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Metacognition in Multisensory Perception

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29 ABSTRACT

28

30 Metacognition, the ability to monitor one's own decisions and representations, their accuracy and 31 uncertainty is considered a hallmark of intelligent behaviour. Little is known about metacognition 32 in real-world situations where the brain is bombarded with signals in different sensory modali-33 ties. To form a coherent percept of our multisensory environment, the brain should integrate signals 34 from a common cause, but segregate those from independent causes. Perception thus relies on infer-35 ring the world's causal structure, raising new challenges for metacognition. We discuss the extent 36 two which observers can monitor their uncertainties not only about their final integrated percept but 37 also about the individual sensory signals and the world's causal structure. The latter causal meta-38 cognition highlights fundamental links between perception and other cognitive domains such as so-39 cial and abstract reasoning.

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41

42 **TRENDS**

43 To form a coherent percept of our multisensory environment the brain needs to integrate signals 44 caused by a common source (e.g. event), but segregate those from different sources; natural multi-45 sensory perception thus relies inherently on inferring the world's causal structure.

Human observers are known to metacognitively monitor the uncertainty of their perceptual estimates in simple sensory tasks, but it is unclear whether they can monitor their uncertainties about their integrated percept, the individual sensory signals and the causal structure of complex multisensory environments.

Causal metacognition highlights fundamental links between perception and other cognitive domains
such as social and abstract reasoning and may be critical for our understanding of neuropsychiatric
diseases such as schizophrenia.

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- 56 KEYWORDS: Metacognition, Multisensory Perception, Crossmodal Integration, Bayesian Causal
 57 Inference, Cue Combination, Uncertainty, Confidence

58 MAIN TEXT

59 Metacognition: Monitoring one's own cognition

60 'Metacognition' refers to cognitive processes about other cognitive processes, knowing about knowing, or beliefs about one's own beliefs. It describes the formation of second-order representa-61 62 tions that allow observers to monitor their first-order representations about objects or events in the real world [1–3]. Metacognitive research investigates the extent to which observers can assess the 63 64 uncertainty or accuracy of their perceptual representations and judgments. For instance, observers 65 cannot only spot a friend in the crowd, but also metacognitively evaluate their uncertainty or doubtfulness about their first-order perceptual interpretation (e.g., "Is this really my friend?"). In a wider 66 67 sense, though, metacognition characterizes an observer's ability to introspect the perceptual infer-68 ence processes that led to their first-order world representations [4]. Metacognition can operate in a 69 number of domains including perception [5-7], memory [8,9], collective decision-making [10] and 70 social learning [11,12].

71 Despite a recent surge of interest in metacognition, the majority of perception research to date has 72 focused on simple visual or auditory tasks that were based on one single signal stream [7,13–16]. 73 Yet, in our natural environment, our senses are constantly bombarded with many different signals. 74 In order to form a coherent percept of the world, the brain is challenged to integrate signals caused 75 by common events, but segregate those caused by independent events. Natural perception thus re-76 lies inherently on inferring the world's causal structure. In this review, we focus on the challenges a 77 natural complex environment poses not only for first-order perception, but also for second-order 78 metacognition. First, we introduce Bayesian Causal Inference as a normative model that describes 79 how an ideal observer should arbitrate between sensory integration and segregation when exposed 80 to multiple sensory signals in our natural environment [17–19]. Next, we discuss whether observers 81 can monitor their uncertainties associated with the different sorts of estimates that Bayesian Causal

Inference involves, such as the uncertainties about their final integrated percept, the individual sensory estimates, and the inferred causal structure of the world [2,20,21]. Finally, we ask er human observers can move beyond the integrated percept and metacognitively introspect those perceptual inference processes. Is multisensory perception encapsulated as an unconscious inference process, or is it open to metacognitive introspection? While we focus on multisensory perception and cue combination as prime examples for the integration of information from independent sensory channels [17,22,23], the fundamental challenges and principles apply more generally to sit89 uations and tasks that require information integration and segregation in perception and wider cog-

90 nition (Box 1).

Metacognition enables human and non-human observers [24] to act more strategically, for instance, to determine whether or not to defer a response and acquire more information [20,25]. Causal metacognition is, in particular, critical for situations with information emanating from potentially different sources not only in perception, but also in social and abstract reasoning [17,26].

95

96 Metacognition in perception

In the 19th Century, Helmholtz described perception as 'unconscious inference' that maps from 97 noisy sensory inputs to perceptual interpretations and choices under the guidance of prior experi-98 99 ence [27]. Likewise, more recent Bayesian statistical models formalize perception as a probabilistic 100 inference process whereby the brain combines prior expectations with uncertain sensory evidence to 101 infer the most likely state of the world [28]. Perception is thus inherently uncertain and error-prone. 102 Metacognitive research investigates whether observers can assess their uncertainty about the per-103 ceptual representations that are formed on the basis of noisy sensory evidence. Are observers ap-104 propriately confident about the accuracy of their perceptual choices and eventually use this infor-105 mation to adjust subsequent responses [21,29]? Accumulating evidence based on decisional confi-106 dence ratings [30], no loss gambling [31], or post-decision wagering [32,33] demonstrates that hu-107 man and non-human observers can indeed access the uncertainty of their perceptual representa-108 tions and adjust their decisional confidence accordingly. In some cases, observers even compute their confidence about the correctness of their perceptual judgment (e.g., motion discrimination) in 109 110 a Bayes-optimal fashion. In other words, their confidence truthfully reflects the probability that 111 their perceptual choices are correct given the sensory signals (e.g., motion) [29]].

112 Critically, observers' decisional confidence depends on the uncertainty of their first-order perceptu-113 al representations (for other influences, see [34]). For instance, when presented with weak motion 114 signals, observers will not only be close to chance when discriminating motion direction but also 115 when judging whether their motion discrimination response was correct. In other words, observers' perceptual sensitivity (e.g., their ability to discriminate left from right motion, say) constrains their 116 117 maximally possible metacognitive sensitivity (i.e., their ability to discriminate between their correct 118 and incorrect choices) [14,35]. While d' is used as a signal-theoretic index to quantify observers' perceptual sensitivity, meta-d' has recently been proposed as a signal-theoretic index to quantify 119 120 observer's metacognitive sensitivity. A large meta-d' indicates that observers can reliably discrimi-121 nate between their correct and incorrect perceptual judgments. Critically, while meta-d' depends on 122 both the quality of the sensory evidence and its metacognitive assessment, directly comparing the 123 perceptual and the metacognitive d' quantifies observer's metacognitive efficiency [14,35]. It provides insights into an observer's ability to evaluate the uncertainty of their perceptual representations and choices. A 'metacognitively-ideal observer' (i.e., where meta-d' is equal to d') can access all information that was used for the first-order perceptual judgment for his/her second-order metacognitive evaluation.

