Research on Behavioral Mechanisms and Intervention Policies Based on Modeling and Simulation Methods

梁昕 Xin LIANG

2025年3月28日

饮 水 思 源 • 爱 国 荣 校

Next frontiers：human behavior

Science

ESSAY

Predicting human behavior: The next frontiers

V. S. Subrahmanian and Srijan Kumar

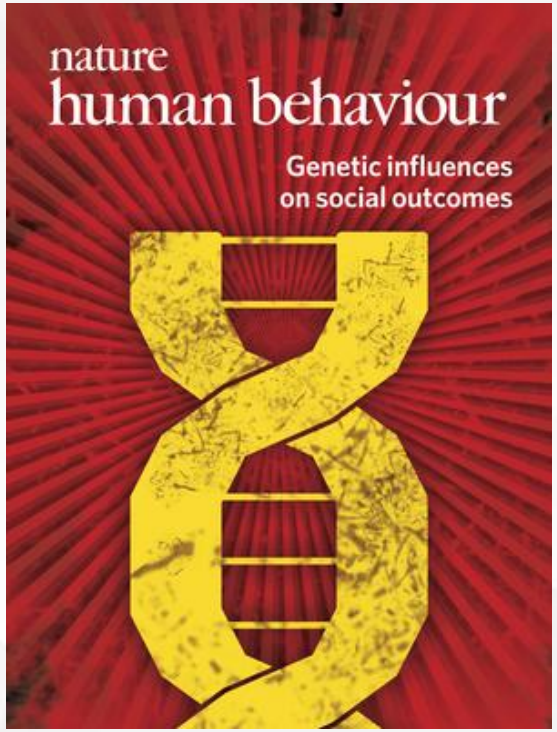
Machine learning has provided researchers with new tools for understanding human behavior. In this article, we briefly describe some successes in predicting behaviors and describe the challenges over the next few years.

Advances in machine learning are revolutionizing how we understand offline and online human behavior. The ability to classify objects of interest from a training set, whether those objects are terrorists (*1*), machines that need maintenance (*2*), or emails containing a malicious link (*3*), represents the greatest success in the field. Typically, no single machine learning algorithm does everything well. Although accuracy is crucial, the acceptable accuracy varies with independent variables to be included in a data set. Often, they will explain predictions using both the technical accuracy measures generated by a predictive model and stories from their discipline that are more understandable to their audiences. All of this suggests that in real-world systems, computer scientists need to team with stakeholders to generate high-impact results.

In our opinion, the next generation of predictive models must deal with four major challenges.

Subrahmanian V S, Kumar S. Predicting human behavior: The next frontiers.[J]. Science, 2017, 355(6324):489.

nature



2017年1月创刊

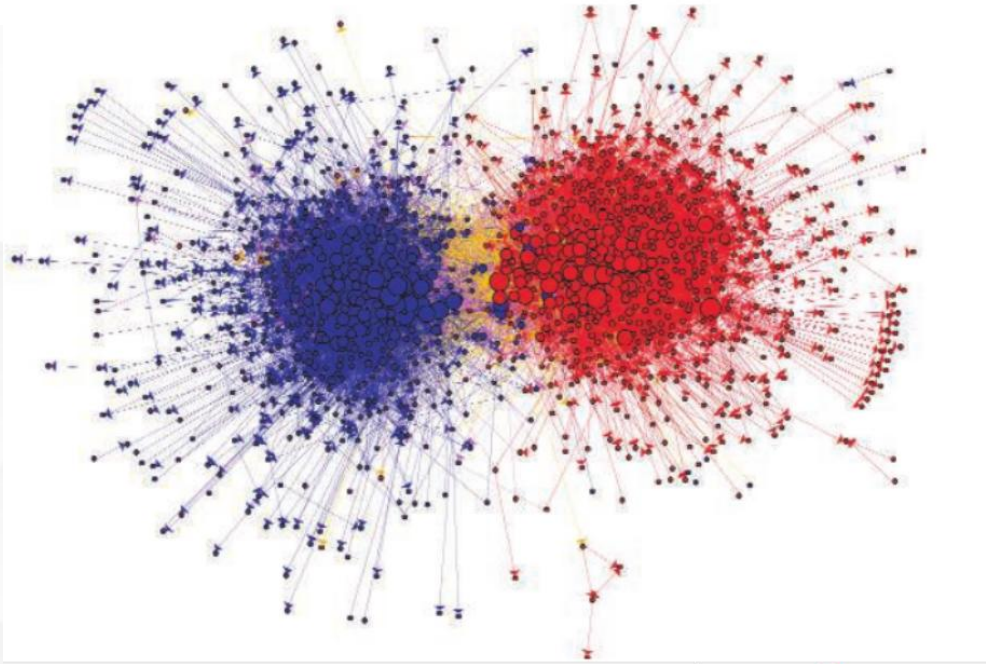
Computational social science

SOCIAL SCIENCE

Computational Social Science

David Lazer,[1] Alex Pentland,[2] Lada Adamic,[3] Sinan Aral,[2,4] Albert-László Barabási,[5]
Devon Brewer,[6] Nicholas Christakis,[1] Noshir Contractor,[7] James Fowler,[8] Myron Gutmann,[3]
Tony Jebara,[9] Gary King,[1] Michael Macy,[10] Deb Roy,[2] Marshall Va[illegible]

A field is emerging that leverages the capacity to collect and analyze data at a scale that may reveal patterns of individual and group behaviors.



Lazer, D., Pentland, A., Adamic, L., Aral, S., Barabasi, A. L., Brewer, D., ... & Van Alstyne, M. (2009). Social science. Computational social science. *Science*, *323*(5915), 721-723.

Computational social science



INSIGHTS

POLICY FORUM

SOCIAL SCIENCE

Computational social science: Obstacles and opportunities

Data sharing, research ethics, and incentives must improve

By David M. J. Lazer[1,2], Alex Pentland[3], Duncan J. Watts[4], Sinan Aral[3], Susan Athey[5], Noshir Contractor[6], Deen Freelon[7], Sandra Gonzalez-Bailon[4], Gary King[2], Helen Margetts[8,9], Alondra Nelson[10,11], Matthew J. Salganik[12], Markus Strohmaier[13,14], Alessandro Vespignani[1], Claudia Wagner[14,15]

dependencies within data. A loosely connected intellectual community of social scientists, computer scientists, statistical physicists, and others has coalesced under this umbrella phrase.

MISALIGNMENT OF UNIVERSITIES

Lazer, D. M., Pentland, A., Watts, D. J., Aral, S., Athey, S., Contractor, N., ... & Wagner, C. (2020). Computational social science: Obstacles and opportunities. *Science*, *369*(6507), 1060-1062.

Research methods for human behavior

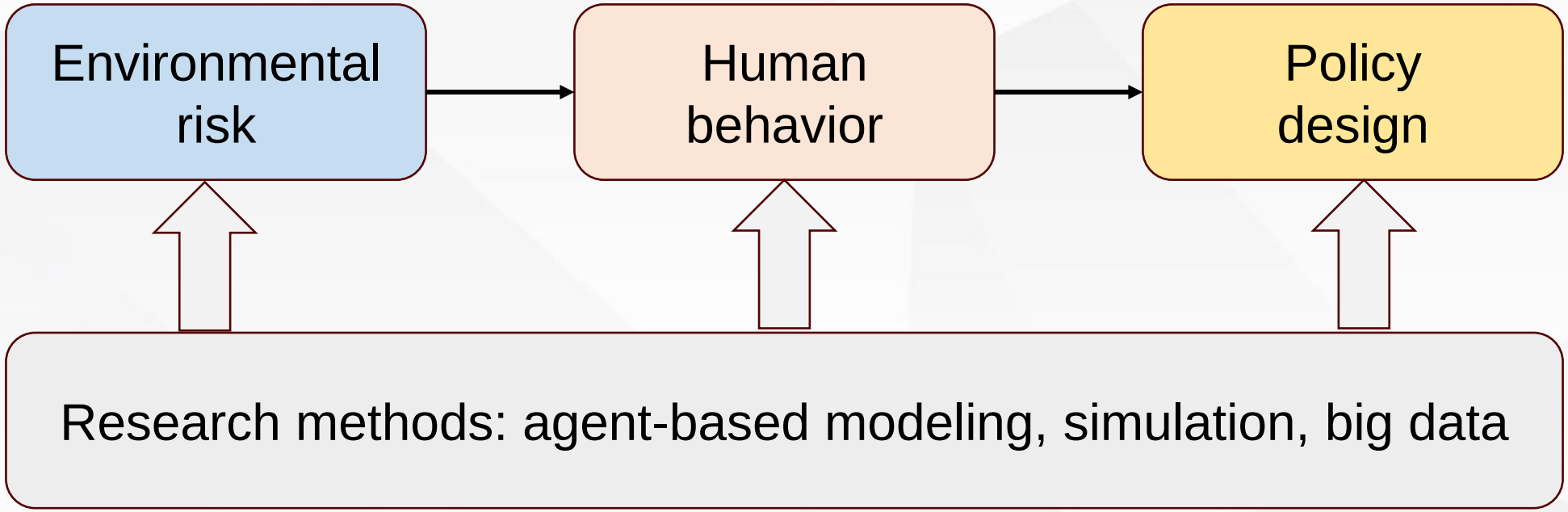
Induction

- Observation
- Survey
- Big data
- Experiment
- Neuroscience

Deduction

- Modelling
- Simulation

My research direction



Part 1： Traditional Inductive Methods



01

Observation

Observation

Observation:

1. Observe visible behavior
2. Find features, summarize rules

Non-intervention
Description
No causal interpretation



Figure 2 Experiments on facing groups: Several experiments were conducted on real pedestrian dynamics, some of which also considered the preser groups of pedestrians, who were instructed that they had to behave as friends or relatives while moving during the experiment.

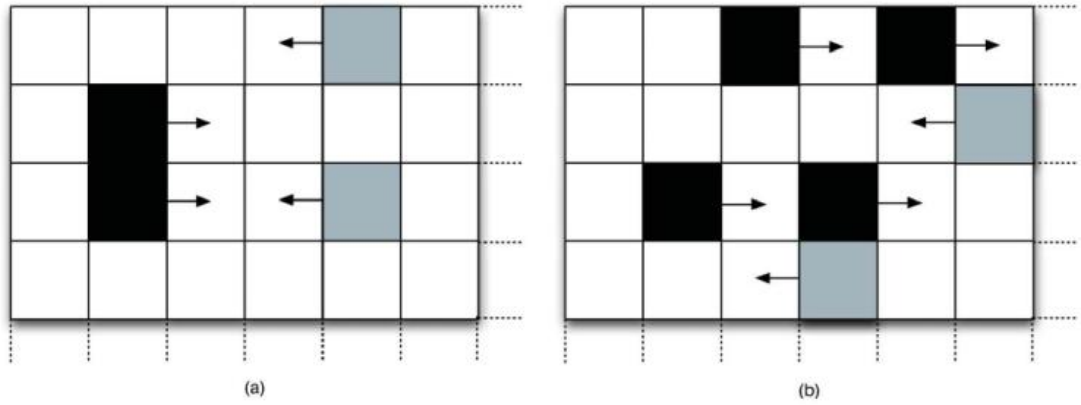


Figure 4 In (a), the black pedestrians have not formed a line and they offer a larger profile to the counterflow. In (b), they formed a line and the follower has a lower probability to find an opposing pedestrian due to the presence of a sort of "emergent" leader.

Observation: cases

Evacuation Behavior: Path selection in emergencies

Daily Behaviors: Curtain usage, light switching habits, waste generation (weight/type), water and electricity usage

Purchasing Behavior: Types of purchases, timing, frequency, etc.



Fig. 1. A shield was mounted to the top of a cubical wall to protect the adjacent occupant from a beam of light that penetrated through a gap in the shading system (left); a sheet of foil was used to cover a window to either block light or solar radiation (right).



02

Survey

questionnaire

interview

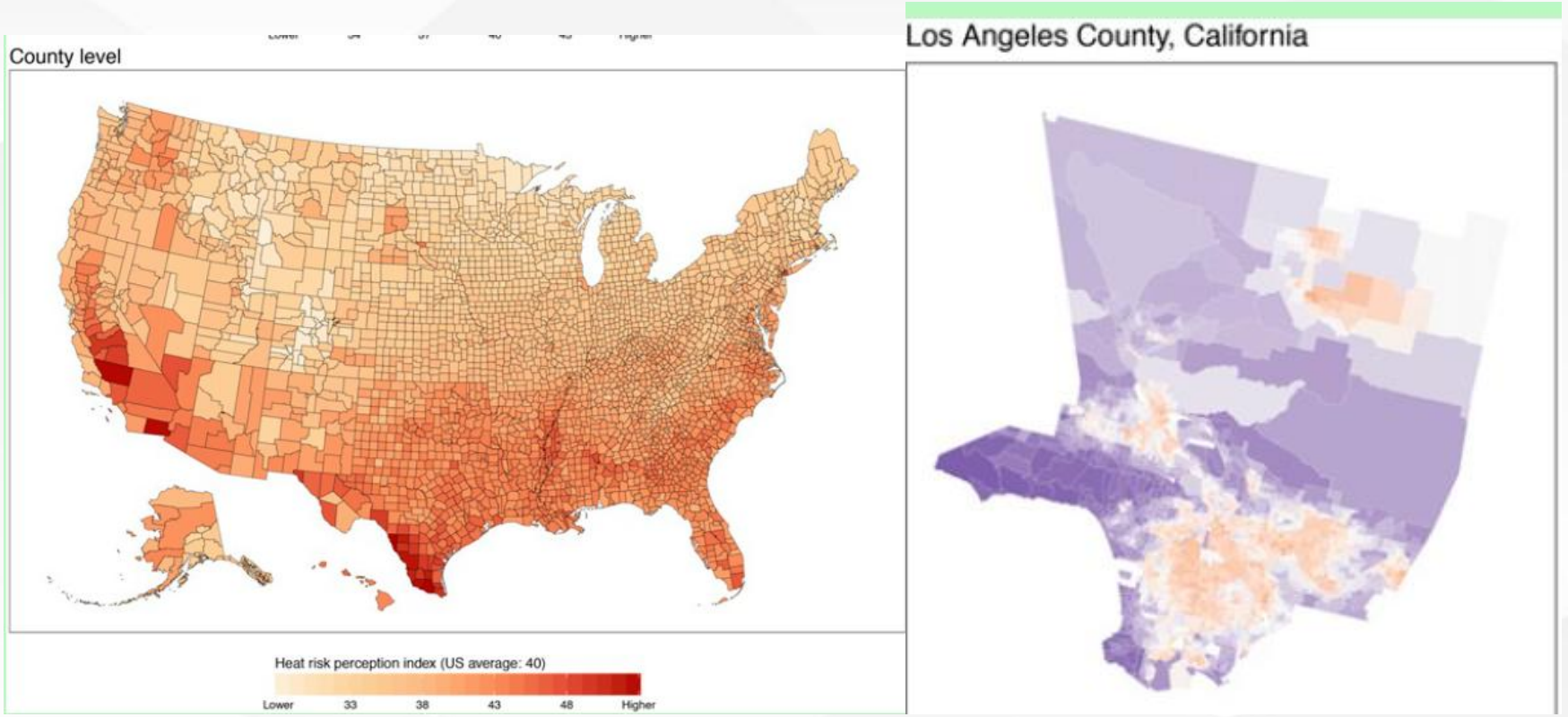
Survey

Survey Method:
Survey research is a social research approach that systematically and directly collects data from a sample population through self-administered questionnaires or structured interviews, and analyzes the data statistically to understand social phenomena and their patterns.

Common Analysis Subjects:
- Pattern analysis of behaviors
- Analysis of influencing factors on behaviors
- Analysis of behavioral formation mechanisms

Non-intervention
Explanation-focused
No causal interpretation

Survey: cases



Howe, P. D., Marlon, J. R., Wang, X., & Leiserowitz, A. (2019). Public perceptions of the health risks of extreme heat across US states, counties, and neighborhoods. *Proceedings of the National Academy of Sciences*, *116*(14), 6743-6748.

