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## Bimodal Inference in Humans and Mice

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## <sup>1</sup> 2 Abstract

<sup>2</sup> Perception is known to cycle through periods of enhanced and reduced sensitivity to external  
<sup>3</sup> information. Here, we asked whether such slow fluctuations arise as a noise-related epiphe-  
<sup>4</sup> nomenon of limited processing capacity or, alternatively, represent a structured mechanism  
<sup>5</sup> of perceptual inference. Using two large-scale datasets, we found that humans and mice  
<sup>6</sup> alternate between externally- and internally-oriented modes of sensory analysis. During  
<sup>7</sup> external mode, perception aligns more closely with the external sensory information, whereas  
<sup>8</sup> internal mode is characterized by enhanced biases toward perceptual history. Computational  
<sup>9</sup> modeling indicated that dynamic changes in mode are enabled by two interlinked factors:  
<sup>10</sup> (i), the integration of subsequent inputs over time and, (ii), slow anti-phase oscillations in  
<sup>11</sup> the perceptual impact of external sensory information versus internal predictions that are  
<sup>12</sup> provided by perceptual history. **We propose that between-mode fluctuations generate**  
<sup>13</sup> **unambiguous error signals that enable optimal inference in volatile environments.**

## <sup>14</sup> 3 One sentence summary

<sup>15</sup> Humans and mice fluctuate between external and internal modes of sensory processing.

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<sup>18</sup> **4 Introduction**

<sup>19</sup> The capacity to respond to changes in the environment is a defining feature of life<sup>1–3</sup>.  
<sup>20</sup> Intriguingly, the ability of living things to process their surroundings fluctuates considerably  
<sup>21</sup> over time<sup>4,5</sup>. In humans and mice, perception<sup>6–12</sup>, cognition<sup>13</sup> and memory<sup>14</sup> cycle through  
<sup>22</sup> prolonged periods of enhanced and reduced sensitivity to external information, suggesting  
<sup>23</sup> that the brain detaches from the world in recurring intervals that last from milliseconds to  
<sup>24</sup> seconds and even minutes<sup>4</sup>. Yet breaking from external information is risky, as swift responses  
<sup>25</sup> to the environment are often crucial to survival.

<sup>26</sup> What could be the reason for these fluctuations in perceptual performance<sup>11</sup>? First, periodic  
<sup>27</sup> fluctuations in the ability to parse external information<sup>11,15,16</sup> may arise simply due to  
<sup>28</sup> bandwidth limitations and noise. Second, it may be advantageous to actively reduce the costs  
<sup>29</sup> of neural processing by seeking sensory information only in recurring intervals<sup>17</sup>, otherwise  
<sup>30</sup> relying on random or stereotypical responses to the external world. Third, spending time away  
<sup>31</sup> from the ongoing stream of sensory inputs may also reflect a functional strategy that facilitates  
<sup>32</sup> flexible behavior and learning<sup>18</sup>: Intermittently relying more strongly on information acquired  
<sup>33</sup> from past experiences may enable agents to build up stable internal predictions about the  
<sup>34</sup> environment despite an ongoing stream of external sensory signals<sup>19</sup>. By the same token,  
<sup>35</sup> recurring intervals of enhanced sensitivity to external information may help to detect changes  
<sup>36</sup> in both the state of the environment and the amount of noise that is inherent in sensory  
<sup>37</sup> encoding<sup>19</sup>.

<sup>38</sup> In this work, we sought to elucidate whether periodicities in the sensitivity to external  
<sup>39</sup> information represent an epiphenomenon of limited processing capacity or, alternatively,  
<sup>40</sup> result from a structured and adaptive mechanism of perceptual inference. To this end, we  
<sup>41</sup> analyzed two large-scale datasets on perceptual decision-making in humans<sup>20</sup> and mice<sup>21</sup>.  
<sup>42</sup> **When less sensitive to external stimulus information, humans and mice did**  
<sup>43</sup> **not behave more randomly, but showed stronger serial dependencies in their**

<sup>44</sup> perceptual choices<sup>22–33</sup>. These serial dependencies may be understood as driven by internal  
<sup>45</sup> predictions that reflect the autocorrelation of natural environments<sup>34</sup> and bias perception  
<sup>46</sup> toward preceding experiences<sup>30,31,35</sup>. Computational modeling indicated that ongoing changes  
<sup>47</sup> in perceptual performance may be driven by systematic fluctuations between externally- and  
<sup>48</sup> internally-oriented *modes* of sensory analysis. We suggest that such *bimodal inference*  
<sup>49</sup> may help to build stable internal representations of the sensory environment  
<sup>50</sup> despite an ongoing stream of sensory information.

## <sup>51</sup> 5 Results

### <sup>52</sup> 5.1 Human perception fluctuates between epochs of enhanced and <sup>53</sup> reduced sensitivity to external information

<sup>54</sup> We began by selecting 66 studies from the Confidence Database<sup>20</sup> that investigated how  
<sup>55</sup> human participants ( $N = 4317$ ) perform binary perceptual decisions (Figure 1A; see Methods  
<sup>56</sup> for details on inclusion criteria). As a metric for perceptual performance (i.e., the sensitivity  
<sup>57</sup> to external sensory information), we asked whether the participant’s response and the  
<sup>58</sup> presented stimulus matched (*stimulus-congruent* choices) or differed from each other (*stimulus-*  
<sup>59</sup> *incongruent* choices; Figure 1B and C) in a total of 21.05 million trials.

<sup>60</sup> In a first step, we asked whether the ability to accurately perceive sensory stimuli is constant  
<sup>61</sup> over time or, alternatively, fluctuates in periods of enhanced and reduced sensitivity to  
<sup>62</sup> external information. We found perception to be stimulus-congruent in  $73.46\% \pm 0.15\%$   
<sup>63</sup> of trials (mean  $\pm$  standard error of the mean; Figure 2A), which was highly consistent  
<sup>64</sup> across the selected studies (Supplemental Figure S1A). In line with previous work<sup>8</sup>, we  
<sup>65</sup> found that the probability of stimulus-congruence was not independent across  
<sup>66</sup> successive trials: At the group level, stimulus-congruent perceptual choices were  
<sup>67</sup> significantly autocorrelated for up to 15 trials (Figure 2B), controlling for task

68 difficulty and the sequence of presented stimuli (Supplemental Figure 2A-B).

69 At the level of individual participants, the autocorrelation of stimulus-congruence exceeded the  
70 respective autocorrelation of randomly permuted data within an interval of  $3.24 \pm 2.39 \times 10^{-3}$   
71 trials (Figure 2C). In other words, if a participant's experience was congruent (or incongruent)  
72 with the external stimulus information at a given trial, her perception was more likely to  
73 remain stimulus-congruent (or -incongruent) for approximately 3 trials into the future. **The**  
74 **autocorrelation of stimulus-congruence was corroborated by logistic regression**  
75 **models that successfully predicted the stimulus-congruence of perception at the**  
76 **index trial  $t = 0$  from the stimulus-congruence at the preceding trials within a**  
77 **lag of 16 trials (Supplemental Figure S3).**

78 These results confirm that the ability to process sensory signals is not constant over time but  
79 unfolds in multi-trial epochs of enhanced and reduced sensitivity to external information<sup>8</sup>.  
80 As a consequence of this autocorrelation, the dynamic probability of stimulus-congruent  
81 perception (i.e., computed in sliding windows of  $\pm 5$  trials; Figure 1C) fluctuated considerably  
82 within participants (average minimum:  $35.46\% \pm 0.22\%$ , maximum:  $98.27\% \pm 0.07\%$ ). In  
83 line with previous findings<sup>9</sup>, such fluctuations in the sensitivity to external information had a  
84 power density that was inversely proportional to the frequency in the slow spectrum<sup>11</sup> (power  
85  $\sim 1/f^\beta$ ,  $\beta = -1.32 \pm 3.14 \times 10^{-3}$ ,  $T(1.84 \times 10^5) = -419.48$ ,  $p < 2.2 \times 10^{-308}$ ; Figure 2D).  
86 This feature, which is also known as a  **$1/f$  power law**<sup>36,37</sup>, represents a characteristic of  
87 scale-free fluctuations in complex dynamic systems such as the brain<sup>38</sup> and the cognitive  
88 processes it entertains<sup>9,10,13,39,40</sup>.

89 **5.2 Humans fluctuate between external and internal modes of**  
90 **sensory processing**

91 In a second step, we sought to explain why perception cycles through periods of enhanced and  
92 reduced sensitivity to external information<sup>4</sup>. We reasoned that observers may intermittently

93 rely more strongly on internal information, i.e., on predictions about the environment that  
94 are constructed from previous experiences<sup>19,31</sup>.

95 In perception, *serial dependencies* represent one of the most basic internal predictions that  
96 cause perceptual decisions to be systematically biased toward preceding choices<sup>22–33</sup>. Such  
97 effects of perceptual history mirror the continuity of the external world, in which the recent  
98 past often predicts the near future<sup>30,31,34,35,41</sup>. Therefore, as a metric for the perceptual  
99 impact of internal information, we computed whether the participant’s response at a given  
100 trial matched or differed from her response at the preceding trial (*history-congruent* and  
101 *history-incongruent perception*, respectively; Figure 1B and C).

102 First, we confirmed that perceptual history played a significant role in perception despite the  
103 ongoing stream of external information. With a global average of  $52.7\% \pm 0.12\%$  history-  
104 congruent trials, we found a small but highly significant perceptual bias towards preceding  
105 experiences ( $\beta = 16.18 \pm 1.07$ ,  $T(1.09 \times 10^3) = 15.07$ ,  $p = 10^{-46}$ ; Figure 2A) that was largely  
106 consistent across studies (Supplemental Figure 1B) and more pronounced in participants who  
107 were less sensitive to external sensory information (Supplemental Figure 1C). Importantly,  
108 history-congruence was not a corollary of the sequence of presented stimuli: History-congruent  
109 perceptual choices were more frequent at trials when perception was stimulus-incongruent  
110 ( $56.03\% \pm 0.2\%$ ) as opposed to stimulus-congruent ( $51.77\% \pm 0.11\%$ ,  $\beta = -4.26 \pm 0.21$ ,  
111  $T(8.57 \times 10^3) = -20.36$ ,  $p = 5.28 \times 10^{-90}$ ; Figure 2A, lower panel). Despite being adaptive  
112 in autocorrelated real-world environments<sup>19,34,35,42</sup>, perceptual history thus represented a  
113 **source of bias** in the randomized experimental designs studied here<sup>24,28,30,31,43</sup>. **These**  
114 **serial biases were effects of choice history, i.e., driven by the experiences reported**  
115 **at the preceding trial, and could not be attributed to stimulus history, i.e., to**  
116 **effects of the stimuli presented at the preceding trial (Supplemental Section 9.1)**.

117 Second, we asked whether perception cycles through multi-trial epochs during which perception  
118 is characterized by stronger or weaker biases toward preceding experiences. **In close**

<sup>119</sup> analogy to stimulus-congruence, we found history-congruence to be significantly  
<sup>120</sup> autocorrelated for up to 21 trials (Figure 2B), while controlling for task difficulty  
<sup>121</sup> and the sequence of presented stimuli (Supplemental Figure 2A-B). In individual  
<sup>122</sup> participants, the autocorrelation of history-congruence was elevated above randomly permuted  
<sup>123</sup> data for a lag of  $4.87 \pm 3.36 \times 10^{-3}$  trials (Figure 2C), confirming that the autocorrelation of  
<sup>124</sup> history-congruence was not only a group-level phenomenon. The autocorrelation of history-  
<sup>125</sup> congruence was corroborated by logistic regression models that successfully predicted the  
<sup>126</sup> history-congruence of perception at an index trial  $t = 0$  from the history-congruence at the  
<sup>127</sup> preceding trials within a lag of 17 trials (Supplemental Figure S3).

<sup>128</sup> Third, we asked whether the impact of internal information fluctuates as **a scale-invariant**  
<sup>129</sup> **process with a 1/f power law** (i.e., the feature typically associated with fluctuations  
<sup>130</sup> in the sensitivity to external information<sup>9,10,13,39,40</sup>). The dynamic probability of history-  
<sup>131</sup> congruent perception (i.e., computed in sliding windows of  $\pm 5$  trials; Figure 1C) varied  
<sup>132</sup> considerably over time, ranging between a minimum of  $12.77\% \pm 0.14\%$  and a maximum  
<sup>133</sup>  $92.23\% \pm 0.14\%$ . In analogy to stimulus-congruence, we found that history-congruence  
<sup>134</sup> fluctuated as at power densities that were inversely proportional to the frequency in the  
<sup>135</sup> slow spectrum<sup>11</sup> (power  $\sim 1/f^\beta$ ,  $\beta = -1.34 \pm 3.16 \times 10^{-3}$ ,  $T(1.84 \times 10^5) = -423.91$ ,  $p <$   
<sup>136</sup>  $2.2 \times 10^{-308}$ ; Figure 2D).

