## Understanding Epistemic Language with a Bayesian Theory of Mind

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## **Abstract**

How do people understand and evaluate claims about others' beliefs, even though these beliefs cannot be directly observed? In this paper, we introduce a cognitive model of epistemic language interpretation, grounded in Bayesian inferences about other agents' goals, beliefs, and intentions: a language-augmented Bayesian theoryof-mind (LaBToM). By translating natural language into an epistemic "language-ofthought", then evaluating these translations against the inferences produced by inverting a probabilistic generative model of rational action and perception, LaBToM captures plausibility judgments about epistemic claims. We validate our model in an experiment where participants watch an agent navigate a maze to find keys hidden in boxes needed to reach their goal, then rate sentences about the agent's beliefs. In contrast with multimodal LLMs (GPT-4o, Gemini Pro) and ablated models, our model correlates highly with human judgments for a wide range of expressions, including modal language, uncertainty expressions, knowledge claims, likelihood comparisons, and attributions of false belief.

## 1 Introduction

People regularly use and interpret language about other agents' beliefs, evaluating rich linguistic constructions that may involve claims about what others' consider necessary ("Grace thinks that if Katie didn't eat the cookie, it must have been Jane"), what they find more probable ("Tom believes Sam is more likely to win the election than the others"), or the relationship of their beliefs to the world ("John didn't know that today was a holiday"). But given that these beliefs are not directly observable, how do people evaluate

the truth or plausibility of epistemic claims? Philosophers and linguists have long investigated the semantics of epistemic language (Hintikka, 1962; Partee, 1973; Loar, 1981), offering detailed theories of how epistemic claims relate to the sets of worlds deemed possible by an agent, and how the truth of these claims derive from their constituent predicates or propositions (Von Fintel and Heim, 2011). However, these theories do not explain how people understand and evaluate epistemic language in its context of utterance. If someone says "Alice believes it might rain", how does her behavior (e.g. bringing an umbrella) render that statement more or less plausible?

In this paper, we introduce a cognitive model of how humans interpret epistemic language in context (Figure 1), grounded in inferences about what agents believe given their actions and observations. We build upon a framework known as Bayesian Theory-of-Mind (BToM), which casts human mentalizing as Bayesian inference over a generative model of rational action and perception (Baker et al., 2017; Jara-Ettinger et al., 2019). We combine this framework with the compositionality afforded by probabilistic extensions of the language-of-thought hypothesis (Piantadosi, 2011; Goodman and Lassiter, 2015), developing an epistemic language of thought (ELoT) to represent how others represent the Using large language models (LLMs) as flexible semantic parsers, we translate natural language into this ELoT representation (Wong et al., 2023), allowing us to quantitatively evaluate epistemic claims against BToM inferences. This gives us our full model: A language-augmented *Bayesian theory-of-mind* (LaBToM).

To evaluate our model, we run an experiment where participants watch animations of a player solving a gridworld puzzle called Doors, Keys, & Gems (Zhi-Xuan et al., 2020). In these puzzles (Figure 1b), the player has to pick up (single-use)

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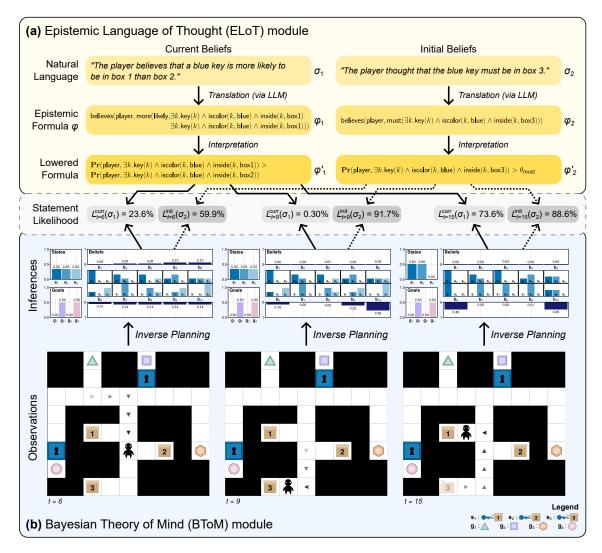


Figure 1: Overview of our model, a Language-augmented Bayesian Theory of Mind (LaBToM). In this example, our model evaluates the plausibility of epistemic language about a player trying to find keys in boxes so as to reach one of four valuable gems. To do so, (a) we use an LLM to translate natural language into an unambiguous epistemic language of thought (ELoT). (b) We then use our Bayesian theory-of-mind (BToM) module to infer the agent's goal g and probabilistic beliefs g, along with the true environment state g. This allows us to evaluate the normalized likelihood g (see Section 3.2.3) of an epistemic statement about the agent's present or past beliefs.

keys that may be hidden in boxes, using them to unlock doors of the same color to reach one of four valuable gems. The player's beliefs and goals are unknown to our participants, so they must *infer* these mental states. We ask one set of participants to write sentences describing the past and present beliefs of the player, collecting a rich dataset of epistemic language that includes modal verbs, uncertainty expressions, knowledge claims, and descriptions of false beliefs. We then task another set of participants with evaluating these statements, asking them to rate how likely a statement is given their observations. We find that the inferences produced by our LaBToM model correlate highly with these ratings. In

contrast, ablated BToM models and multimodal LLM baselines fail to explain human judgments, illustrating the importance of a coherent theory-of-mind for understanding epistemic language.

## 2 Related Work

Semantics of Epistemic Language. Sentences about belief and knowledge have been studied at length in philosophy and linguistics (Hawthorne et al., 2016; Egan and Weatherson, 2011; Yalcin, 2007). Standard treatments associate belief sentences with sets of compatible worlds (Hintikka, 1962; Von Fintel and Heim, 2011), while more recent work grounds the gradedness of belief claims in probabilities (Lassiter, 2017;

Moss, 2015). While our model draws upon these frameworks, such theories do not explain how people evaluate belief claims in context.

## Cognitive Models of Language Interpretation.

In contrast to the above line of research, our goal is to build a cognitive model of epistemic language understanding, drawing upon accounts of word meaning that prioritize the role of mental states (Loar, 1981; Block, 1987; Lake and Murphy, 2023), including cognitive semantics (Lakoff, 1988; Jackendoff, 2003), functional role semantics (Harman, 1982), and work that grounds linguistic meaning in a (probabilistic) language of thought (Fodor et al., 1975; Goodman and Lassiter, 2015; Wong et al., 2023; Zhang et al., 2023).

Bayesian Theory-of-Mind. To model how epistemic sentences relates to (inferred) mental states, our paper builds upon work in Bayesian Theory-of-Mind (Baker et al., 2017; Zhi-Xuan et al., 2022), along with related work on epistemic action understanding (Croom et al., 2023; Shvo et al., 2020), leveraging the connection between symbolic representations of the world (used in planning and inverse planning (McDermott et al., 1998)) and our representations of others' minds.

Theory-of-Mind in Language Models. With recent advances in the capabilities of neural large language models (LLMs), some researchers have suggested that LLMs might serve as cognitive models (Binz and Schulz, 2023), including as models of theory-of-mind (Strachan et al., 2024). However, while LLMs achieve humanlike performance on some ToM tasks, they do not reliably generalize to simple alterations (Shapira et al., 2024), multi-step conversations (Kim et al., 2023), or multi-modal scenarios (Jin et al., 2023; Ying et al., 2024a). Our model represents an alternative structured approach, which leverages LLMs as flexible translators between natural language and formal representations of meaning (Wong et al., 2023; Ying et al., 2023a,b; Zhi-Xuan et al., 2024b).

## 3 Computational Model

Our LaBToM model comprises two interlinked modules for reasoning about beliefs. The first module (Figure 1a), an *epistemic language of thought*, models our capacity to compositionally represent concepts that describe the world (including the contents of other agents' minds)

by combining more basic concepts into richer thoughts and expressions (Goodman and Lassiter, 2015), and how we translate such thoughts from natural language (Wong et al., 2023). The second module (Figure 1b), a *Bayesian theory-of-mind* (Baker et al., 2017), captures our intuitive inferences about others' mental states via probabilistic inference over a generative model of how agents update their beliefs and act towards their goals. By combining these two modules, epistemic language understanding can be modeled by first translating natural language into our ELoT representation, then evaluating these representations against inferences produced by rational mentalizing.

# 3.1 Interpreting Belief Sentences with an Epistemic Language of Thought

To represent epistemic sentences in a way that admits systematic compositionality, we introduce a formal language (Table 1) that serves as our epistemic language of thought. This language can be viewed as a form of epistemic logic (Gochet and Gribomont, 2006) with a richer set of modal operators. We adopt a degree-based semantics for epistemic modals grounded in probability comparisons, due to its advantages in handling the gradability of epistemic expressions (Lassiter, 2010; Moss, 2015), but crucially also because it allows us to evaluate formulas using probabilities inferred by our BToM module.