Survey: cases

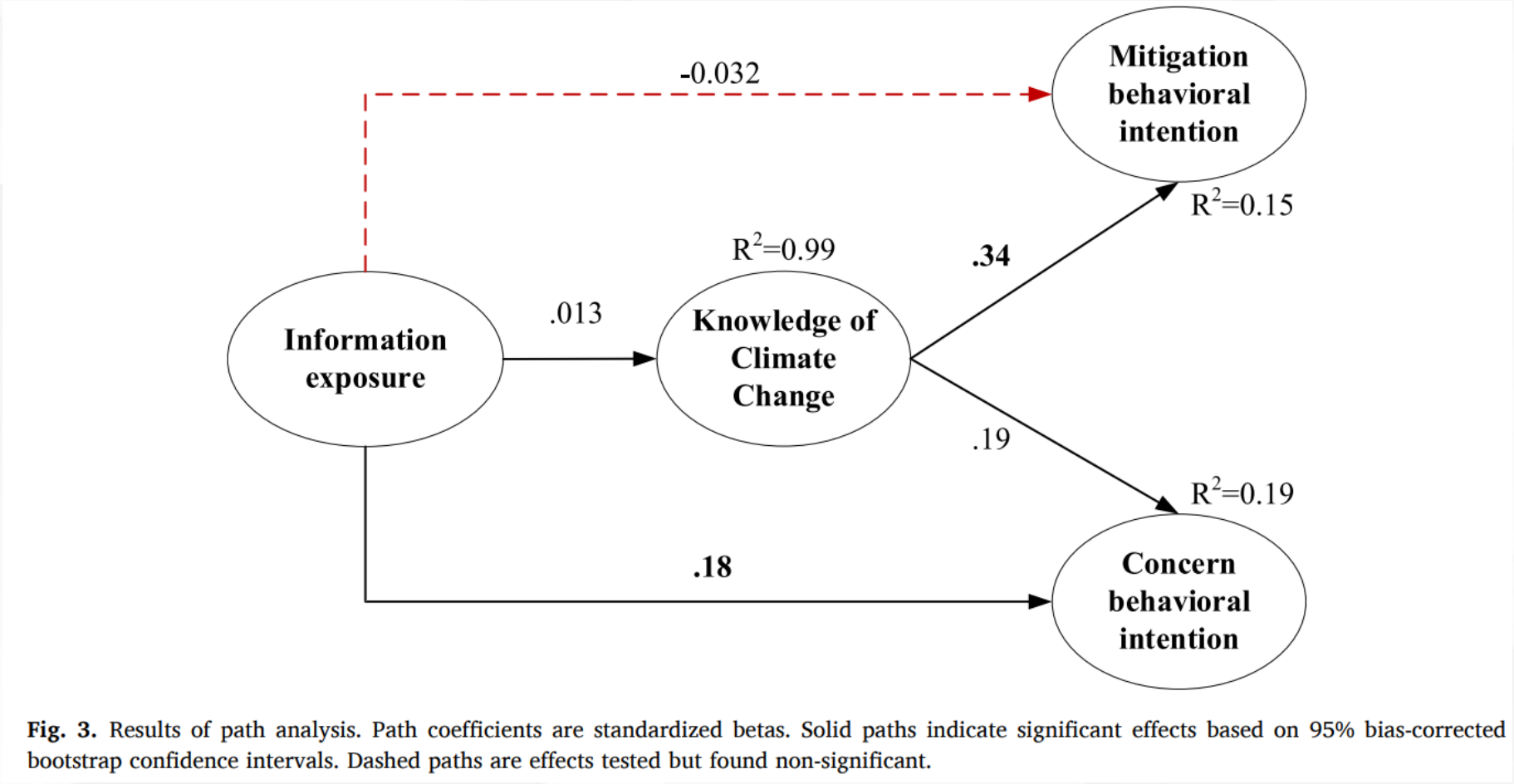


Fig. 3. Results of path analysis. Path coefficients are standardized betas. Solid paths indicate significant effects based on 95% bias-corrected bootstrap confidence intervals. Dashed paths are effects tested but found non-significant.

[1] Liang, X. , Wei, Y. , & Huang, W. . (2024). Fast or slow system: how does information exposure affect individual climate change mitigation responses?. Urban Climate, 56.



03

Big data analysis

Multi-source data



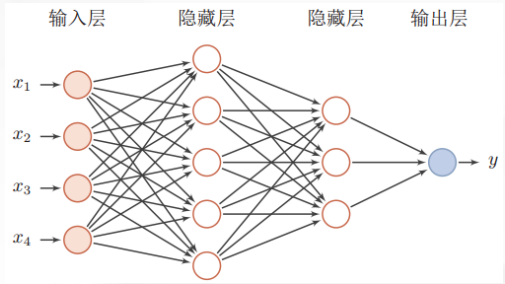
Big data



Human behavior



AI



Machine learning





IoT

Big data analysis: cases

Prediction based on decision tree:

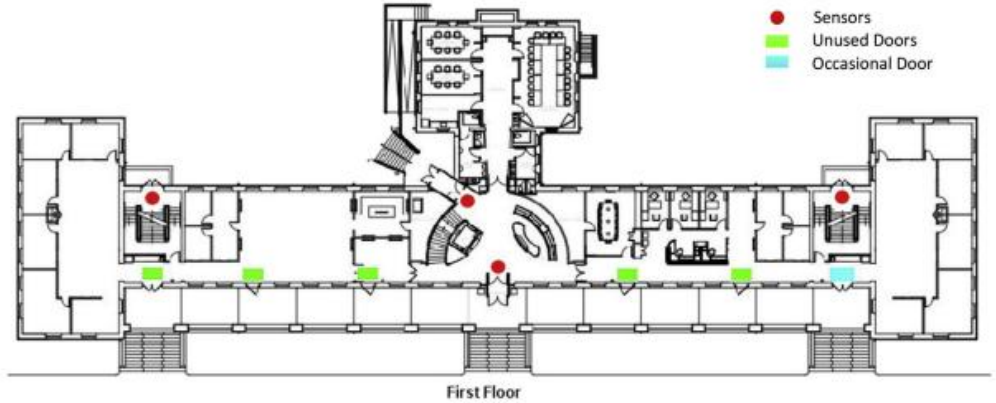
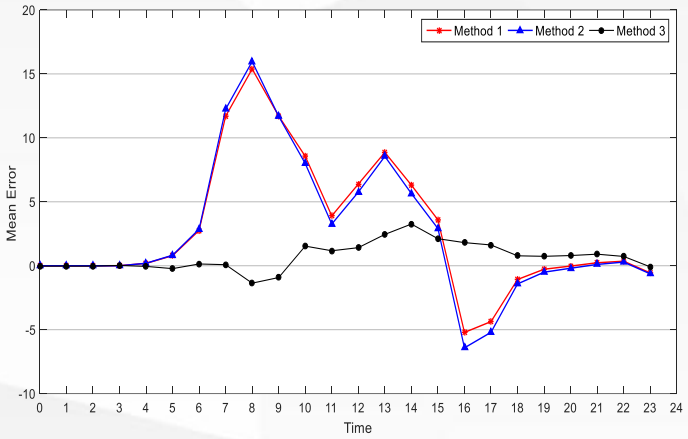
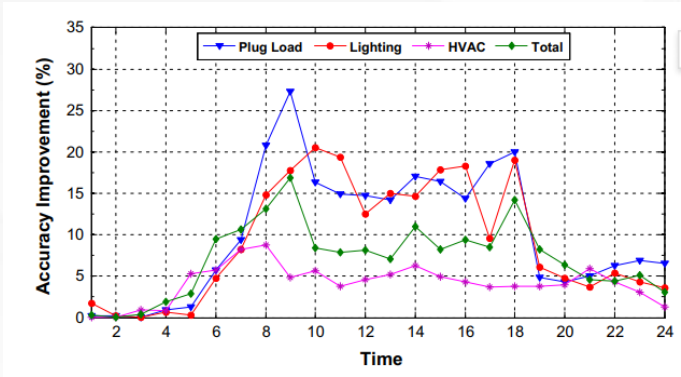


Fig. 6. Sensor locations in Building 101.



MSE of predicition



Residents' activity

- Big data analysis methods help us gain a deeper understanding of residents' behavioral patterns.
- Big data analysis methods enable us to more accurately predict residents' behaviors.

[1] B, X. L. A. , B, T. H. , & C, G. Q. S. . (2016). Improving the accuracy of energy baseline models for commercial buildings with occupancy data. Applied Energy, 179(Oct.1), 247-260.

[2] Liang, X. , Hong, T. , & Shen, G. Q. . (2016). Occupancy data analytics and prediction: a case study. Building & Environment, 102(Jun.), 179-192.

Big data analysis: cases

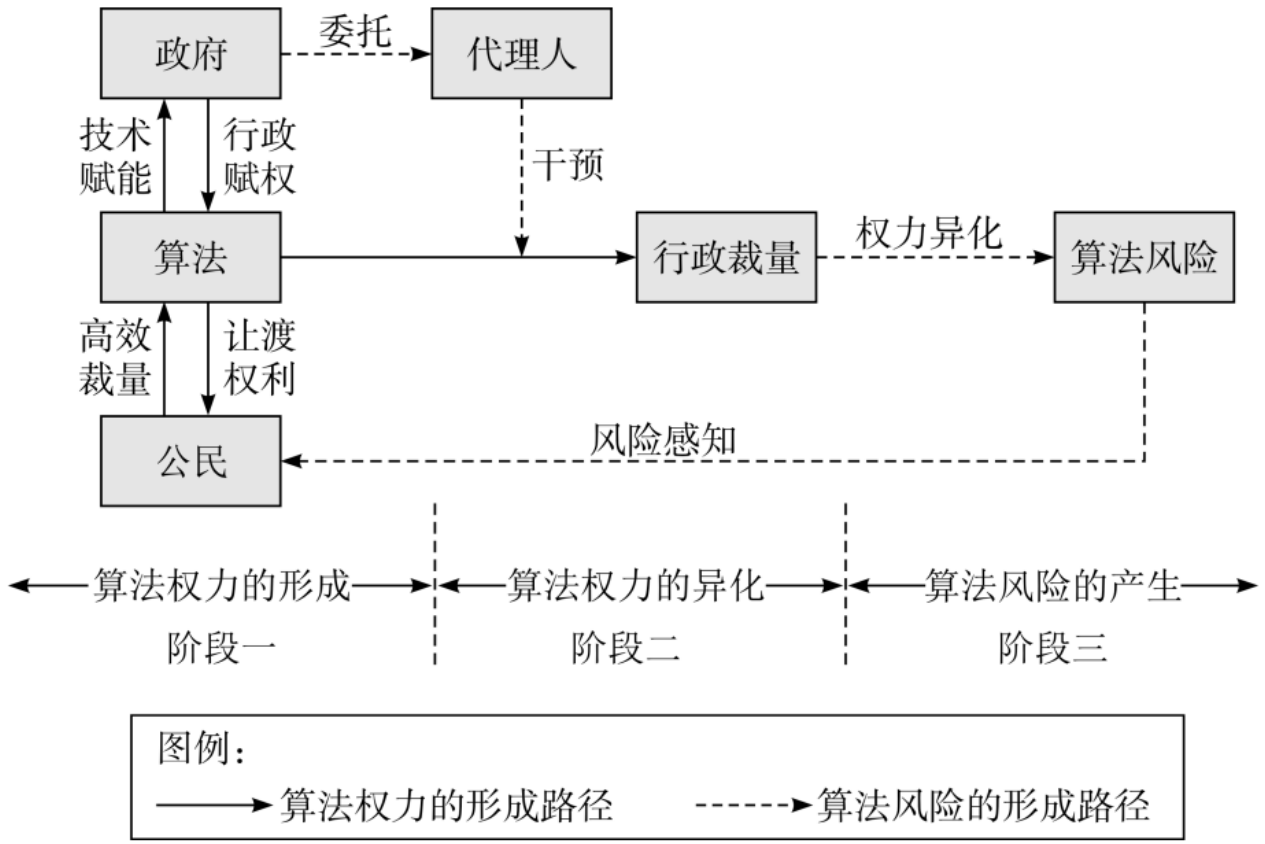


图 1　行政裁量中算法权力与算法风险分析框架

资料来源：作者自制。

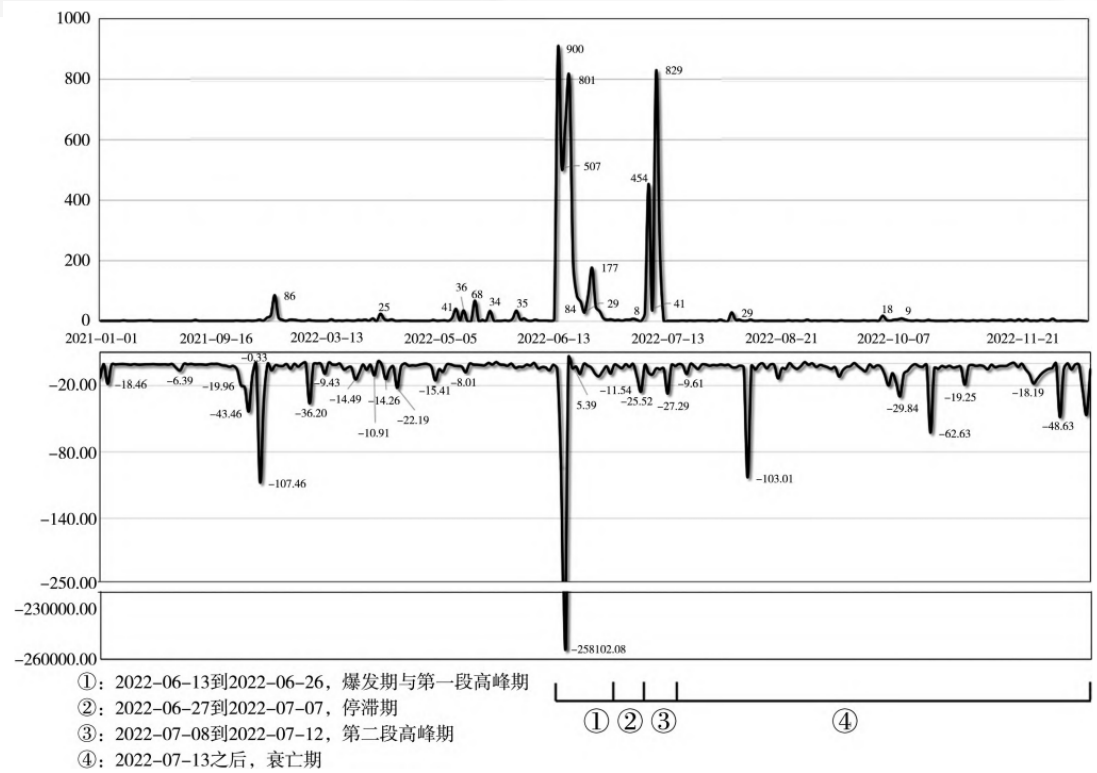


图 3　微博数量和信任度的时间序列折线图

资料来源：作者自制。

[1]梁昕, & 刘天颖. (2024). 自动化行政裁量中算法风险感知的特征与演化研究——基于网络舆情的大数据分析. 公共行政评论, 17(1), 45-65.



05

experiment

Natural experiment

Field experiment

Lab experiment

Survey experiment

Natural experiment

PNAS

Evidence on the impact of sustained exposure to air pollution on life expectancy from China's Huai River policy

Yuyu Chen[a,1], Avraham Ebenstein[b,1], Michael Greenstone[c,d,1,2], and Hongbin Li[e,1]

[a]Applied Economics Department, Guanghua School of Management, Peking University, Beijing 100871, China; [b]Department of Economics, Hebrew University of Jerusalem, Mount Scopus 91905, Israel; [c]Department of Economics, Massachusetts Institute of Technology, Cambridge, MA 02142; [d]National Bureau of Economic Research, Cambridge, MA 02138; and [e]China Data Center and Department of Economics, School of Economics and Management, Tsinghua University, Beijing 100084, China

Edited by William C. Clark, Harvard University, Cambridge, MA, and approved May 28, 2013 (received for review January 2, 2013)

es). The estimates suggest that the 500 million residents of

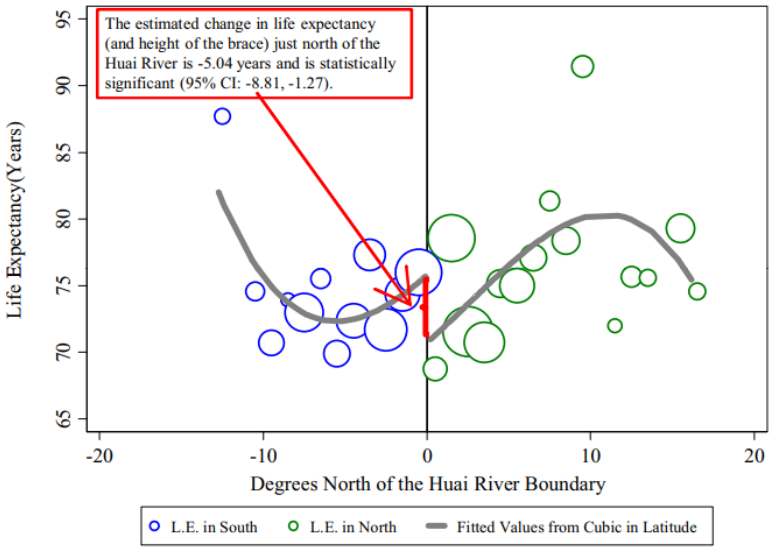


Fig. 3. The plotted line reports the fitted values from a regression of life expectancy on a cubic in latitude using the sample of DSP locations, weighted by the population at each location.