<sup>137</sup> Finally, we ensured that fluctuations in stimulus- and history-congruence are linked to each  
<sup>138</sup> other. When perceptual choices were less biased toward external information, participants  
<sup>139</sup> relied more strongly on internal information acquired from perceptual history (and vice  
<sup>140</sup> versa,  $\beta = -0.05 \pm 5.63 \times 10^{-4}$ ,  $T(2.1 \times 10^6) = -84.21$ ,  $p < 2.2 \times 10^{-308}$ , **controlling for**  
<sup>141</sup> **fluctuations in general response biases**; Supplemental Section 9.2). Thus, while sharing  
<sup>142</sup> the **1/f power law** characteristic, fluctuations in stimulus- and history-congruence were  
<sup>143</sup> shifted against each other by approximately half a cycle and showed a squared coherence  
<sup>144</sup> of  $6.49 \pm 2.07 \times 10^{-3}\%$  (Figure 2E and F; we report the average phase and coherence for

<sup>145</sup> frequencies below  $0.1 \text{ } 1/N_{trials}$ ; see Methods for details).

<sup>146</sup> In sum, our analyses indicate that perceptual decisions may result from a competition between  
<sup>147</sup> external sensory signals with internal predictions provided by perceptual history. We show  
<sup>148</sup> that the impact of these external and internal sources of information is not stable over time,  
<sup>149</sup> but fluctuates systematically, emitting overlapping autocorrelation curves and antiphase  $1/f$   
<sup>150</sup> profiles.

<sup>151</sup> These links between stimulus- and history-congruence suggest that the fluctuations in the  
<sup>152</sup> impact of external and internal information may be generated by a unifying mechanism that  
<sup>153</sup> causes perception to alternate between two opposing *modes*<sup>18</sup> (Figure 1D): During *external*  
<sup>154</sup> *mode*, perception is more strongly driven by the available external stimulus information.  
<sup>155</sup> Conversely, during *internal mode*, participants rely more heavily on internal predictions  
<sup>156</sup> that are implicitly provided by preceding perceptual experiences. The fluctuations in the  
<sup>157</sup> degree of bias toward external versus internal information created by such *bimodal inference*  
<sup>158</sup> may thus provide a novel explanation for ongoing fluctuations in the sensitivity to external  
<sup>159</sup> information<sup>4,5,18</sup>.

### <sup>160</sup> **5.3 Internal and external modes of processing facilitate response 161 behavior and enhance confidence in human perceptual decision- 162 making**

<sup>163</sup> The above results point to systematic fluctuations in the *decision variable*<sup>44</sup>  
<sup>164</sup> that determines perceptual choices, causing enhanced sensitivity to external  
<sup>165</sup> stimulus information during external mode and increased biases toward preceding  
<sup>166</sup> choices during internal mode. As such, fluctuations in mode should influence  
<sup>167</sup> downstream aspects of behavior and cognition that operate on the perceptual  
<sup>168</sup> decision variable<sup>44</sup>. To test this hypothesis with respect to motor behavior and  
<sup>169</sup> metacognition, we asked how bimodal inference relates to response times (RTs)

<sup>170</sup> and confidence reports.

<sup>171</sup> With respect to RTs, we observed faster responses for stimulus-congruent as opposed to  
<sup>172</sup> stimulus-incongruent choices ( $\beta = -0.14 \pm 1.6 \times 10^{-3}$ ,  $T(1.99 \times 10^6) = -85.84$ ,  $p < 2.2 \times 10^{-308}$ ;  
<sup>173</sup> Figure 2G). Intriguingly, whilst controlling for the effect of stimulus-congruence, we found  
<sup>174</sup> that history-congruent (as opposed to history-incongruent) choices were also characterized by  
<sup>175</sup> faster responses ( $\beta = -9.56 \times 10^{-3} \pm 1.37 \times 10^{-3}$ ,  $T(1.98 \times 10^6) = -6.97$ ,  $p = 3.15 \times 10^{-12}$ ;  
<sup>176</sup> Figure 2G).

<sup>177</sup> When analyzing the speed of response against the mode of sensory processing (Figure 2H),  
<sup>178</sup> we found that RTs were shorter during externally-oriented perception ( $\beta_1 = -11.07 \pm 0.55$ ,  
<sup>179</sup>  $T(1.98 \times 10^6) = -20.14$ ,  $p = 3.17 \times 10^{-90}$ ). Crucially, as indicated by a quadratic relationship  
<sup>180</sup> between the mode of sensory processing and RTs ( $\beta_2 = -19.86 \pm 0.52$ ,  $T(1.98 \times 10^6) =$   
<sup>181</sup>  $-38.43$ ,  $p = 5 \times 10^{-323}$ ), participants became faster at indicating their perceptual decision  
<sup>182</sup> when biases toward both internal and external mode grew stronger.

<sup>183</sup> In analogy to the speed of response, confidence was higher for stimulus-congruent as opposed  
<sup>184</sup> to stimulus-incongruent choices ( $\beta = 0.04 \pm 1.18 \times 10^{-3}$ ,  $T(2.06 \times 10^6) = 36.85$ ,  $p =$   
<sup>185</sup>  $3.25 \times 10^{-297}$ ; Figure 2I). Yet whilst controlling for the effect of stimulus-congruence, we found  
<sup>186</sup> that history-congruence also increased confidence ( $\beta = 0.48 \pm 1.38 \times 10^{-3}$ ,  $T(2.06 \times 10^6) =$   
<sup>187</sup>  $351.54$ ,  $p < 2.2 \times 10^{-308}$ ; Figure 2I).

<sup>188</sup> When depicted against the mode of sensory processing (Figure 2J), subjective confidence was  
<sup>189</sup> indeed enhanced when perception was more externally-oriented ( $\beta_1 = 92.63 \pm 1$ ,  $T(2.06 \times 10^6)$   
<sup>190</sup>  $= 92.89$ ,  $p < 2.2 \times 10^{-308}$ ). Importantly, however, participants were more confident in their  
<sup>191</sup> perceptual decision for stronger biases toward both internal and external mode ( $\beta_2 = 39.3 \pm$   
<sup>192</sup>  $0.94$ ,  $T(2.06 \times 10^6) = 41.95$ ,  $p < 2.2 \times 10^{-308}$ ). In analogy to RTs, subjective confidence thus  
<sup>193</sup> showed a quadratic relationship to the mode of sensory processing (Figure 2J).

<sup>194</sup> Consequently, our findings predict that human participants lack full metacognitive insight  
<sup>195</sup> into how strongly external signals and internal predictions contribute to perceptual decision-

<sup>196</sup> making. Stronger biases toward perceptual history thus lead to two seemingly contradictory  
<sup>197</sup> effects, more frequent errors (Supplemental Figure 1C) and increasing subjective confidence  
<sup>198</sup> (Figure 2I-J). This observation generates an intriguing prediction regarding the association of  
<sup>199</sup> between-mode fluctuations and perceptual metacognition: Metacognitive efficiency should be  
<sup>200</sup> lower in individuals who spend more time in internal mode, since their confidence reports are  
<sup>201</sup> less predictive of whether the corresponding perceptual decision is correct. We computed each  
<sup>202</sup> participant's M-ratio<sup>45</sup> ( $\text{meta-d}'/\text{d}' = 0.85 \pm 0.02$ ) to probe this hypothesis independently  
<sup>203</sup> of inter-individual differences in perceptual performance. Indeed, we found that biases  
<sup>204</sup> toward internal information (as defined by the average probability of history-congruence) were  
<sup>205</sup> stronger in participants with lower metacognitive efficiency ( $\beta = -2.98 \times 10^{-3} \pm 9.82 \times 10^{-4}$ ,  
<sup>206</sup>  $T(4.14 \times 10^3) = -3.03$ ,  $p = 2.43 \times 10^{-3}$ ).

<sup>207</sup> In sum, the above results indicate that reporting behavior and metacognition do not map  
<sup>208</sup> linearly onto the mode of sensory processing. Rather, they suggest that slow fluctuations in the  
<sup>209</sup> respective impact of external and internal information are most likely to affect perception at  
<sup>210</sup> an early level of sensory analysis<sup>46,47</sup>. Such low-level processing may thus integrate perceptual  
<sup>211</sup> history with external inputs into a decision variable<sup>44</sup> that influences not only perceptual  
<sup>212</sup> choices, but also the speed and confidence at which they are made.

<sup>213</sup> **In what follows, we probe alternative explanations for between-mode fluctuations,**  
<sup>214</sup> **test for the existence of modes in mice, and propose a predictive processing model**  
<sup>215</sup> **that explains fluctuations in mode ongoing shifts in the precision afforded to**  
<sup>216</sup> **external sensory information relative to internal predictions driven by perceptual**  
<sup>217</sup> **history.**

218 5.4 Fluctuations between internal and external mode cannot be  
219 reduced to general response biases or random choices

220 The core assumption of bimodal inference - that ongoing changes in the sensitivity  
221 to external information are driven by internal predictions induced via perceptual  
222 history - needs to be contrasted against two alternative hypotheses: When making  
223 errors, observers may not engage with the task and respond stereotypically, i.e.,  
224 exhibit stronger general biases toward one of the two potential outcomes, or  
225 simply choose randomly.

226 Logistic regression confirmed that perceptual history made a significant contrib-  
227 ution to perception ( $\beta = 0.11 \pm 5.79 \times 10^{-3}$ ,  $z = 18.53$ ,  $p = 1.1 \times 10^{-76}$ ) over and  
228 above the ongoing stream of external sensory information ( $\beta = 2.2 \pm 5.87 \times 10^{-3}$ ,  
229  $z = 375.11$ ,  $p < 2.2 \times 10^{-308}$ ) and general response biases toward ( $\beta = 15.19 \pm 0.08$ ,  
230  $z = 184.98$ ,  $p < 2.2 \times 10^{-308}$ ).

231 When eliminating perceptual history as a predictor of individual choices at  
232 individual trials, Akaike Information Criterion (AIC<sup>48</sup>) increased by  $\delta_{AIC} =$   
233  $1.64 \times 10^3$  (see Supplemental Figure S4A-B for parameter- and model-level inference  
234 at the level of individual observers). Likewise, when eliminating slow fluctuations  
235 in history-congruence as a predictor of slow fluctuations in stimulus-congruence  
236 across trials, we observed an increase in AIC by  $\delta_{AIC} = 7.06 \times 10^3$ . These results  
237 provided model-level evidence against the null hypotheses that fluctuations in  
238 stimulus-congruence are driven exclusively by choice randomness or general  
239 response bias (see Supplemental Section 9.2 and Supplemental Figure S5 for an  
240 in-depth assessment of general response bias).

241 To confirm that changes in the sensitivity to external information are indicative of  
242 internal mode processing, we estimated full and history-dependent psychometric  
243 curves during internal, external, and across modes<sup>21</sup>. If, as we hypothesized,

<sup>244</sup> internal mode processing reflects an enhanced impact of perceptual history,  
<sup>245</sup> one would expect a history-dependent increase in biases and lapses as well as a  
<sup>246</sup> history-independent increase in threshold. Conversely, if internal mode processing  
<sup>247</sup> were driven by random choices, one would expect a history-independent increase  
<sup>248</sup> in lapses and threshold, and no change in bias. In line with our prediction, we  
<sup>249</sup> found that internal mode processing was associated with a history-dependent  
<sup>250</sup> increase in bias and lapse as well as a history-independent increase in threshold  
<sup>251</sup> (Supplemental Section 9.3.1 and Supplemental Figure S6). This confirmed that  
<sup>252</sup> internal mode processing is indeed driven by an enhanced impact of perceptual  
<sup>253</sup> history.

<sup>254</sup> In line with this, the quadratic relationship between mode and confidence (Figure  
<sup>255</sup> 2J) suggested that biases toward internal information do not reflect a post-  
<sup>256</sup> perceptual strategy of repeating preceding choices when the subjective confidence  
<sup>257</sup> in the perceptual decision is low. Moreover, while responses became faster with  
<sup>258</sup> increased exposure to the experiments of the Confidence database, the frequency  
<sup>259</sup> of history-congruent choices increased over time, speaking against the proposition  
<sup>260</sup> that participants stereotypically repeat preceding choices when not yet familiar  
<sup>261</sup> with the experimental task (Supplemental Section 9.4.1).

<sup>262</sup> Taken together, our results thus argue against recurring intervals of low task  
<sup>263</sup> engagement, which may be signaled by stereotypical or random responses, as an  
<sup>264</sup> alternative explanation for the phenomenon that we identify as bimodal inference.