Abundant evidence suggests that the brain is able to represent and use estimates of uncertainty for 128 129 neural computations in perception, learning, and cognition more widely [21-23,36,37]. Yet, the un-130 derlying neural coding principles remain debated. For instance, uncertainty may be represented in 131 probabilistic population codes [38,39] or else rely on sampling-based methods [40]. Likewise, it 132 remains controversial whether metacognitive 'confidence estimates' are directly read-out from first-133 order neural representations [13,20] or formed in distinct 'metacognitive' neural circuitries [7,41,42]. In support of a shared system, or common mechanism, underlying perceptual decisions 134 135 and confidence, neurophysiological research has demonstrated that the same neurons in a lateral 136 parietal area encode both monkey's perceptual choice and its confidence [43,44]. Dissociations be-137 tween perceptual choice and confidence may emerge when decision confidence is interrogated after 138 the subject committed to a perceptual choice thereby relying on different sensory evidence [3,13,45]. By contrast, neuropsychological and neuroimaging studies in humans point toward dedi-139 140 cated metacognitive neural circuitries in the prefrontal cortex [7,42,46]. For instance, fMRI work 141 revealed that activations in anterior prefrontal cortex reflect changes in confidence when perceptual 142 performance is held constant [47]. Likewise, patients with anterior prefrontal lesions showed a se-143 lective deficit in metacognitive accuracy [42]. Decisional confidence estimates encoded in dedicat-144 ed circuitries may serve as a common currency and enable direct comparisons across different cog-145 nitive tasks [15] or sensory modalities [5].

146

147 The multisensory challenge: Causal inference and reliability-weighted integration

Imagine you are packing your shopping items from your trolley into the back of your car which is 148 149 parked on a busy street. Suddenly you hear a loud horn. Is this sound coming from a car on the op-150 posite side of the road, competing for a parking spot, or from a car hidden behind your back indicat-151 ing that your trolley is blocking the traffic? Or is the sound perhaps coming from one of your shop-152 ping items? While the latter suggestion seems rather unlikely, the other two may be valid interpreta-153 tions of the sensory inputs (see figure 1). This example illustrates the two fundamental computa-154 tional challenges that the brain faces in our everyday multisensory world: First, it needs to solve the 155 so-called causal inference problem [17-19] and determine whether or not signals come from com-156 mon sources and should be integrated. Second, if two signals come from a common source, the brain is challenged to integrate them into the most reliable percept by weighting them optimally in proportion to their reliabilities (i.e., inverse of sensory variance [22,23,48,49]).

159 In the laboratory, the principles of multisensory integration can be studied by presenting conflicting 160 and non-conflicting signals. For instance, if auditory and visual signals are presented in synchrony 161 yet at different spatial locations, the ventriloquist illusion emerges. The perceived sound location 162 shifts towards the location of a spatially distant visual signal and vice versa depending on the rela-163 tive auditory and visual reliabilities. Importantly, spatial biasing is reduced at large spatial dispari-164 ties when it is unlikely that the two signals come from a common source [50,51]. This attenuation 165 of sensory integration at large spatial disparities is well accommodated by hierarchical 'Bayesian 166 Causal Inference' that explicitly models the potential causal structures that could have generated the 167 sensory signals i.e., whether auditory and visual signals come from common or independent sources 168 [18,52] (for related models based on heavy tailed prior distributions, please see [17,53,54]). During 169 perceptual inference, the observer is then thought to invert this generative process. Under the as-170 sumption of a common signal source, the two unisensory estimates of a physical property are com-171 bined and weighted according to their relative reliabilities (i.e., inverse of variance). For instance, to 172 estimate the location of a singing bird from audition and vision the observer should give a stronger 173 weight to the visual signal at day time than at night. Under the hypothesis of two different sources, 174 the auditory and visual signals are treated independently. On a particular instance, the brain needs to 175 infer the causal structure of the world (e.g., one or two sources) from the sensory inputs. Multiple 176 sorts of intersensory correspondences [55] such as spatiotemporal coincidence (i.e. auditory and 177 visual signals happening at the same time and location [56-62], semantic (e.g. the shape and 178 singing of a bird) [63–65] or higher-order correspondences (e.g., gender: female voice with female 179 face) can inform the brain as to whether signals are likely to come from a common source or 180 independent sources. Finally, an estimate of the physical property in question (e.g., auditory loca-181 tion) is obtained by combining the estimates under the two causal structures using different deci-182 sional functions [18,52,66]. For instance, using model averaging observers may form a final esti-183 mate by averaging the estimates from the two causal structures weighted by their posterior probabil-

184 ities. Alternatively, they may report the estimate of the most likely causal structure as final estimate,185 a decisional strategy referred to as model selection.

186

187 Monitoring uncertainties about the world's causal structure and environmental properties

188 The additional complexity of multisensory perception or more generally tasks that rely on multiple 189 information channels raise questions and challenges that go beyond metacognition studied, for ex-190 ample, with simple visual discrimination or detections tasks. In particular, it raises the question of 191 whether observers can monitor the different sorts of uncertainties involved in Bayesian Causal In-

192 ference:

193 First, observers may monitor their uncertainty about the causal structure that has generated the 194 sensory signals [18,19,66]. The uncertainty about the causal structure increases with the noise in the 195 sensory channels. For instance, at dawn, it is more difficult (i.e. associated with greater uncertainty) 196 to attribute a singing voice to a specific bird in the bush than in bright sunlight. Hence, the 197 uncertainty about the inferred causal structure critically depends on the sensory uncertainty given in 198 all sensory channels [52]. Moreover, causal uncertainty emerges because there is some natural 199 variability in the temporal, spatial or higher-order (e.g. semantic) relationship of the sensory signals. 200 Even when two signals are generated by a common source, they do not need to be precisely 201 temporally synchronous or spatially collocated. For speech signals, it is well established that visual 202 facial movements often precede the auditory signal to variable degrees at speech onset [67]. 203 Further, differences in velocity of light and sound induce variability in arrival times of the visual 204 and auditory signals at the receptor level that depend on the distance of the physical source from the 205 observer [68,69]. Likewise, higher-order correspondences, such as gender or semantics may relate 206 probabilistically to low level physical features (e.g. a low-pitched voice is more likely to be 207 associated with a male than a female person). Experimentally, we therefore need to determine 208 whether observers' causal uncertainty reflects the uncertainty determined by the signal-to-noise 209 ratio of the sensory signals and their spatiotemporal and higher-order (e.g. semantic) statistical 210 relationships. Moreover, causal uncertainty may be influenced by participants' prior expectations 211 [70,71] that sensory signals are likely to come from a common external source, or be generated by 212 one's own voluntary actions [72,73] (see Box 3).

