Learning preventative and generative causal structures from point events in continuous time

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Background

- How do people use temporal information to make causal inferences?
- We investigate whether people can infer causal structures involving both **generative** and **preventative** relationships.
- We build both normative- and process-level models to explain human judgment (Marr, 1982).

Task Setting

Participants learn structure of several causal "devices" by watching their patterns of activation over time.

- Generative links: *produce* an activation of the effect after 1.5±0.5 s.
- Preventative links: *block* any activations of the effect within 3±0.5 s.
- The effect component also has a base rate each 5±0.5 s.

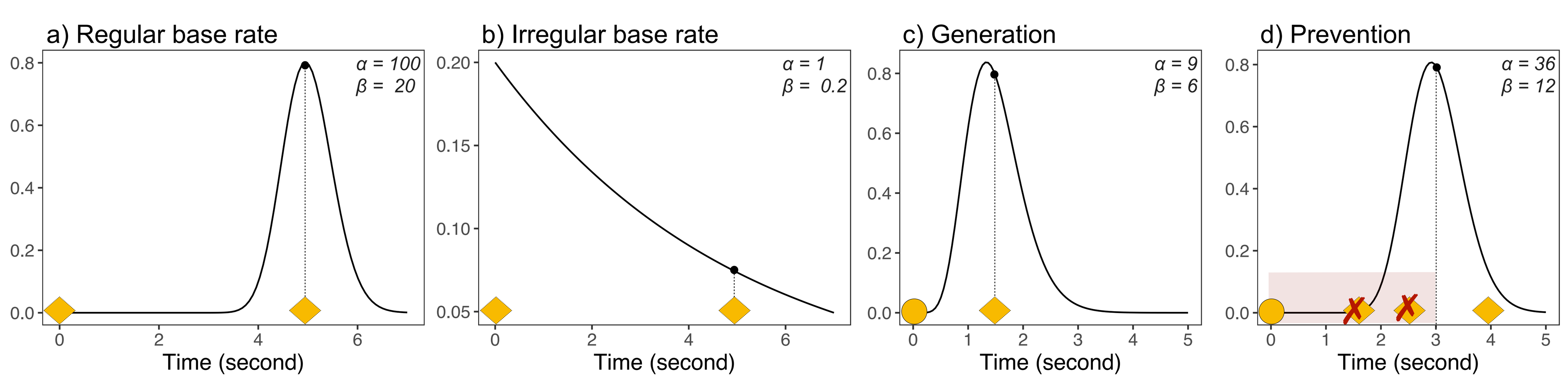

Fig1. Gamma probability density functions

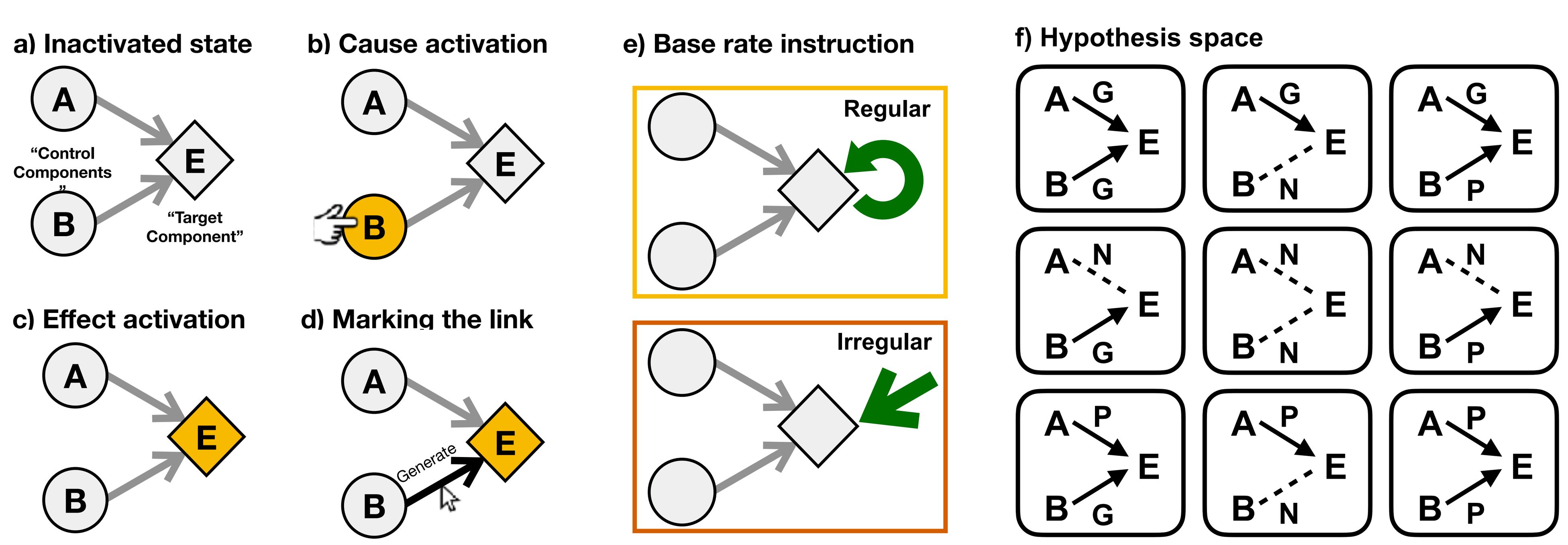

Fig 2. Causal devices tested in this paper

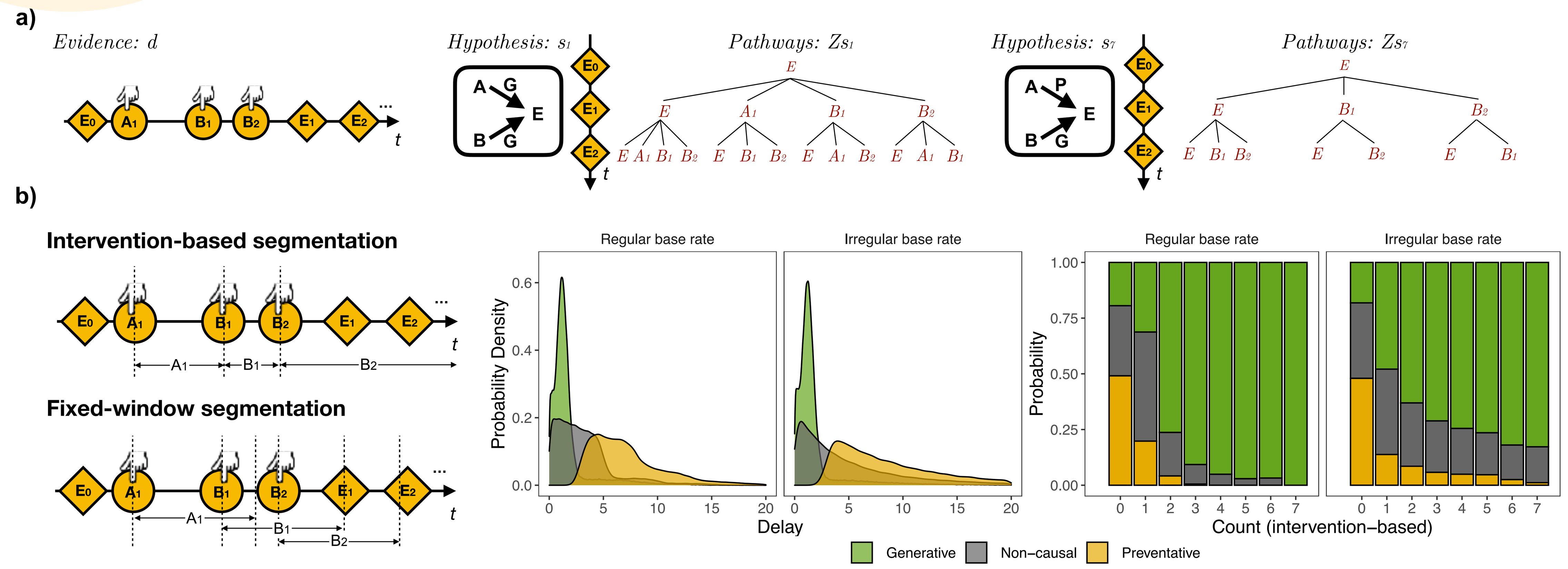

Fig 3. Models. a) normative Bayesian reasoner; b) simulation-and-summary approximation