## <sup>265</sup> 5.5 Mice fluctuate between external and internal modes of sensory <sup>266</sup> processing

<sup>267</sup> In a prominent functional explanation for serial dependencies<sup>22–28,32,33,46</sup>, perceptual history  
<sup>268</sup> is cast as an internal prediction that leverages the temporal autocorrelation of natural

<sup>269</sup> environments for efficient decision-making<sup>30,31,34,35,41</sup>. Since this autocorrelation is one of  
<sup>270</sup> the most basic features of our sensory world, fluctuating biases toward preceding perceptual  
<sup>271</sup> choices should not be a uniquely human phenomenon.

<sup>272</sup> To test whether externally- and internally-oriented modes of processing exist beyond the  
<sup>273</sup> human mind, we analyzed data on perceptual decision-making in mice that were extracted  
<sup>274</sup> from the International Brain Laboratory (IBL) dataset<sup>21</sup>. We restricted our analyses to the  
<sup>275</sup> *basic task*<sup>21</sup>, in which mice responded to gratings of varying contrast that appeared either  
<sup>276</sup> in the left or right hemifield with equal probability. We excluded sessions in which mice  
<sup>277</sup> did not respond correctly to stimuli presented at a contrast above 50% in more than 80% of  
<sup>278</sup> trials (see Methods for details), which yielded a final sample of  $N = 165$  adequately trained  
<sup>279</sup> mice that went through 1.46 million trials.

<sup>280</sup> We found perception to be stimulus-congruent in  $81.37\% \pm 0.3\%$  of trials (Figure 3A, upper  
<sup>281</sup> panel). In line with humans, mice were biased toward perceptual history in  $54.03\% \pm 0.17\%$   
<sup>282</sup> of trials ( $T(164) = 23.65$ ,  $p = 9.98 \times 10^{-55}$ ; Figure 3A and Supplemental Figure S1D). Since  
<sup>283</sup> the *basic task* of the IBL dataset presented stimuli at random in either the left or right  
<sup>284</sup> hemifield<sup>21</sup>, we expected stronger biases toward perceptual history to decrease perceptual  
<sup>285</sup> performance. Indeed, history-congruent choices were more frequent when perception was  
<sup>286</sup> stimulus-incongruent ( $61.59\% \pm 0.07\%$ ) as opposed to stimulus-congruent ( $51.81\% \pm 0.02\%$ ,  
<sup>287</sup>  $T(164) = 31.37$ ,  $p = 3.36 \times 10^{-71}$ ;  $T(164) = 31.37$ ,  $p = 3.36 \times 10^{-71}$ ; Figure 3A, lower panel),  
<sup>288</sup> confirming that perceptual history was a **source of bias**<sup>24,28,30,31,43</sup> as opposed to a feature  
<sup>289</sup> of the experimental paradigm.

<sup>290</sup> **At the group level, we found significant autocorrelations in both stimulus-**  
<sup>291</sup> **congruence (42 consecutive trials) and history-congruence (8 consecutive trials;**  
<sup>292</sup> **Figure 3B), while controlling for the respective autocorrelation of task difficulty**  
<sup>293</sup> **and external stimulation (Supplemental Figure 2C-D).** In contrast to humans, mice  
<sup>294</sup> showed a negative autocorrelation coefficient of stimulus-congruence at trial 2, which was

<sup>295</sup> due to a feature of the experimental design: Errors at a contrast above 50% were followed by  
<sup>296</sup> a high-contrast stimulus at the same location. Thus, stimulus-incongruent choices on easy  
<sup>297</sup> trials were more likely to be followed by stimulus-congruent perceptual choices that were  
<sup>298</sup> facilitated by high-contrast visual stimuli<sup>21</sup>.

<sup>299</sup> At the level of individual mice, autocorrelation coefficients were elevated above randomly  
<sup>300</sup> permuted data within a lag of  $4.59 \pm 0.06$  trials for stimulus-congruence and  $2.58 \pm 0.01$  trials  
<sup>301</sup> for history-congruence (Figure 3C). **We corroborated these autocorrelations in logistic**  
<sup>302</sup> **regression models that successfully predicted the stimulus-/history-congruence**  
<sup>303</sup> **of perception at the index trial  $t = 0$  from the stimulus-/history-congruence**  
<sup>304</sup> **at the 33 preceding trials for stimulus-congruence and 8 preceding trials for**  
<sup>305</sup> **history-congruence (Supplemental Figure S3)**. In analogy to humans, mice showed  
<sup>306</sup> anti-phase 1/f fluctuations in the sensitivity to internal and external information (Figure  
<sup>307</sup> 3D-F).

<sup>308</sup> **The above results confirm that fluctuations between internally- and externally-**  
<sup>309</sup> **biased modes generalize to perceptual decision-making in mice. Following our**  
<sup>310</sup> **hypothesis that bimodal inference operates at the level of perception, we predicted**  
<sup>311</sup> **that between-mode fluctuations modulate a decision variable<sup>44</sup> that determines**  
<sup>312</sup> **not only perceptual choices, but also downstream aspects of mouse behavior<sup>44</sup>.**

<sup>313</sup> We therefore asked how external and internal modes relate to the trial duration (TD, a  
<sup>314</sup> coarse measure of RT in mice that spans the interval from stimulus onset to feedback<sup>21</sup>).  
<sup>315</sup> Stimulus-congruent (as opposed to stimulus-incongruent) choices were associated with shorter  
<sup>316</sup> TDs ( $\delta = -262.48 \pm 17.1$ ,  $T(164) = -15.35$ ,  $p = 1.55 \times 10^{-33}$ ), while history-congruent choices  
<sup>317</sup> were characterized by longer TDs ( $\delta = 30.47 \pm 5.57$ ,  $T(164) = 5.47$ ,  $p = 1.66 \times 10^{-7}$ ; Figure  
<sup>318</sup> 3G).

<sup>319</sup> Across the full spectrum of the available data, TDs showed a linear relationship with the  
<sup>320</sup> mode of sensory processing, with shorter TDs during external mode ( $\beta_1 = -4.16 \times 10^4 \pm$

<sup>321</sup>  $1.29 \times 10^3$ ,  $T(1.35 \times 10^6) = -32.31$ ,  $p = 6.03 \times 10^{-229}$ , Figure 3H). However, an explorative  
<sup>322</sup> post-hoc analysis limited to TDs that differed from the median TD by no more than  $1.5 \times$   
<sup>323</sup> MAD (median absolute distance<sup>49</sup>) indicated that, when mice engaged with the task more  
<sup>324</sup> swiftly, TDs did indeed show a quadratic relationship with the mode of sensory processing  
<sup>325</sup> ( $\beta_2 = -1.97 \times 10^3 \pm 843.74$ ,  $T(1.19 \times 10^6) = -2.34$ ,  $p = 0.02$ , Figure 3I).

<sup>326</sup> As in humans, it is important to ensure that ongoing changes in the sensitivity to external  
<sup>327</sup> information are indeed driven by perceptual history and cannot be reduced to general choice  
<sup>328</sup> biases or random behavior. Logistic regression confirmed a significant effect perceptual  
<sup>329</sup> history on perceptual choices ( $\beta = 0.51 \pm 4.49 \times 10^{-3}$ ,  $z = 112.84$ ,  $p < 2.2 \times 10^{-308}$ ),  
<sup>330</sup> while controlling for external sensory information ( $\beta = 2.96 \pm 4.58 \times 10^{-3}$ ,  $z = 646.1$ ,  $p <$   
<sup>331</sup>  $2.2 \times 10^{-308}$ ) and general response biases toward one of the two outcomes ( $\beta = -1.78 \pm 0.02$ ,  
<sup>332</sup>  $z = -80.64$ ,  $p < 2.2 \times 10^{-308}$ ). **When eliminating perceptual history as a predictor of**  
<sup>333</sup> **individual choices, AIC increased by  $\delta_{AIC} = 1.48 \times 10^4$ , arguing against the notion**  
<sup>334</sup> **that choice randomness and general response bias are the only determinants of**  
<sup>335</sup> **perceptual performance in mice (see Supplemental Figure S4C-D for parameter-**  
<sup>336</sup> **and model-level inference in individual subjects).**

<sup>337</sup> **In mice, fluctuations in the strength of history-congruent biases had a significant**  
<sup>338</sup> **effect on stimulus-congruence ( $\beta_1 = -0.12 \pm 7.17 \times 10^{-4}$ ,  $T(1.34 \times 10^6) = -168.39$ ,  $p$**   
<sup>339</sup>  **$< 2.2 \times 10^{-308}$ ) beyond the effect of ongoing changes in general response biases**  
<sup>340</sup> **( $\beta_2 = -0.03 \pm 6.94 \times 10^{-4}$ ,  $T(1.34 \times 10^6) = -48.14$ ,  $p < 2.2 \times 10^{-308}$ ). Eliminating**  
<sup>341</sup> **the dynamic fluctuations in history-congruence as a predictor of fluctuations**  
<sup>342</sup> **in stimulus-congruence resulted in an increase in AIC by  $\delta_{AIC} = 2.8 \times 10^4$  (see**  
<sup>343</sup> **Supplemental Section 9.2 and Supplemental Figure S5 for an in-depth assessment**  
<sup>344</sup> **of general response bias).**

<sup>345</sup> **When fitting full and history-conditioned psychometric curves to the IBL data<sup>21</sup>,**  
<sup>346</sup> **we observed that internal mode processing was associated with a history-**

347 dependent increase in bias and lapse as well as a history-independent increase  
348 in threshold (Supplemental Section 9.3.2 and Supplemental Figure S7). Over  
349 time, the frequency of history-congruent choices increased alongside stimulus-  
350 congruence and speed of response as mice were exposed to the experiment,  
351 arguing against the proposition that biases toward perceptual history reflected  
352 an unspecific response strategy in mice who were not sufficiently trained on the  
353 IBL task (Supplemental Section 9.4.2 and Supplemental Figure S8).

354 In sum, these analyses confirmed that the observed fluctuations in sensitivity  
355 to external sensory information are driven by dynamic changes in impact of  
356 perceptual history and cannot be reduced to general response bias and random  
357 choice behavior.

## 358 5.6 Fluctuations in mode result from coordinated changes in the 359 impact of external and internal information on perception

360 The empirical data presented above indicate that, for both humans and mice, perception  
361 fluctuates between external and modes, i.e., multi-trial epochs that are characterized by  
362 enhanced sensitivity toward either external sensory information or internal predictions  
363 generated by perceptual history. Since natural environments typically show high temporal  
364 redundancy<sup>34</sup>, previous experiences are often good predictors of new stimuli<sup>30,31,35,41</sup>. Serial  
365 dependencies may therefore induce autocorrelations in perception by serving as internal  
366 predictions (or *memory* processes<sup>9,13</sup>) that actively integrate noisy sensory information over  
367 time<sup>50</sup>.

368 Previous work has shown that such internal predictions can be built by dynamically updating  
369 the estimated probability of being in a particular perceptual state from the sequence of  
370 preceding experiences<sup>35,46,51</sup>. The integration of sequential inputs may lead to accumulating  
371 effects of perceptual history that progressively override incoming sensory information, enabling

<sup>372</sup> internal mode processing<sup>19</sup>. However, since such a process would lead to internal biases that  
<sup>373</sup> may eventually become impossible to overcome<sup>52</sup>, **changes in mode may require** ongoing  
<sup>374</sup> wave-like fluctuations<sup>9,13</sup> in the perceptual impact of external and internal information that  
<sup>375</sup> occur *irrespective* of the sequence of previous experiences and temporarily de-couple the  
<sup>376</sup> decision variable from implicit internal representations of the environment<sup>19</sup>.