213 Second, it is well-established that observers use the uncertainty associated with the individual cues 214 or sensory signals to assign the appropriate weighting during cue combination or multisensory 215 integration. Yet, an unresolved question is whether these uncertainty estimates for individual cues 216 are then lost or accessible for metacognition. To approach these questions, future experiments may 217 consider asking observers to explore objects visuo-haptically (i.e., via vision and touch) and report 218 both the haptic size they perceived and their uncertainty about their perceptual estimate in the 219 context of the visual information as well as if they had fully ignored the visual information (e.g., 220 they may be asked to imagine that they had closed their eyes and only haptically explored the 221 object). If observers maintain partial access to the unisensory estimates and their associated 222 uncertainties we would expect that the two reports differ.

Finally, observers may monitor their uncertainty associated with their final perceptual estimate (e.g. the reported location during audiovisual localization tasks). According to Bayesian Causal Inference, these final (e.g., auditory and visual) perceptual estimates are formed by combining the estimates under the assumptions of common and independent sources according to various decision functions such as model averaging, probability matching or model selection [66]. As a result, the uncertainty of these final Bayesian Causal Inference perceptual estimates is dependent on observer's sensory and causal uncertainty. A critical question for future investigation is to determine the extent to which observers' uncertainty about their reported perceptual estimate reflects their perceived causal uncertainty or the causal uncertainty as predicted based on their sensory uncertainties.

233 A few studies have started to directly tackle the question of metacognitive uncertainty or confidence 234 estimates in multisensory perception, albeit not always with these different sorts of uncertainties in 235 mind. For instance, a recent psychophysical study [74] demonstrated that observers' correctly 236 assessed the accuracy of their temporal order judgments in confidence ratings. These results 237 indicate that the precision of audiovisual temporal relation estimates is accessible to metacognition. 238 Further, a recent study by White and colleagues [75] presented observers with audiovisually non-239 conflicting (e.g., visual <<ba>> with auditory /ba/), conflicting phonemic cues that could be 240 integrated into a so-called McGurk percept (e.g., McGurk: visual << ga>> with auditory /ba/ 241 resulting in an illusory [da] percept) and conflicting phonemic cues that could not be integrated into 242 one unified percept (i.e., non McGurk: visual <<pre>visual <</pre>visual <</pre>visual visual vis 243 perceived auditory phoneme, immediately before providing a second-order confidence rating. The 244 authors demonstrated that observers were less confident about their illusory McGurk percepts than 245 about their auditory percept for conflicting or non-conflicting stimuli. From a Bayesian Causal 246 Inference perspective, observers' lower confidence about their McGurk responses may emerge from 247 an increase in causal uncertainty for McGurk stimuli. While non-conflicting signals are likely to 248 come from a common source and conflicting signals from independent sources, McGurk stimuli 249 introduce an intermediate phonological conflict that introduces uncertainty about the underlying 250 causal structure. This causal uncertainty may indirectly influence and increase observers' 251 uncertainty about their final phoneme percept. However, this is only one of several possible 252 explanations for the observed response profile (see also [76]). It highlights the need for future dual-253 task paradigms that ask observers concurrently to rate not only their confidence about their 254 phonological percept, but also their causal uncertainty about whether sensory signals (e.g. auditory 255 phoneme and facial movements in speech recognition) were generated by a common source.

256

257 Perceptual and causal metamers

Further insights into whether observers can move beyond the integrated percept and metacognitively monitor the perceptual inference can be obtained from so-called metamers, i.e. (near)-identical perceptual interpretations formed from different combinations of sensory signals [77]. Let's assume

we present an observer with two signals in synchrony, a brief flash at -2° visual angle (i.e. left) and 261 262 a spatially equally reliable beep at $+2^{\circ}$ visual angle (i.e. right). Where will the observer perceive this 263 event? Because of the small audiovisual spatial disparity, the observer may infer that the two sig-264 nals come from a common source and hence integrate them weighted by their relative reliabilities. 265 As a result, he would perceive the audiovisual event at 0° degree visual angle, where in fact no sig-266 nal was presented at all. Hence, this conflicting flash-beep event would elicit the same percept as 267 a non-conflicting flash-beep event where both auditory and visual signals are presented at 0° degree 268 visual angle. In other words, the conflicting and the non-conflicting flash-beep events elicit percep-269 tual metamers. Moreover, the observer inferred that the auditory and visual signals come from a 270 single event in both situations. Hence, the two cases elicit not only perceptual but also causal met-271 amers. The critical question is whether observers may nevertheless be able to discriminate between 272 the conflicting and non-conflicting flash-beep events indicating that they can metacognitively ac-273 cess additional information about the underlying perceptual inference process.

274 First, observers would be able to discriminate between the non-conflicting and conflicting signals, if 275 they monitor their uncertainty about their perceptual interpretation and causal inference. In the 276 small conflict case, those observers who use Bayesian Causal Inference with model selection may 277 decide that the two signals come from a common source and integrate them weighted by their rela-278 tive reliabilities. Critically, even though they commit to one single event as the more likely causal 279 structure, they should be less certain about their causal inference. In other words, monitoring their 280 causal uncertainty would allow observers to discriminate between conflicting and non-conflicting 281 sensory signals, even if they elicit perceptual and causal metamers. Within the framework of Bayesian Causal Inference and depending on decisional functions and biases [66], it is also conceivable 282 283 that observers may integrate different combinations of auditory and visual signals into the same 284 perceptual (e.g. auditory, visual) estimates and yet report different causal structures. Hence, percep-285 tual metamers may not necessarily imply causal metamers.

Second, observers may be able to go beyond the integrated percept and maintain at least partial access to the individual sensory signals (see discussion above). Again, this partial access would allow them to discriminate between conflicting and non-conflicting flash-beep events. In a wider sense of metacognition it would demonstrate that multisensory perception is not informationally encapsulated, but that observers can introspect and metacognitively monitor the unisensory representations that form the basis for their perceptual inference.