## 3.1.1 Representing Epistemic Formulas

We first define our non-epistemic base language. Building on the Planning Domain Definition Language (McDermott et al., 1998), our language is constructed from a set of predicates  $\mathcal{P}$  and functions  $\mathcal{F}$  used to describe a set of objects  $\mathcal{O}$ . Predicates can be combined into formulas  $\phi \in \Phi$  via logical operators or quantification. For example, "A key is in box 2" can be represented as  $\exists k. \text{key}(k) \land \text{inside}(k, \text{box2})$ . Conceptually, a state s of the environment (or some agent's mental representation of state s) is just a large formula: A conjunction of predicates and function assignments which fully describe the state. We denote the truth value of  $\phi$  in s as  $\llbracket \phi \rrbracket_s$ .

On top of this base language, we introduce a set of epistemic expressions to model assertions of belief, knowledge, or modal qualifications thereof (Table 1a). The semantics of these expressions are ultimately grounded in the probability function

Expression	Type	Arg. Types	Definition
Belief Operators			
$believes(A, \phi)$	${\cal E}$	$\mathcal{A},\Phi$	$\mathbf{Pr}(A,\phi) \geq  heta_{believes}$
$believes_{modal}(A, M)$	${\cal E}$	$\mathcal{A}, \mathcal{E}/\mathcal{A}$	M(A)
Knowledge Operators			
$knows_{that}(A,\phi)$	${\cal E}$	$\mathcal{A},\Phi$	$believes(A,\phi) \wedge \phi$
$knows_{if}(A,\phi)$	${\cal E}$	$\mathcal{A},\Phi$	$knows_{that}(A,\phi) \lor knows_{that}(A,\neg\phi)$
$knows_{about}(A,C,\phi)$	${\cal E}$	$\mathcal{A},\Phi/\mathcal{O},\Phi/\mathcal{O}$	$\exists x. C(x) \land knows_{that}(A, \phi(x))$
$not ext{-}knows_that(A,\phi)$	${\cal E}$	$\mathcal{A},\Phi$	$\neg believes(A, \phi) \land \phi$
Certainty Operators			
$certain_{that}(A,\phi)$	${\cal E}$	$\mathcal{A},\Phi$	$\mathbf{Pr}(A,\phi) \geq  heta_{certain}$
$\operatorname{certain}_{\operatorname{about}}(A,C,\phi)$	${\cal E}$	$\mathcal{A},\Phi/\mathcal{O},\Phi/\mathcal{O}$	$\exists x. C(x) \land (\mathbf{Pr}(A, \phi(x)) \ge \theta_{certain})$
$uncertain_{if}(A,\phi,\psi)$	${\cal E}$	$\mathcal{A},\Phi,\Phi$	$(\mathbf{Pr}(A,\phi) < \theta_{uncertain}) \wedge (\mathbf{Pr}(A,\psi) < \theta_{uncertain})$
$uncertain_{about}(A,C,\phi)$	${\cal E}$	$\mathcal{A},\Phi/\mathcal{O},\Phi/\mathcal{O}$	$\forall x. C(x) \to (\mathbf{Pr}(A, \phi(x)) < \theta_{uncertain})$
Modal Verbs			
$could(\phi)$	$\mathcal{E}/\mathcal{A}$	$\Phi$	$\lambda A.\mathbf{Pr}(A,\phi) \geq  heta_{could}$
$might(\phi)$	$\mathcal{E}/\mathcal{A}$	$\Phi$	$\lambda A.\mathbf{Pr}(A,\phi) \geq  heta_{might}$
$may(\phi)$	$\mathcal{E}/\mathcal{A}$	Φ	$\lambda A.\mathbf{Pr}(A,\phi) \geq  heta_{may}$
$should(\phi)$	$\mathcal{E}/\mathcal{A}$	Φ	$\lambda A.\mathbf{Pr}(A,\phi) \ge \theta_{should}$
$must(\phi)$	$\mathcal{E}/\mathcal{A}$	$\Phi$	$\lambda A.\mathbf{Pr}(A,\phi) \geq  heta_{must}$
Modal Adjectives		_	
$likely(\phi)$	$\mathcal{E}/\mathcal{A}$	Φ	$\lambda A.\mathbf{Pr}(A,\phi) \geq  heta_{likely}$
$degree(likely, A, \phi)$	$\Phi_{\mathcal{F}}$	$\mathcal{A},\Phi$	$\mathbf{Pr}(A,\phi)$
Comparatives			
$more(P,\phi,\psi)$		$\mathcal{P}, \Phi, \Phi$	$\lambda A. degree(P, A, \phi) > degree(P, A, \psi)$
$most_{sup}(P, O, C, \phi)$	,	$\mathcal{P}, \mathcal{O}, \Phi/\mathcal{O}, \Phi/\mathcal{O}$	$\lambda A.degree(P, A, \phi(O)) \ge \max_{x:C(x)} degree(P, A, \phi(x))$
$most_{str}(P,\phi)$	$\mathcal{E}/\mathcal{A}$	$\mathcal{P},\Phi$	$\lambda A.degree(P,A,\phi) \geq \alpha_{most} \cdot \theta_P$

(a) Epistemic terms and definitions (unlikely, less and least are omitted due to space limits).

Thresholds $\theta$								Multipliers $\alpha$		
believes	certain 0.95	uncertain 0.55	likely 0.70	unlikely 0.40	could 0.20	might 0.20	may 0.30	should 0.80	must 0.95	most

(b) Probability thresholds and multipliers (fitted against human data).

Table 1: Expressions in our epistemic language of thought (ELoT), including (a) epistemic terms and (b) probability thresholds  $\Theta$ . ELoT terms may have the following types:  $\mathcal{E}$ : epistemic formula,  $\Phi$ : base formula,  $\Phi_{\mathcal{F}}$ : function term,  $\mathcal{P}$ : predicate symbol,  $\mathcal{A}$ : agent,  $\mathcal{O}$ : object,  $\mathcal{X}/\mathcal{Y}$ : function from  $\mathcal{X} \to \mathcal{Y}$ .

 $\mathbf{Pr}(A, \phi)$  — the probability assigned by agent A to formula  $\phi$  — and comparisons against termspecific thresholds (Table 1b). For example, the operator might( $\phi$ ) takes a formula  $\phi$  and returns a function  $\lambda A.\mathbf{Pr}(A,\phi) \geq \theta_{\mathsf{might}}$ . Combined with the operator believes<sub>modal</sub>(A, F) = F(A), we can express the claim that "A believes it *might be that*  $\phi$ " as believes<sub>modal</sub> $(A, might(\phi))$ . This term can be lowered into the probability comparison  $\mathbf{Pr}(A, \phi) \geq \theta_{\mathsf{might}}$ , which uses  $\theta_{\mathsf{might}}$ as the threshold instead of  $\theta_{\text{believes}}$  due to the way our operators compose. Similar to CCGbased semantic frameworks, our ELoT module also supports comparatives (Haruta et al., 2019) and typed higher-order terms (Mineshima et al., 2015; Martínez-Gómez et al., 2016).

## 3.1.2 Translating Epistemic Language

Epistemic formulas  $\varphi$  in our ELoT representation are unambiguous and precise. In contrast, natural language might be used to communicate the same epistemic information in multiple ways.

To handle this diversity of surface forms, we make use of LLMs as general-purpose semantic parsers (Shin et al., 2021) that translate a wide variety of expressions into formal representations, substituting for the human ability to flexibly interpret natural language in-context (Wong et al., 2023). In particular, we prompt an LLM (Gemini Flash) with example translations from English to our ELoT representation, and append a new sentence  $\sigma$  to translate. We then sample up to  $n_{\sigma}$  outputs, rejecting any which are syntactically or semantically invalid, retaining the first formula  $\varphi$  that is successfully translated. (See Appendix for the translation prompt and other details.)