<sup>377</sup> Following Bayes' theorem, binary perceptual decisions depend on the log posterior ratio  $L$  of  
<sup>378</sup> the two alternative states of the environment that participants learn about via noisy sensory  
<sup>379</sup> information<sup>51</sup>. We computed the posterior by combining the sensory evidence available at  
<sup>380</sup> time-point  $t$  (i.e., the log likelihood ratio  $LLR$ ) with the prior probability  $\psi$ , weighted by the  
<sup>381</sup> respective precision terms  $\omega_{LLR}$  and  $\omega_\psi^{**}$ :

$$L_t = LLR_t * \omega_{LLR} + \psi_t(L_{t-1}, H) * \omega_\psi \quad (1)$$

<sup>382</sup> We derived the prior probability  $\psi$  at timepoint  $t$  from the posterior probability of perceptual  
<sup>383</sup> outcomes at timepoint  $L_{t-1}$ . Since a switch between the two states can occur at any time,  
<sup>384</sup> the effect of perceptual history varies according to both the sequence of preceding experiences  
<sup>385</sup> and the estimated stability of the external environment (i.e., the *hazard rate*  $H^{51}$ ):

$$\psi_t(L_{t-1}, H) = L_{t-1} + \log\left(\frac{1-H}{H}\right) + \exp(-L_{t-1}) - \log\left(\frac{1-H}{H}\right) - \exp(L_{t-1}) \quad (2)$$

<sup>386</sup> The  $LLR$  was computed from inputs  $s_t$  by applying a sigmoid function defined by parameter  
<sup>387</sup>  $\alpha$  that controls the sensitivity of perception to the available sensory information (see Methods  
<sup>388</sup> for details on  $s_t$  in humans and mice):

$$u_t = \frac{1}{1 + \exp(-\alpha * s_t)} \quad (3)$$

$$LLR_t = \log\left(\frac{u_t}{1-u_t}\right) \quad (4)$$

389 To allow for bimodal inference, i.e., alternating periods of internally- and  
 390 externally-biased modes of perceptual processing that occur irrespective of the  
 391 sequence of preceding experiences, we assumed that likelihood and prior vary  
 392 in their influence on the perceptual decision according to fluctuations governed  
 393 by  $\omega_{LLR}$  and  $\omega_\psi$ . These anti-phase sine functions (defined by amplitudes  $a_{LLR/\psi}$ ,  
 394 frequency  $f$  and phase  $p$ ) determine the precision afforded to the likelihood and  
 395 prior<sup>53</sup>. The implicit anti-phase fluctuations are mandated by Bayes-optimal  
 396 formulations in which inference depends only on the relative values of prior and  
 397 likelihood precision (i.e., the Kalman gain<sup>54</sup>). As such,  $\omega_{LLR}$  and  $\omega_\psi$  implement a  
 398 hyperprior<sup>55</sup> in which the likelihood and prior precisions are shifted against each  
 399 other at a dominant timescale defined by  $f$ :

$$\omega_{LLR} = a_{LLR} * \sin(f * t + p) + 1 \quad (5)$$

$$\omega_\psi = a_\psi * \sin(f * t + p + \pi) + 1 \quad (6)$$

400 Finally, a sigmoid transform of the posterior  $L_t$  yields the probability of observing the  
 401 perceptual decision  $y_t$  at a temperature determined by  $\zeta^{-1}$ :

$$P(y_t = 1) = 1 - P(y_t = 0) = \frac{1}{1 + \exp(-\zeta * L_t)} \quad (7)$$

402 We used a maximum likelihood procedure to fit the bimodal inference model  
 403 (M1, Figure 1F) to the behavioral data from the Confidence database<sup>20</sup> and the  
 404 IBL database<sup>21</sup>, optimizing the parameters  $\alpha$ ,  $H$ ,  $amp_{LLR}$ ,  $amp_\psi$ ,  $f$ ,  $p$  and  $\zeta$  (see

405 Methods for details and Supplemental Table T2 for a summary of the parameters  
406 of the bimodal inference model). We validated our model in three steps:

407 First, to show that bimodal inference does not emerge spontaneously in normative  
408 Bayesian models of evidence accumulation, but requires the ad-hoc addition of  
409 anti-phase oscillations in prior and likelihood precision, we compared the bimodal  
410 inference model to four control models (M2-5, Figure 1G). In these models, we  
411 successively removed the anti-phase oscillations (M2-M4) and the integration of  
412 information across trials (M5) from the bimodal inference model and performed  
413 a model comparison based on AIC.

414 Model M2 ( $AIC_2 = 5.7 \times 10^4$  in humans and  $4.94 \times 10^4$  in mice) and Model M3  
415 ( $AIC_3 = 6.9 \times 10^4$  in humans and  $5.99 \times 10^4$  in mice) incorporated only oscillations  
416 of either likelihood or prior precision. Model M4 ( $AIC_4 = 9.8 \times 10^4$  in humans  
417 and  $9.19 \times 10^4$  in mice) lacked any oscillations of likelihood and prior precision  
418 and corresponded to the normative model proposed by Glaze et al.<sup>51</sup>. In model  
419 M5 ( $AIC_4 = 1.16 \times 10^5$  in humans and  $1.14 \times 10^5$  in mice), we furthermore removed  
420 the integration of information across trials, such that perception depended only  
421 in incoming sensory information (Figure 1G).

422 The bimodal inference model achieved the lowest AIC across the full model space  
423 ( $AIC_1 = 4.73 \times 10^4$  in humans and  $4.28 \times 10^4$  in mice) and was clearly superior to  
424 the normative Bayesian model of evidence accumulation ( $\delta_{AIC} = -5.08 \times 10^4$  in  
425 humans and  $-4.91 \times 10^4$  in mice; Supplemental Figure S9).

426 As a second validation of the bimodal inference model, we tested whether the  
427 posterior model predicted within-training and out-of-training variables. The  
428 bimodal inference model characterizes each subject by a sensitivity parameter  
429  $\alpha$  (humans:  $\alpha = 0.5 \pm 1.12 \times 10^{-4}$ ; mice:  $\alpha = 1.06 \pm 2.88 \times 10^{-3}$ ) that captures  
430 how strongly perception is driven by the available sensory information, and a

431 hazard rate parameter  $H$  (humans:  $H = 0.45 \pm 4.8 \times 10^{-5}$ ; mice:  $H = 0.46 \pm$   
432  $2.97 \times 10^{-4}$ ) that controls how heavily perception is biased by perceptual history.  
433 The parameter  $f$  captures the dominant time scale at which likelihood (amplitude  
434 humans:  $a_{LLR} = 0.5 \pm 2.02 \times 10^{-4}$ ; mice:  $a_{LLR} = 0.39 \pm 1.08 \times 10^{-3}$ ) and prior  
435 precision (amplitude humans:  $a_\psi = 1.44 \pm 5.27 \times 10^{-4}$ ; mice:  $a_\psi = 1.71 \pm 7.15 \times 10^{-3}$ )  
436 fluctuated and was estimated at  $0.11 \pm 1.68 \times 10^{-5}$   $1/N_{trials}$  and  $0.11 \pm 1.63 \times 10^{-4}$   
437  $1/N_{trials}$  in mice.

438 As a sanity check for model fit, we tested whether the frequency of stimulus- and history-  
439 congruent trials in the Confidence database<sup>20</sup> and IBL database<sup>21</sup> correlated with the estimated  
440 parameters  $\alpha$  and  $H$ , respectively. As expected, the estimated sensitivity toward stimulus  
441 information  $\alpha$  was positively correlated with the frequency of stimulus-congruent perceptual  
442 choices (humans:  $\beta = 8.4 \pm 0.26$ ,  $T(4.31 \times 10^3) = 32.87$ ,  $p = 1.3 \times 10^{-211}$ ; mice:  $\beta = 1.93$   
443  $\pm 0.12$ ,  $T(2.07 \times 10^3) = 16.21$ ,  $p = 9.37 \times 10^{-56}$ ). Likewise,  $H$  was negatively correlated  
444 with the frequency of history-congruent perceptual choices (humans:  $\beta = -11.84 \pm 0.5$ ,  
445  $T(4.29 \times 10^3) = -23.5$ ,  $p = 5.16 \times 10^{-115}$ ; mice:  $\beta = -6.18 \pm 0.66$ ,  $T(2.08 \times 10^3) = -9.37$ ,  
446  $p = 1.85 \times 10^{-20}$ ).

447 Our behavioral analyses reveal that humans and mice show significant effects of perceptual  
448 history that impaired performance in randomized psychophysical experiments<sup>24,28,30,31,43</sup>  
449 (Figure 2A and 3A). We therefore expected that humans and mice underestimated the true  
450 hazard rate  $\hat{H}$  of the experimental environments (Confidence database<sup>20</sup>:  $\hat{H}_{Humans} = 0.5$   
451  $\pm 1.58 \times 10^{-5}$ ); IBL database<sup>21</sup>:  $\hat{H}_{Mice} = 0.49 \pm 6.47 \times 10^{-5}$ ). Indeed, when fitting the  
452 bimodal inference model to the trial-wise perceptual choices, we found that the estimated (i.e.,  
453 subjective) hazard rate  $H$  was lower than  $\hat{H}$  for both humans ( $\beta = -6.87 \pm 0.94$ ,  $T(61.87) =$   
454  $-7.33$ ,  $p = 5.76 \times 10^{-10}$ ) and mice ( $\beta = -2.91 \pm 0.34$ ,  $T(112.57) = -8.51$ ,  $p = 8.65 \times 10^{-14}$ ).

455 To further probe the validity of the bimodal inference model, we asked whether posterior  
456 model quantities could explain aspects of the behavioral data that the model was not fitted

457 to. We predicted that the posterior decision variable  $L_t$  not only encodes perceptual choices  
458 (i.e., the variable used for model estimation), but also predicts the speed of response and  
459 subjective confidence<sup>30,44</sup>. Indeed, the estimated trial-wise posterior decision certainty  $|L_t|$   
460 correlated negatively with RTs in humans ( $\beta = -4.36 \times 10^{-3} \pm 4.64 \times 10^{-4}$ ,  $T(1.98 \times 10^6)$   
461  $= -9.41$ ,  $p = 5.19 \times 10^{-21}$ ) and TDs mice ( $\beta = -35.45 \pm 0.86$ ,  $T(1.28 \times 10^6) = -41.13$ ,  $p$   
462  $< 2.2 \times 10^{-308}$ ). Likewise, subjective confidence reports were positively correlated with the  
463 estimated posterior decision certainty in humans ( $\beta = 7.63 \times 10^{-3} \pm 8.32 \times 10^{-4}$ ,  $T(2.06 \times 10^6)$   
464  $= 9.18$ ,  $p = 4.48 \times 10^{-20}$ ).

465 **The dynamic accumulation of information inherent to our model entails that biases**  
466 **toward perceptual history are stronger when the posterior decision certainty**  
467 **at the preceding trial is high<sup>30,31,51</sup>.** Due to the link between posterior decision  
468 **certainty and confidence, confident perceptual choices should be more likely to**  
469 **induce history-congruent perception at the subsequent trial<sup>30,31</sup>.** In line with our  
470 **prediction, logistic regression indicated that history-congruence was predicted**  
471 **by the posterior decision certainty  $|L_{t-1}|$  extracted from the model** (humans:  $\beta =$   
472  $8.22 \times 10^{-3} \pm 1.94 \times 10^{-3}$ ,  $z = 4.25$ ,  $p = 2.17 \times 10^{-5}$ ; mice:  $\beta = -3.72 \times 10^{-3} \pm 1.83 \times 10^{-3}$ ,  
473  $z = -2.03$ ,  $p = 0.04$ ) and the subjective confidence reported by the participants (humans:  $\beta$   
474  $= 0.04 \pm 1.62 \times 10^{-3}$ ,  $z = 27.21$ ,  $p = 4.56 \times 10^{-163}$ ) at the preceding trial.

475 **As a third validation of the bimodal inference model, we used the posterior**  
476 **model parameters to simulate synthetic perceptual choices and repeated the**  
477 **behavioral analyses conducted for the empirical data.** Simulations from the bimodal  
478 inference model closely replicated our empirical results: Simulated perceptual decisions  
479 resulted from a competition of perceptual history with incoming sensory signals (Figure 4A).  
480 Stimulus- and history-congruence were significantly autocorrelated (Figure 4B-C), fluctuating  
481 in anti-phase as a scale-invariant process with a 1/f power law (Figure 4D-F). Simulated  
482 posterior certainty<sup>28,30,44</sup> (i.e., the absolute of the log posterior ratio  $|L_t|$ ) showed a quadratic

483 relationship to the mode of sensory processing (Figure 4H), mirroring the relation of RTs  
484 and confidence reports to external and internal biases in perception (Figure 2G-H and Figure  
485 3G-H). Crucially, the overlap between empirical and simulated data broke down when we  
486 removed the anti-phase oscillations or the accumulation of evidence over time from the  
487 bimodal inference model (Supplemental Figures S10-13).

488 **In sum, computational modeling suggested that between-mode fluctuations are**  
489 **best explained by two interlinked processes (Figure 1E and F): (i), the dynamic**  
490 **accumulation of information across successive trials mandated by normative**  
491 **Bayesian models of evidence accumulation and, (ii), ongoing anti-phase oscillations**  
492 **in the impact of external and internal information.**

## 493 6 Discussion

494 This work investigates the behavioral and computational characteristics of ongoing fluctuations  
495 in perceptual decision-making using two large-scale datasets in humans<sup>20</sup> and mice<sup>21</sup>. We  
496 found that humans and mice cycle through recurring intervals of reduced sensitivity to  
497 external sensory information, during which they rely more strongly on perceptual history, i.e.,  
498 an internal prediction that is provided by the sequence of preceding choices. Computational  
499 modeling indicated that these slow periodicities are governed by two interlinked factors: (i),  
500 the dynamic integration of sensory inputs over time and, (ii), anti-phase oscillations in the  
501 strength at which perception is driven by internal versus external sources of information.  
502 These cross-species results suggest that ongoing fluctuations in perceptual decision-making  
503 arise not merely as a noise-related epiphenomenon of limited processing capacity, but result  
504 from a structured and adaptive mechanism that fluctuates between internally- and externally-  
505 oriented modes of sensory analysis.