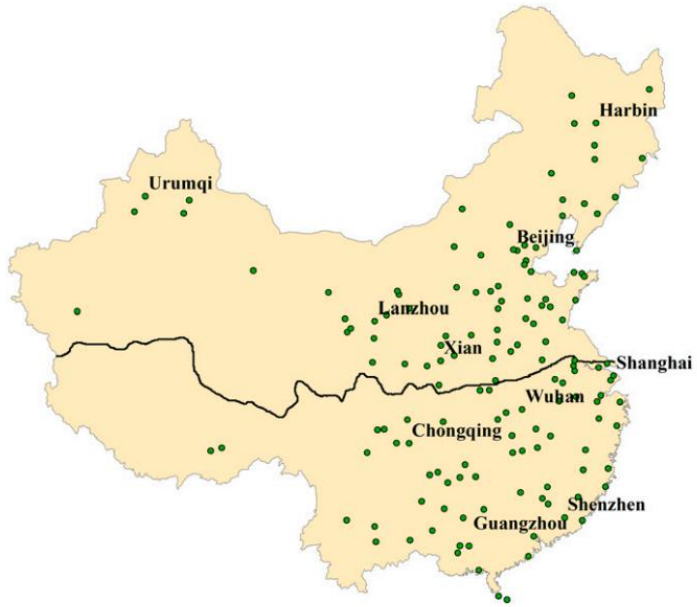
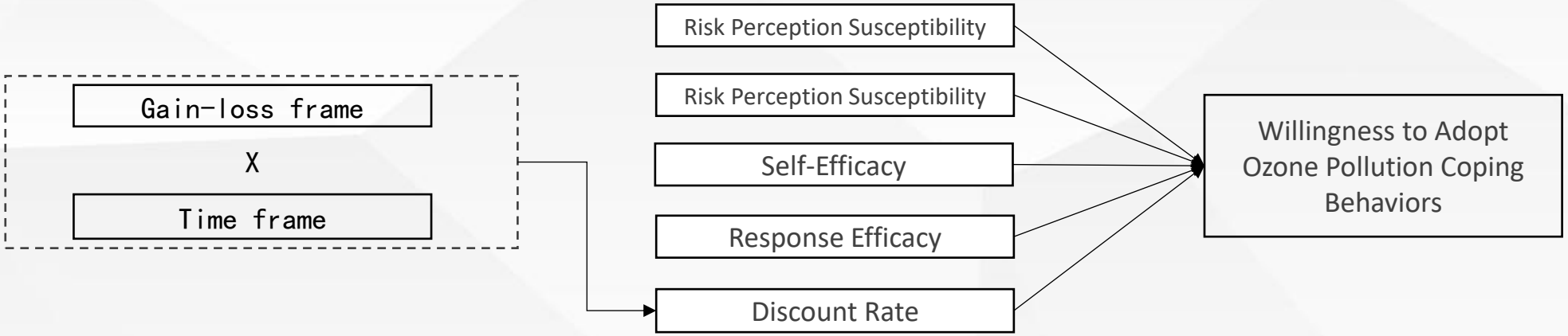
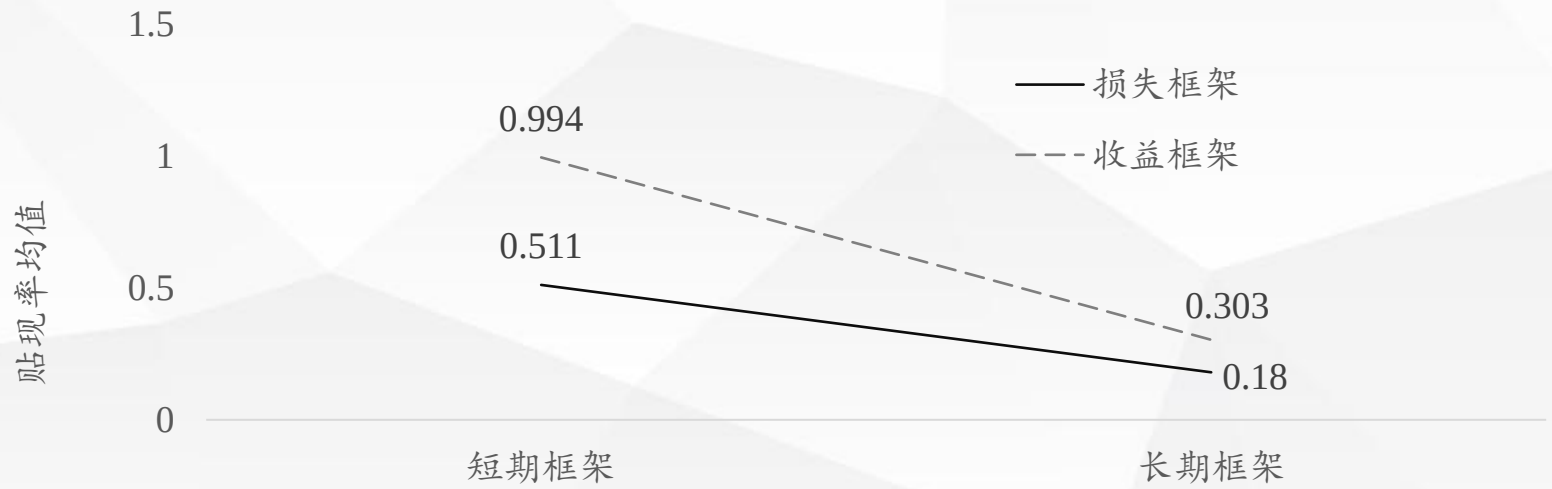


Fig. 1. The cities shown are the locations of the Disease Surveillance Points. Cities north of the solid line were covered by the home heating policy.

Chen, Y., Ebenstein, A., Greenstone, M., & Li, H. (2013). Evidence on the impact of sustained exposure to air pollution on life expectancy from China's Huai River policy. *Proceedings of the National Academy of Sciences*, *110*(32), 12936-12941.

Survey experiment





Lab experiment

nature human behaviour

LETTERS

https://doi.org/10.1038/s41562-018-0418-0

Differentiated responsibilities and prosocial behaviour in climate change mitigation

Reuben Kline[1,2*], Nicholas Seltzer[3], Evgeniya Lukinova[4,5] and Autumn Bynum[6]

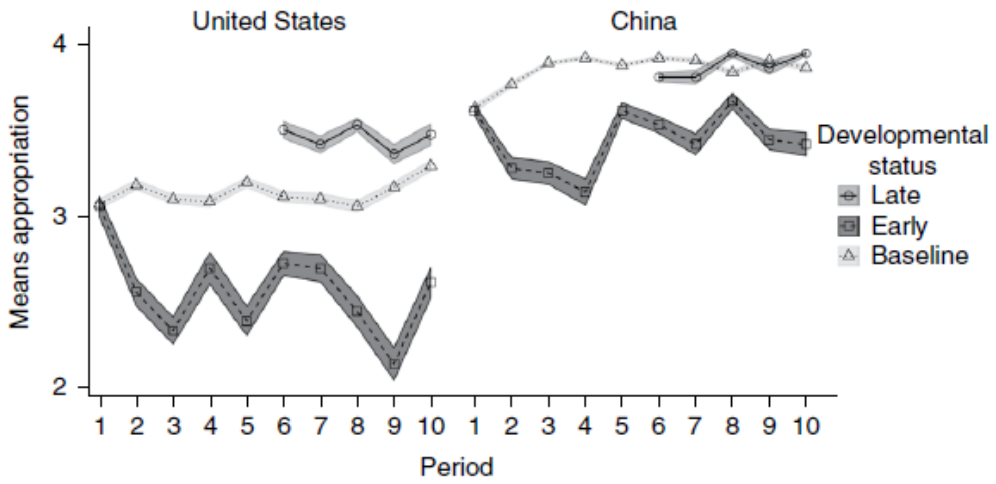


Fig. 1 | Average appropriation by period and development status. Early developers in differentiated group are represented by squares, ($n = 36$), late developers are shown as circles ($n = 36$) and baseline values are shown as triangles ($n = 72$). Shaded areas indicate the 95% CIs.

Field experiment



American Economic Review
ISSN 0002-8282 (Print) | ISSN 1944-7981 (Online)

About the *AER* | Articles and Issues | Information for Authors and Reviewers

The Impact of Media Censorship: 1984 or Brave New World?

Yuyu Chen

David Y. Yang

AMERICAN ECONOMIC REVIEW
VOL. 109, NO. 6, JUNE 2019
(pp. 2294–2332)

We randomly assign 1,800 university students in Beijing to either a control condition in which their internet use is subject to status quo censorship, or to a treatment condition in which they are given tools to bypass internet censorship for free for 18 months.

Science

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HOME > SCIENCE > VOL. 365, NO. 6448 > CIVIC HONESTY AROUND THE GLOBE

REPORT

Civic honesty around the globe

ALAIN COHN, MICHEL ANDRÉ MARÉCHAL, DAVID TANNENBAUM, AND CHRISTIAN LUKAS ZÜND Authors Info & Affiliations

SCIENCE · 20 Jun 2019 · Vol 365, Issue 6448 · pp. 70-73 · DOI: 10.1126/science.aau8712

70,154 101

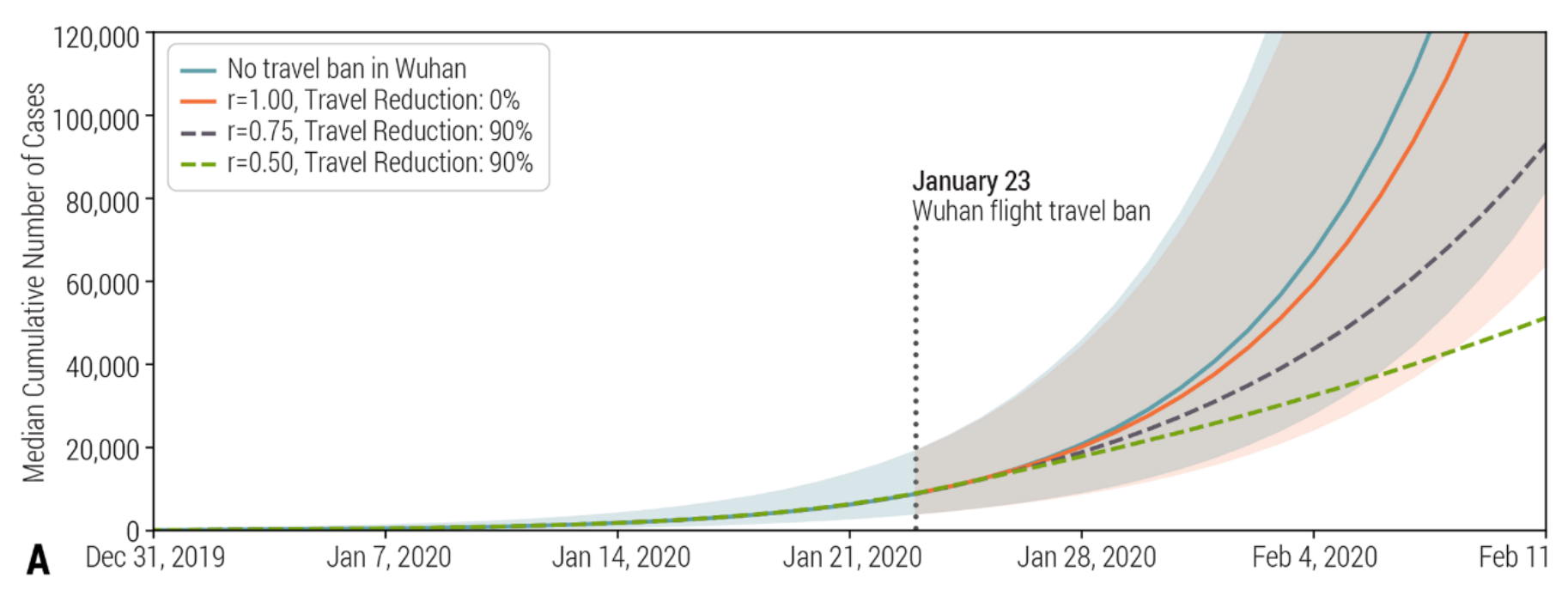
They distributed more than 17,000 wallets containing various sums of money in 355 cities across 40 countries.

Limitations of Inductive Reasoning

1.Inability to handle extreme cases

2.Limited to generalizing existing observations, with minimal extrapolation beyond established patterns

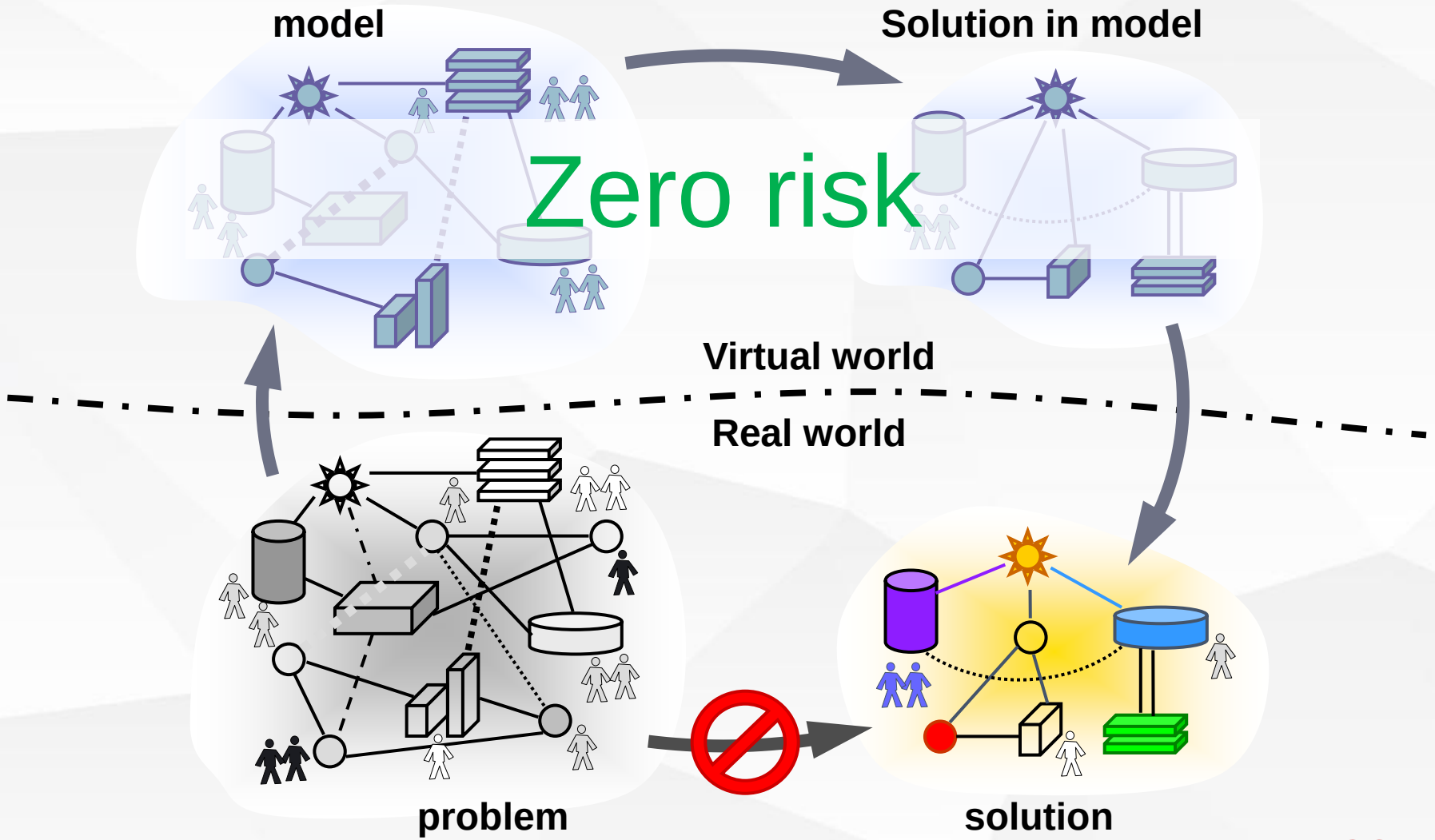
3.Difficulty in conducting scenario simulations or counterfactual analyses



M. Chinazzi *et al.*, "The effect of travel restrictions on the spread of the 2019 novel coronavirus (COVID-19) outbreak," *Science,* vol. 368, no. 6489, pp. 395-400, 2020.

Part 2：behavioral research based on modeling and simulation

Why need modeling?