Computational- & algorithmic level Models

a) Normative Bayesian Reasoner

Considers all possible causal paths that could describe what actually happened conditional on each possible structural hypothesis (Bramley et al., 2017)

- Explaining each effect that has been observed.
- Explaining away effects that might have occurred but were not observed.

b) Simulation-and-summary Approx.

Simulates data under different structures and favours whichever structure has closest match to the observed data (Ullman et al., 2018).

- **Delay**: the interval between a cause activation and the subsequent effect.
- **Count**: the number of subsequent effect activations after the cause activation.

Human Performance

- **Participants**: 310 people (regular vs. irregular base rate instruction: 156 vs. 154).
- **Procedure**: Participants watched clips from 18 devices and judge the causal structure.
- **Results**: Accuracy was substantially higher than chance. Participants performed better in structures without non-causal links, and better when causes were intervened on repetitively.

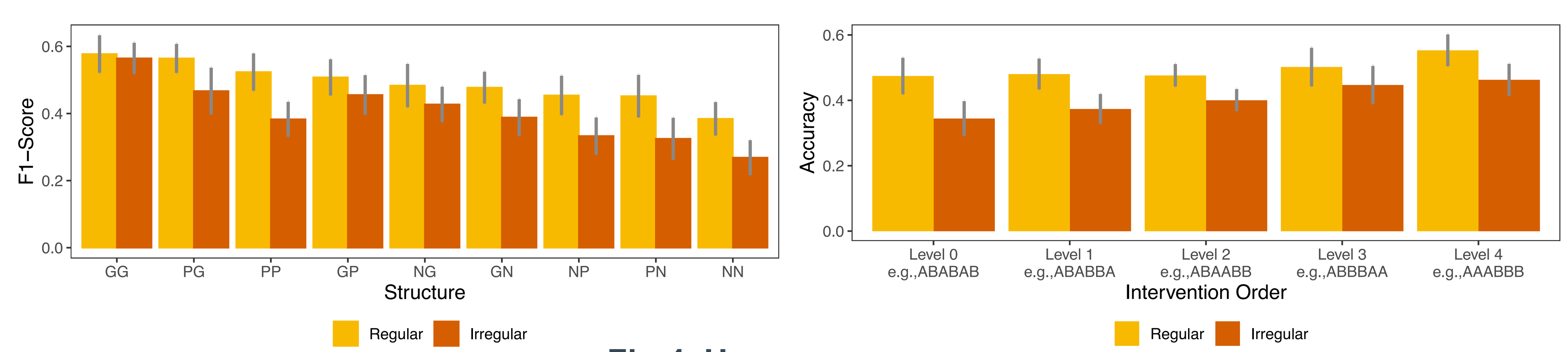

Fig 4. Human accuracy

Model Fitting

Participants' judgment were best fit by the simulation-and-summary approach that combines both the "**delay**" and "**count**" cues with the intervention-based segmentation.

(Although the normative model and the simulation-and-summary model with fixed-window segmentation were more accurate in detecting the structures.)

Conclusion

- People are able to use rich information in continuous time to infer causal structure including prevention.
- Their performance is better explained by our process model based on delay and count heuristic cues.

References

Bramley et al. (2017). "Causal learning from interventions and dynamics in continuous time" In: 39th annual conference of the cognitive science society, pp. 150-155.

Marr (1982). "Vision" Cambridge: MIT Press.

Ullman et al. (2018). "Learning physical parameters from dynamic scenes" In Cognitive psychology 104, pp. 57-82.

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