506 **6.1 Bimodal inference represents a pervasive aspect of perceptual**  
507 **decision-making in humans and mice**

508 A growing body of literature has highlighted that perception is modulated by preceding  
509 choices<sup>22–28,30,32,33</sup>. Our work provides converging cross-species evidence supporting the  
510 notion that such serial dependencies are a pervasive and general phenomenon of perceptual  
511 decision-making (Figures 2 and 3). While introducing errors in randomized psychophysical  
512 designs<sup>24,28,30,31,43</sup> (Figures 2A and 3A), we found that perceptual history facilitates post-  
513 perceptual processes such as speed of response<sup>42</sup> (Figure 2G and 3G) and subjective confidence  
514 in humans (Figure 2I).

515 At the level of individual traits, increased biases toward preceding choices were associated  
516 with reduced sensitivity to external information (Supplemental Figure 1C-D) and lower  
517 metacognitive efficiency. When investigating how serial dependencies evolve over time, we  
518 observed dynamic changes in the strength of perceptual history (Figures 2 and 3B) that  
519 created wavering biases toward internally- and externally-biased modes of sensory processing.  
520 Between-mode fluctuations may thus provide a new explanation for ongoing changes in  
521 perceptual performance<sup>6–11</sup>.

522 In computational terms, serial dependencies may leverage the temporal autocorrelation of  
523 natural environments<sup>31,46</sup> to increase the efficiency of decision-making<sup>35,43</sup>. Such temporal  
524 smoothing<sup>46</sup> of sensory inputs may be achieved by updating dynamic predictions about the  
525 world based on the sequence of noisy perceptual experiences<sup>22,31</sup>, **using algorithms based**  
526 **on sequential Bayes<sup>25,42,51</sup> such as Kalman<sup>35</sup> or Hierarchical Gaussian filtering<sup>54</sup>.**  
527 At the level of neural mechanisms, the integration of internal with external information may  
528 be realized by combining feedback from higher levels in the cortical hierarchy with incoming  
529 sensory signals that are fed forward from lower levels<sup>56</sup>.

530 Yet relying too strongly on serial dependencies may come at a cost: When accumulating over  
531 time, internal predictions may eventually override external information, leading to circular

532 and false inferences about the state of the environment<sup>57</sup>. Akin to the wake-sleep-algorithm  
533 in machine learning<sup>58</sup>, bimodal inference may help to determine whether errors result from  
534 external input or from internally-stored predictions: During internal mode, sensory processing  
535 is more strongly constrained by predictive processes that auto-encode the agent’s environment.  
536 Conversely, during external mode, the network is driven predominantly by sensory inputs<sup>18</sup>.  
537 Between-mode fluctuations may thus generate an unambiguous error signal that aligns internal  
538 predictions with the current state of the environment in iterative test-update-cycles<sup>58</sup>. On a  
539 broader scale, between-mode fluctuations may thus regulate the balance between feedforward  
540 versus feedback contributions to perception and thereby play a adaptive role in metacognition  
541 and reality monitoring<sup>59</sup>.

542 **From the perspective of the Bayesian brain hypothesis, we hypothesized that**  
543 **observers have certain hyperpriors that are apt for accommodating fluctua-**  
544 **tions in the predictability of their environment, i.e., people believe that their**  
545 **world is inherently volatile. To be Bayes optimal, it is therefore necessary to**  
546 **periodically re-evaluate posterior beliefs about the parameters that define an**  
547 **internal generative model of the external sensory environment. One way to do**  
548 **this is to periodically suspend the precision of prior beliefs and increase the**  
549 **precision afforded to sensory evidence, thus updating Bayesian beliefs about**  
550 **model parameters.**

551 The empirical evidence above suggests that the timescale of this periodic schedul-  
552 ing of evidence accumulation may be scale-invariant. This means that there  
553 may exist a timescale of periodic fluctuations in precision over every window  
554 or length of perceptual decision-making. Bimodal inference predicts perceptual  
555 decisions under a generative model (based upon a hazard function to model  
556 serial dependencies between subsequent trials) with periodic fluctuations in the  
557 precision of sensory evidence relative to prior beliefs at a particular timescale.

558 Remarkably, a systematic model comparison based on AIC indicated that a  
559 model with fluctuating precisions has much greater evidence, relative to a model  
560 in the absence of fluctuating precisions. This ad-hoc addition of oscillations to a  
561 normative Bayesian model of evidence accumulation<sup>51</sup> allowed us to quantify the  
562 dominant timescale of periodic fluctuations mode at approximately  $0.11 \text{ } 1/N_{trials}$   
563 in humans and mice that is appropriate for these kinds of paradigms.

564 **6.2 Bimodal inference versus normative Bayesian evidence accu-**  
565 **mulation**

566 Could bimodal inference emerge spontaneously in normative models of perceptual  
567 decision-making? In predictive processing, the relative precision of prior and  
568 likelihood determines their integration into the posterior that determines the  
569 content of perception. At the level of individual trials, the perceptual impact  
570 of internal predictions generated from perceptual history (prior precision) and  
571 external sensory information (likelihood precision) are thus necessarily anti-  
572 correlated. The same holds for mechanistic models of drift diffusion, which  
573 understand choice history biases as driven by changes in the starting point<sup>51</sup>  
574 or the drift rate of evidence accumulation<sup>32</sup>. Under the former formulation,  
575 perceptual history is bound to have a stronger influence on perception when less  
576 weight is given to incoming sensory evidence, assuming that the last choice is  
577 represented as a starting point bias. The effects of choice history in normative  
578 Bayesian and mechanistic drift diffusion models can be mapped onto one another  
579 via the Bayesian formulation of drift diffusion<sup>60</sup>, where the inverse of likelihood  
580 precision determines the amount of noise in the accumulation of new evidence,  
581 and prior precision determines the absolute shift in its starting point<sup>60</sup>.

582 While it is thus clear that the impact of perceptual history and sensory evidence

583 are anti-correlated *at each individual trial*, we here introduce anti-phase oscillations  
584 as an ad-hoc modification to model slow fluctuations in prior and likelihood  
585 precision that evolve *over many consecutive trials* and are not mandated by  
586 normative Bayesian or mechanistic drift diffusion models. The bimodal infer-  
587 ence model provides a reasonable explanation of the linked autocorrelations in  
588 stimulus- and history-congruence, as evidenced by formal model comparison,  
589 successful prediction of RTs and confidence as out-of-training variables, and a  
590 qualitative reproduction of our empirical data from posterior model parameter  
591 as evidence against over- or under-fitting.

592 Of note, similar non-stationarities have been observed in descriptive models that  
593 assume continuous<sup>61</sup> or discrete<sup>12</sup> changes in the latent states that modulate  
594 perceptual decision-making at slow timescales. A recent computational study<sup>62</sup> has  
595 used a Hidden Markov model to investigate perceptual decision-making in the IBL database<sup>21</sup>.  
596 In analogy to our findings, the authors observed that mice switch between temporally extended  
597 *strategies* that last for more than 100 trials: During *engaged* states, perception was highly  
598 sensitive to external sensory information. During *disengaged* states, in turn, choice behavior  
599 was prone to errors due to enhanced biases toward one of the two perceptual outcomes<sup>62</sup>.  
600 Despite the conceptual differences to our approach (discrete states in a Hidden Markov  
601 model that correspond to switches between distinct decision-making strategies<sup>62</sup> vs. gradual  
602 changes in mode that emerge from sequential Bayesian inference and ongoing **oscillations**  
603 in the impact of external relative to internal information), it is tempting to speculate that  
604 engaged/disengaged states and between-mode fluctuations might tap into the same underlying  
605 phenomenon.

606 **6.3 Task engagement and residual motor activation as alternative  
607 explanations for bimodal inference**

608 As a functional explanation for bimodal inference, we propose that perception temporarily  
609 disengages from internal predictions to form stable inferences about the statistical properties  
610 of the sensory environment. **Between-mode fluctuations may thus elude circular  
611 inferences that occur when both the causes and the encoding of sensory stimuli  
612 are volatile<sup>19,57</sup>.** By the same token, we suggest that fluctuations in mode occur at the  
613 level of perceptual processing<sup>26,30,46,47</sup>, and are not a passive phenomenon that is primarily  
614 driven by factors situated up- or downstream of sensory analysis.

615 **How does attention relate to phenomenon of between-mode fluctuations?** Ac-  
616 cording to predictive processing, attention corresponds to the precision afforded  
617 to the probability distributions that underlie perceptual inference<sup>53</sup>. From this  
618 perspective, fluctuations between external and internal mode can be understood  
619 as ongoing shifts in the attention afforded to either external sensory information  
620 (regulated via likelihood precision) or internal predictions (regulated via prior  
621 precision). When the precision of either likelihood or prior increases, posterior  
622 precision increases, which leads to faster RTs and higher confidence. Therefore,  
623 when defined from the perspective of predictive processing as the precision af-  
624 forded to likelihood and prior<sup>53</sup>, fluctuations in attention may provide a plausible  
625 explanation for the quadratic relationship of mode to RTs and confidence (Figure  
626 2H and J; Figure 3I, Figure 4I).

627 **Outside of the predictive processing field, attention is often understood in the  
628 context of task engagement<sup>63</sup>, which varies according to the availability of cognitive  
629 resources that are modulated by factors such as tonic arousal, familiarity with  
630 the task, or fatigue<sup>63</sup>.** Our results suggest that internal mode processing cannot  
631 be completely reduced to intervals of low task engagement: In addition to shorter

632 RTs and elevated confidence, choices during internal mode were not random  
633 or globally biased, but driven by perceptual history (Supplemental Section).  
634 Moreover, our computational model identified the dominant timescale of between-  
635 mode fluctuations at  $0.11\sqrt{1/N_{trials}}$ , which may be compatible with fluctuations in  
636 arousal<sup>64</sup>, but is faster than to be expected for the development of task familiarity  
637 or fatigue.

638 However, in interpreting the impact of between-mode fluctuations on perceptual  
639 accuracy, speed of response and confidence, it is important to consider that global  
640 modulators such as tonic arousal are known to have non-linear effects on task  
641 performance<sup>65</sup>: In perceptual tasks, performance seems to be highest during  
642 mid-level arousal, whereas low- and high-level arousal lead to reduced accuracy  
643 and slower responses<sup>65</sup>. This contrasts with the effects of bimodal inference,  
644 where accuracy increases linearly as one moves from internal to external mode,  
645 and responses become faster at both ends of the mode spectrum.

646 Of note, high phasic arousal has been shown to suppress biases in decision-making  
647 in humans and mice across domains<sup>66–68</sup>, including biases toward perceptual  
648 history<sup>28</sup> that we implicate in internal mode processing. While the increase in  
649 response speed and history congruence over time (Supplemental Section 9.4) may  
650 argue against insufficient training as an alternative explanation for internal mode  
651 processing, it may also be indicative of waning arousal. The multiple mechanistic  
652 mappings to RTs and confidence warrant more direct measures of arousal (such  
653 as pupil size<sup>28,65,66,68–70</sup>, motor behavior<sup>69,70</sup>, or neural data<sup>71</sup>) to better delineate  
654 bimodal inference from fluctuations in global modulators of task performance.

655 Residual activation of the motor system may provide another contribution to  
656 serial biases in perceptual choices<sup>72</sup>. Such motor-driven priming may lead to  
657 errors in randomized psychophysical designs, resembling the phenomenon that

658 we identify as internally-biased processing<sup>73</sup>. Moreover, residual activation of the  
659 motor system may lead to faster responses, and thus constitutes an alternative  
660 explanation for the quadratic relationship of mode with RTs<sup>72</sup>. The observation  
661 of elevated confidence for stronger biases toward internal mode speaks against  
662 the proposition that residual activation of the motor system is the primary  
663 driver of serial choice biases, since strong motor-driven priming should lead to  
664 frequent lapses that are typically associated reduced confidence<sup>74</sup>. Likewise,  
665 perceptual history effects have repeatedly been replicated in experiments with  
666 counter-balanced stimulus-response mappings<sup>30</sup>: Feigin<sup>2021</sup>.

667 No-response paradigms, in which perceptual decision are inferred from eye-  
668 movements alone, could help to better differentiate perceptual from motor-  
669 related effects. Likewise, video-tracking of response behavior and neural record-  
670 ing from motor- and premotor, which has recently been released for the IBL  
671 database[IBL2023], may provide further insight into the relation of motor behavior  
672 to the perceptual phenomenon of between-mode fluctuations.