Nature Science V.S. Social Science

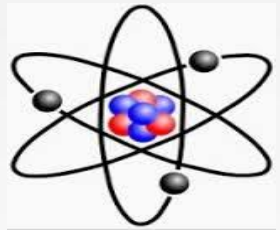
Nature Science



Object

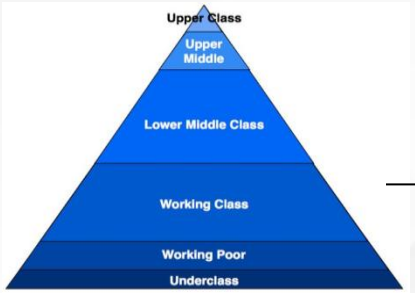


molecule

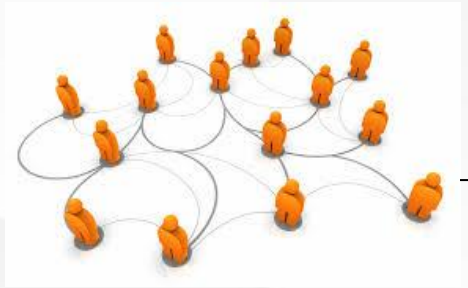


Atom

Social Science



Social Class



Social Network



Agent

Energy



Fire

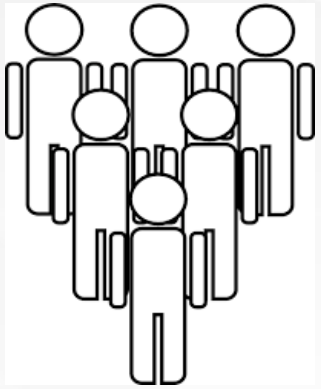


Bomb



Cognitive process in social science

More systematic and descriptive



- Population
- Average age
- Median income
- Rate of education



- Relationship
- Social network

More individual and deconstructive



- Individual characteristics
- Preference
- Behavior

Development of modeling

More systematic and descriptive



More individual and deconstructive

- Statistical Modeling (Data Driven Models)
- Social Network Analysis (SNA)
- Dynamic Social Networks (DSN)
- Systems Dynamics (SD)
- **Agent-based Modeling (ABM)**

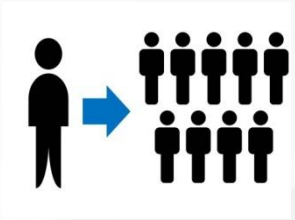
Why use agent-based modeling?

- A natural and intuitive way to model human behavior (e.g., modeling self-interested, heterogeneous stakeholders)
- A key towards implementing group relationship and interactions (communication, negotiation)
- Bottom up modeling: from the perspective of individual' activities more so than the system's processes
- A solution for distributed problems
- A adaptive system in dynamic environment

What can an agent model for?



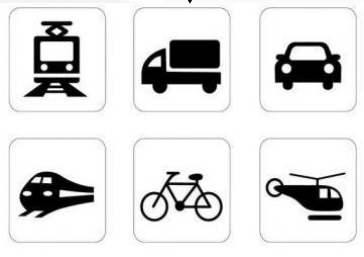
Agent



Individual



Group/Organization



Vehicle

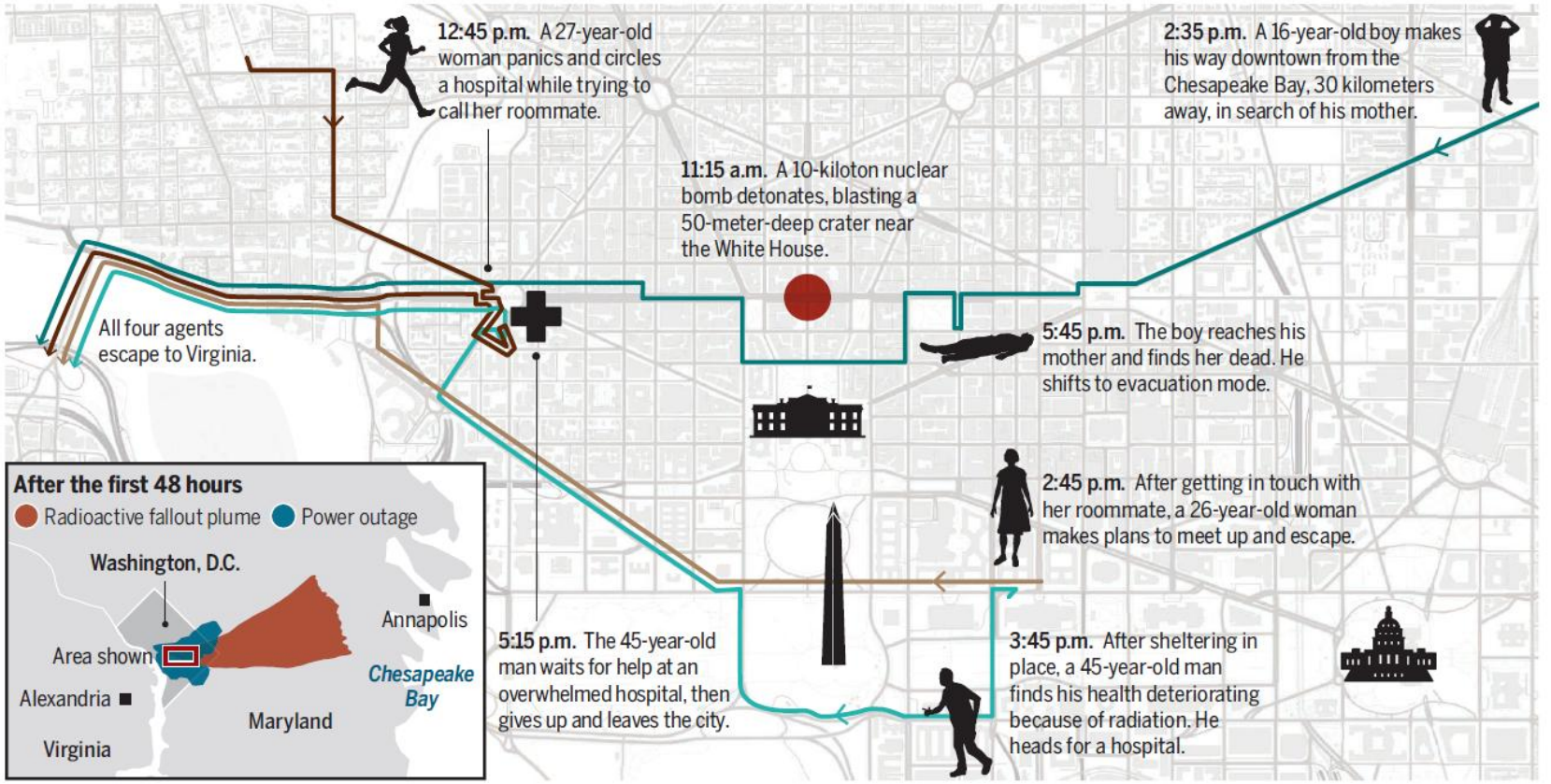


Land Use

For extreme situation

FREE AGENTS

Monumentally complex models are gaming out disaster scenarios with millions of simulated people *By* **M. Mitchell Waldrop**



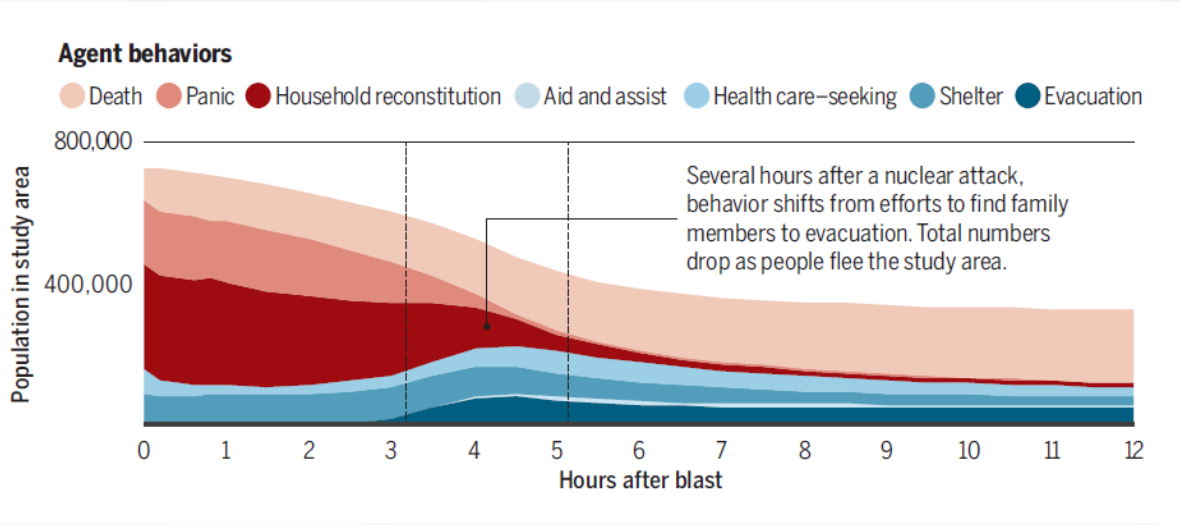
Waldrop, M. M. (2018). *Free agents. Science*, 360(6385), 144-147.

For extreme situation



FREE AGENTS

Monumentally complex models are gaming out disaster scenarios with millions of simulated people *By* **M. Mitchell Waldrop**



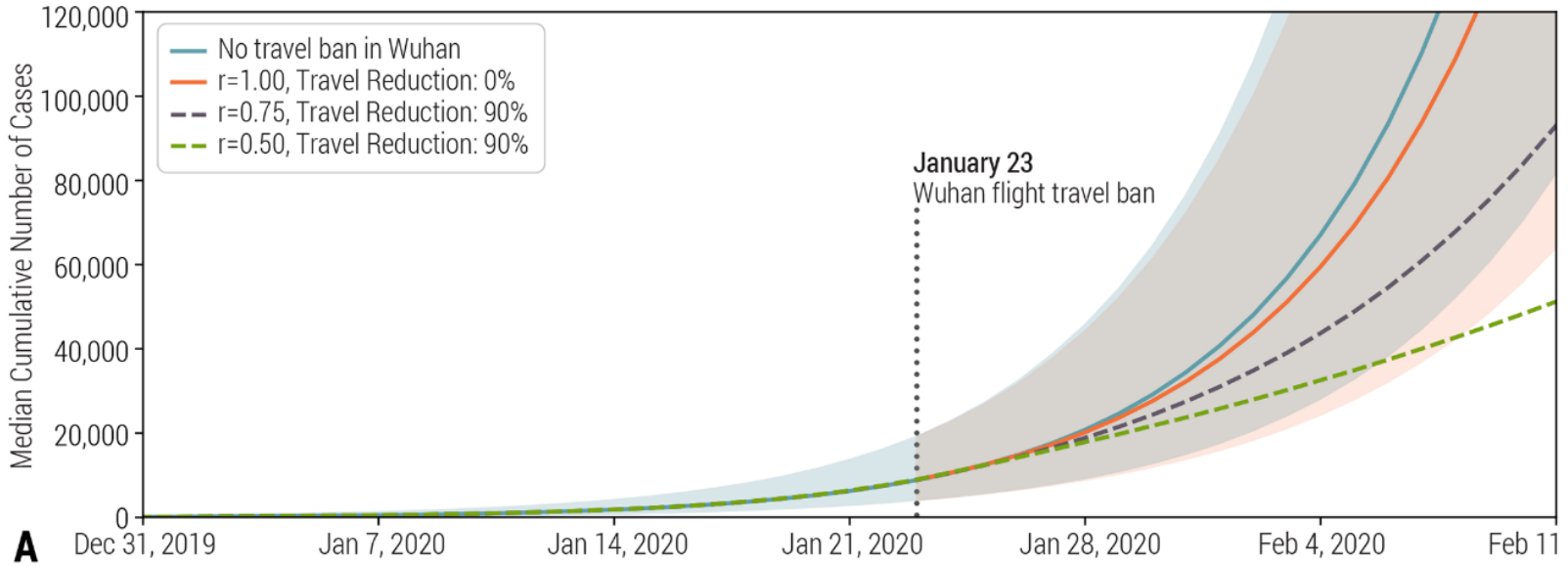
Counterfactual research

Science

RESEARCH ARTICLES

Cite as: M. Chinazzi *et al.*, *Science*
10.1126/science.aba9757 (2020).

The effect of travel restrictions on the spread of the 2019 novel coronavirus (COVID-19) outbreak



M. Chinazzi *et al.*, "The effect of travel restrictions on the spread of the 2019 novel coronavirus (COVID-19) outbreak," *Science,* vol. 368, no. 6489, pp. 395-400, 2020.

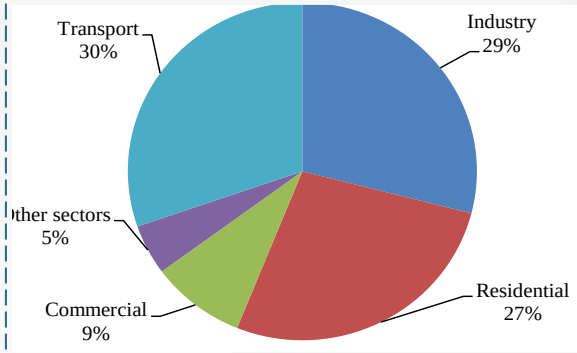
Making incentive policies more effective: An agent-based model for energy-efficiency retrofit in China

Liang, X., Yu, T.*, Hong, J., & Shen, G. Q. (2019). Making incentive policies more effective: An agent-based model for energy-efficiency retrofit in China. *Energy Policy*, 126, 177-189.

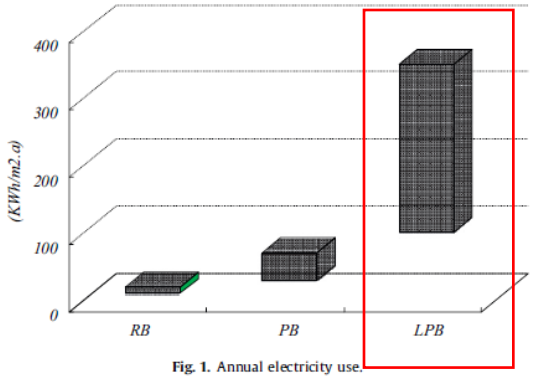
Research background

Energy consumption and GHG emission of the building sector

- The building sector was responsible for around **40%** of the final energy use in the world (IEA 2013b)
- And approximately **30%** of global greenhouse gas emissions (Kammen and Sunter, 2016)
- In the United States (US), buildings consume approximately **50%** of the total energy and 40% of GHG emissions (EIA, 2010)
- In China, building energy consumption increased by more than **10%** annually (Xu et al., 2011)



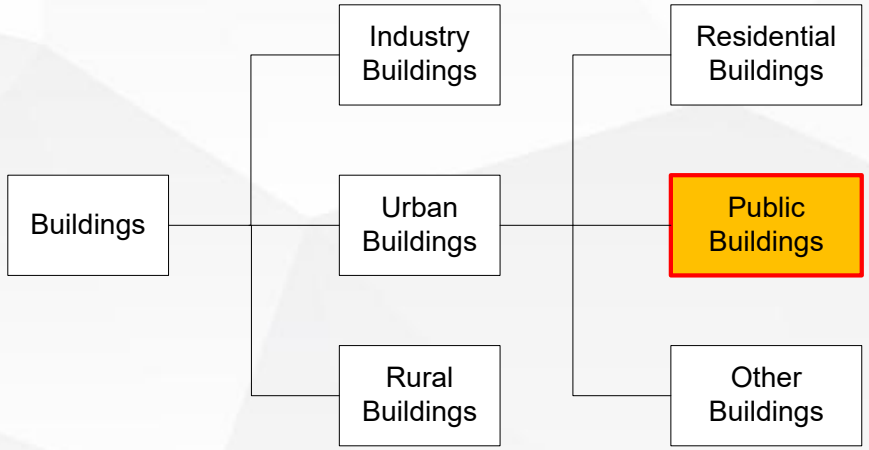
Energy consumption in different sectors
Source: IEA 2008



Annual electricity use in different building types
Source: Feng et al. 2009

Public buildings VS. Residential buildings

- Public buildings have high energy use intensity, which can reach 300 kWh/m^2 and **5–15 times** of that in residential buildings (THUBERC, 2007)
- Large public buildings accounted for around **20%** of total urban electricity consumption (Wu and Liu, 2007).