# 3.2 Inferring and Evaluating Beliefs with a Bayesian Theory-of-Mind

Our ELoT module gives us a way to interpret belief claims in terms of the probability  $\mathbf{Pr}(A, \phi)$  an agent A assigns to sentences  $\phi$ . But how is the value of  $\mathbf{Pr}(A, \phi)$  computed? This is the

function of our BToM module: By modeling the functional role that belief plays in guiding an agent's actions, along with the causal influence of the agent's perceptions on their beliefs, an observer can infer what the agent thinks based on what the agent sees and does. Following the structure of Partially Observable Markov Decision Processes (POMDPs) (Kaelbling et al., 1998), this theory of approximately rational agency can be formalized as a probabilistic generative model:

Goal Prior: 
$$g \sim P(g)$$
 (1)

State Prior: 
$$s_0 \sim P(s_0)$$
 (2)

Belief Prior: 
$$b_0 \sim P(b_0|s_0)$$
 (3)

State Transition: 
$$s_t \sim P(s_t | s_{t-1}, a_{t-1})$$
 (4)

Belief Update: 
$$b_t \sim P(b_t|s_t, b_{t-1})$$
 (5)

Action Selection: 
$$a_t \sim P(a_t|b_t,g)$$
 (6)

Observations: 
$$o_t \sim P(o_t|s_t)$$
 (7)

## 3.2.1 Modeling Perception and Action

Two crucial aspects of our BToM module are how it models belief updating (Eq. 5) as the result of perception, and how it models goal-directed action given the agent's uncertain beliefs (Eq. 6). To model perception, we represent an agent's belief  $b_t$  as a probability-weighted collection  $\{(\tilde{s}_i, w_i)\}_{i=1}^{n_s}$  of possible environment states  $\tilde{s}_i$  (which are represented in turn as collections of ELoT predicates). Given an observation of the environment  $s_t$  (e.g. observing that a box is empty), the agent updates its belief by *filtering* out inconsistent hypotheses  $\tilde{s}_i$ , setting  $w_i = 0$ .

As for goal-directed action, our model builds upon methods for epistemic planning (Bolander, 2017) and belief-space planning in POMDPs (Littman et al., 1995). Given a belief  $b_t$ , the agent engages in *instrumental planning* to achieve their goal g, which requires achieving instrumental subgoals (e.g. picking up keys), but also gathering goal-relevant information (e.g. finding out if a key is in a certain box). We model this by assuming that the agent acts by approximately minimizing a cost-to-go estimate  $\hat{Q}_g(b_t, a)$ : An estimate of the optimal cost  $Q_g^*(b_t, a)$  of reaching g after action g starting from one's (uncertain) belief g. Action selection can thus be modeled by a Boltzmann distribution over these  $\hat{Q}_g$  estimates:

$$P(a_t|b_t,g) \propto \exp\left(-\beta \hat{Q}_g(b_t,a)\right)$$
 (8)

To estimate  $Q_g^*$  efficiently, we follow recent advances in inverse planning (Zhi-Xuan et al.,

2024b) by computing the  $Q_{\text{MDP}}$  approximation (Hauskrecht, 2000) of  $Q_g^*$ , averaging over the Q-values for each hypothesis  $(\tilde{s}_i, w_i)$  in the belief  $b_t$ :

$$\hat{Q}_g(b_t, a) = \sum_{(\tilde{s}_i, w_i) \in b_t} w_i \cdot Q_g^*(\tilde{s}_i, a) \quad (9)$$

The cost-to-go  $Q_g^*(s, a)$  from a known state s can itself be efficiently estimated by searching for a shortest path to g from s (Monfort et al., 2015).

#### 3.2.2 Joint Inference of Goals and Beliefs

With this generative model, observers can jointly infer the agent's goal g, belief history  $b_{0:T}$ , and environment trajectory  $s_{0:T}$  given observations of the agent's actions  $a_{1:T}$  and partial observations  $o_{0:T}$  of the environment:

$$P(g, b_{0:T}, s_{0:T} | a_{1:T}, o_{0:T}) \propto$$
 (10)

$$P(g, s_0, b_0) \prod_{t=1}^{T} P(b_t, a_t, s_t, o_t | b_{t-1}, s_{t-1})$$

Computing this posterior is intractable in general due to the large space of possible initial beliefs  $b_0$ , which may in turn be defined over a large space of environment states  $s_0$ . However, if the space of possible beliefs and states is sufficiently small, it can be reasonable to model human observers as approximating the Bayesian ideal (Blokpoel et al., 2010). Therefore, we consider only the set of initial states  $S_0$  consistent with the initial observation  $o_0$ , and a discrete set  $\mathcal{B}_0$  of possible beliefs  $b_0$  sufficient to model comparative likelihood claims (e.g. "The key is more likely in box 1 than 2."). Specifically, we consider all beliefs formed by distributing k particles across  $n_s:=|\mathcal{S}_0|$  states, resulting in  $n_b:=|\mathcal{B}_0|=\binom{n_s+k-1}{k}$  distributions. We then perform exact Bayesian inference over all combinations of goals g, initial beliefs  $b_0$ , and states  $s_0$ , which we implement as a variant of Sequential Inverse Plan Search (Zhi-Xuan et al., 2020) using the Gen probabilistic programming system (Cusumano-Towner et al., 2019). More algorithmic details are provided in the Appendix.

#### 3.2.3 Evaluating Epistemic Sentences

By inferring the agent's belief history  $b_{0:T}$ , we can now compute the probability  $\mathbf{Pr}(A, \phi)$  assigned to a formula  $\phi$  at time t as the weighted sum of truth values under the agent's belief  $b_t$ :

$$\mathbf{Pr}(A,\phi) = \sum_{(\tilde{s}_i, w_i) \in b_t} w_i \cdot \llbracket \phi \rrbracket_s$$
 (11)

We can thus evaluate a epistemic formula  $\varphi$  given a belief  $b_t$  and environment state  $s_t$  by replacing

Factor	Description Examples	Count Current	Initial
Possibility	Sentences with modal verbs such as might, could and must.  The player believes box 1 may contain a blue key or a red key.  The player believes if the red key is not in box 2 then it must be in box 3.	66 / 241	46 / 228
Probability	Sentences with probability expressions such as likely, uncertain, etc.  The player thought that box 1 was most likely to contain a red key.  The player is unsure what color the key in box 2 will be.	28 / 241	28 / 228
Compositionality	Sentences that embed compound propositions (conjunctions, disjunctions, etc.). <i>The player thinks that there's more likely to be a red key in box 1 or 3 than box 2. The player believes that if box 1 does not have a blue key, then box 3 has a blue key.</i>	49 / 241	69 / 228
Knowledge	Sentences that make knowledge or ignorance claims.  The player already knows for sure there is no key in box 1 or box 2.  The player did not know if box 2 contained a red key.	17 / 241	20 / 228

**Table 2:** Overview of our dataset of 464 human-written epistemic sentences, broken down by factors.

**Pr** terms with their values, then determining the truth of the resulting expression in state s. We denote this operation by  $[\![\varphi]\!]_{(s_t,b_t)}$ .

However, observers do not have direct access to the true  $s_t$  or  $b_t$ , only probabilistic inferences about them. As such, we model human evaluation of a sentence  $\varphi$  as a quantitative probabilistic judgment given their posterior inferences:

$$P(\llbracket \varphi \rrbracket_{(s_t,b_t)} | a_{1:T}, o_{0:T})$$

$$= \mathbb{E}_{s_t,b_t \sim P(s_t,b_t | a_{1:T}, o_{0:T})} \left[ \llbracket \varphi \rrbracket_{(s_t,b_t)} \right]$$

While these judgements are made after observing actions up to time T,  $\varphi$  may be *retrospectively* evaluated as a description of the agent's beliefs at any  $t \in [0,T]$ , with t=0 and t=T corresponding to initial and current beliefs respectively.

Following Ying et al. (2024b), we also assume that people provide ratings as if they have a uniform prior  $U_{\varphi}$  about the truth of  $\varphi$ . Under this prior, ratings of  $\varphi$  can be interpreted as a normalized likelihood  $\bar{L}(\llbracket \varphi \rrbracket_{(s_t,b_t)} | a_{1:T}, o_{0:T})$ , which measures the likelihood of statement  $\varphi$  relative to its negation  $\neg \varphi$ . In other words, we assume that humans rate an epistemic claim more highly when they have *evidence* for it. With no evidence,  $\bar{L}(\llbracket \varphi \rrbracket_{(s_t,b_t)} | a_{1:T}, o_{0:T}) = 0.5$ . Results investigating the importance of this assumption can be found in the Appendix.

## 4 Experiments

To evaluate our model on a diverse set of belief statements, we conducted a two-part experiment. We first recruited participants to write English sentences describing the current and initial beliefs of a player character as it navigated a gridworld puzzle that required finding keys hidden in boxes, collecting a dataset of epistemic language (Table 2). Next, we asked two groups of participants to rate how likely these sentences were to be true given the player's observed behavior, with one group rating sentences about the player's current beliefs, and the other group rating sentences about initial beliefs. These ratings were collected at multiple points over the course of the player's trajectory. We then compared these ratings against the inferences produced by our model.

#### 4.1 Scenario Construction

We constructed 20 scenarios in the Doors, Keys, & Gems environment with varied maze designs and item locations (Figure 3). In each scenario, there were 4 goal gems with different shapes (triangle, square, hexagon, circle), some of which were locked behind doors. Scenarios also had 2 to 3 boxes with up to 2 colored keys among them. The player's actions were varied across scenarios to elicit inferences about a diversity of epistemic states, such as ignorance about key locations or false confidence about the location of a key.