Surprisingly, only a few studies to date have used perceptual metamers as an approach to characterize observers' metacognitive access in cue combination. An intriguing early study by Hillis et al. [77] focused on the emergence of perceptual metamers in visual (slant from disparity and texture cues in vision) and visuo-haptic (object size from vision and touch, i.e., haptic cues) contexts. In an 296 oddity judgment task, observers were asked to identify the odd stimulus in a sequence of three 297 stimuli: two identical standard stimuli defined by non-conflicting cues and one odd stimulus defined 298 by conflicting cues that could be fused into a perceptual metamer of the standard stimulus [77,78]. 299 The results revealed that observers lost access to individual cues in the visual, but not in the visuo-300 haptic setting: Only conflicting visual cues were mandatorily fused into perceptual metamers of the 301 non-conflicting standard stimulus. Yet, even in the visual case participants were able to discriminate 302 the conflicting stimulus from the non-conflicting ones for larger conflict sizes indicating that meta-303 mers emerge only for small conflict size. What happened, though, in those unisensory cases with 304 larger conflict? As the oddity judgment task does not explicitly define the dimension according to 305 which participants should compare the stimuli, it remains unclear whether observers identified the 306 conflicting stimulus because they did not integrate the conflicting cues into one unified slant esti-307 mate, i.e., into a perceptual metamer of the non-conflicting stimulus, or whether instead they inte-308 grated them, but were aware that their metameric percepts emerged from different causal structures 309 or at least associated with different causal uncertainties. Observers may still have fused conflicting 310 signals into approximate perceptual metamers without them being causally metameric to the non-311 conflicting standard stimulus. In other words, observers may potentially have identified the odd-312 one-out because of partial access to the causal structure that has generated the sensory inputs. In-313 deed, observers reported a 'weird' percept for larger conflict sizes (personal communication, Marc 314 Ernst) indicating that they were aware of the conflict manipulation while still integrating signals 315 into a near-unified percept. This may perhaps be taken as initial evidence that perceptual and causal 316 metamers may be to some extent dissociable. Future studies that explicitly assess the emergence of 317 perceptual and causal metamers are needed to experimentally determine whether participants can 318 form perceptual metamers while recognizing that they are based on different causal structures.

319 Another approach to dissociate perceptual and causal metamers is to introduce conflicts along mul-320 tiple dimensions such as lower temporal and higher-order phonological dimensions. For instance, 321 observers may be presented with conflicting and non-conflicting visual and auditory phonetic cues 322 at multiple audiovisual asynchronies. For small audiovisual asynchronies, conflicting audiovisual 323 signals, such as a visual <<ga>> and an auditory /ba/, may be fused into a [da] percept at the pho-324 nological level as in the classical McGurk-MacDonald illusion [79] (Figure 2). The critical question 325 is whether the fusion of conflicting audiovisual signals into a [da] percept as a perceptual metamer 326 of a non-conflicting audiovisual [da] emerges in cases where observers inferred that the two signals 327 come from different sources because of their audiovisual asynchrony (i.e., no causal metamer).

Research showing that the temporal integration windows that allow the McGurk illusion to emerge mostly correspond to those where observers perceive the audiovisual signals as being synchronous has suggested that the detection of temporal conflicts precludes the emergence of perceptual meta331 mers [80]. However, other evidence suggests that conflicting visual phonetic information influences 332 the perceived auditory phonemes even when observers are able to detect low-level temporal con-333 flicts [81]. In the light of this controversial evidence, future studies are needed to determine whether 334 perceptual metamers at higher representational levels emerge even when lower level temporal con-335 flicts prevent the emergence of causal metamers.

336

337 Concluding remarks

338 Accumulating evidence shows that human observers can metacognitively assess the uncertainty of 339 perceptual estimates formed from vision, touch or audition, in unisensory perception. Conversely, 340 research in multisensory perception demonstrates that observers integrate signals from multiple 341 sensory modalities into percepts that take into account the uncertainty about the world's causal 342 structure. In this review, we have merged these two research fields and discuss the new challenges 343 and questions that metacognition poses for situations where the brain needs to integrate information from multiple channels such as in multisensory perception and cue combination. Recent 344 345 developments of hierarchical Bayesian models of multisensory perception raise the possibility that 346 human observers can introspect perceptual inference processes and monitor not only the final 347 integrated percept, but also the unisensory estimates and the causal relationship - thereby challenging the long-dominant view in philosophy that observers are causally naive about 348 349 perceptual inference (Box 2). Future studies in causal metacognition will need to determine the 350 extent to which human observers can accurately assess their uncertainty about the perceptual 351 estimates and the inferred causal structure of the environment. They open up new research avenues 352 that link metacognition in perception more tightly with higher-order cognitive capacities such as 353 abstract causal reasoning [82] or the aggregation of information across agents (Box 1 and 354 Outstanding Questions). Causal metacognition sheds new light on the emergence of the sense of 355 agency [83] (Box 3) and will be critical for our understanding of neuropsychiatric diseases such as 356 schizophrenia that affect multisensory binding, causal inference and metacognitive control [75,84-

357 87]

Box 1: Monitoring causal uncertainty beyond perception.

359 Causal inference is not only critical for perception but, more generally, for many other cognitive 360 domains such as inductive, abstract, or social reasoning [82]. If two burglaries occur in the same 361 town on the same day, the police ought to inquire as to whether they are likely to be performed by 362 the same or different criminal gangs. Likewise, if a patient presents initially with a rash followed by 363 high fever, cough, shortness of breath and wheezing, the medical doctor needs to infer whether all 364 these symptoms are caused by measles infection or whether some of them may be caused by a 365 subsequent bacterial (e.g., streptococcal) superinfection which requires antibiotic treatment. These 366 examples highlight that causal inference is pervasive in our everyday lives. Causal metacognition 367 enables observers to monitor their uncertainty about the underlying causal structure and decide 368 whether to seek additional evidence in order to arbitrate between several potential causal structures. 369 If the medical doctor is in doubt whether the patient may have incurred an additional streptococcal 370 infection, s/he may order blood tests, chest x-ray, etc.

371 Causal inference is also fundamental for successful communication and interactions across social 372 agents. For instance, if two social agents talk about a person called 'Peter' they usually assume that 373 they refer to the same person as the causal source that generates their thoughts and representations 374 associated with 'Peter'. In fact, this shared causal perspective is fundamental for successful 375 collective decision making [10]. Surprises and comic moments may emerge if agents discover 376 during the course of their conversation that their inference was wrong and they had actually been 377 referring to two different individuals that were both called 'Peter'. In other words, they suddenly 378 discovered that their thoughts and representations were not caused by one common source 'Peter', 379 but by two different individuals.

Causal Inference as a process to arbitrate between one or multiple causes for sensory signals, medical symptoms or mental representations is part of the wider question of how observers can infer hidden structure from statistical correlations in observed data (e.g. correlations between different symptoms). How can they build veridical or at least useful models of the world? As reviewed in more detail in [17,88–90], Bayesian models can be used to accommodate human structure inference across numerous domains including inductive reasoning [82], semantics [91], social cognition [10] or aggregation of information across individuals [92].