Incentive policy

Green retrofit

- **80%** of the energy consumed throughout a building's lifecycle occurs when it is occupied and in use (UNEP, 2007)
- The US government passed the Energy Policy Act (EPA), which require retrofitting **15%** of the total number of existing buildings (EPA, 2005).
- The UK government launched the Carbon Reduction Commitment (CRC) Energy Efficiency Scheme to save **1.2 million** tons of CO2 emissions annually by 2020.
- **60 million** m^2 public building retrofit in China during 2011-2015 (12th five-year plan of building energy efficiency)
- Four pilot cities are selected to try green retrofit policies of public buildings in China, which are **Tianjin, Chongqing, Shanghai, and Shenzhen.**

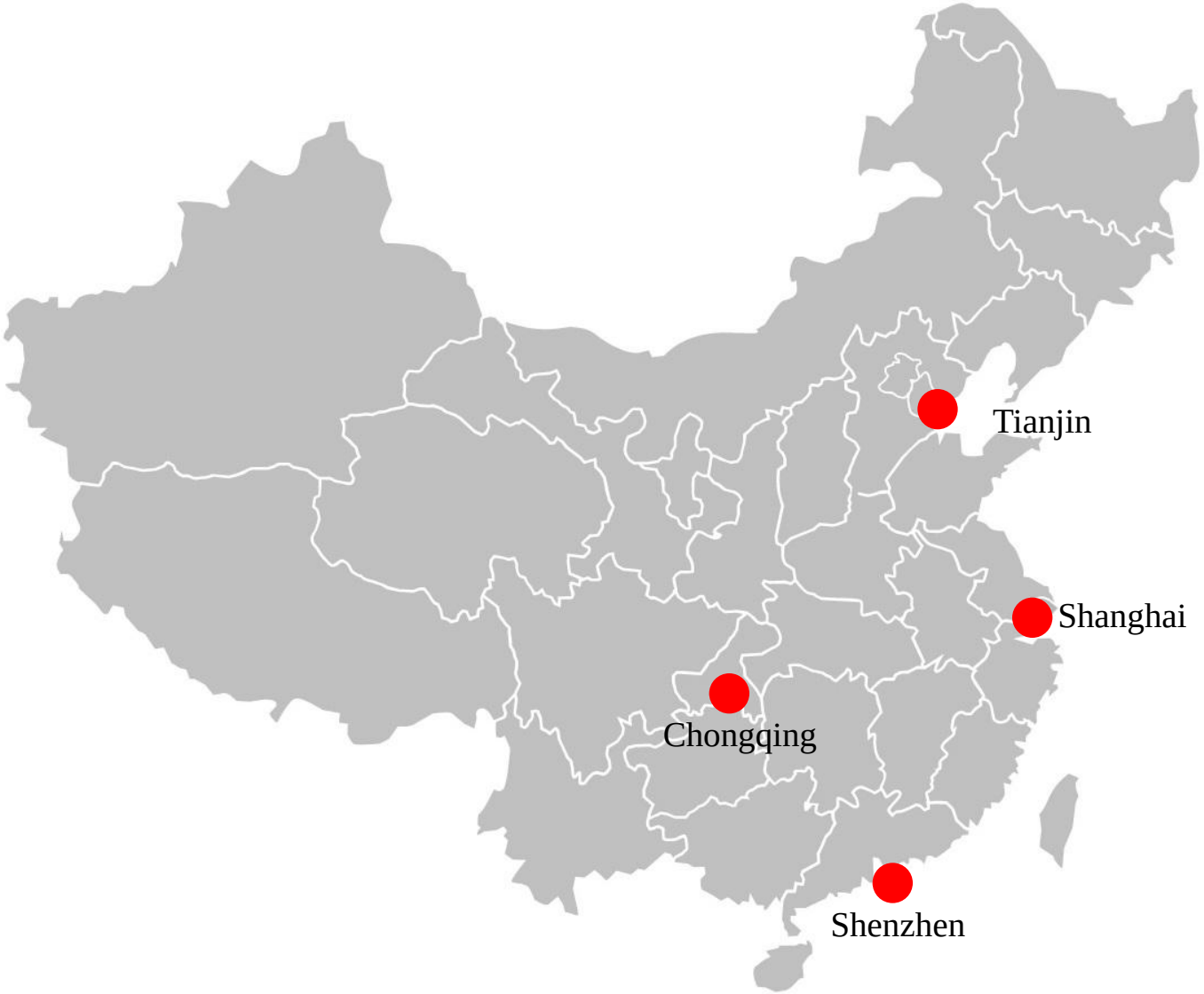
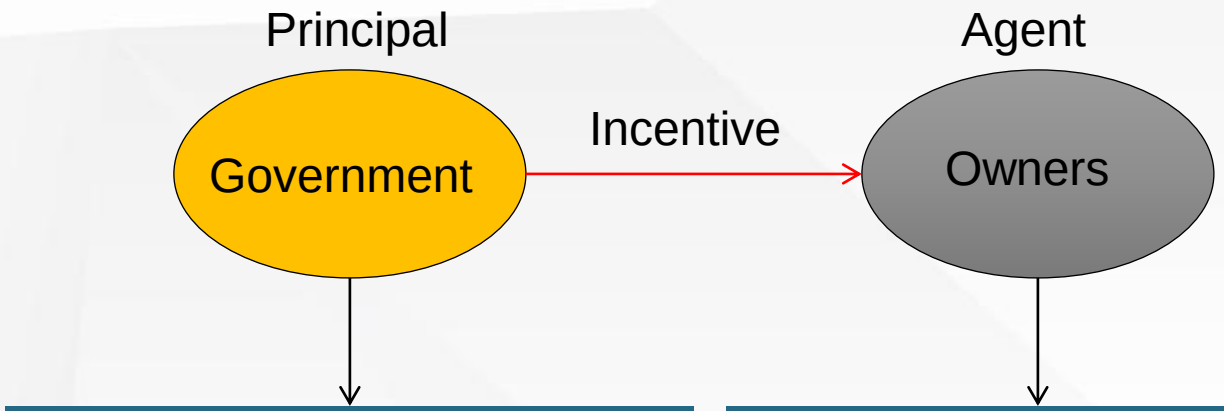


Figure. Four pilot cities for green retrofit of public buildings in China

Agent modeling

Agents and their relations



Aim: maximize the owners' effort on green retrofit

Environmental benefit-Incentive

Aim: maximize their benefit from green retrofit

Incentive+(bill saving)-cost

IR: Individual Rationality (benefit is more than opportunity cost)

IC: Incentive Compatibility (compatible with the owners)

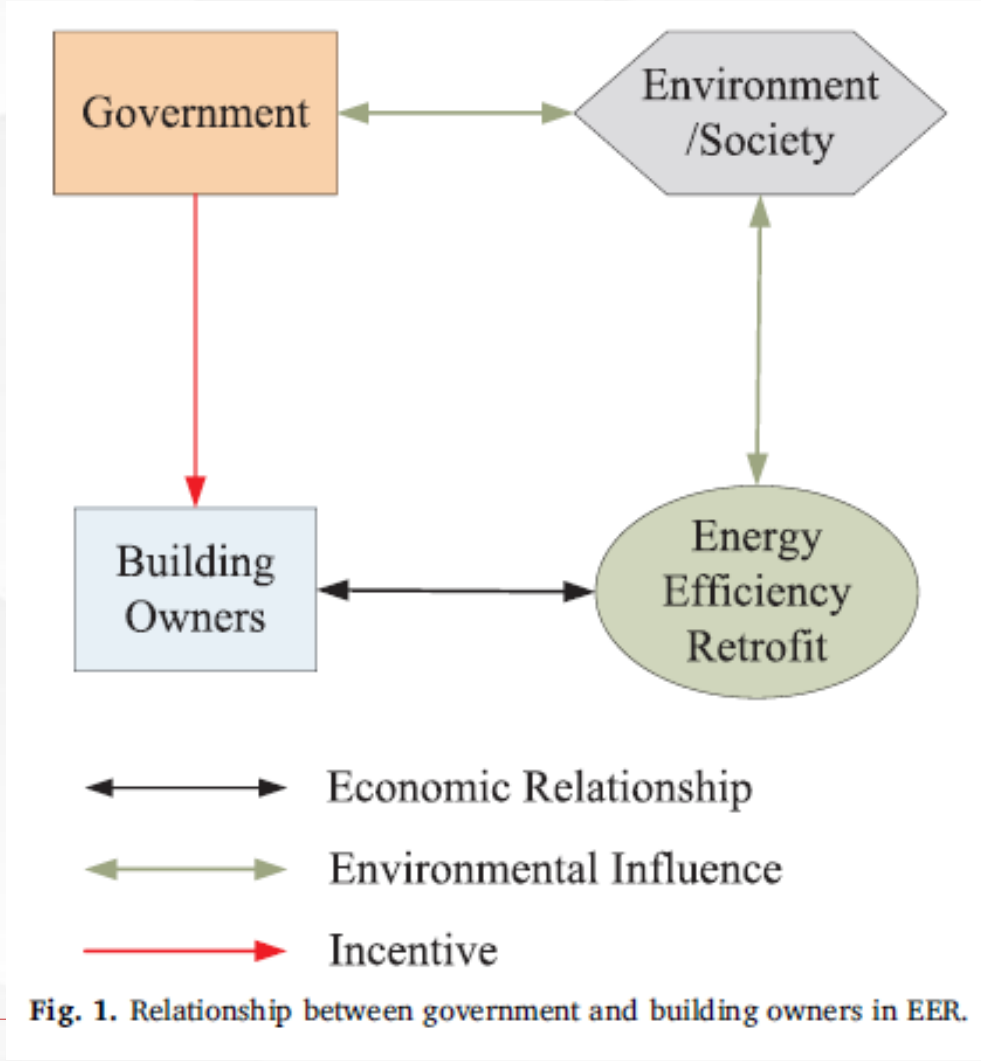


Fig. 1. Relationship between government and building owners in EER.

Variables and interactions

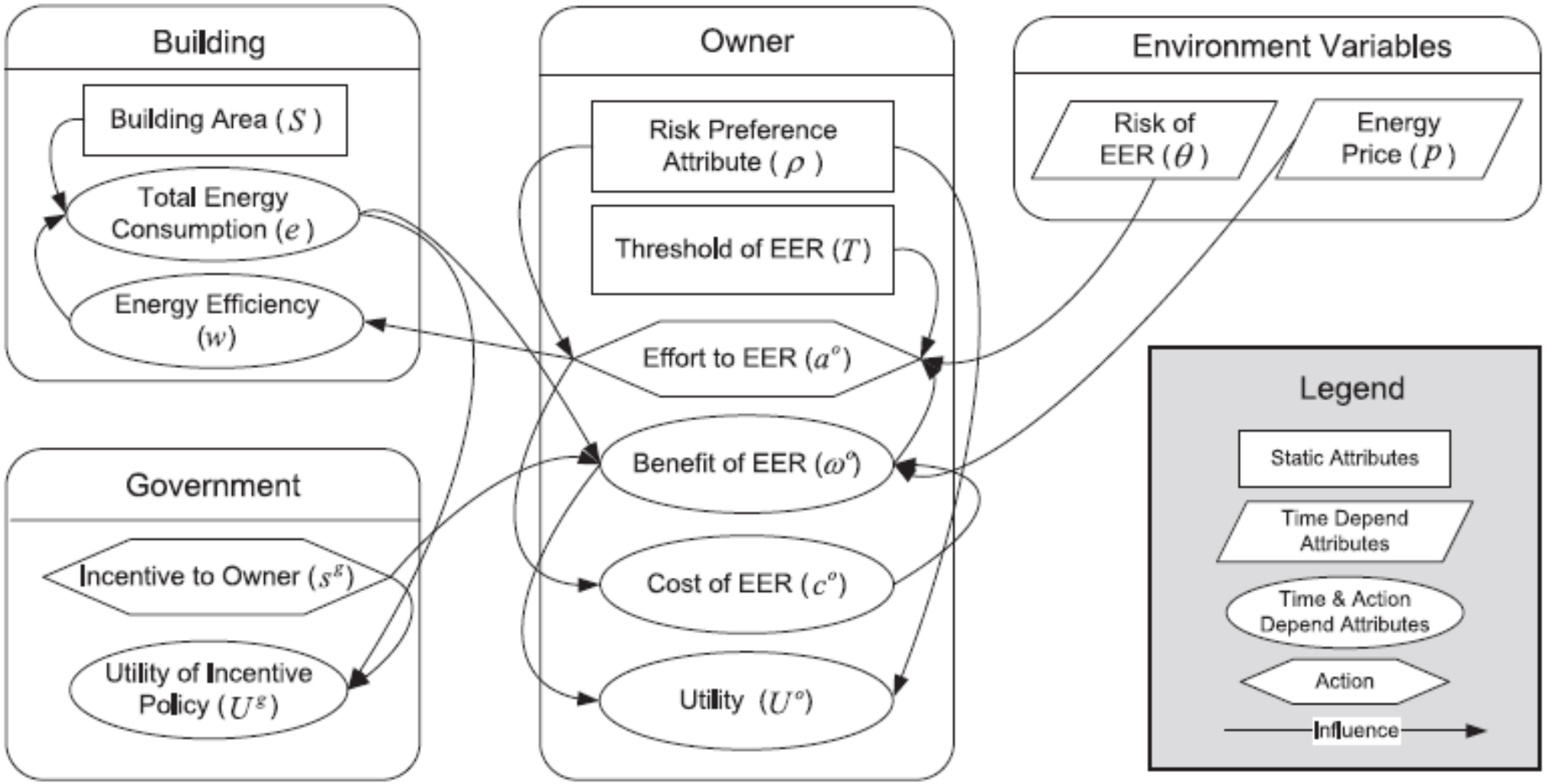


Fig. 3. Variables and agent interactions in the model.

Policy scenarios

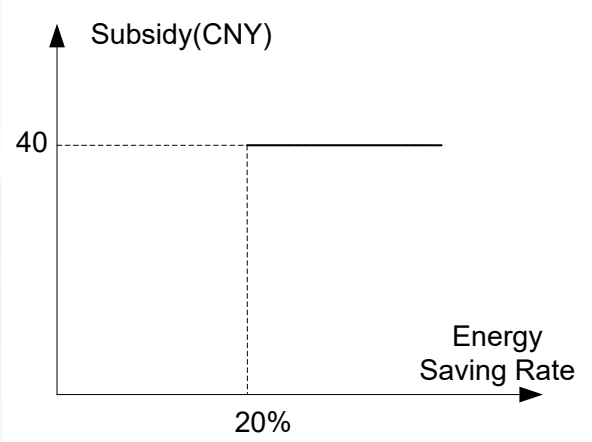


Figure. Policy of Shanghai for green retrofit

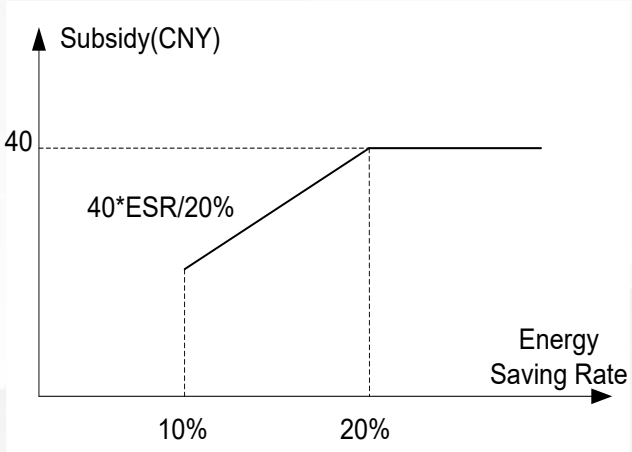


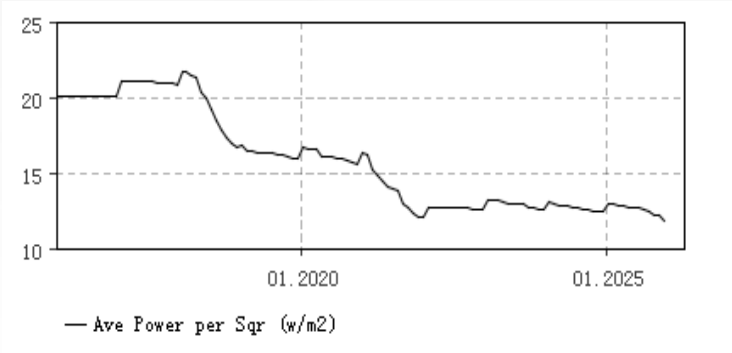
Figure. Policy of Shenzhen for green retrofit

Variable	Unit	Initial Value	Definition
Building number	NA	100	Number of buildings in a city
Age of building	year	0–30	Building age
Area of building	k m^2	2–10	Building area
Variance of uncertainty	NA	6	Risk of green retrofit
Effort of green retrofit	%	NA	Owners' effort paid on green retrofit
Effort coefficient	NA	0.5	Energy improvement rate of max effort
Cost coefficient	CNY	200	Cost of green retrofit effort
Risk coefficient	NA	3	Degree of risk aversion
Environment coefficient	%	0.6	Degree of environment
Energy price	CNY/kWh	1	Electric cost per kWh
Electric power	W/m^2	1	Electric power per square meter
Technology improvement	%	1-20%	Technology improvement rate
Technology breakthrough	Times/year	0.2-0.5	Technology breakthrough times per year
Threshold of owner	%	0	The least acceptable benefit rate of owner