## 4.2 Collecting Epistemic Language

In the first part of the experiment, we recruited 42 US participants via Prolific (mean age: 36.02, SD: 10.1; 16 women, 26 men). Following a tutorial, participants watched 10 scenario animations, with each stopping before the player reached their goal and all relevant keys were revealed. Participants were then asked to write at least two sentences about the player's likely beliefs at the end of the scenario (*current beliefs*), and another two sentences about the player's beliefs at the start of the scenario (*initial beliefs*). To ensure that these sentences focused on beliefs about the environment, we instructed participants to

describe the player's beliefs about the contents of the boxes. We excluded 8 participants for failing to follow these instructions, and about one third of remaining sentences. This process left us with 241 (228) statements about current (initial) beliefs, which were then annotated with factors by two experimenters. Table 2 shows examples illustrating the diversity of language we collected.

## 4.3 Evaluating Epistemic Language

For the next part of our experiment, we recruited 94 US participants via Prolific to evaluate current belief statements (mean age = 35.7, SD = 12.4, 67women, 27 men), and another 104 US participants to evaluate initial belief statements (mean age = 35.27, SD = 11.7, 69 women, 33 men, 2 nonbinary). Each participant was shown 10 out of 20 scenario animations, and was asked to rate the goals and beliefs of the player at several judgment points during each animation. For goals, participants were shown a checkbox for each gem, and asked to select all gems likely to be the agent's goal. This served as both an attention check and an additional data source for model validation. For beliefs, participants were shown 2 belief statements selected from our dataset of human-written statements, and asked to rate how likely each statement was on a scale from 1 to 7. These ratings were normalized between 0 and 1 for our analysis. We excluded 7 participants from the current belief condition and 5 from the initial belief condition for low outlying scores on the goal inference subtask.

## 4.3.1 Statement Selection

To ensure that the belief statements evaluated by our participants were (i) diverse and (ii) rated enough times to ensure sufficient statistical power (88% power at Cohen's d=0.8), we selected a set of 5 statements per scenario (3 plausible, 2 implausible) from our full dataset of collected statements. The plausible statements were chosen by repeatedly sampling sets of 3 statements out of all those written for a particular scenario, then selecting the set that scored highest on a diversity metric derived from the factors in Table 2 (see Appendix for the definition of this metric). We

then manually added 2 more statements that were originally written for other scenarios, and which we evaluated to be implausible descriptions of the target scenario. Participants were shown 2 of these 5 statements at random in each scenario.

## 4.4 Model Fitting and Evaluation

We evaluated our LaBToM model on all 20 scenarios, producing normalized likelihood scores for the 5 current and 5 initial belief statements per scenario. We then computed the correlation coefficient r between these scores and average human ratings. We fit our model parameters to maximize r, fitting the belief thresholds  $\Theta := (\theta_{\text{believes}}, \theta_{\text{could}}...)$  via coordinate ascent, and the inverse temperature  $\beta$  of our action model via grid search. This produced the fitted values for  $\Theta$  shown in Table 1, and  $\beta = 2^{3/2}$ . For the set of possible initial agent beliefs  $\mathcal{B}_0$ , we fixed the number of belief particles to k=3 to ensure the tractability of exact Bayesian inference.

Alongside this direct comparison with human-provided ratings, we evaluated our model on the full dataset of 469 human-written statements by pairing each statement with either the scenario it was written for (in-context) or 1–2 other scenarios with the same map layout but distinct agent trajectories (out-of-context). This allowed us to compare each statement's in-context normalized likelihood  $\bar{L}$  with its (average) out-of-context likelihood score. Reasonable models of epistemic language interpretation should assign higher likelihood scores to most statements when they are evaluated in-context vs. out-of-context.

## 4.5 Baselines

To assess the import of a sufficiently rich theory of mind for epistemic language understanding, we evaluated several ablations of our LabToM model which made simplified assumptions about the agent's beliefs or planning abilities. We also evaluated two state-of-the-art multi-modal LLMs, thereby testing the degree to which grounded evaluation of epistemic language can be achieved with sufficient scale and finetuning:

**True Belief.** The True Belief ablation assumes that the observed agent has fully accurate beliefs about the environment (i.e. they already know where all the keys are located), equivalent to the full model from Ying et al. (2024b). The observer starts with a uniform prior over these true beliefs.

<sup>&</sup>lt;sup>1</sup>See Appendix for exclusion and post-processing steps. Interestingly, some excluded sentences described the player's beliefs about what keys were *needed* (e.g. "The player thinks that they need to open box 3 to get to the hexagonal gem."). We save the study of these sentences for future work.

Model	Huma	n Correlation	r (s.e.)					
	All	Current	Initial					
LaBToM								
Full (ours)	0.81 (0.01)	0.81 (0.01)	0.80 (0.01)					
Non-Planning	0.47 (0.01)	0.60 (0.02)	0.20 (0.01)					
True Belief	0.12 (0.01)	0.09 (0.01)	0.13 (0.02)					
GPT-40 (Open.	AI et al., 2023)	)						
I+Na+FS	0.52 (0.01)	0.59 (0.01)	0.41 (0.01)					
I+Na	0.48 (0.01)	0.52 (0.01)	0.41 (0.01)					
I+Pl	0.28 (0.01)	0.32 (0.01)	0.18 (0.01)					
Gemini 1.5 Pro (Gemini Team et al., 2024)								
V+Na+FS	0.23 (0.01)	0.28 (0.01)	0.14 (0.02)					
I+Na+FS	0.22 (0.01)	0.29 (0.01)	0.11 (0.02)					

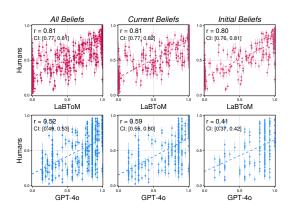
I - Image, V - Video, Pl - Plans, Na - Narratives, FS - Few-Shot

Table 3: Model correlations with human ratings of epistemic language. LaBToM correlates strongly with humans, whereas multimodal LLMs struggle.

**Non-Planning.** The Non-Planning ablation assumes that the agent is incapable of planning towards instrumental subgoals (such as keys), and instead optimizes the heuristic of moving physically closer to the goal. This is implemented by using the Manhattan distance to the goal as the agent's cost-to-go estimate  $\hat{Q}_q$ .

Multi-modal LLMs We use GPT-40 (text & image input, gpt-40-2024-05-13) and Gemini 1.5 Pro (text & image or video input) as multi-modal LLM baselines, providing them the same instructions as human participants. Each baseline was run 3 times with a temperature of 1.0. In addition to providing an image or video of the scenario showing the actions up to each judgment point, we used the following prompting methods:

- **Plans**: The prompt plainly describes the agent's actions over time (e.g. *the player moves right five times*), and also describes the agent's observations (e.g. *the player opens box 1 and finds a red key inside*).
- Narratives: The prompt contains a rich narrative of the agent's actions, providing key information about the scene (e.g. which gems are locked behind doors, which keys are visible), while also describing the agent's movements in relation to relevant objects (e.g. the player moves right five times, going past box 1 towards box 2).
- Few-Shot Prompting: After describing the plan or narrative, we provide the LLM with human ratings for the 4 other belief statements tied that scenario, before querying its rating for the target statement.

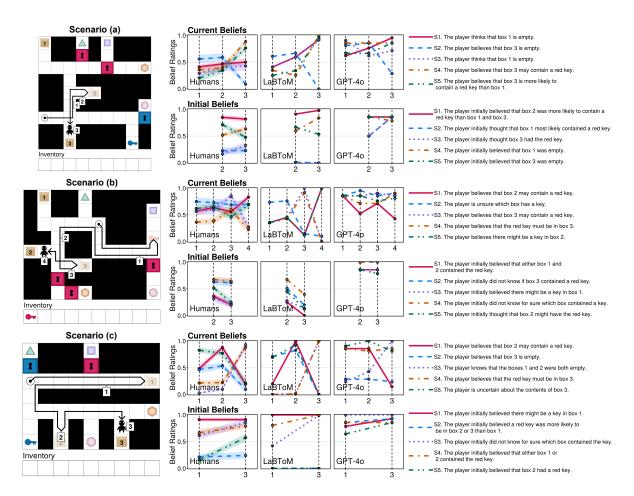


**Figure 2:** Human correlation plots for LaBToM and GPT-4o. LaBToM provides a much stronger qualitative fit with human ratings compared to the best GPT-4o baseline, which fails to use the full scale.

#### 5 Results

LaBToM correlates highly with human ratings of epistemic statements. As Table 3 shows, we find that that our full model produces statement scores that correlate highly with human ratings (r = 0.81) across both current and initial belief conditions (a per-factor breakdown can be found in the Appendix). Plotting average human judgments against LaBToM inferences (Figure 2, Row 1), we also find a strong qualitative fit: LaBToM generally assigns high or low ratings to sentences when humans do, using the ends of the scale as appropriate. In contrast, our ablated models do poorly, either because they fail to track how the player updates their beliefs (True Belief, Current r = 0.09), or fail to infer the player's initial beliefs from their actions towards instrumental subgoals (Non-Planning, Initial r = 0.13).