387 Box 2: Challenging causal naivety assumptions in philosophy

The capacity to represent causation is usually granted only on the evidence that explicit causal reasoning, and inferences to hidden or distant causes are performed. As Hume's challenge goes, there is a difference in predicting that one event regularly follows another, and in representing that it was caused by this first event. This view, started in philosophical discussions [93], is also widespread in psychology [94]. Does causal metacognition challenge this claim, suggesting that we are sensitive to differences between hidden causal structures when we perceive events? How sophisticated do we need to be to monitor the uncertainty of our causal models of the world?

395 Evidence of causal metacognition in younger children and non-human animals should address this 396 question, and possibly reveal whether hidden causal structures are accessed and monitored as such, 397 even in the absence of more explicit causal reasoning. But causal metacognition brings a broader 398 challenge to philosophical models of perception. It is widely assumed indeed that we are causally 399 naive when it comes to perceiving the world: Perception does not make us aware of objects as caus-400 es of our perception [95]. When we perceive a singing bird, we do not see that a physical bird, or 401 light, is causing our perception: We perceive a bird, as a mind-independent object, not as a likely 402 cause of our percept. The claim that perception rests on a process of causal inference, at the subpersonal level [96,97], though widely accepted by cognitive neuroscientists, explains from the out-403 404 side what the system is set up to do, but does not suppose that causes are represented as such, even less consciously accessed [98,99]. Sensitivity to differences in the causal origin of our integrated 405 406 percepts offers an intermediate step where the causal character of perception is made manifest.

407 How this form of causal metacognition fits within causal cognition in general, and whether it is also 408 present in more explicit forms of reasoning is an open question. While it is common to stress the 409 difference between aggregating information between agents, and combining information from dif-410 ferent sensory modalities, it might be the case that both are optimal if the uncertainty about the un-411 derlying causal model dictating the problem is adequately monitored.

412 **Box 3: Causal metacognition and sense of agency**

413 Causal inference enables the brain to dissociate the sensory effects caused by one's own actions 414 from those caused by other agents or events in the outside world. Previous neuroimaging and 415 neurophysiological studies have suggested that the cerebellum may form a predictive forward 416 model that maps from the action plan to the motor outputs and their sensory consequences. These 417 forward models enable the brain to distinguish between self- and other-generated sensory signals 418 leading to effects such as sensory attenuation (e.g., predicted outputs of our own tickling are not felt 419 as tickling [100]) or intentional binding (e.g. the temporal interval between a voluntary action and 420 its sensory consequences is subjectively compressed [72,73,83], see figure I). Both effects are 421 considered central to our sense of agency that is the subjective judgment or feeling that we are 422 causally responsible for changes in the environment. Critically, the temporal compression effect 423 was increased in patients with schizophrenia indicating an enhanced sense of agency [85-87]. From 424 the perspective of causal metacognition, we would expect the sense of agency to be related to the 425 degree of confidence about our beliefs that a certain sensory outcome was self- rather than other-426 generated [84]. Further, manipulating biases in confidence by prior context or instructions may 427 influence sensory attenuation and intentional binding, even when the sensory and motor 428 components are held constant. For instance, if an agent is more confident that he/she has generated 429 certain sensory signals, he/she should experience the same signal as less tickling and the interval 430 between the action and the occurrence of the tickling sensation to be less compressed in time. A 431 critical question for future research is therefore whether the altered sense of agency in patients with 432 schizophrenia [85], may be associated with more general changes in causal metacognition.

433

435 GLOSSARY

436 Causal metamers: identical causal structures inferred from signals generated by physically different437 causal structures.

438 Causal metacognition: monitoring the inferred causal structure underlying certain signals (e.g.439 sensory signals)

440 Confidence rating, post-decision wagering, no loss gambling [30]: are methods to assess an 441 observer's metacognitive insights or awareness. For instance, observers may rate their confidence 442 about the correctness of their decision on a numerical scale. In post-decision wagering, they are 443 asked to bet on the correctness of their reported choices. As a result, observers should place higher 444 wagers when they are more confident about the correctness of their decision to maximize their 445 gains. In no-loss gambling, observers need to choose whether they are given a reward depending on 446 the correctness of their perceptual choice, or depending on a lottery with pre-specified probabilities. 447 Both post-decision wagering and no-loss gambling provide observers with an incentive to reveal 448 their decisional confidence and subjective probabilities truthfully. Yet, post-decision wagering may 449 be sensitive to additional biases such as risk aversiveness.

Bayesian Causal Inference models: normative Bayesian models that describe how an observer
should integrate sensory signals to compute an estimate of an environmental property. Bayesian
Causal Inference [17–19,52,66] explicitly models the potential causal structures (i.e. common or
independent sources) that could have generated the two signals.

454 Intersensory correspondences: the observer uses different sorts of correspondences such as spatial 455 colocation [50–52,58,59], temporal coincidence [56,57,60] and correlations [61,62], semantic or

456 phonological congruency [63–65] to determine which signals are likely to come from a common

457 source and should be bound during perception.

458 Perceptual metamers: are identical perceptual (e.g. spatial, phoneme) estimates formed from459 physically different signals.

460 Metacognition: cognitive processes about other cognitive processes (e.g. formation of 461 representations about world representations [1–3,24]).

462 McGurk illusion: an audiovisual illusion [71,79,81] where observers perceive for instance the 463 phoneme [da] when presented with a video of a face articulating <<ga>> and a voice uttering /ba/.

- 464 The McGurk illusion is a prime example of a perceptual metamer; i.e. the conflicting signals are 465 perceived as identical to a face and voice articulating [da].
- 466 Sense of agency: the subjective feeling that one initiates and controls one's own actions [72,73,83].

467 Sensory reliability: is the inverse of sensory variance (or uncertainty). Reliability decreases with the468 noise of a sensory signal.

Ventriloquist illusion: a multisensory perceptual illusion induced by presenting two signals from
different sensory modalities in synchrony, but at different spatial locations. In classical audio-visual
cases, the perceived location of a sound is shifted towards the actual location of the visual signal,
and vice versa [18,50–52].

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478 **OUTSTANDING QUESTIONS**

479 To what extent can observers metacognitively monitor the individual signals, the inferred causal
480 structure, and their respective uncertainties in sensory or cue-integration? Do their perceptual
481 uncertainties reflect their causal uncertainties, and vice versa?

+How does causal metacognition in perception relate to metacognition in other cognitive domains
such as causal reasoning or social interactions?

484 •What are the benefits of causal metacognition in perception? Do observers adjust their future
485 perceptual interpretations based on their causal metacognitive assessments?