#### 673 6.4 Limitations and open questions

674 Our results suggest bimodal inference as a pervasive aspect in perceptual decision-  
675 making in humans and mice. However, a number of limitations and open questions  
676 have to be considered:

677 First, this work sought to understand whether fluctuations between internal and  
678 external mode, which we initially observed in an experiment on bistable perception  
679 in humans<sup>19</sup>, are general phenomenon that occurs across a diverse set of perceptual  
680 decision-making tasks. Our analysis of the Confidence database<sup>20</sup> therefore  
681 collapsed across all available experiments on binary perceptual decision-making.  
682 Individual experiments differed with respect to the stimuli, the manipulation

683 of difficulty, the timing of trials, and the way responses were collected, but  
684 were highly comparable with respect to the central variables of stimulus- and  
685 history-congruence (Supplemental Figure S1A-B).

686 The variability across experiments, which we considered as random effects in all  
687 statistical analyses, enabled us to assess whether bimodal inference represents a  
688 general phenomenon in perceptual decision-making, but limited the precision at  
689 which we were able to investigate the relation of mode to behavioral variables such  
690 as timing, task difficulty, RT or confidence. This issue is partially resolved by our  
691 analyses of the IBL database, which replicated our findings in an experiment that  
692 was highly standardized with respect to timing, task difficulty, and behavioral  
693 read-out<sup>21</sup>. It will be an important task for future research to validate our results  
694 on bimodal inference in a standardized dataset of comparable volume in humans,  
695 which is, to our knowledge, not yet available.

696 Second, our results point to an attraction of perception toward preceding choices.  
697 Previous work has shown that perceptual decision-making is concurrently affected  
698 by both attractive and repulsive serial biases that operate on distinct time-scales  
699 and serve complementary functions for sensory processing<sup>27,75,76</sup>: Short-term  
700 attraction may serve the decoding of noisy sensory inputs and increase the  
701 stability of perception, whereas long-term repulsion may enable efficient encoding  
702 and sensitivity to change<sup>27</sup>. In the data analyzed here, history biases tended to be  
703 repetitive (Figure 2A, Figure 3A, Supplemental Figure S6 and S7), as only 2 of the  
704 66 experiments of the Confidence database<sup>20</sup> showed significant alternating biases  
705 (Supplemental Figure S1). However, as we show in Supplemental Figure S14,  
706 fluctuations in both alternating and repeating history biases generate overlapping  
707 autocorrelation curves. Our analysis of between-mode fluctuations is therefore  
708 not tied exclusively to repeating biases, but accommodates alternating biases

709 as well, such that both may lead to internally-biased processing and reduced  
710 sensitivity to external sensory information. Future work could apply our approach  
711 to paradigms that boost alternating as opposed to repeating biases, as this would  
712 help to better understand how repetition and alternation are linked in terms of  
713 their computational function and neural implementation<sup>27</sup>.

714 A third open question concerns the computational underpinnings of bimodal  
715 inference. The addition of slow anti-phase oscillations to the integration of prior  
716 and likelihood represents an ad-hoc modification of a normative Bayesian model  
717 of evidence accumulation<sup>51</sup>. While the bimodal inference model is supported  
718 by formal model comparison, the successful prediction of out-of-training vari-  
719 ables and the qualitative reproduction of our empirical data in simulations from  
720 posterior model parameters, it is an important task for future research to test  
721 whether between-mode fluctuations can emerge spontaneously in hierarchical  
722 models of Bayesian inference, whether modes are continuous<sup>19</sup> or discrete<sup>62</sup>, and  
723 whether bimodal inference can be causally manipulated by experimental vari-  
724 ables. We speculate that between-mode fluctuations may separate the perceptual  
725 contribution of internal predictions and external sensory data in time, creating  
726 unambiguous learning signals that benefit inference about the precision of prior  
727 and likelihood, respectively. This proposition should be tested empirically by  
728 relating the phenomenon of bimodal inference to performance in, e.g., reversal  
729 learning, probabilistic reasoning, or metacognition.

730 A final important avenue for further research on bimodal inference is identify-  
731 ing the neurobiological underpinnings of bimodal inference. Since between-mode  
732 fluctuations were found in humans and mice, future studies can apply non-invasive and  
733 invasive neuro-imaging and electrophysiology to better understand the neural mechanisms  
734 that generate ongoing changes in mode in terms of their neuro-anatomy, -chemistry and

<sup>735</sup> -circuitry.

<sup>736</sup> Establishing the neural correlates of externally- an internally-biased modes will enable exiting  
<sup>737</sup> opportunities to investigate their role for adaptive perception and decision-making: Causal  
<sup>738</sup> interventions via pharmacological challenges, optogenetic manipulations or (non-)invasive  
<sup>739</sup> brain stimulation will help to understand whether between-mode fluctuations are implicated  
<sup>740</sup> in resolving credit-assignment problems<sup>18,77</sup> or in calibrating metacognition and reality  
<sup>741</sup> monitoring<sup>59</sup>. Answers to these questions may provide new insights into the pathophysiology  
<sup>742</sup> of hallucinations and delusions, which have been characterized by an imbalance in the impact  
<sup>743</sup> of external versus internal information<sup>56,78,79</sup> and are typically associated with metacognitive  
<sup>744</sup> failures and a departure from consensual reality<sup>79</sup>.

<sup>745</sup> **7 Methods**

<sup>746</sup> **7.1 Resource availability**

<sup>747</sup> **7.1.1 Lead contact**

<sup>748</sup> Further information and requests for resources should be directed to and will be fulfilled by  
<sup>749</sup> the lead contact, Veith Weilnhammer (veith.weilnhammer@gmail.com).

<sup>750</sup> **7.1.2 Materials availability**

<sup>751</sup> This study did not generate new unique reagents.

<sup>752</sup> **7.1.3 Data and code availability**

<sup>753</sup> All custom code and behavioral data are available on <https://github.com/veithweilnhammer/>  
<sup>754</sup> Modes. This manuscript was created using the *R Markdown* framework, which integrates all  
<sup>755</sup> data-related computations and the formatted text within one document. With this, we wish  
<sup>756</sup> to make our approach fully transparent and reproducible for reviewers and future readers.

<sup>757</sup> **7.2 Experimental model and subject details**

<sup>758</sup> **7.2.1 Confidence database**

<sup>759</sup> We downloaded the human data from the Confidence database<sup>20</sup> on 10/21/2020,  
<sup>760</sup> limiting our analyses to the category *perception*. Within this category, we  
<sup>761</sup> selected studies in which participants made binary perceptual decisions between  
<sup>762</sup> two alternatives. We excluded two experiments in which the average perceptual  
<sup>763</sup> accuracy fell below 50%. After excluding these experiments, our sample consisted  
<sup>764</sup> of 21.05 million trials obtained from 4317 human participants and 66 individual  
<sup>765</sup> experiments (Supplemental Table 1). Out of the 66 included experiments, 62  
<sup>766</sup> investigated visual, 1 auditory, 2 proprioceptive, and 1 multimodal perception.

767 **59 experiments were based on discrimination and 6 on detection, with one**  
768 **investigating both.**

769 **7.2.2 IBL database**

770 We downloaded the data from the IBL database<sup>21</sup> on 04/28/2021. We limited our analyses to  
771 the *basic task*, during which mice responded to gratings that appeared with equal probability  
772 in the left or right hemifield. Within each mouse, we excluded sessions in which perceptual  
773 accuracy was below 80% for stimuli presented at a contrast  $\geq 50\%$ . After exclusion, our  
774 sample consisted of 1.46 million trials obtained from  $N = 165$  mice.

775 **7.3 Method details**

776 **7.3.1 Variables of interest**

777 **Primary variables of interest:** We extracted trial-wise data on the presented stimulus and  
778 the associated perceptual decision. Stimulus-congruent choices were defined by perceptual  
779 decisions that matched the presented stimuli. History-congruent choices were defined by  
780 perceptual choices that matched the perceptual choice at the immediately preceding trial.  
781 The dynamic probabilities of stimulus- and history-congruence were computed in sliding  
782 windows of  $\pm 5$  trials.

783 The *mode* of sensory processing was derived by subtracting the dynamic probability of history-  
784 congruence from the dynamic probability of stimulus-congruence, such that positive values  
785 indicate externally-oriented processing, whereas negative values indicate internally-oriented  
786 processing. When visualizing the relation of the mode of sensory processing to confidence,  
787 RTs or trial duration (see below), we binned the mode variable in 10% intervals. We excluded  
788 bins that contained less than 0.5% of the total number of available data-points.

789 **Secondary variables of interest:** From the Confidence Database<sup>20</sup>, we furthermore  
790 extracted trial-wise confidence reports and RTs. **Out of the 58 experiments that provide**

791 information on RTs, 46 cued the response by the onset of a response screen or  
792 an additional response cue, whereas 14 allowed participants to response at any  
793 time after stimulus onset. If RTs were available for both the perceptual decision and  
794 the confidence report, we only extracted the RT associated with the perceptual decision.  
795 To enable comparability between studies, we normalized RTs and confidence reports within  
796 individual studies using the *scale* R function. If not available for a particular study, RTs were  
797 treated as missing variables. From the IBL database<sup>21</sup>, we extracted trial durations (TDs) as  
798 defined by interval between stimulus onset and feedback, which represents a coarse measure  
799 of RT<sup>21</sup>.

800 **Exclusion criteria for individual data-points:** For non-normalized data (TDs from  
801 the IBL database<sup>21</sup>; d-prime, meta-dprime and M-ratio from the Confidence database<sup>20</sup> and  
802 simulated confidence reports), we excluded data-points that differed from the median by  
803 more than 3 x MAD (median absolute distance<sup>49</sup>). For normalized data (RTs and confidence  
804 reports from the Confidence database<sup>20</sup>), we excluded data-points that differed from the  
805 mean by more than 3 x SD (standard deviation).

### 806 7.3.2 Control variables

807 Next to the sequence of presented stimuli, we assessed the autocorrelation of task difficulty  
808 as an alternative explanation for any autocorrelation in stimulus- and history-congruence. In  
809 the Confidence Database<sup>20</sup>, **21 of the 66 included experiments used fixed difficulty**  
810 **levels, whereas 45 manipulated difficulty levels within participants.** Difficulty  
811 **was manipulated via noise masks, contrast, luminance, presentation time, or**  
812 **stimulus probability for gabors, dot coherence for random dot kinematograms,**  
813 **difference in elements and set size for comparisons of numerosity, difference in**  
814 **clicks for auditory discrimination, temporal distance for meta-contrast masking,**  
815 **and amount of self-motion for proprioception.** We treated task difficulty as a  
816 **missing variable for the experiments that fixed it at the participant-level, as**

817 **this precluded the computation of autocorrelation curves.** In analogy to RTs and  
818 confidence, difficulty levels were normalized within individual studies. For the IBL Database<sup>21</sup>,  
819 task difficulty was defined by the contrast of the presented grating.

820 **7.3.3 Autocorrelations**

821 For each participant, trial-wise autocorrelation coefficients were estimated using the R-function  
822 *acf* with a maximum lag defined by the number of trials available per subject. Autocorrelation  
823 coefficients are displayed against the lag (in numbers of trials, ranging from 1 to 20) relative to  
824 the index trial ( $t = 0$ ; Figure 2B-C, 3B-C and 4B-C). To account for spurious autocorrelations  
825 that occur due to imbalances in the analyzed variables, we estimated autocorrelations for  
826 randomly permuted data (100 iterations). For group-level autocorrelations, we computed  
827 the differences between the true autocorrelation coefficients and the mean autocorrelation  
828 observed for randomly permuted data and averaged across participants.

829 At a given trial, group-level autocorrelation coefficients were considered significant when  
830 linear mixed effects modeling indicated that the difference between real and permuted  
831 autocorrelation coefficients was above zero at an alpha level of 0.05%. To test whether the  
832 autocorrelation of stimulus- and history-congruence remained significant when controlling for  
833 task difficulty and the sequence of presented stimuli, we added the respective autocorrelation  
834 as an additional factor to the linear mixed effects model that computed the group-level  
835 statistics (see also *Mixed effects modeling*).

836 To assess autocorrelations at the level of individual participants, we counted the number of  
837 subsequent trials (starting at the first trial after the index trial) for which less than 50% of  
838 the permuted autocorrelation coefficients exceeded the true autocorrelation coefficient. For  
839 example, a count of zero indicates that the true autocorrelation coefficients exceeded *less*  
840 *than 50%* of the autocorrelation coefficients computed for randomly permuted data at the  
841 first trial following the index trial. A count of five indicates that, for the first five trials  
842 following the index trial, the true autocorrelation coefficients exceeded *more than 50%* of

843 the respective autocorrelation coefficients for the randomly permuted data; at the 6th trial  
844 following the index trial, however, *less than 50%* of the autocorrelation coefficients exceeded  
845 the respective permuted autocorrelation coefficients.