SotA multimodal LLMs struggle at grounded evaluation of epistemic language. The multimodal LLM baselines also perform less well than LaBToM despite extensive prompting, with the strongest LLM baseline (GPT-40 with images, narratives, and few-shot prompting) achieving human correlations of only 0.59 and 0.41 respectively. Increasing information in the prompt improves performance, although the Gemini models perform poorly regardless, and do not improve even when provided full video of the We find that LLM performance is scenarios. lower when evaluating initial belief sentences, suggesting that they are better at tracking how agents' current beliefs change in response to observations, but worse at inferring past beliefs.



**Figure 3: Step-by-step ratings by humans and models across three scenarios.** Judgement points are annotated on each map, and show the player's location *before* opening the nearest box. Keys picked up along the way are shown in light colors. Our model largely matches human responses qualitatively and quantitatively, unlike GPT-40.

Figure 2 illustrates the difference between our model and the best performing GPT-40 baseline (I+Na+FS) in greater detail. Despite few-shot prompting, GPT-40 tends to assign ratings of 0.8 or more to many statements that humans find quite unlikely, suggesting that LLMs struggle to account for evidence *against* a belief claim.

# LaBToM captures how human evaluations of epistemic language change with agent behavior.

Our model predicts that human evaluations of epistemic sentences should change systematically as they gain more information about an agent's percepts and actions. As Figure 3 illustrates, this is what we find. When the player sees that a box is empty, both humans and our model sharply decrease their ratings for statements claiming that the player believes a key is in that box (e.g. Fig. 3b, S4 Current). When the player approaches one box instead of another, both humans and LaBToM gain confidence in statements about the *relative likelihood* of key locations (Fig. 3a, S5 Current).

We analyze just one scenario (Figure 3a) in detail due to space constraints. In this scenario, the player first walks upwards away from box 3 (Judgment Point 1), leading both humans and LaBToM to assign scores of greater than 0.5 to "The player believes that box 3 is empty" and "The player initially believed that box 3 was empty". In contrast, the modal sentence "The player believes that box 3 may contain a red key" is rated as less likely. This is because if the player did believe strongly that box 3 had a (red) key, then acting rationally, it should have looked inside that box, but this does not occur.

After the player opens box 2 and finds it empty, then walks back down towards box 3 (Judgment Point 3), both humans and our model decrease their confidence in the statement "The player believes that box 3 is empty", as expected. They also decrease confidence in "The player initially believed that box 3 was empty", but less sharply. This is because there are at least two possibilities consistent with the player's actions: They could

Model	Statement Likelihoods In-Ctx / Out-of-Ctx / Diff.	Accuracy In vs. Out	
Curi	rent Beliefs (241 statements)		
LaBToM (ours)	0.78 / 0.48 / +0.30 (0.03)	0.71 (0.03)	
Non-Planning	0.70 / 0.54 / +0.16 (0.02)	0.65 (0.03)	
True Belief	0.35 / 0.35 / +0.01 (0.01)	0.11 (0.02)	
GPT-4o (I+Na)	0.80 / 0.62 / +0.18 (0.03)	0.59 (0.03)	
Inii	tial Beliefs (228 statements)		
LaBToM (ours)	0.73 / 0.51 / +0.22 (0.03)	0.70 (0.03)	
Non-Planning	0.70 / 0.70 / -0.01 (0.01)	0.39 (0.03)	
True Belief	0.51 / 0.50 / +0.00 (0.01)	0.16 (0.02)	
GPT-4o (I+Na)	0.76 / 0.68 / +0.07 (0.02)	0.38 (0.03)	

**Table 4: In vs. out-of-context statement evaluation.** LaBToM most accurately distinguishes when epistemic language is evaluated in vs. out-of-context, assigning significantly higher scores in-context (s.e. in brackets).

have firmly believed that box 3 was empty, or they could have just believed that box 3 was *less likely* to contain the relevant key than box 2, without all-out believing that it was empty. This ability to understand beliefs about relative likelihood is made explicit by how ratings change over time for "The player believes that box 3 is more likely to contain a red key than box 1." Consistent with the principle of rational action, both humans and LaBToM assign a high score to this sentence once the player goes back to box 3, forgoing box 1.

Across a range of other settings (Figure 3b-c), our model largely captures fine-grained changes in how people evaluate a variety of epistemic expressions, including modal sentences, ignorance claims, and expressions of uncertainty. Unlike prior BToM models that lack language-like belief representations (Baker et al., 2017), LaBToM also distinguishes observer and agent uncertainty, assigning high ratings to claims that the agent is uncertain (Figure 3c, S5 Current), and vice In contrast, the best performing LLM versa. baseline (GPT-4o, I+Na+FS) often fails to adjust its ratings in the same direction as humans, while giving high ratings to implausible statements. We discuss the step-by-step results in greater detail in the Appendix, alongside cases where our model comes apart from human judgments.

**LaBToM distinguishes in-context and out-of-context epistemic language.** To investigate how our model generalizes to a larger set of epistemic expressions, we performed the in-context vs. out-of-context likelihood comparison described in Section 4.4 for our full dataset of 469 sentences.

We tested the full LaBToM model, ablations and the best applicable LLM baseline from Table 3 (GPT-40, I+Na). Results are shown in Table 4. For both current and initial belief statements, we find that LaBToM assigns significantly higher scores when a statement is evaluated in-context vs. out-of-context, correctly classifying the context about 70% of the time by assigning a strictly higher incontext score. As we examine in the Appendix, many statements that are not correctly classified turn out to be plausible in either context, resulting in equal or close-to-equal scores. The ablated models and GPT-40 perform significantly worse than LaBToM, especially for initial beliefs, where all baselines perform worse-than-chance.

#### 6 Discussion

Our experiments show that, similar to humans, our LaBToM model is able to coherently interpret and adjust its evaluations of natural language statements about agents' beliefs, whereas state-of-the-art multimodal LLMs struggle with this task. We also find that LaBToM largely distinguishes in vs. out-of-context sentence usage on a large and diverse set of crowd-sourced epistemic language, indicating the generalizability of our approach.

That said, our model is not without limitations. As we discuss at greater length in the Appendix, LaBToM's outputs depart from human judgments in several interesting ways, suggesting the need to account for (i) contextual adaptation of probability thresholds (Schuster and Degen, 2020), (ii) the role of justification in human's intuitive evaluation of knowledge claims (Alston, 1989), and (iii) bounded human reasoning about logical implications (Smets and Solaki, 2018). LaBToM is also an ideal observer model that does not scale readily to large belief spaces, leaving open how humans tractably infer and evaluate claims about others' beliefs (Van Rooij, 2008), perhaps by focusing on *occurent* beliefs (Bartlett, 2018) that are relevant to others' goals. Finally, LaBToM is a model of how people interpret epistemic language, but full understanding also includes the ability to produce such language. This could potentially be achieved by inverting the ELoT module of our model, using it to translate salient inferences about an agent's beliefs into natural language. By extending our model in this way, we stand to gain an even richer account of what it means to understand epistemic language.

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## **A Dataset Collection**

## A.1 Experimental Procedure

The interface useds for collecting the statements and evaluating statements are shown in Figure A1. Participants first completed a tutorial that explained the task and experimental interface, then answered 5 comprehension questions before proceeding to the main experiment. In the main experiment, they were shown 10 out of the 20 stimuli in a randomized order.

To incentivize accurate but calibrated responses, participants were rewarded for accurately guessing the true goal. Specifically, they earned 1/N bonus points if they selected N goals out of which one was the true goal, but 0 points if none of their selected goals was the true goal. Participants were paid US\$1 for every 40 bonus points they earned, on top of a base pay of US\$15/hr.

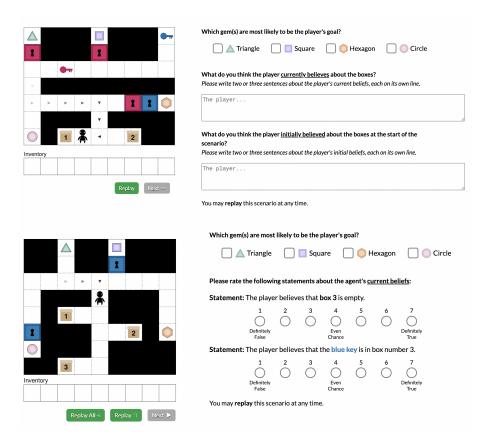


Figure A1: Interfaces used for collecting (top) and evaluating (bottom) epistemic language.