486 Is the sense of agency grounded in causal metacognition?

487 Which neural circuitries sustain causal metacognition during perceptual and other cognitive tasks488 in the human brain?

489 Is causal metacognition impaired in neuropsychiatric diseases such as schizophrenia?

How does causal metacognition develop during infancy and childhood? Does it emerge later than
metacognition about perceptual decisions based on a single information stream?

492 Non-human organisms have been shown to monitor their uncertainties about their perceptual
493 decisions. Can they also monitor their uncertainty about the causal structure of the world?

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502 FIGURE LEGENDS

503 **Figure 1**

504 Metacognition in multisensory perception

Left: Generative Model: The generative model of Bayesian Causal Inference for spatial localization determines whether the 'visual car' and the 'sound of the horn' are generated by common (C=1) or independent (C=2) sources (for details, see [18]). For common source, the 'true' audiovisual location (S_{AV}) is drawn from one prior spatial distribution. For independent sources, the 'true' auditory (S_A) and 'true' visual (S_V) locations are drawn independently from this prior spatial distribution. We introduce independent sensory noise to generate auditory (x_A) and visual (x_V) inputs [18].

Middle: Bayesian Inference Model: During perceptual inference the observer is thought to compute 512 513 three sorts of estimates from the auditory and visual signals for spatial localization: 1. spatial 514 estimates under the assumption of common source (i.e., forced fusion estimate: $S_{AV,C=1}$) and independent sources (i.e. full segregation estimates separately for auditory and visual locations: 515 516 $\widehat{S_{V,c=2}}, \widehat{S_{A,c=2}}$, 2. estimates of the causal structure and 3. the final auditory and visual Bayesian Causal Inference spatial estimates based on model averaging that take into account the observer's 517 causal uncertainty by marginalizing (i.e. integrating) over the different causal structures: $\widehat{S_V}, \widehat{S_A}$). 518 519 Each of those estimates is associated with uncertainties as indicated by the specified probability 520 distributions.

521 Right: Metacognition may be able to access and monitor the three sorts of estimates and their 522 uncertainty: 1. forced fusion and full segregation spatial estimates, 2. the inferred causal structure 523 and 3. the final auditory and visual Bayesian Causal Inference spatial estimates.

524

525 **Figure 2**

526 Perceptual and causal metamers in the audiovisual McGurk illusion

Left: Observers are presented with non-conflicting audiovisual stimuli, i.e. a video of a face articulating <<<da>> and a voice uttering /da/. They will perceive the audiovisual signals as coming from one source and integrate them into a [da] percept.

530 Right: Observers are presented with conflicting audiovisual stimuli, i.e., a video of a face 531 articulating <<ga>> and a voice uttering /ba/. In the McGurk illusion, they should perceive the audiovisual signals as coming from one source and integrate them into a [da] percept, which would be a causal and perceptual metamer to the estimates formed from the non-conflicting audiovisual signals. However, perceptual and causal inference may also result in other outcomes. Observers may potentially perceive a [da] and yet recognize the audiovisual conflict and hence infer that the two signals come from independent sources (i.e. perceptual metamer but no causal metamer).

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539 **Figure I (Box 3)**

540 Intentional binding, sense of agency and causal metacognition

541 Observers have been shown to perceive the interval between an action and its sensory consequences 542 (e.g., a 'beep') of a certain duration that is temporally compressed, when the action was voluntary 543 and associated with a sense of agency – a phenomenon referred to as 'intentional binding' [72]. 544 Causal metacognition may be closely related to the sense of agency by virtue of monitoring the 545 uncertainty about the causal relationship between one's own voluntary actions and their sensory 546 consequences.

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554 REFERENCES

555 556	1	Flavell, J.H. (1979) Metacognition and cognitive monitoring: A new area of cognitive– developmental inquiry. <i>Am. Psychol.</i> 34, 906–911
557 558	2	Fleming, S.M. <i>et al.</i> (2012) Metacognition: computation, biology and function. <i>Philos. Trans. R. Soc. Lond. B. Biol. Sci.</i> 367, 1280–6
559	3	Yeung, N. and Summerfield, C. (2012) Metacognition in human decision-making:
560		confidence and error monitoring. Philos. Trans. R. Soc. Lond. B. Biol. Sci. 367, 1310-21
561	4	Overgaard, M. and Sandberg, K. (2012) Kinds of access: different methods for report reveal
562		different kinds of metacognitive access. Philos. Trans. R. Soc. B Biol. Sci. 367, 1287–1296
563	5	De Gardelle, V. et al. (2016) Confidence as a common currency between vision and audition.
564		PLoS One 11,
565	6	Ais, J. et al. (2016) Individual consistency in the accuracy and distribution of confidence
566		judgments. Cognition 146, 377-386
567	7	Fleming, S.M. et al. (2012) Prefrontal contributions to metacognition in perceptual decision
568		making. J. Neurosci. 32, 6117–25
569	8	Ratcliff, R. and Starns, J.J. (2013) Modeling confidence judgments, response times, and
570		multiple choices in decision making: recognition memory and motion discrimination.
571		Psychol. Rev. 120, 697–719
572	9	Rutishauser, U. et al. (2015) Representation of retrieval confidence by single neurons in the
573		human medial temporal lobe. Nat. Neurosci. 18, 1–12
574	10	Bahrami, B. et al. (2010) Optimally interacting minds. Science (80). 329, 1081-5
575	11	Goupil, L. et al. (2016) Infants ask for help when they know they don't know. Proc. Natl.
576		Acad. Sci. 113, 3492–3496
577	12	Heyes, C. Who Knows? Metacognitive Social Learning Strategies. , Trends in Cognitive
578		Sciences, 20. (2016), 204–213
579	13	Van Den Berg, R. et al. (2016) A common mechanism underlies changes of mind about
580		decisions and confidence. <i>Elife</i> 5,