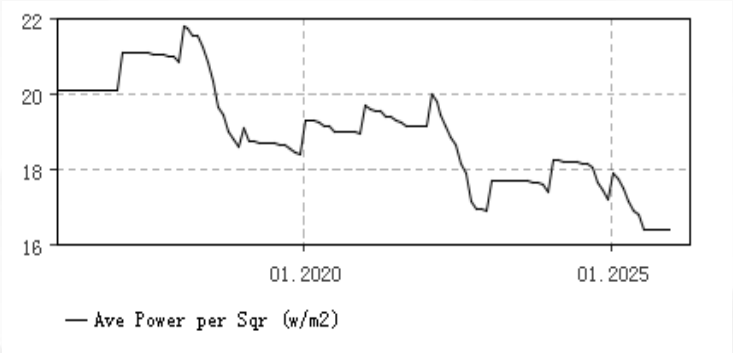
Results

Table. Simulation results of the three scenarios

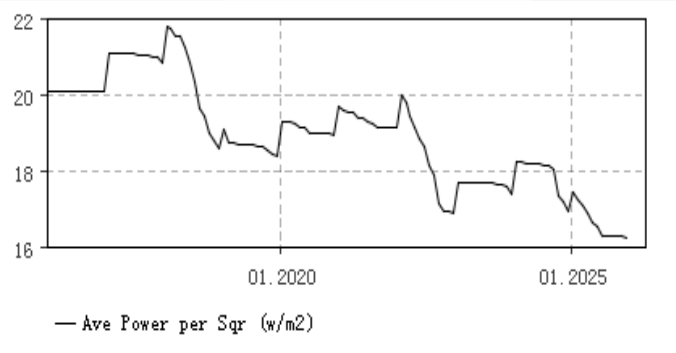
Simulation Results	Proposed	Shanghai	Shenzhen
(a) Incentive (M CNY)	169	366	360
(b) Efficiency Improvement (%)	39	15	14
(c) Cost to Owner (M CNY)	351	234	233
(d) Total Energy Save (MWh)	1,589,616	434,051	423,024
(e) Improvement per Incentive (b)/(a)	0.231	0.039	0.041
(f) Improvement per Total Cost (b)/((a)+(c))	0.075	0.024	0.025
(g) Energy Save per Total Cost (d)/((a)+(c))	3057	713	723



(a)



(b)



(c)

Figure. Change of electric power per square meter during simulation for 10 years
(a) the proposed model, (b) Shanghai, and (c) Shenzhen

How to promote residents' use of green space: An empirically grounded agent-based modeling approach

Liang, X., Lu, T., & Yishake, G. (2022). How to promote residents' use of green space: An empirically grounded agent-based modeling approach. *Urban Forestry & Urban Greening*, 127435.

Research background





- **The challenges of green space policy optimization in Chinese cities** (Ji et al., 2017; Wu, 2012; Yu, 2014)
  - Unprecedented speed of urban sprawl, loss and alienation of green space
  - The ‘environmental turn’ in economic development
  - Eco-cities, 15-minutes neighborhoods

Research framework

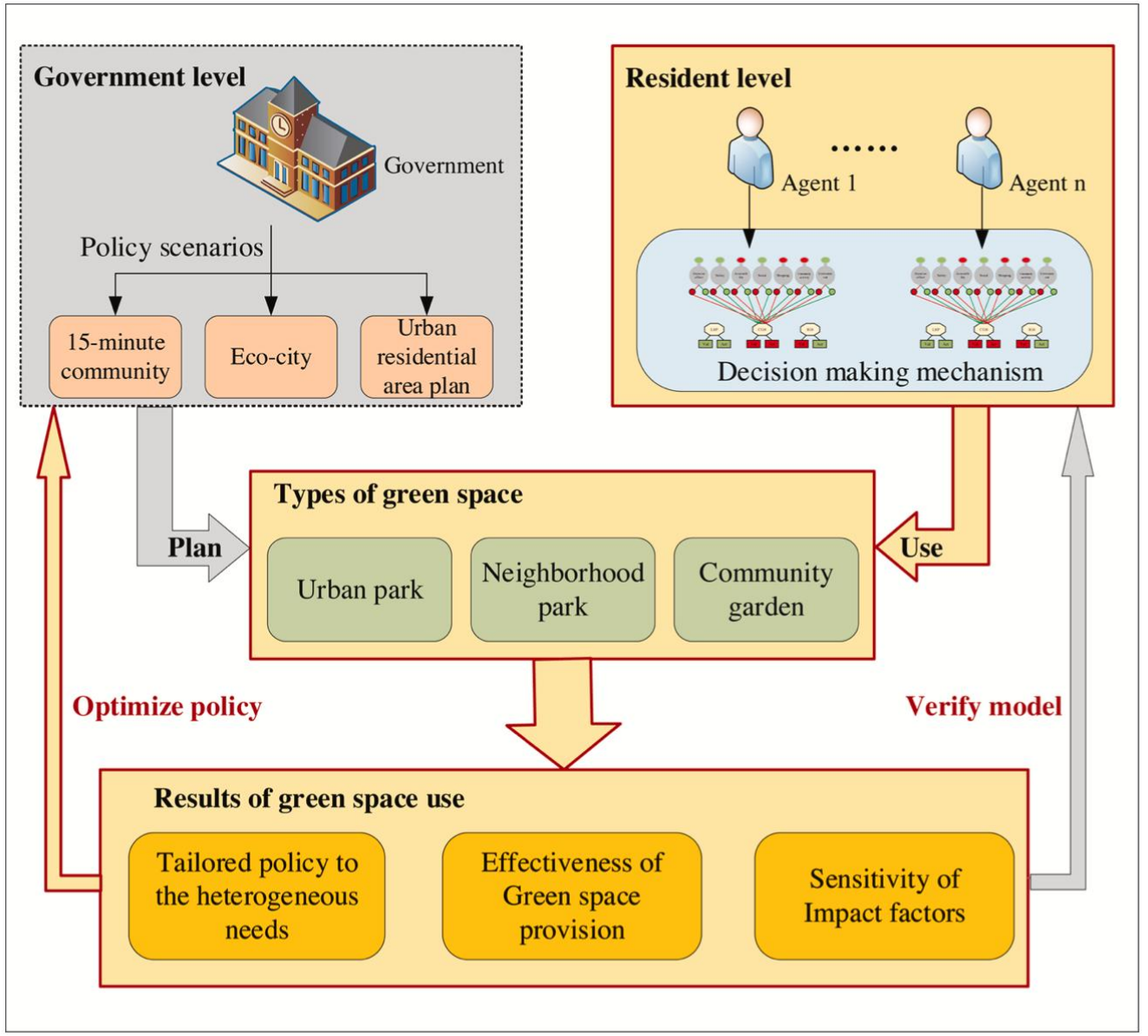


Fig. 1. Framework of the ABM for green space use.

Decision-making model

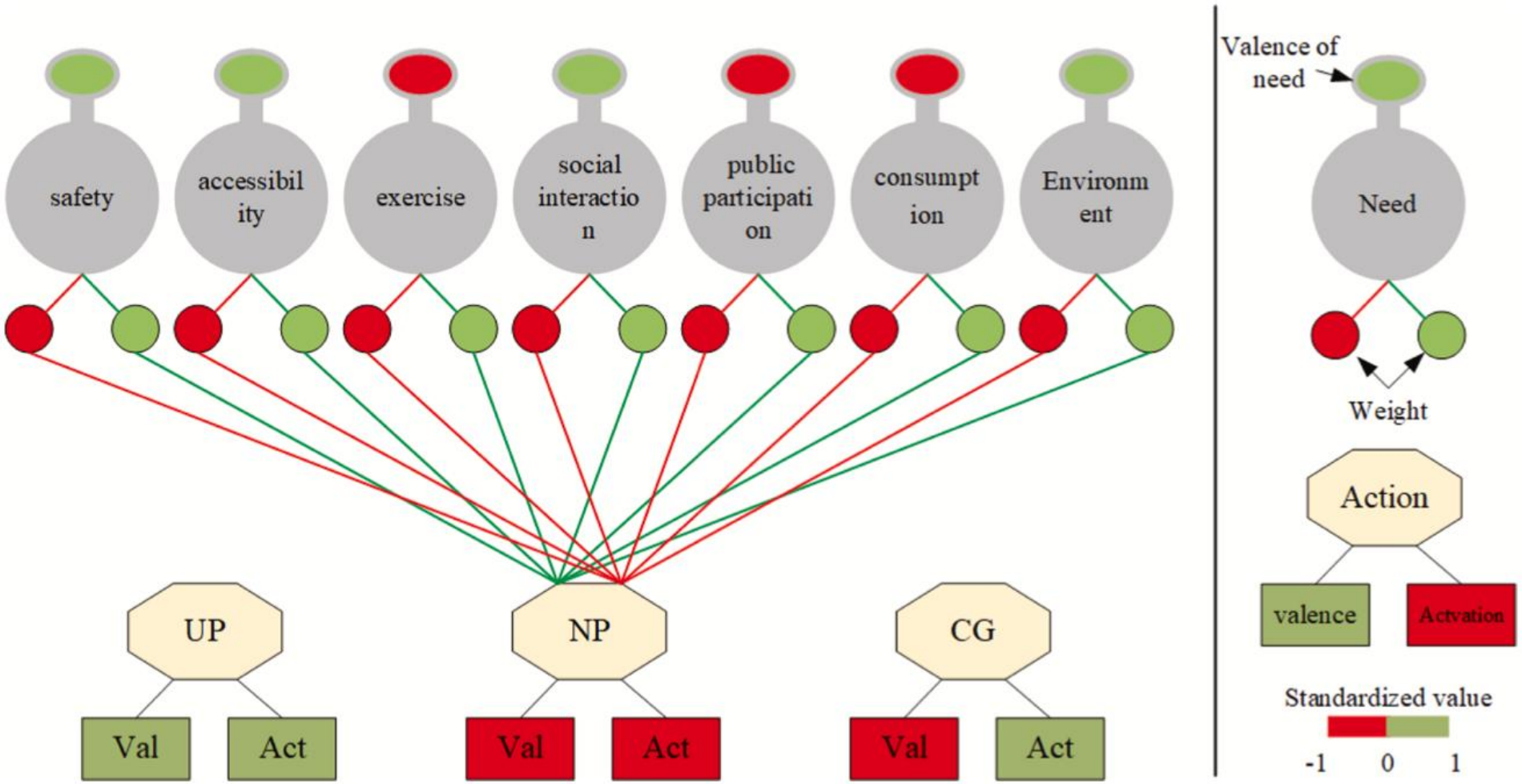


Fig. 2. A schematic diagram of the decision-making mechanism of residents.

Results

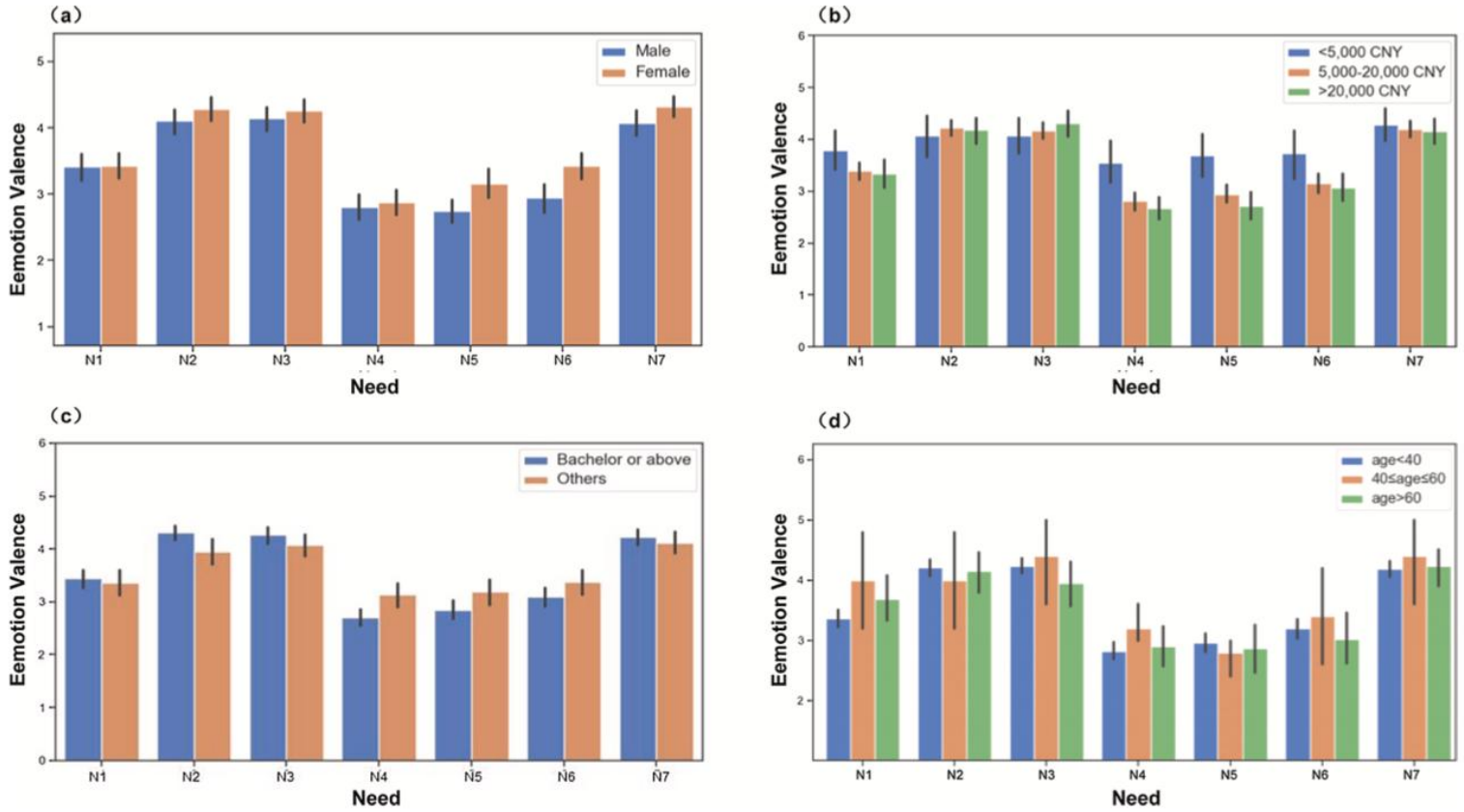


Fig. 5. Emotion valence of needs among groups.

N1–exercise, N2–safety, N3–accessibility, N4–social interaction, N5–consumption, N6–public participation, N7–environmental connection

Results

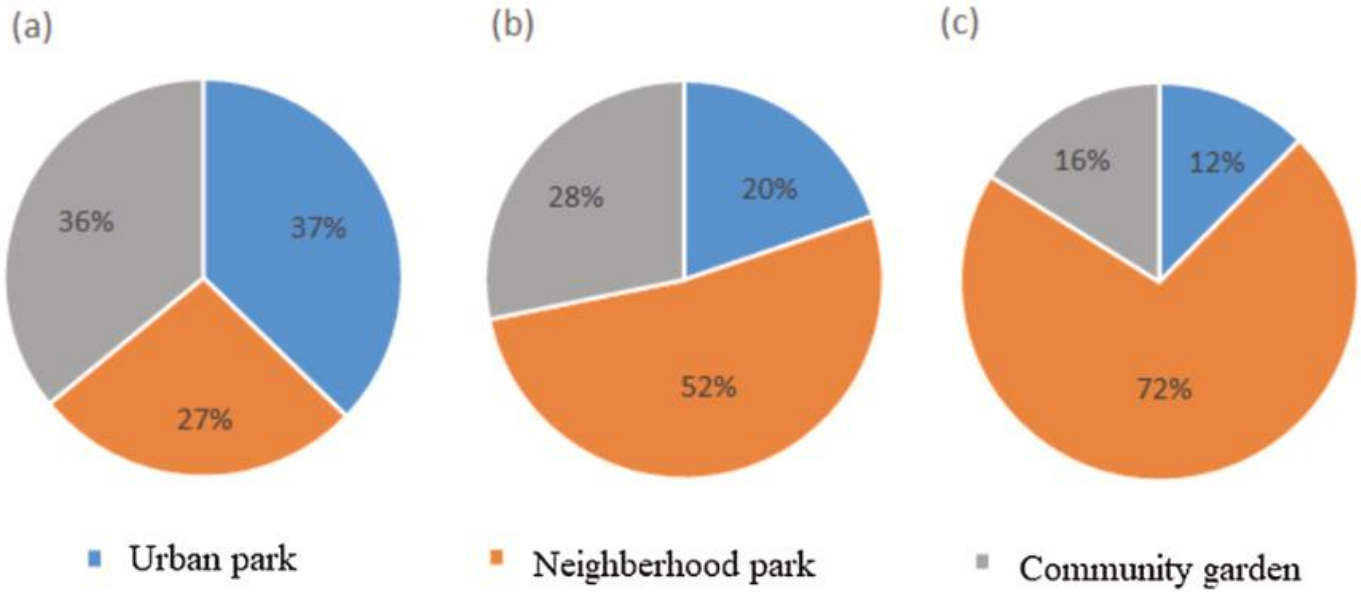


Fig. 6. Residents' decision results of using green space under different scenarios.
(a) Scenario 1: the urban residential area plan; (b) Scenario 2: the eco-city plan; (c) Scenario 3: the 15-minute community plan.