## A.2 Statement Post-Processing and Annotation

Once statements were collected, two experimenters independently annotated whether each statement was valid for inclusion. We excluded invalid sentences based on two criteria: (i) whether the statement had the right tense (present for current beliefs, past for initial beliefs) and (ii) whether the statement referred to beliefs about the boxes. We also corrected minor grammatical errors and normalized statements to the form "The player + [believes/knows/thinks/expects/is sure/is uncertain, etc.]..." for current beliefs and "The player initially + [believed/knew/thought/expected/was sure/uncertain, etc.]..." for initial beliefs.

After filtering and normalization, two experimenters independently annotated the statements based on four factors: possibility, probability, compositionality, and knowledge. These factors are not mutually exclusive, so a statement could be annotated with any combination of factors. The codes for possibility were [may, might, can, could, should, must, none] and the codes for probability were [certain, uncertain, likely, unlikely, none]. The codes for compositionality and knowledge were binary [0, 1]. The annotators agreed on 95% of the codes and discussed to resolve their differences.

## A.3 Selecting Diverse Statements for Human Evaluation

After annotation, we selected a set of 3 plausible and 2 implausible statements per scenario for evaluation by human raters. Implausible statements were manually selected from other scenarios to be implausible in their scenario of evaluation. To select the 3 plausible statements, we sampled 100 subsets of 3 statements out of all statements written for that scenario, then computed a diversity score for each set S:

$$Score(S) = \frac{1}{4}|S_{possibility}| + \frac{1}{4}|S_{probability}| + \frac{1}{4}|S_{compositionality}| + \frac{1}{4}|S_{knowledge}|$$
 (12)

where  $|S_{possibility}|$  indicates the number of unique possibility codes in set S and vice versa. We then chose the set with the highest diversity score among the 100 sampled sets.

## **B** Model Configuration

## **B.1** Belief-Space Sequential Inverse Plan Search (BSIPS)

Our BToM inference algorithm is a belief-space policy variant of Sequential Inverse Plan Search (SIPS, Zhi-Xuan et al. (2020)), which uses policies instead partial plans to evaluate action likelihoods as in more recent extensions of SIPS (Zhi-Xuan et al., 2024b,a). Perhaps surprisingly, Belief-Space SIPS (BSIPS) is able to *exactly* compute the posterior over beliefs, goals, and states (Equation 10) without any Monte Carlo approximation: For the scenarios we considered, there were between 120 and 5940 possible combinations of goals, initial states, and belief distributions, and enumerative inference over these hypothesis spaces could run as fast as 0.1s per action (120 hypotheses), going up to 20s per action (for 5490 hypotheses). Experiments were conducted with a i7-1370P 1.90 GHz CPU and 64 GB RAM.

Algorithm 1 provides the pseudocode for BSIPS. At each step t, we simulate how the environment changes, and how the agent updates their beliefs based on what they see (L6-7). Next, we efficiently compute belief-space Q-values by leveraging the  $Q_{\rm MDP}$  approximation described in Section 3.2.1. This involves averaging over Q-values for each state hypothesis  $\tilde{s}$  in the agent's belief  $b_t^i$ , which can be done cheaply by memoizing and reusing shortest-path computations across all belief hypotheses (L9-13). The Q-values allow us to compute the likelihood of the observed action  $a_t$ , allowing us to reweight each hypothesis by how well it explains the observations (L14-16).

For epistemic language evaluation at this scale, the technical challenges are mostly representational, not algorithmic. However, scaling to larger spaces of goals (Zhi-Xuan et al., 2024a) and (belief) states will require additional layers of Monte Carlo approximation. Our implementation in Gen (Cusumano-Towner et al., 2019) can naturally be extended to these cases, e.g. by leveraging Sequential Monte Carlo for approximate inference of initial states (Del Moral et al., 2006; Lew et al., 2023).

## **Algorithm 1** Belief-Space Sequential Inverse Plan Search (BSIPS)

```
1: procedure BSIPS(\mathcal{G}, \mathcal{S}_0, \mathcal{B}_0, a_{1:T}, o_{0:T})
           \mathcal{H} \leftarrow \mathcal{G} \times \mathcal{S}_0 \times \mathcal{B}_0
                                                                                            ▶ Enumerate all hypotheses (goal, belief & state combinations).
 2:
           \mathcal{W} \leftarrow \{w^i := P(o_0|s_0^i)\}_{i=1}^{|\mathcal{H}|}
 3:
                                                                                                          ▷ Initialize (unnormalized) weights for all hypotheses.
 4:
           for t \in [1, T] do
 5:
                 for h^i := (g^i, s^i_{0:t-1}, b^i_{0:t-1}) \in \mathcal{H} do
                       s_t^i \leftarrow \text{STATE-TRANSITION}(s_{t-1}^i, a_{t-1})
 6:
                                                                                                                                       ▷ Simulate next environment state.
 7:
                      b_t^i \leftarrow \text{BELIEF-UPDATE}(b_{t-1}^i, s_t^i, a_{t-1})
                                                                                                                                          ▷ Simulate agent's belief update.
                      h^i \leftarrow (g^i, s^i_{0:t}, b^i_{0:t})
 8:
                       Q_{\text{Bel}}(g^i, b_t^i, \tilde{a}) \leftarrow 0 \text{ for } \tilde{a} \in \text{VALID-ACTIONS}(b_t^i)
 9:
                                                                                                                                        \triangleright Initialize belief-space Q-values.
10:
                       for (\tilde{s}, \tilde{w}) \in b_t^i and \tilde{a} \in VALID\text{-}ACTIONS(\tilde{s}) do
                                                                                                                ▶ Iterate over environment states in agent's belief.
                            Q^*(g^i, \tilde{s}, \tilde{a}) \leftarrow \text{MEMOIZED}(\text{PATH-COST}(\tilde{s}, \tilde{a}, g^i))
                                                                                                                ▷ Compute shortest path cost to goal (memoized).
11:
12:
                            Q_{\text{Bel}}(g^i, b_t^i, \tilde{a}) \leftarrow Q^*(g^i, b_t^i, \tilde{a}) + \tilde{w} \cdot Q(g^i, \tilde{s}, \tilde{a})
                                                                                                                                          ▶ Update belief-space Q-values.
13:
                       end for
                       P(a_t|b_t^i, g^i) \leftarrow \exp(-\beta Q_{\text{Bel}}(g^i, b_t^i, a_t)) / \sum_a \exp(-\beta Q_{\text{Bel}}(g^i, b_t^i, a))
14:
                                                                                                                                      \triangleright Compute likelihood of action a_t.
                       w^i \leftarrow w^i \cdot P(a_t|b_t^i, g^i)
15:
                                                                                                                               ▶ Update weight with action likelihood.
                       w^i \leftarrow w^i \cdot P(o_t|s_t^i)
                                                                                                                        ▶ Update weight with observation likelihood.
16:
                 end for
17:
18:
            end for
19:
            return (\mathcal{H}, \mathcal{W})
                                                                                                    ▶ Return all hypotheses and their (unnormalized) weights.
20: end procedure
```

## **B.2** Parameter Fitting

We performed a grid search over parameters for the LaBToM model. The range of inverse temperatures  $\beta$  for the Boltzmann policy went from 0.5 to 4 in multiplicative increments of  $\sqrt{2}$ . This produced human correlations between r=0.75 (at  $\beta=0.5$ ) and r=0.81 (at  $\beta=4$ ) for current beliefs, and between r=0.64 (at  $\beta=0.5$ ) and r=0.80 (at  $\beta=2^{3/2}$ ), with  $\beta=2^{3/2}$  producing the best fit overall.

We also fitted the threshold parameters  $\Theta$  used in our ELoT representation. We performed grid-based coordinate ascent with a step size of 0.05, starting from values derived from the literature mapping modal words to probabilities (Wesson and Pulford, 2009; Hahn and Engelmann, 2014; Meder et al., 2022), and limiting the search to a range of 0.2 above and below this starting point. Our initial and final threshold parameters are shown in Table B1. To evaluate threshold sensitivity, we also ran the same procedure to *minimize* correlation with humans. This produced a value of r=0.71, which was still much higher than the next best model (GPT-4o I+Na+FS, r=0.52).