- 581 14 Fleming, S.M. and Lau, H.C. (2014) How to measure metacognition. *Front. Hum. Neurosci.*582 8, 443
- de Gardelle, V. and Mamassian, P. (2014) Does Confidence Use a Common Currency Across
 Two Visual Tasks? *Psychol. Sci.* 25, 1286–1288
- 585 16 Barthelmé, S. and Mamassian, P. (2010) Flexible mechanisms underlie the evaluation of
 586 visual confidence. *Proc. Natl. Acad. Sci. U. S. A.* 107, 20834–9
- 587 17 Shams, L. and Beierholm, U.R. Causal inference in perception. , *Trends in Cognitive*588 *Sciences*, 14. (2010) , 425–432
- 589 18 Kording, K.P. et al. (2007) Causal inference in multisensory perception. PLoS One 2,
- Rohe, T. and Noppeney, U. (2015) Cortical Hierarchies Perform Bayesian Causal Inference
 in Multisensory Perception. *PLoS Biol.* 13,
- 592 20 Meyniel, F. *et al.* Confidence as Bayesian Probability: From Neural Origins to Behavior. ,
 593 *Neuron*, 88. (2015) , 78–92
- 594 21 Pouget, A. *et al.* (2016) Confidence and certainty: distinct probabilistic quantities for
 595 different goals. *Nat. Neurosci.* 19, 366–374
- 596 22 Ernst, M.O. and Banks, M.S. (2002) Humans integrate visual and haptic information in a
 597 statistically optimal fashion. *Nature* 415, 429–433
- 598 23 Knill, D.C. and Saunders, J.A. (2003) Do humans optimally integrate stereo and texture
 599 information for judgments of surface slant? *Vision Res.* 43, 2539–2558
- Smith, J.D. *et al.* (2012) The highs and lows of theoretical interpretation in animalmetacognition research. *Philos. Trans. R. Soc. B Biol. Sci.* 367, 1297–1309
- Shea, N. *et al.* Supra-personal cognitive control and metacognition. , *Trends in Cognitive Sciences*, 18. (2014) , 186–193
- Tenenbaum, J.B. and Griffiths, T.L. (2003) Theory-based causal inference. *Adv. Neural Inf. Process. Syst.* DOI: 10.1037/a0017201
- 606 27 von Helmholtz, H. (1867) Handbuch der Physiologischen Optik, Leopold Voss.
- 607 28 Kersten, D. et al. (2004) Object perception as Bayesian inference. Annu. Rev. Psychol. 55,

608		271–304
609	29	Aitchison, L. et al. (2015) Doubly Bayesian Analysis of Confidence in Perceptual Decision-
610		Making. PLoS Comput. Biol. 11,
611	30	Massoni, S. et al. (2014) Confidence measurement in the light of signal detection theory.
612		Front. Psychol. 5,
613	31	Dienes, Z. and Seth, A. (2010) Gambling on the unconscious: A comparison of wagering and
614		confidence ratings as measures of awareness in an artificial grammar task. Conscious. Cogn.
615		19, 674–681
616	32	Persaud, N. et al. (2007) Post-decision wagering objectively measures awareness. Nat.
617		Neurosci. 10, 257–61
618	33	Clifford, C.W.G. et al. (2008) Getting technical about awareness. Trends Cogn. Sci. 12, 54-
619		58
620	34	Fleming, S.M. et al. (2015) Action-specific disruption of perceptual confidence. Psychol. Sci.
621		26, 89–98
622	35	Maniscalco, B. and Lau, H. (2012) A signal detection theoretic approach for estimating
623		metacognitive sensitivity from confidence ratings. Conscious. Cogn. 21, 422-430
624	36	Knill, D.C. and Pouget, A. The Bayesian brain: The role of uncertainty in neural coding and
625		computation., Trends in Neurosciences, 27. (2004), 712-719
626	37	Körding, K.P. and Wolpert, D.M. (2004) Bayesian integration in sensorimotor learning.
627		Nature 427, 244–247
628	38	Ma, W.J. et al. (2006) Bayesian inference with probabilistic population codes. Nat. Neurosci.
629		9, 1432–8
630	39	Pouget, A. et al. (2003) Inference and computation with population codes. Annu. Rev.
631		Neurosci. 26, 381–410
632	40	Fiser, J. et al. (2010) Statistically optimal perception and learning: from behavior to neural
633		representations. Trends Cogn. Sci. 14, 119-130
634	41	Middlebrooks, P.G. and Sommer, M.A. (2012) Neuronal Correlates of Metacognition in
		-

Primate Frontal Cortex. Neuron 75, 517-530 Del Cul, A. et al. (2009) Causal role of prefrontal cortex in the threshold for access to consciousness. Brain 132, 2531–2540 Kiani, R. and Shadlen, M.N. (2009) Representation of confidence associated with a decision by neurons in the parietal cortex. Science (80-.). 324, 759-764 Fetsch, C.R. et al. (2014) Effects of Cortical Microstimulation on Confidence in a Perceptual Decision. Neuron 83, 797-804 Murphy, P.R. et al. (2015) Neural evidence accumulation persists after choice to inform metacognitive judgments. Elife 4, Grimaldi, P. et al. There are things that we know that we know, and there are things that we do not know we do not know: Confidence in decision-making., Neuroscience and Biobehavioral Reviews, 55. (2015), 88–97 Lau, H.C. and Passingham, R.E. (2006) Relative blindsight in normal observers and the neural correlate of visual consciousness. Proc. Natl. Acad. Sci. U. S. A. 103, 18763-18768 Helbig, H.B. et al. (2012) The neural mechanisms of reliability weighted integration of shape information from vision and touch. Neuroimage 60, 1063-1072 Fetsch, C.R. et al. (2012) Neural correlates of reliability-based cue weighting during multisensory integration. Nat. Neurosci. 15, 146-54 Bertelson, P. and Radeau, M. (1981) Cross-modal bias and perceptual fusion with auditory-visual spatial discordance. Percept. Psychophys. 29, 578-584 Wallace, M.T. et al. (2004) Unifying multisensory signals across time and space. Exp. Brain Res. 158, 252–258 Rohe, T. and Noppeney, U. (2015) Sensory reliability shapes perceptual inference via two mechanisms. J. Vis. 15, 22 Roach, N.W. et al. (2006) Resolving multisensory conflict: a strategy for balancing the costs and benefits of audio-visual integration. Proc. R. Soc. B Biol. Sci. 273, 2159-2168 Knill, D.C. (2003) Mixture models and the probabilistic structure of depth cues. Vision Res.