Results

- when policy intensity is above 4 (the average level), the intention to use NP is more sensitive to safety, environmental connection, and accessibility (steep slope of curves)
- when policy intensity is below 4 (the average level), the intention to use NP is more sensitive to public participation, social interaction, and consumption

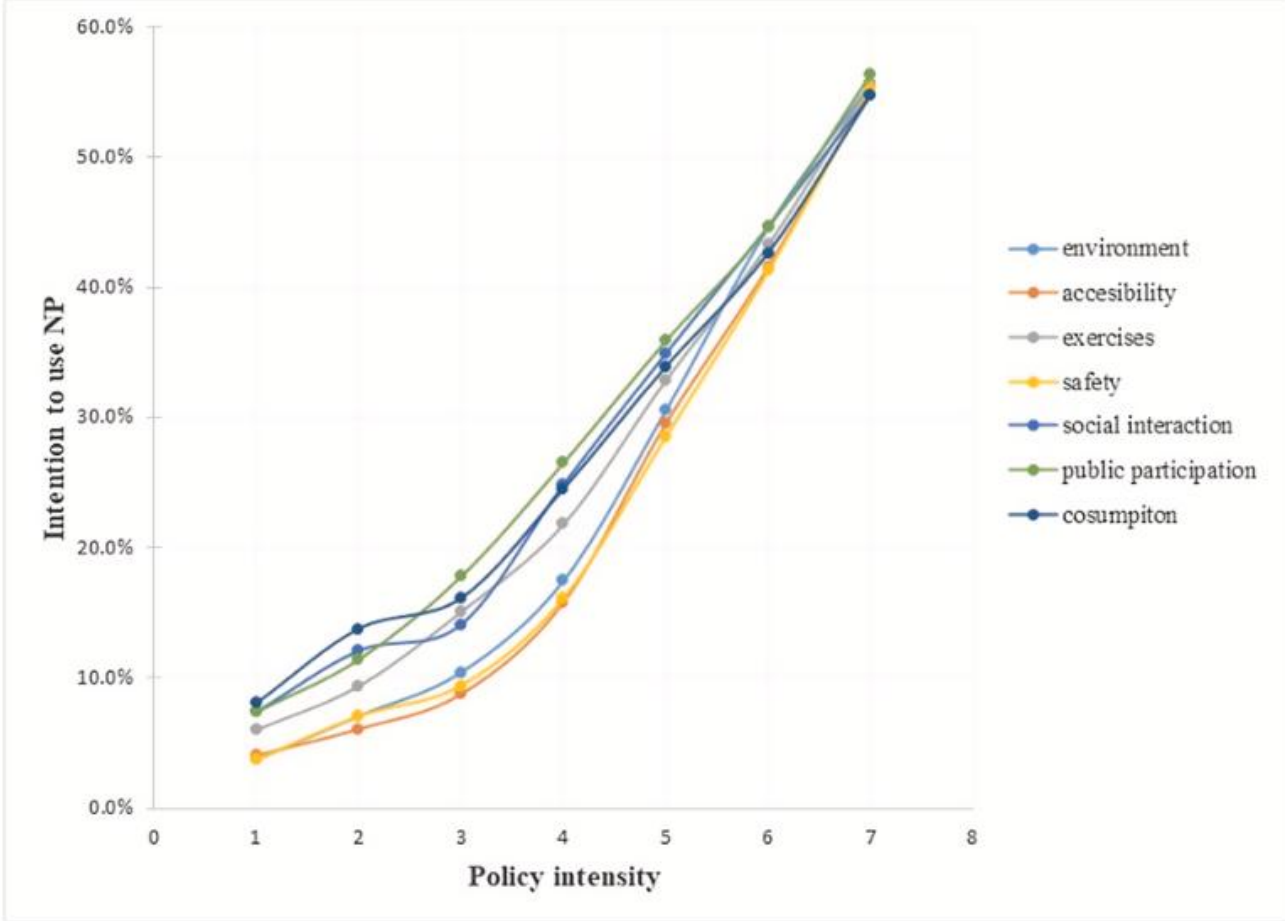


Fig. 7. Results of sensitivity analysis of NP in Scenario 3.

Results

Table 7
Optimized policy through improving the need of social interaction.

Scenario	Policy intensity	UP (%)	NP (%)	CG (%)	Total (%)
	5	31.2	29.2	39.6	100.0
S1	6	25.5	42.6	31.9	100.0
	7	18.5	56.7	24.8	100.0
	5	20.8	49.3	29.9	100.0
S2	6	15.1	61.1	23.8	100.0
	7	13.1	70.5	16.4	100.0
	5	13.1	71.8	15.1	100.0
S3	6	9.4	78.5	12.1	100.0
	7	6.7	85.6	7.7	100.0

Table 8
Optimized policy through improving the need of public participation.

Scenario	Policy intensity	UP (%)	NP (%)	CG (%)	Total (%)
	5	28.9	35.2	35.9	100.0
S1	6	24.8	45.6	29.5	100.0
	7	17.1	57.0	25.8	100.0
	5	18.1	56.0	25.8	100.0
S2	6	14.4	63.4	22.1	100.0
	7	13.4	68.8	17.8	100.0
	5	11.4	73.2	15.4	100.0
S3	6	8.7	80.2	11.1	100.0
	7	6.7	84.9	8.4	100.0

Two-way catalytic effect: the impact of travel behaviours on carbon emissions of road transportation

Research background

Human behavior + environment system

Nature： “coupled climate–social system” （Moore et al., 2022）

Nature Human Behavior: “Incorporating human behaviour into Earth system modelling” (Beckage et al., 2022)

Nature Climate Change: “Behaviour as leverage” (Editorial in 2022)

- Behaviour change is essential for effective solutions to climate threats.
- Thus, policy-relevant behavioural science studies are needed for a shift towards human-centred climate actions

Coupling framework

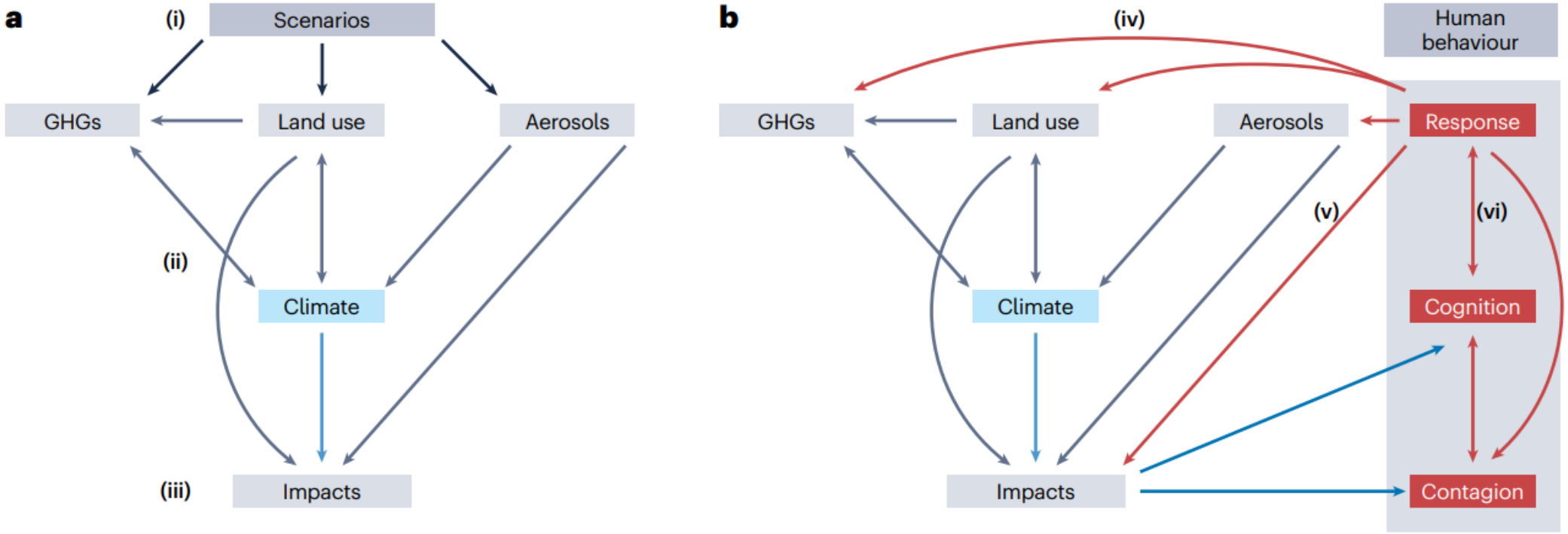


Fig. 1 | Traditional climate models and social climate models. a, Extrinsic scenarios for emissions, land use change and aerosols have traditionally been used to force global climate models. In this approach, a set of possible behavioural pathways are identified (i), and these trajectories determine anthropogenic forcing of climate (ii), mediated by feedbacks internal to the Earth system, to project climate change and impacts (iii). **b**, Coupling climate models with human behaviour allows the models to capture dynamic human responses to climate change that can improve projections of anthropogenic forcing (iv), better represent human adaptation to climate change for improved impact models (v) and characterize behavioural feedbacks that reinforce or balance human responses to climate change to identify points of high leverage for climate change mitigation (vi). Economic, political, and technical dynamics are embedded in the scenarios in **a** and in the behavioural response in **b**.

Beckage, Brian, Frances C. Moore, and Katherine Lacasse. "Incorporating human behaviour into Earth system modelling." *Nature Human Behaviour* 6.11 (2022): 1493-1502.

人类行为与环境系统耦合研究

Research question

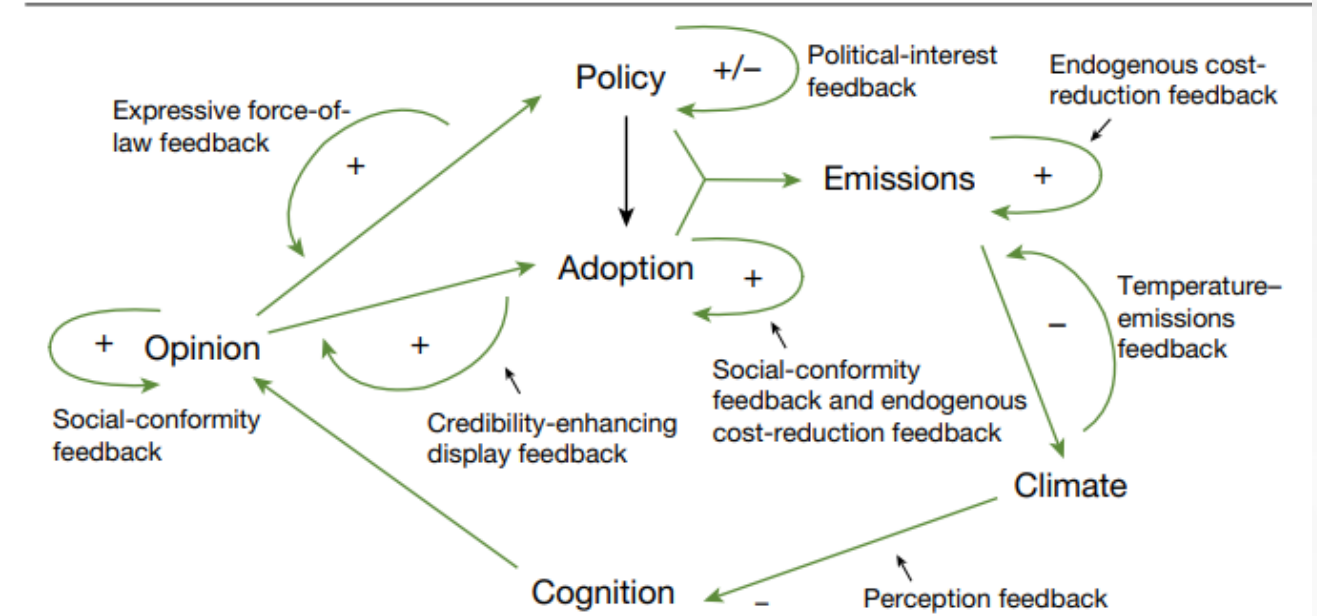


Fig. 1 | The climate–social model components and feedback processes.

Are human behavioral feedbacks to environmental systems necessarily positive? Could there be simultaneous positive and negative effects? What kind of composite mechanisms might ultimately emerge?

Is it possible to integrate not only macro-level simulated data but also real-world empirical data?

Moore, Frances C., et al. "Determinants of emissions pathways in the coupled climate–social system." *Nature* 603.7899 (2022): 103-111.

modeling

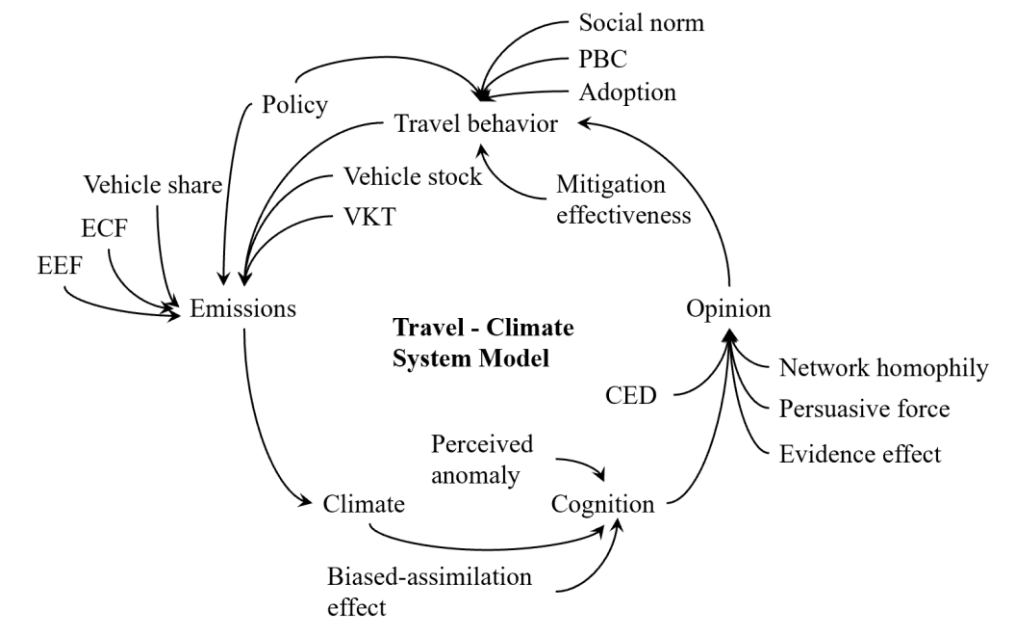


Figure 2 Conceptual framework of the model

Table 6 Description of each scenario

Scenario	Focus	Scenario Description	Parameter	Parameter Description
SSP1_DER	Deep emission reduction scenario	Integrate scenarios, and focus on technological progress to improve and limit private car stock	Population	It reaches a maximum of 1.45 billion in 2028 and declines to 1.25 billion by 2060.
			Economy	Annual growth rate decreases from 5.75% in 2020 to 0.11% in 2060.
			Vehicle share	By 2035, the share of electric buses will reach 100%, and by 2060, the share of electric taxis and private cars will account for 85% and 65% respectively.
			Energy Efficiency	The energy efficiency improvement rates of various energy types of vehicles are 0.15% -1.5%, 0.225% -2.25%, and 0.3% -3% in 2021-2025, 2026-2030, and 2031-2035, respectively. After 2036, the energy efficiency reaches saturation.
			Emission factors	The emission factors for CNG and LPG remain unchanged, and the emission factors for gasoline, diesel, electricity, and hydrogen

Five modules: Climate, Cognition, Attitude, Behavior, Emissions

Policy scenarios: Primarily based on the Shared Socioeconomic Pathways (SSPs), specifically including indicators such as population, economy, vehicle share, energy efficiency emission factors, and private car ownership.