Thresholds $ heta$										
	believes	certain	uncertain	likely	unlikely	could	might	may	should	must
Initial	0.75	0.95	0.50	0.60	0.40	0.20	0.20	0.30	0.80	0.95
Fitted	0.75	0.95	0.55	0.70	0.40	0.20	0.20	0.30	0.80	0.95

**Table B1:** ELoT probability thresholds before and after fitting.

## **B.3** ELoT Translation Prompt

We used Gemini 1.5 Flash (Gemini Team et al., 2024) prompted with 34 examples to translate natural language statements into ELoT formulae. ELoT formulae were represented in a Prolog-like syntax analogous to the mathematical syntax we show in Table 1. The prompt used is shown below. We only show the first 10 out of 34 examples due to space constraints, and provide the full set in our code release.

```
Please translate the statement below into logical form. Here are some examples of statements
  and their translations:
Input: The player knows that box 2 and box 3 are empty.
Output: knows_that(player, formula(and(empty(box2), empty(box3))))
Input: The player knows the color of the keys in all of the boxes.
Output: forall(box(B), knows_about(player, color(C), exists(and(key(K), inside(K, B)), iscolor
  (K, C))))
Input: The player doesn't know that there is a blue key in box 2.
Output: not_knows_that(player, formula(exists(and(key(K), iscolor(K, red)), inside(K, box2))))
Input: The player is sure of the color of the key in box 4.
\texttt{Output: certain\_about(player, color(C), exists(and(key(K), inside(K, box4)), iscolor(K, C)))}\\
Input: The player is uncertain about what's in box 2.
 \texttt{Output: uncertain\_about(player, color(C), exists(and(key(K), inside(K, box2)), iscolor(K, C)))} \\
Input: The player believes that there is a key in box 4.
Output: believes(player, formula(exists(key(K), inside(K, box4))))
Input: The player thinks that there is a red key in either box 1 or box 3.
Output: believes(player, formula(exists(and(key(K), iscolor(K, red)), or(inside(K, box1),
 inside(K, box3)))))
Input: The player thinks there might be a key in box 1 or box 2.
Output: believes(player, might(exists(key(K), or(inside(K, box1), inside(K, box2)))))
Input: The player thinks there is likely a key in box 2.
Output: believes(player, likely(exists(key(K), inside(K, box2))))
```

## **B.4** LLM Baseline Prompts

Below we show the prompts we used for our multimodal LLM baselines (GPT-40 and Gemini 1.5 Pro). Associated images and videos can be found in our code and dataset release.

```
[IMAGE OR VIDEO]
You're watching someone play the treasure game shown above.
```

```
The player controls a character, and their goal is collect one of the four gems (triangle,
  square, hexagon, or circle).
The rules of the game are as follows:
 - The player can move on the white squares.
  - The player has a full view of the map at all time.
 - The player's goal is to collect exactly one target \operatorname{\mathsf{gem}}\nolimits.
  - Keys unlock doors of the same color (e.g. red keys unlock red doors).
  - Each key can only be used once. Keys disappear after use.
 - Each box may be empty or contain exactly one key.
  - The player may or may not know what's in each box.
 - Neither you nor the player can see what's hidden in each box. But both of you can see all
    other objects in the scene.
  - There are at most two keys hidden among the boxes.
  - The player knows that the puzzle is solvable, which means there are just enough keys to
    reach any of the target gems.
  - The keys and doors are labeled. The labels are shown on the top right corner of each cell.
  - Your task is to figure out what the player's goal is, and also what the player initially
    believed about the contents of the boxes.
Now you observe the following:
[INSERT PLAN OR NARRATIVE]
Given this information, which gem(s) are most likely to be the human agent's goal? And how
  would you rate the following statement about the player's current belief from 1 (definitely
  false) to 7 (definitely true)? Rate 4 if you think there is an equal chance of the statement
  being true and false.
Please rate the following statement:
[INSERT STATEMENT]
Please respond in the following JSON format, indicating all gems that you think are likely to
 be the human's goal, and your rating as a number from 1 to 7.
goal: [gems...],
rating: x ,
The gems should be any of [triangle, square, hexagon, circle] and you can indicate all the
 likely goal gems in your response. The rating should be an integer from 1 to 7. Please
  provide an explanation to your response.
```

## An example of plan-based prompting:

```
The player moves right three times, then down twice, and finally left.
```

## An example of narrative-based prompting, which provides more contextual information:

```
The square gem is locked behind a red door. The triangle, circle and hexagon gems are not locked behind any doors. There are three boxes. No keys are visible in the scene.

The player moves right three times, then down twice, and finally left towards box 2 and away from box 3.
```

For few shot prompting, the following text is added before showing the statement to be evaluated. We provide 4 examples of human ratings:

```
Here is how other people have rated other statements for this stimulus:

{% for statement in statements %}

statement {{ loop.index }}: {{ statement.text }}

rating: {{ statement.rating }}

{% end for %}
```

#### C Additional Results

#### C.1 Direct Translation w/o ELoT

To investigate the importance of our ELoT formalism, we also experimented with an ablated translation model which skips the ELoT representation and directly translates from natural language to the lower-level representation using Gemini 1.5 Flash with few-shot prompting. We find that this approach can handle most simple belief sentences, but makes errors when the statement becomes more complex, or involves distinguishing knowledge from belief. We highlight some failure cases in Table C2.

#### **Example Translations and Errors**

Statement: The player initially did not have confidence box 1 would hold the red key.

Trans.: prob\_of(player, exists(and(key(K), iscolor(K, red)), inside(K, box1))) <= threshold(confidence)

Error: Non-existent threshold for confidence.

**Statement**: The player knows box 3 contains a blue key.

Trans.: prob\_of(player, exists(and(key(K), iscolor(K, blue)), inside(K, box3))) >= threshold(knows)

Error: Non-existent threshold for knows, fails to assert that box 3 contains a blue key (knowledge should be factive).

Statement: The player is unsure which box has a key.

 $\textbf{Trans.:} \ \ \text{forall(box(B), or(prob\_of(player, exists(key(K), inside(K, B))))} < \text{threshold(uncertain), not(exists(key(K), inside(K, B)))))} \\$ 

Error: Incorrectly depends on whether box B actually has a key (uncertainty claims are not factive).

**Table C2:** Erroneous translations from English to probability comparisons, without using ELoT expressions.

## C.2 Impact of a Normalized Statement Prior

In the main text, we report results under the assumption that human observers respond as if they have a normalized 50-50 prior  $U_{\varphi}$  over whether each statement  $\varphi$  is true. Under this assumption, the posterior truth-value of a statement  $P(\llbracket \varphi \rrbracket_{(s_t,b_t)} | a_{1:T}, o_{0:T})$  can be interpreted as a normalized likelihood:

$$\bar{L}(\llbracket\varphi\rrbracket_{(s_t,b_t)}|a_{1:T},o_{0:T}) = \frac{P(a_{1:T},o_{0:T}|\llbracket\varphi\rrbracket_{(s_t,b_t)})}{P(a_{1:T},o_{0:T}|\llbracket\varphi\rrbracket_{(s_t,b_t)}) + P(a_{1:T},o_{0:T}|\llbracket\neg\varphi\rrbracket_{(s_t,b_t)})}$$
(13)

An alternative assumption is to use a uniform prior  $U_{S_0 \times B_0}$  over all possible initial states  $S_0$  and belief distributions  $B_0$ . This has the effect of up-weighting statements which are true in *more possible worlds*, e.g. "The player believes that a red key might be in box 1, 2, or 3.".

Table C3 shows the impact of making either assumption, in terms of the Pearson's correlation coefficient (PCC) r and mean absolute error (MAE) with human judgments. Consistent with Ying et al. (2024b), using a normalized statement prior largely improves the correlation while reducing the mean absolute error for the full LaBToM model. In other words, people appear more willing to say that a statement  $\varphi$  is true only if they have *evidence* for  $\varphi$ , and otherwise default to a 50-50 rating. We see sharper differences for initial belief statements, which is likely because priors have a stronger effect on initial beliefs, whereas an agent's current beliefs are more strongly determined by their percepts: If an agent sees that a box is empty, an observer's judgment about whether the agent believes that the box is empty should not depend on the observer's prior.

Model	Prior Overall		erall	Cu	rrent	Initial		
		PCC $r \uparrow$	$MAE\downarrow$	PCC $r \uparrow$	$MAE\downarrow$	PCC $r \uparrow$	$MAE \downarrow$	
LaBToM (ours)	$U_{\varphi}$	0.81 (0.01)	0.195 (0.004)	0.81 (0.01)	0.193 (0.006)	0.80 (0.01)	0.196 (0.006)	
	$U_{\mathcal{S}_0 \times \mathcal{B}_0}$	0.78 (0.01)	0.226 (0.004)	0.82 (0.01)	0.211 (0.006)	0.71 (0.01)	0.244 (0.005)	
Non-Planning	$U_{\varphi}$	0.47 (0.01)	0.200 (0.003)	0.60 (0.02)	0.185 (0.004)	0.20 (0.01)	0.219 (0.006)	
	$U_{\mathcal{S}_0 \times \mathcal{B}_0}$	0.55 (0.01)	0.252 (0.003)	0.70 (0.01)	0.215 (0.005)	0.34 (0.02)	0.300 (0.005)	
True Belief	$U_{arphi}$	0.12 (0.01)	0.475 (0.003)	0.09 (0.01)	0.482 (0.004)	0.13 (0.02)	0.466 (0.004)	
	$U_{\mathcal{S}_0 \times \mathcal{B}_0}$	0.12 (0.01)	0.475 (0.003)	0.09 (0.01)	0.482 (0.004)	0.13 (0.02)	0.467 (0.004)	

**Table C3:** Similarity of human and model ratings for a normalized  $(U_{\varphi})$  vs. unnormalized  $(U_{S_0 \times B_0})$  prior.