- 43, 831–854
- 55 Spence, C. and Deroy, O. How automatic are crossmodal correspondences?, *Consciousness and Cognition*, 22. (2013), 245–260
- 665 56 Bonath, B. *et al.* (2014) Audio-visual synchrony modulates the ventriloquist illusion and its
 666 neural/spatial representation in the auditory cortex. *Neuroimage* 98, 425–434
- 57 Lee, H. and Noppeney, U. Temporal prediction errors in visual and auditory cortices. ,
 668 *Current Biology*, 24. (2014) , Cell Press
- Rohe, T. and Noppeney, U. (2016) Distinct computational principles govern multisensory
 integration in primary sensory and association cortices. *Curr. Biol.* 26, 509–514
- 59 Spence, C. (2013) Just how important is spatial coincidence to multisensory integration?
 672 Evaluating the spatial rule. *Ann. N. Y. Acad. Sci.* 1296, 31–49
- 673 60 Vatakis, A. and Spence, C. (2010) Audiovisual temporal integration for complex speech,
 674 object-action, animal call, and musical stimuli. In *Multisensory Object Perception in the*675 *Primate Brain* pp. 95–121
- 676 61 Parise, C. V. *et al.* (2012) When correlation implies causation in multisensory integration.
 677 *Curr. Biol.* 22, 46–49
- 678 62 Lee, H. and Noppeney, U. (2011) Long-term music training tunes how the brain temporally
 679 binds signals from multiple senses. *Proc. Natl. Acad. Sci. U. S. A.* 108, E1441–50
- 680 63 Hein, G. *et al.* (2007) Object familiarity and semantic congruency modulate responses in
 681 cortical audiovisual integration areas. *J. Neurosci.* 27, 7881–7
- 64 Laurienti, P.J. *et al.* (2004) Semantic congruence is a critical factor in multisensory
 behavioral performance. *Exp. Brain Res.* 158, 405–414
- 684 65 Adam, R. and Noppeney, U. (2010) Prior auditory information shapes visual category685 selectivity in ventral occipito-temporal cortex. *Neuroimage* 52, 1592–1602
- 686 66 Wozny, D.R. *et al.* (2010) Probability matching as a computational strategy used in
 687 perception. *PLoS Comput. Biol.* 6,
- 688 67 Chandrasekaran, C. et al. (2009) The natural statistics of audiovisual speech. PLoS Comput.

689		Biol. 5,
690 691	68	Spence, C. and Squire, S. Multisensory integration: Maintaining the perception of synchrony, <i>Current Biology</i> , 13. (2003)
692	69	Fujisaki, W. et al. (2004) Recalibration of audiovisual simultaneity. Nat. Neurosci. 7, 773-8
693 694	70	Gau, R. and Noppeney, U. (2016) How prior expectations shape multisensory perception. <i>Neuroimage</i> 124, 876–886
695 696	71	Nahorna, O. <i>et al.</i> (2012) Binding and unbinding the auditory and visual streams in the McGurk effect. <i>J. Acoust. Soc. Am.</i> 132, 1061–1077
697 698	72	Haggard, P. Conscious intention and motor cognition. , <i>Trends in Cognitive Sciences</i> , 9. (2005), 290–295
699 700	73	Wolpe, N. <i>et al.</i> (2013) Cue integration and the perception of action in intentional binding. <i>Exp. Brain Res.</i> 229, 467–474
701	74	Keane, B. et al. (2015) Metacognition of time perception. J. Vis. 15, 814
702 703	75	White, T.P. <i>et al.</i> (2014) Eluding the illusion? Schizophrenia, dopamine and the McGurk effect. <i>Front. Hum. Neurosci.</i> 8, 565
704 705	76	Abadi, R. V. and Murphy, J.S. (2014) Phenomenology of the sound-induced flash illusion. <i>Exp. Brain Res.</i> 232, 2207–2220
706 707	77	Hillis, J.M. <i>et al.</i> (2002) Combining sensory information: mandatory fusion within, but not between, senses. <i>Science</i> 298, 1627–1630
708 709	78	Hospedales, T. and Vijayakumar, S. (2009) Multisensory oddity detection as bayesian inference. <i>PLoS One</i> 4,
710	79	McGurk, H. and Macdonald, J. (1976) Hearing lips and seeing voices. Nature 264, 691-811
711 712	80	van Wassenhove, V. <i>et al.</i> (2007) Temporal window of integration in auditory-visual speech perception. <i>Neuropsychologia</i> 45, 598–607
713 714	81	Soto-Faraco, S. and Alsius, A. (2009) Deconstructing the McGurk-MacDonald illusion. J. <i>Exp. Psychol. Hum. Percept. Perform.</i> 35, 580–7

715 716	82	Tenenbaum, J.B. <i>et al.</i> (2006) Theory-based Bayesian models of inductive learning and reasoning. <i>Trends Cogn. Sci.</i> 10, 309–318
717 718	83	Haggard, P. <i>et al.</i> (2002) Voluntary action and conscious awareness. <i>Nat. Neurosci.</i> 5, 382–385
719	84	Adams, R.A. et al. (2013) The Computational Anatomy of Psychosis. Front. Psychiatry 4,
720 721	85	Frith, C.D. <i>et al.</i> (2000) Explaining the symptoms of schizophrenia: abnormalities in the awareness of action. <i>Brain Res. Brain Res. Rev.</i> 31, 357–63
722	86	Haggard, P. et al. (2003) Awareness of action in schizophrenia. Neuroreport 14, 1081-5
723 724	87	Voss, M. <i>et al.</i> (2010) Altered awareness of action in schizophrenia: A specific deficit in predicting action consequences. <i>Brain</i> 133, 3104–3112
725 726	88	Tenenbaum, J.B. <i>et al.</i> (2011) How to grow a mind: statistics, structure, and abstraction. <i>Science</i> 331, 1279–1285
727 728	89	Williamson, J. (2005) Bayesian Nets and Causality: Philosophical and Computational Foundations, Oxford University Press.
729 730	90	Spirtes, P., Glymour, C., & Scheines, R. (2000) <i>Causation, Prediction, and Search</i> , 2nd editio.MIT Press.
731	91	Griffiths, T.L. et al. (2007) Topics in semantic representation. Psychol. Rev. 114, 211-244
732	92	Bradley, R. et al. (2014) Aggregating Causal Judgments. Philos. Sci. 81, 491–515
733 734	93	Hume, D. and Beauchamp, T.L. (1998) An enquiry concerning the principles of morals : a critical edition,
735 736	94	Sperber, D. et al. Causal cognition: A multidisciplinary debate. , Symposia of the Fyssen Foundation. (1995) , xx, 670
737 738	95	Matthen, M., ed. (2015) Oxford Handbook of Philosophy of Perception, Oxford University Press.
739	96	Dennett, D.C. (1969) Content and Consciousness, Routledge.
740	97	Drayson, Z. (2014) The Personal/Subpersonal Distinction. Philos. Compass 9, 338–346

741	98	Block, N. Perceptual consciousness overflows cognitive access., Trends in Cognitive
742		Sciences, 15. (2011), 567–575
743	99	Bayne, T. et al. (2016), Are There Levels of Consciousness?, Trends in Cognitive Sciences
744	100	Blakemore, S.J. et al. (1998) Central cancellation of self-produced tickle sensation. Nat.
745		Neurosci. 1, 635–640



GENERATIVE MODEL

INFERENCE MODEL

METACOGNITION