#### 846 7.3.4 Spectral analysis

847 We used the R function *spectrum* to compute the spectral densities for the dynamic probabil-  
848 ities of stimulus- and history-congruence as well as the phase (i.e., frequency-specific shift  
849 between the two time-series ranging from 0 to  $2 * \pi$ ) and squared coherence (frequency-specific  
850 variable that denotes the degree to which the shift between the two time-series is constant,  
851 ranging from 0 to 100%). Periodograms were smoothed using modified Daniell smoothers at  
852 a width of 50.

853 Since the dynamic probabilities of history- and stimulus-congruence were computed using  
854 a sliding windows of  $\pm 5$  trials (i.e., intervals containing a total of 11 trials), we report the  
855 spectral density, coherence and phase for frequencies below  $1/11$   $1/N_{trials}$ . Spectral densities  
856 have one value per subject and frequency (data shown in Figures 2D and 3D). To assess the  
857 relation between stimulus- and history-congruence in this frequency range, we report average  
858 phase and average squared coherence for all frequencies below  $1/11$   $1/N_{trials}$  (i.e., one value  
859 per subject; data shown in Figure 2E-F and 3E-F).

860 Since the data extracted from the Confidence Database<sup>20</sup> consist of a large set of individual  
861 studies that differ with respect to inter-trial intervals, we defined the variable *frequency* in  
862 the dimension of cycles per trial  $1/N_{trials}$  rather than cycles per second (Hz). For consistency,  
863 we chose  $1/N_{trials}$  as the unit of frequency for the IBL database<sup>21</sup> as well.

### 864 7.4 Quantification and statistical procedures

865 All aggregate data are reported and displayed with errorbars as mean  $\pm$  standard error of  
866 the mean.

867 **7.4.1 Mixed effects modeling**

868 Unless indicated otherwise, we performed group-level inference using the R-packages *lmer*  
869 and *afer* for linear mixed effects modeling and *glmer* with a binomial link-function for logistic  
870 regression. We compared models based on AIC. To account for variability between the studies  
871 available from the Confidence Database<sup>20</sup>, mixed modeling was conducted using random  
872 intercepts defined for each study. To account for variability across experimental session within  
873 the IBL database<sup>21</sup>, mixed modeling was conducted using random intercepts defined for each  
874 individual session. When multiple within-participant datapoints were analyzed, we estimated  
875 random intercepts for each participant that were *nested* within the respective study of the  
876 Confidence database<sup>20</sup>. By analogy, for the IBL database<sup>21</sup>, we estimated random intercepts  
877 for each session that were nested within the respective mouse. We report  $\beta$  values referring  
878 to the estimates provided by mixed effects modeling, followed by the respective T statistic  
879 (linear models) or z statistic (logistic models).

880 The effects of stimulus- and history-congruence on RTs and confidence reports (Figure 2, 3  
881 and 4, subpanels G-I) were assessed in linear mixed effects models that tested for main effects  
882 of both stimulus- and history-congruence as well as the between-factor interaction. Thus, the  
883 significance of any effect of history-congruence on RTs and confidence reports was assessed  
884 while controlling for the respective effect of stimulus-congruence (and vice versa).

885 **7.4.2 Psychometric function**

886 We obtained psychometric curves by fitting the following error function to the behavioral  
887 data:

$$y_p = \gamma + (1 - \gamma - \delta) * (\text{erf}(\frac{s_w + \mu}{t}) + 1)/2 \quad (8)$$

888 We used the Broyden–Fletcher–Goldfarb–Shanno algorithm in maximum likelihood  
889 estimation<sup>80</sup> to predict individual choices  $y$  (outcome A:  $y = 0$ ; outcome B:  $y = 1$ ) from the

choice probability  $y_p$ . In humans, we computed  $s_w$  by multiplying the inputs  $s$  (stimulus A: 0; outcome B: 1) with the task difficulty  $D_b$  (binarized across 7 levels):

$$s_w = (s - 0.5) * D_b \quad (9)$$

In mice,  $s_w$  was defined by the respective stimulus contrast in the two hemifields:

$$s_w = Contrast_{Right} - Contrast_{Left} \quad (10)$$

Parameters of the psychometric error function were fitted using the R-package *optimx*<sup>80</sup>. The psychometric error function was defined via the parameters  $\gamma$  (lower lapse; lower bound = 0, upper bound = 0.5),  $\delta$  (upper lapse; lower bound = 0, upper bound = 0.5),  $\mu$  (bias; lower bound humans = -5; upper bound humans = 5, lower bound mice = -0.5, upper bound mice = 0.5) and threshold  $t$  (lower bound humans = 0.5, upper bound humans = 25; lower bound mice = 0.01, upper bound mice = 1.5).

#### 7.4.3 Computational modeling

**Model definition:** Our modeling analysis is an extension of a model proposed by Glaze et al.<sup>51</sup>, who defined a normative account of evidence accumulation for decision-making. In this model, trial-wise choices are explained by applying Bayes theorem to infer moment-by-moment changes in the state of environment from trial-wise noisy observations across trials.

Following Glaze et al.<sup>51</sup>, we applied Bayes rule to compute the posterior evidence for the two alternative choices (i.e., the log posterior ratio  $L$ ) from the sensory evidence available at time-point  $t$  (i.e., the log likelihood ratio  $LLR$ ) with the prior probability  $\psi$ , **weighted by the respective precision terms  $\omega_{LLR}$  and  $\omega_\psi$** :

$$L_t = LLR_t * \omega_{LLR} + \psi_t(L_{t-1}, H) * \omega_\psi \quad (11)$$

908 In the trial-wise design studied here, a transition between the two states of the environment  
 909 (i.e., the sources generating the noisy observations available to the participant) can occur  
 910 at any time. Despite the random nature of the psychophysical paradigms studied here<sup>20,21</sup>,  
 911 humans and mice showed significant biases toward preceding choices (Figure 2A and 3A).  
 912 We thus assumed that the prior probability of the two possible outcomes depends on the  
 913 posterior choice probability at the preceding trial and the hazard rate  $H$  assumed by the  
 914 participant. Following Glaze et al.<sup>51</sup>, the prior  $\psi$  is thus computed as follows:

$$\psi_t(L_{t-1}, H) = L_{t-1} + \log\left(\frac{1-H}{H} + \exp(-L_{t-1})\right) - \log\left(\frac{1-H}{H} + \exp(L_{t-1})\right) \quad (12)$$

915 In this model, humans, mice and simulated agents make perceptual choices based on noisy  
 916 observations  $u$ . These are computed by applying a sensitivity parameter  $\alpha$  to the content of  
 917 external sensory information  $s$ . For humans, we defined the input  $s$  by the two alternative  
 918 states of the environment (stimulus A:  $s = 0$ ; stimulus B:  $s = 1$ ), which generated the  
 919 observations  $u$  through a sigmoid function that applied a sensitivity parameter  $\alpha$ :

$$u_t = \frac{1}{1 + \exp(-\alpha * (s_t - 0.5))} \quad (13)$$

920 In mice, the inputs  $s$  were defined by the respective stimulus contrast in the two hemifields:

$$s_t = \text{Contrast}_{Right} - \text{Contrast}_{Left} \quad (14)$$

921 As in humans, we derived the input  $u$  by applying a sigmoid function with a sensitivity  
 922 parameter  $\alpha$  to input  $s$ :

$$u_t = \frac{1}{1 + \exp(-\alpha * s_t)} \quad (15)$$

923 For humans, mice and in simulations, the log likelihood ratio  $LLR$  was computed from  $u$  as  
 924 follows:

$$LLR_t = \log\left(\frac{u_t}{1 - u_t}\right) \quad (16)$$

925 To allow for long-range autocorrelation in stimulus- and history-congruence (Figure 2B and  
 926 3B), our modeling approach differed from Glaze et al.<sup>51</sup> in that it allowed for systematic  
 927 fluctuation in the impact of sensory information (i.e.,  $LLR$ ) and the prior probability  
 928 of choices  $\psi$  on the posterior probability  $L$ . This was achieved by multiplying the log  
 929 likelihood ratio and the log prior ratio with coherent anti-phase fluctuations according to  
 930  $\omega_{LLR} = a_{LLR} * \sin(f * t + phase) + 1$  and  $\omega_\psi = a_\psi * \sin(f * t + phase + \pi) + 1$ .

931 **Model fitting:** In model fitting, we predicted the trial-wise choices  $y_t$  (option A: 0; option B:  
 932 1) from inputs  $s$ . To this end, we minimized the log loss between  $y_t$  and the choice probability  
 933  $y_{pt}$  in the unit interval.  $y_{pt}$  was derived from  $L_t$  using a sigmoid function defined by the  
 934 inverse decision temperature  $\zeta$ :

$$y_{pt} = \frac{1}{1 + \exp(-\zeta * L_t)} \quad (17)$$

935 This allowed us to infer the free parameters  $H$  (lower bound = 0, upper bound = 1; human  
 936 posterior =  $0.45 \pm 4.8 \times 10^{-5}$ ; mouse posterior =  $0.46 \pm 2.97 \times 10^{-4}$ ),  $\alpha$  (lower bound  
 937 = 0, upper bound = 5; human posterior =  $0.5 \pm 1.12 \times 10^{-4}$ ; mouse posterior =  $1.06 \pm$   
 938  $2.88 \times 10^{-3}$ ),  $a_\psi$  (lower bound = 0, upper bound = 10; human posterior =  $1.44 \pm 5.27 \times 10^{-4}$ ;  
 939 mouse posterior =  $1.71 \pm 7.15 \times 10^{-3}$ ),  $amp_{LLR}$  (lower bound = 0, upper bound = 10;  
 940 human posterior =  $0.5 \pm 2.02 \times 10^{-4}$ ; mouse posterior =  $0.39 \pm 1.08 \times 10^{-3}$ ), frequency  $f$   
 941 (lower bound = 1/40, upper bound = 1/5; human posterior =  $0.11 \pm 1.68 \times 10^{-5}$ ; mouse  
 942 posterior =  $0.11 \pm 1.63 \times 10^{-4}$ ),  $p$  (lower bound = 0, upper bound =  $2 * \pi$ ; human posterior  
 943 =  $2.72 \pm 4.41 \times 10^{-4}$ ; mouse posterior =  $2.83 \pm 3.95 \times 10^{-3}$ ) and inverse decision temperature  $\zeta$

944 (lower bound = 1, upper bound = 10; human posterior =  $4.63 \pm 1.95 \times 10^{-4}$ ; mouse posterior  
945 =  $4.82 \pm 3.03 \times 10^{-3}$ ) using maximum likelihood estimation with the Broyden–Fletcher–  
946 Goldfarb–Shanno algorithm as implemented in the R-function *optimx*<sup>80</sup> (see Supplemental  
947 **Table T2** for a description of our model parameters).

948 We validated the bimodal inference model in three steps: a formal model com-  
949 parison to reduced models based on AIC (Figure 1F-G; Supplemental Figure  
950 S9), the prediction of within-training (stimulus- and history-congruence) as well  
951 as out-of-training variables (RT and confidence), and a qualitative reproduction  
952 of the empirical data from model simulations based on estimated parameters  
953 (Figure 4).

954 Model comparison. We assessed the following model space based on AIC:

- 955 • The full *bimodal inference model* (M1; Figure 1F) incorporates the influ-  
956 ence of sensory information according to the parameter  $\alpha$  (likelihood); the  
957 integration of evidence across trials according to the parameter  $H$  (prior);  
958 anti-phase oscillations in between likelihood and prior precision according  
959 to  $\omega_{LLR}$  and  $\omega_\psi$  with parameters  $a_{LLR}$  (amplitude likelihood fluctuation),  $a_\psi$   
960 (amplitude prior fluctuation),  $f$  (frequency) and  $p$  (phase).
- 961 • The *likelihood-oscillation-only model* (M2; Figure 1G) incorporates the  
962 influence of sensory information according to parameter  $\alpha$  (likelihood); the  
963 integration of evidence across trials according to parameter  $H$  (prior); os-  
964 cillations in likelihood precision according to  $\omega_{LLR}$  with parameters  $a_{LLR}$   
965 (amplitude likelihood fluctuation),  $f$  (frequency) and  $p$  (phase).
- 966 • The *prior-oscillation-only model* (M3; Figure 1G) incorporates the influence  
967 of sensory information according to parameter  $\alpha$  (likelihood); the integration  
968 of evidence across trials according to parameter  $H$  (prior); oscillations in

969 the prior precision according to  $\omega_\psi$  with parameters  $a_\psi$  (amplitude prior  
970 fluctuation),  $f$  (frequency) and  $p$  (phase). Please note that all models M1-3  
971 lead to shifts in the relative precision of likelihood and prior.