Mo	odel	<b>Human Correlation</b> $r$ (s.e.)							
		Current	Curr. Poss.	Curr. Prob.	Curr. Comp.	Curr. Know.			
LaBToM	Full (ours)	0.81 (0.01)	0.80 (0.02)	0.76 (0.03)	0.76 (0.03)	0.89 (0.01)			
	Non-Planning	0.60 (0.02)	0.65 (0.02)	0.48 (0.04)	0.34 (0.04)	0.75 (0.02)			
	True Belief	0.09 (0.01)	0.14 (0.03)	0.17 (0.03)	0.02 (0.03)	0.43 (0.02)			
GPT-40	I, Na, FS	0.59 (0.01)	0.62 (0.03)	0.63 (0.03)	0.64 (0.02)	0.67 (0.02)			
	I, Na	0.52 (0.01)	0.50 (0.03)	0.54 (0.04)	0.61 (0.03)	0.58 (0.02)			
	I, Pl	0.32 (0.01)	0.50 (0.03)	0.30 (0.03)	0.42 (0.02)	0.21 (0.02)			
Gemini 1.5 Pro	V, Na, FS	0.28 (0.01)	0.23 (0.03)	0.32 (0.03)	0.10 (0.03)	0.28 (0.02)			
	I, Na, FS	0.29 (0.01)	0.25 (0.03)	0.39 (0.03)	0.17 (0.03)	0.26 (0.02)			
		Initial	Init. Poss.	Init. Prob.	Init. Comp.	Init. Know.			
LaBToM	Full (ours)	0.80 (0.01)	0.84 (0.02)	0.81 (0.03)	0.78 (0.02)	0.31 (0.05)			
	Non-Planning	0.20 (0.01)	0.32 (0.02)	-0.05 (0.03)	0.21 (0.03)	0.34 (0.05)			
	True Belief	0.13 (0.02)	-0.09 (0.03)	0.12 (0.05)	-0.03 (0.04)	0.31 (0.05)			
GPT-4o	I, Na, FS	0.41 (0.01)	0.41 (0.03)	0.01 (0.03)	0.26 (0.03)	0.31 (0.05)			
	I, Na	0.41 (0.01)	0.30 (0.03)	0.48 (0.04)	0.31 (0.02)	0.51 (0.05)			
	I, Pl	0.18 (0.01)	0.05 (0.03)	0.15 (0.04)	0.23 (0.03)	0.30 (0.05)			
Gemini 1.5 Pro	V, Na, FS	0.14 (0.02)	-0.02 (0.03)	-0.04 (0.04)	-0.08 (0.03)	0.27 (0.05)			
	I, Na, FS	0.11 (0.02)	0.02 (0.03)	-0.04 (0.04)	-0.02 (0.03)	0.29 (0.05)			

Table C4: Human vs. model correlations broken down by factors present in epistemic language.

#### C.3 Per-Factor Breakdown of Model Performance

Table C4 shows the correlation between human judgments and model outputs broken down by the annotated factors described in Table 2. LaBToM robustly outperforms the baselines on almost all of these data splits, achieving a correlation around r=0.8 in each case. The one exception is the set of statements about what the agent initially knows (*Init. Know.*, r=0.31), such as "The player initially knew that the red key was in box 3". As we discuss in the next section, this is likely because human participants assume that direct perception or justification is necessary for other agents to know some proposition  $\phi$ . In contrast, our model treats knowledge claims as equivalent to claims of true belief.

## C.4 Differences in Human Ratings vs. Model Inferences

While LaBToM largely matches human evaluations of epistemic language both in aggregate and at the individual scenario level, there a number of interesting ways in which they differ.

**People are less certain than LaBToM.** One difference is simply that our model tends to be more certain than people, using the extremes of the 0-1 scale in ways that our participants tended to avoid. This effect did not appear to be driven by the choice of the Boltzmann inverse temperature  $\beta$ , since lower values of  $\beta$  (which increase model uncertainty) led to poorer fits with human data. Instead, humans may be evaluating the truth a statement  $\phi$  less strictly than our model does, perhaps by maintaining uncertainty over the probability thresholds  $\theta$  associated with each statement.

**People appear to adapt probability thresholds.** Threshold uncertainty is closely related to another potential driver of difference: Unlike our model, participants appear to contextually adapt probability thresholds associated with modal words, in line with work on the pragmatics of epistemic modals (Schuster and Degen, 2020; Rudin, 2016; Lassiter, 2017). This is evinced by human responses for current belief statement S2 in Fig. 3b. People rate "The player is unsure which box has a key" highly despite the apparent confidence that the player exhibits in looking for a key in box 3 (at the expense of looking in box 1 or box 2). This is consistent with an upwards adjustment of  $\theta_{\text{uncertain}}$  from 0.55, such that the player is judged as uncertain even when they seem to think it is quite likely for a key to be in box 3. In contrast, our model thinks it is unlikely that the player is uncertain. Similar effects can be seen for current statement S1 and S5 in the same scenario, except that people appear to adjust their threshold for may and might downwards from 0.3 and 0.2 to accommodate even highly unlikely possibilities.

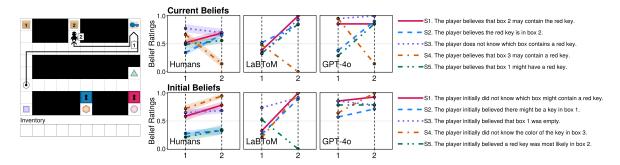


Figure C2: Scenario illustrating differences in human and model ratings of knowledge claims.

**People respond as if knowledge requires justification.** Unlike our model, which reduces knowledge statements to true belief claims (Table 1), people appear to assume that some form of justification (e.g. via direct perception) is necessary for agents to *know* that some proposition  $\phi$  is true. This is clearly illustrated in Figure C2: In this scenario, the player very confidently walks past boxes 1 and 2 towards box 3, suggesting a strong belief about its contents. Since our model just treats knowledge as true belief (and it is quite possible that the player is correct), LaBToM assigns less than 50% probability to "The player does not know which box contains a red key" and "The player initially did not know the color of the key in box 3" at Judgment Point 1 (which occurs before box 3 is opened). Human judgments differ significantly, assigning more than 50% to these ignorance claims. This is consistent with people understanding knowledge to require justification or direct perception: Since the player has not seen what is in box 3 by Judgment Point 1, they cannot *know* what is in that box.

**People reason boundedly about logical implications.** A final difference between humans and our model is that people appear to exhibit bounded reasoning when evaluating statements with non-obvious implications. In Figure C2, for example, "*The player initially believed a red key was most likely in box* 2" is rated lowly by humans initially, then more highly, whereas our model assigns a zero rating to that statement by Judgment Point 2. This is because by then, it is clear that the player did not need a blue key, and was instead looking for a red key in box 1. The fact that they looked in box 1 first also implies that they initially thought box 1 was most likely to contain a red key, not box 2. Our model captures this reasoning, but people do not seem to independently grasp these multi-step implications, consistent with studies on the boundedness of human reasoning (Smets and Solaki, 2018; Mercier and Sperber, 2017).

#### C.5 Misclassified In-Context vs. Out-of-Context Statements

As Table 4 in the main text shows, LaBToM accurately classifies most statements by assigning them a higher likelihood in their original context. However, about 30% of statements were assigned either equal or higher likelihoods out-of-context. By inspecting these cases more closely, we found that misclassification largely occurred due to the following reasons:

- Dataset Noise. A few participants wrote statements that were implausible in their original context.
- Similar Plausibility Across Contexts. Some statements described beliefs that were equally likely to be true out-of-context, or plausible in-context but even more plausible out-of-context.
- **Translation Errors.** The ELoT translation step sometimes resulted in syntactically or semantically invalid translations. These statements were assigned a 0.5 likelihood across all contexts.

To illustrate the second point, we use an example statement from the scenario in Figure C2: ""The player believes that box 1 or 2 contains the red key." By the end of the trajectory shown in Figure C2, this statement is assigned a normalized likelihood of 1.0 (since box 3 contains the blue key, the red key must be in box 1 or 2). In our two out-of-context trajectories, the player is shown finding a red key in box 1 and box 2 respectively. As such, it should be equally true that ""The player believes that box 1 or 2 contains the red key", and our model assigns a likelihood of 1.0 in both cases. As a result, there is no difference in statement likelihoods in-context vs. out-of-context, even though our model is assigning statement likelihoods in an entirely reasonable manner.