modeling

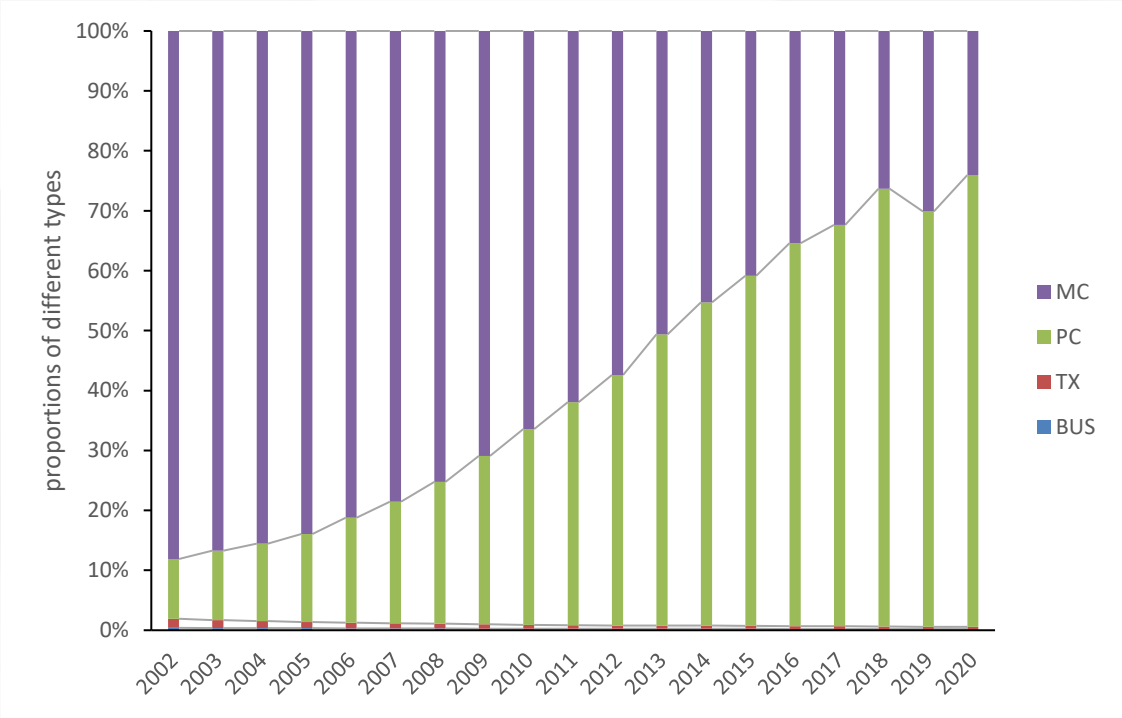


Figure 1 Proportion of different types of vehicle stock in China

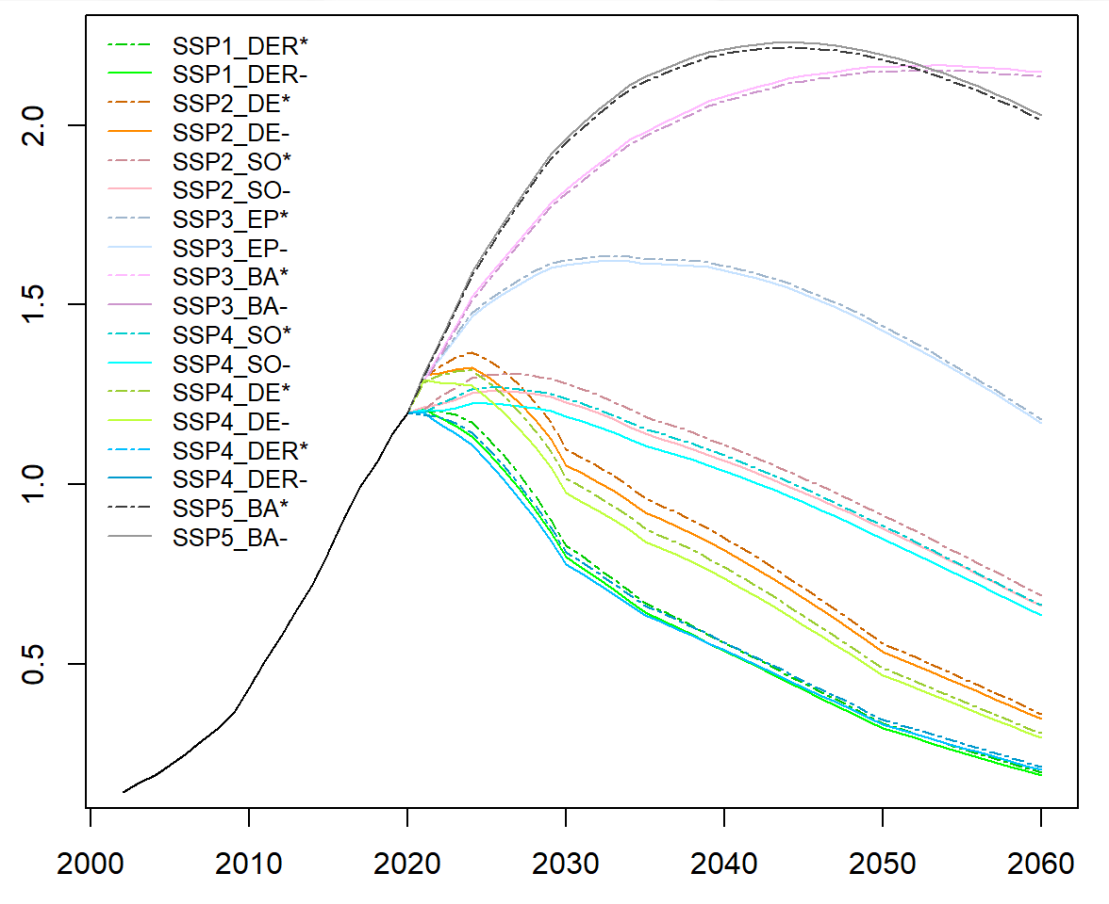
Table 1 Energy consumption factor of each energy type vehicle (unit: MJ/km)

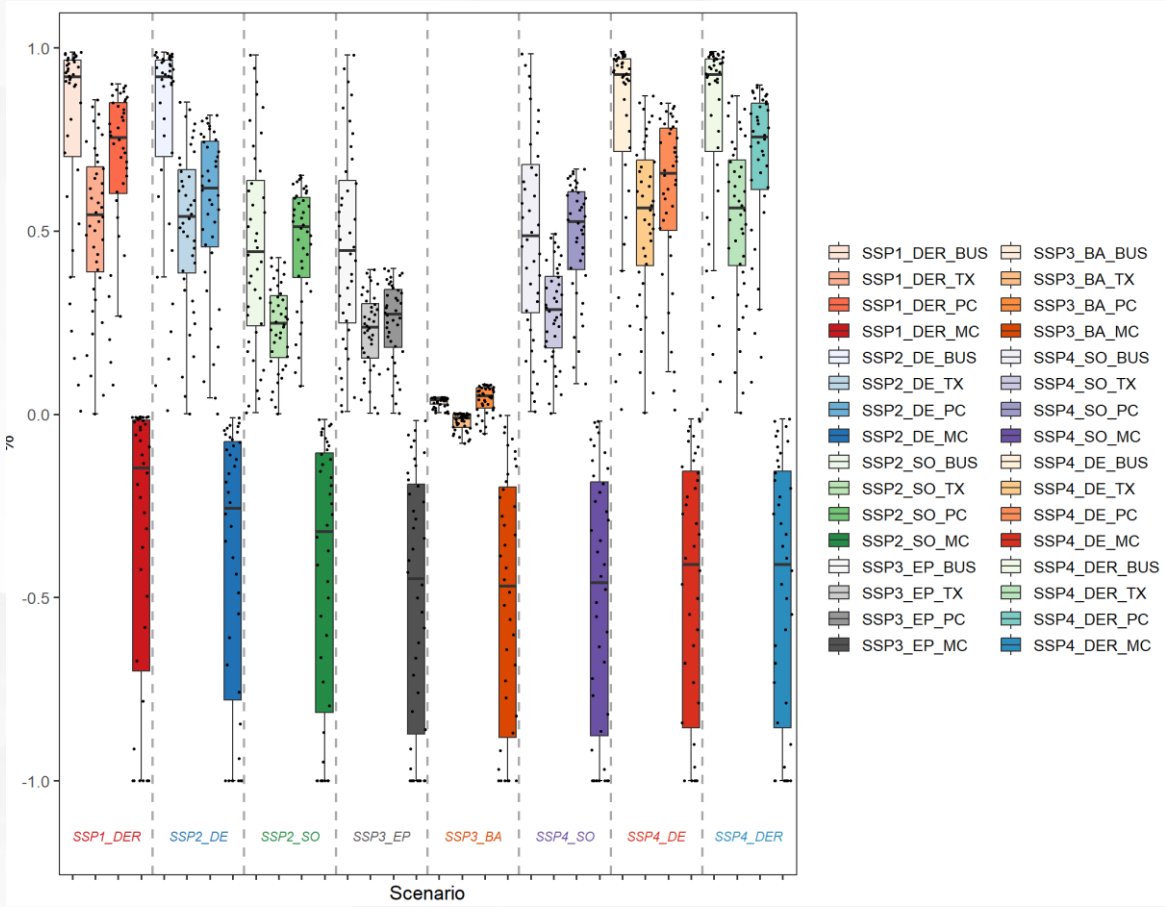
Vehicle type	Energy type	Value	References
BUS	Gasoline	10.41	Duan et al., 2021;Liu et al., 2021
	Diesel	14.29	Duan et al., 2021;Liu et al., 2021;Sheng&He et al., 2016;Zhang et al., 2014
	CNG	16.24	
	LPG	23.32	Liu et al., 2021;Sheng&He et al., 2016
	Electricity	2.72	Liu et al., 2021;Sheng&He et al., 2016;Zhang et al., 2014
	HEV	9.55	
TX	Gasoline	3.20	Duan et al., 2021;Liu et al., 2021;Sheng&He et al., 2016
	Diesel	3.52	Zhang et al., 2014
	LPG	4.15	Liu et al., 2021
	CNG	3.60	Duan et al., 2021;Liu et al., 2021;Sheng&He et al., 2016;Zhang et al., 2014
	DF	2.24	Jie et al.,2011

Scenario: The coupling relationship between human travel behavior (transportation mode choice) and environmental systems

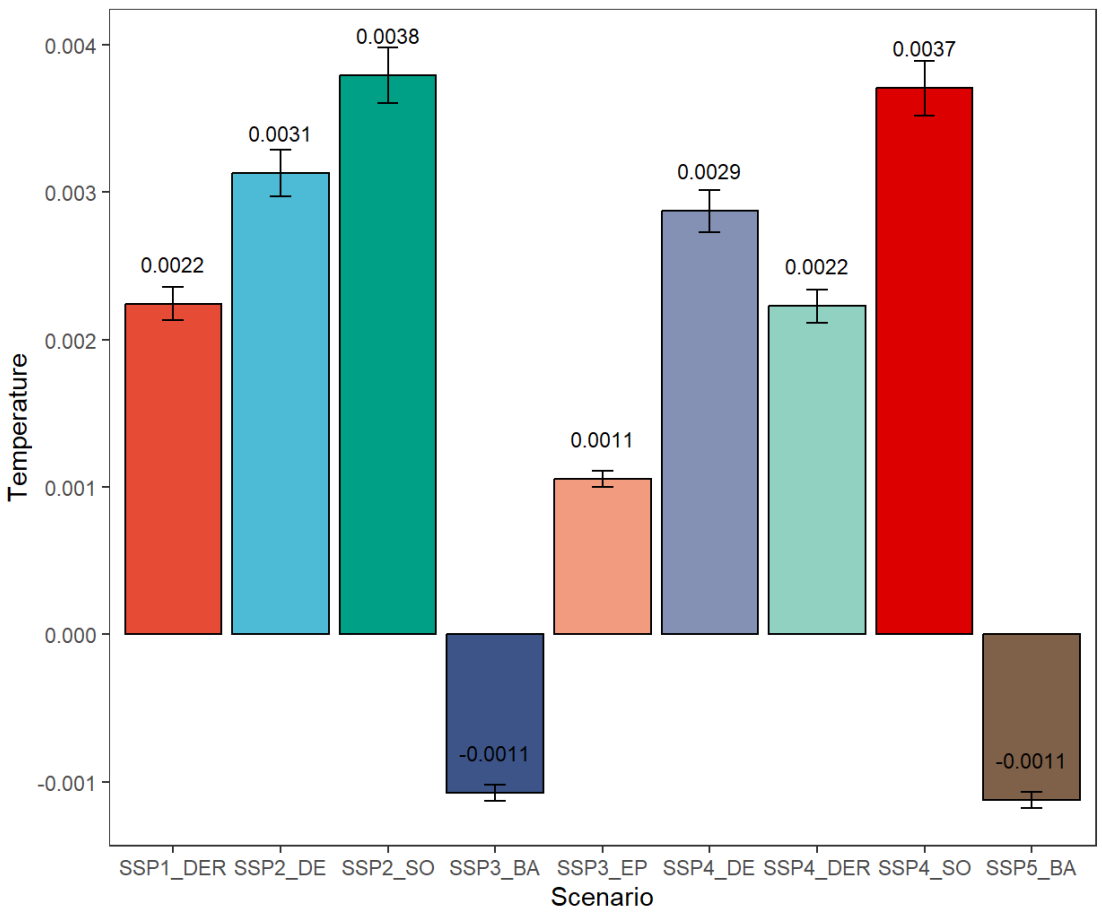
Characteristics: Travel behavior may be subject to bidirectional influences, both positive and negative.

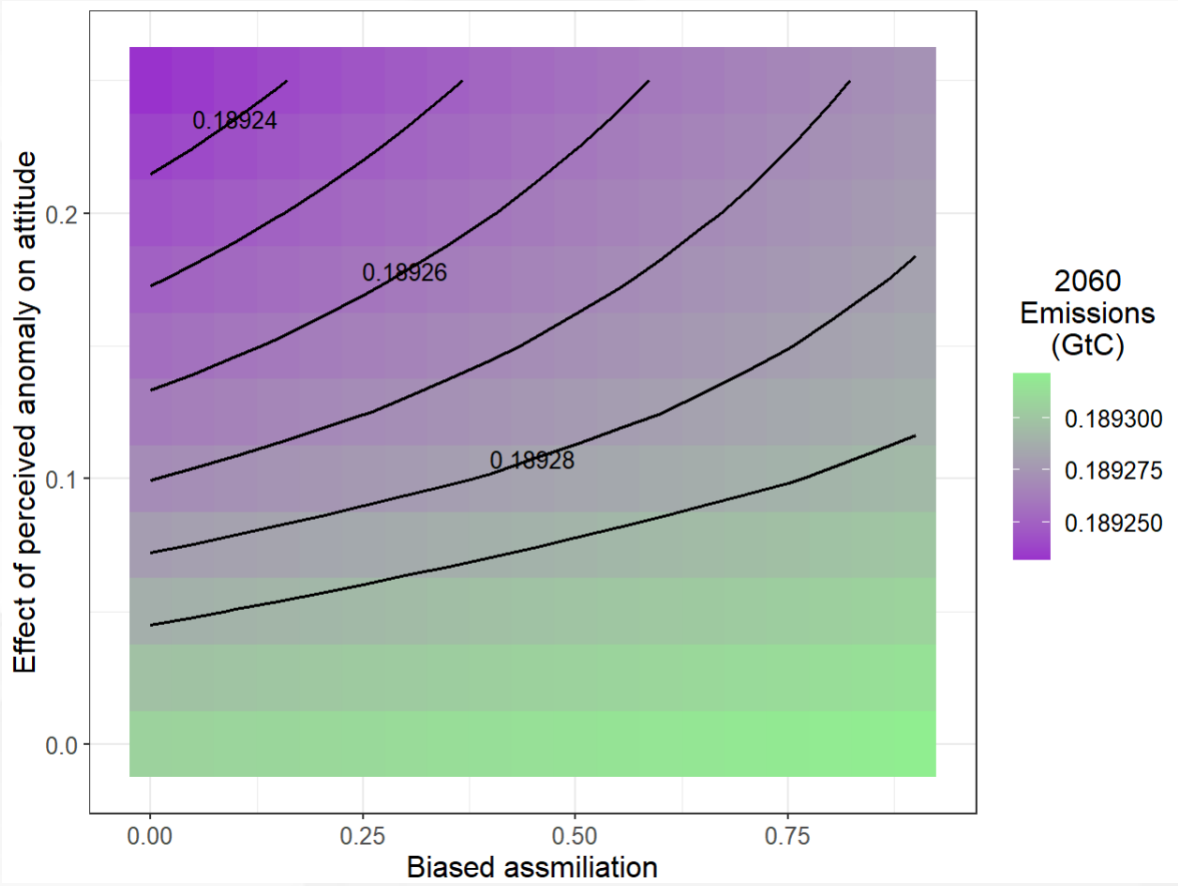
Preliminary results





Preliminary results





Sensitivity analysis

Thanks

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