\left((t_{ij})^{d(S)}\right) \qquad U_i = \sum_j A_{ij} \cdot U_{ij}$$

- **Experience sampling**
- **Small questionnaire on the smartphone completed on every trip**
  - **data of the trip (mode, route, purpose, etc.)**
  - **emotional state of the traveller during the trip (arousal and valence)**
  - **satisfaction judgement (experienced utility)**
- **In-situ measurement of affective experiences of travelers (Ettema et al. 2014)**

Implications for policy making and modeling

- **Policy making - theory stresses:**
  - **importance of reliability of transport services on satisfaction and risk assessment**
    - **avoid negative peak experiences**
  - **importance of avoiding losses in the behavior change targeted**
    - **losses generate negative emotion**

- **Transport modeling**
  - **the memory-based models of learning and jugement can be incorporated in dynamic travel-demand models**

Conclusion

- It was argued that
  - taking bounded rationality into account matters – human biases are well-documented
  - to realize this, static models should be replaced by dynamic models
- I highlighted new modeling approaches in areas of
  - habitual behavior and spatial search
  - learning and wellbeing

Conclusion

- **The new approaches are only in its infancy**
- **New data collection and estimation methods are needed to estimate parameters of**
  - **habitual behavior and search**
  - **learning and wellbeing**
- **New agent-based platforms are needed to develop full-scale applications**

Thank you for your attention!

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