- 972 • The *normative-evidence-accumulation* (M4; Figure 1G) incorporates the  
973 influence of sensory information according to parameter  $\alpha$  (likelihood); the  
974 integration of evidence across trials according to parameter  $H$  (prior), There  
975 are no additional oscillations. Model M4 thus corresponds to the model  
976 proposed by Glaze et al. and captures normative evidence accumulation  
977 in unpredictable environments using a Bayesian update scheme<sup>51</sup>. The  
978 comparison against M4 tests the null hypothesis that fluctuations in mode  
979 emerge from a normative Bayesian model without the ad-hoc addition of  
980 oscillations as in models M1-3.
- 981 • The *no-evidence-accumulation* (M5; Figure 1G) incorporates the influence  
982 of sensory information according to parameter  $\alpha$  (likelihood). The model  
983 lacks integration of evidence across trials (flat prior) and oscillations. The  
984 comparison against M5 tests the null hypothesis that observers do not use  
985 prior information derived from serial dependency in perception.

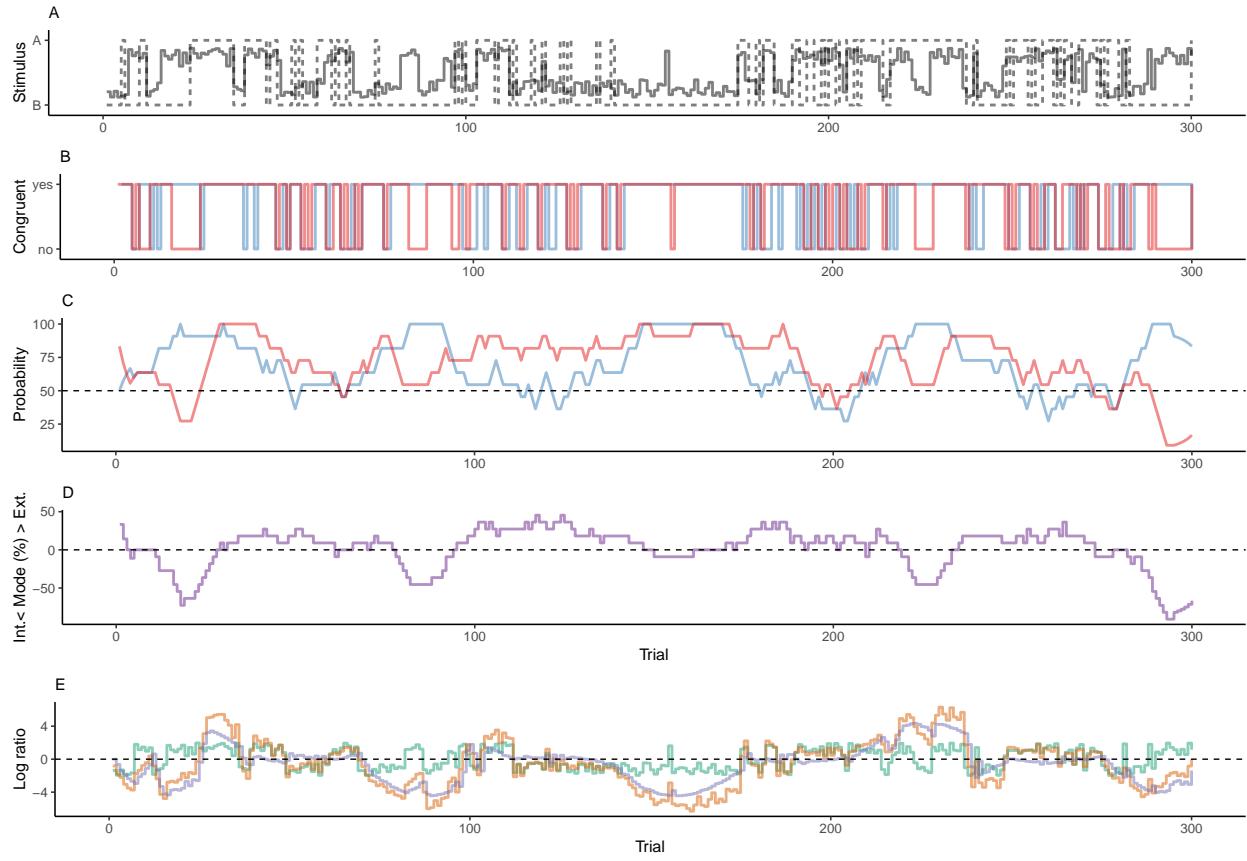
986 Prediction of within-training and out-of-training variables. To validate our model,  
987 we correlated individual posterior parameter estimates with the respective con-  
988 ventional variables. As a sanity check, we tested (i), whether the estimated hazard  
989 rate  $H$  correlated negatively with the frequency of history-congruent choices  
990 and, (ii), whether the estimated sensitivity to sensory information  $\alpha$  correlated  
991 positively with the frequency of stimulus-congruent choices. In addition, we  
992 tested whether the posterior decision certainty (i.e.. the absolute of the log  
993 posterior ratio) correlated negatively with RTs and positively with confidence.  
994 This allowed us to assess whether our model could explain aspects of the data it

995 was not fitted to (i.e., RTs and confidence).

996 **Simulations.** Finally, we used simulations (Figure 4, Supplemental Figures S10-  
997 13) to show that all model components, including the anti-phase oscillations  
998 governed by  $a_\psi$ ,  $a_{LLR}$ ,  $f$  and  $p$ , were necessary for our model to reproduce the  
999 characteristics of the empirical data. This enabled us to assess over- or under-  
1000 fitting in the bimodal inference model and all reduced models M2-M5. We used  
1001 the posterior model parameters observed for humans ( $H$ ,  $\alpha$ ,  $a_\psi$ ,  $a_{LLR}$ ,  $f$ ,  $p$  and  
1002  $\zeta$ ) to define individual parameters for simulation in 4317 simulated participants  
1003 (i.e., equivalent to the number of human participants). For each participant, the  
1004 number of simulated trials was drawn at random between 300 to 700. Inputs  $s$   
1005 were drawn at random for each trial, such that the sequence of inputs to the  
1006 simulation did not contain any systematic seriality. Noisy observations  $u$  were  
1007 generated by applying the posterior parameter  $\alpha$  to inputs  $s$ , thus generating  
1008 stimulus-congruent choices in  $71.36 \pm 2.6 \times 10^{-3}\%$  of trials. Choices were simulated  
1009 based on the trial-wise choice probabilities  $y_p$  obtained from our model. Simulated  
1010 data were analyzed in analogy to the human and mouse data. As a substitute of  
1011 subjective confidence, we computed the absolute of the trial-wise log posterior  
1012 ratio  $|L|$  (i.e., the posterior decision certainty).

1013 **8 Figures**

1014 **8.1 Figure 1**



1015 **Figure 1. Concept.**

1016 A. In binary perceptual decision-making, a participant is presented with stimuli from two

1017 categories (A vs. B; dotted line) and reports consecutive perceptual choices via button presses

1018 (solid line). All panels below refer to these simulated example data.

1019

1020 B. When the response matches the external stimulus information (i.e., overlap between dotted

1021 and solid line in panel A), perceptual choices are *stimulus-congruent* (red line). When the

1022 response matches the response at the preceding trial, perceptual choices are *history-congruent*

1023 (blue line).

1024 C. The dynamic probabilities of stimulus- and history-congruence (i.e., computed in sliding

1025 windows of  $\pm 5$  trials) fluctuate over time.

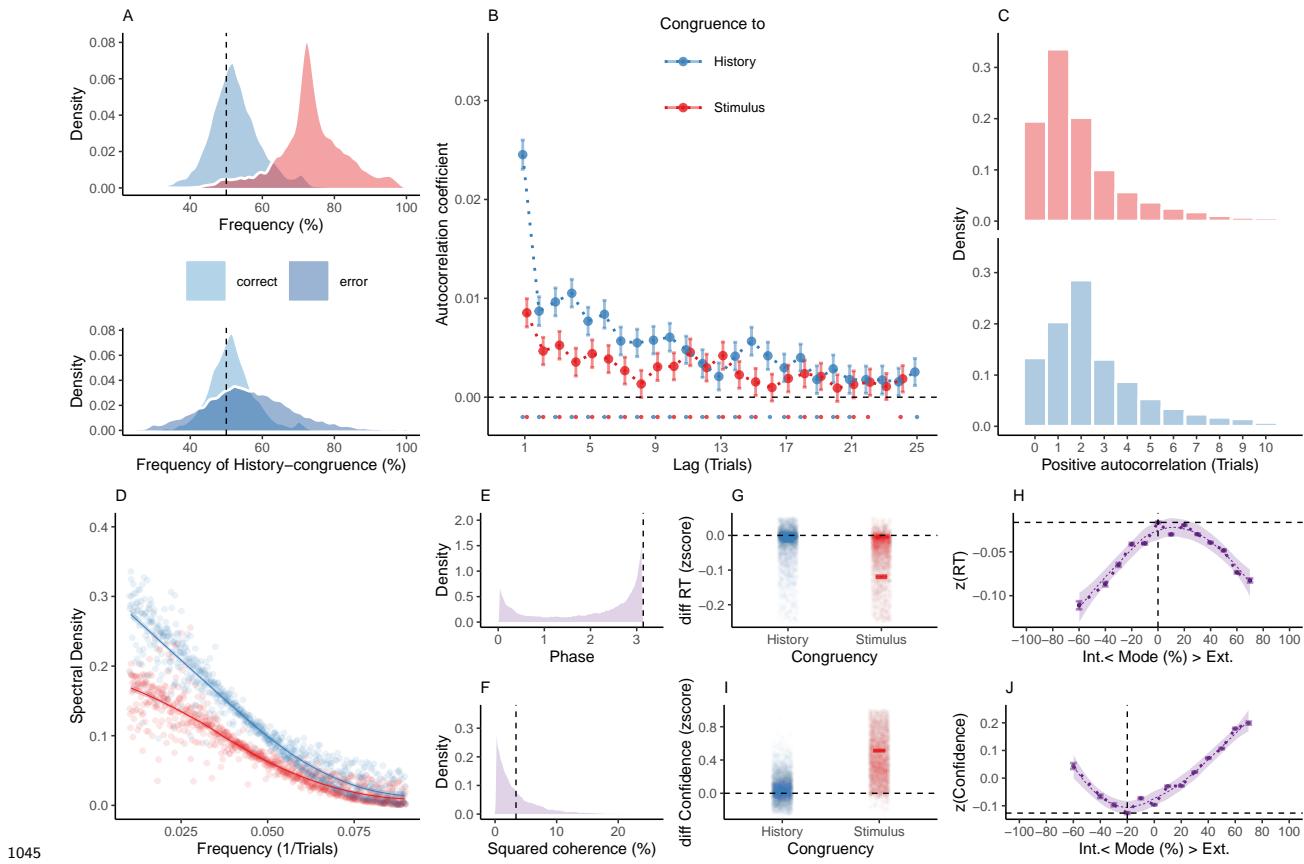
1026 D. The *mode* of perceptual processing is derived by computing the difference between the  
1027 dynamic probabilities of stimulus- and history-congruence. Values above 0% indicate a  
1028 bias toward external information, whereas values below 0% indicate a bias toward internal  
1029 information.

1030 E. In computational modeling, internal mode is caused by an enhanced impact of perceptual  
1031 history. This causes the posterior (black line) to be close to the prior (blue line). Conversely,  
1032 during external mode, the posterior is close to the sensory information (log likelihood ratio,  
1033 red line).

1034 **F. The bimodal inference model (M1) explains fluctuations between externally-  
1035 and externally-biased modes (left panel) by two interacting factors: a normative  
1036 accumulation of evidence according to parameters  $H$  (middle panel), and anti-  
1037 phase oscillations in the precision terms  $\omega_{LLR}$  and  $\omega_\psi$  (right panel).**

1038 **G. The control models M2-M5 were constructed by successively removing the anti-  
1039 phase oscillations and the integration of information from the bimodal inference  
1040 model. Please note that the normative-evidence-accumulation-model (M4) corre-  
1041 sponds to the model proposed by Glaze et al.<sup>51</sup>. In the no-evidence-accumulation  
1042 model (M5), perceptual decisions depend only on likelihood information (flat  
1043 priors).**

1044 **8.2 Figure 2**



1045 **Figure 2. Internal and external modes in human perceptual decision-making.**

1046 A. In humans, perception was stimulus-congruent in  $73.46\% \pm 0.15\%$  (in red) and history-congruent in  $52.7\% \pm 0.12\%$  of trials (in blue; upper panel). History-congruent perceptual choices were more frequent when perception was stimulus-incongruent (i.e., on *error* trials; lower panel), indicating that history effects impair performance in randomized psychophysical designs.

1047 B. Relative to randomly permuted data, we found highly significant autocorrelations of stimulus-congruence and history-congruence (dots indicate intercepts  $\neq 0$  in trial-wise linear mixed effects modeling at  $p < 0.05$ ). Across trials, the autocorrelation coefficients were best fit by an exponential function (adjusted  $R^2$  for stimulus-congruence: 0.53; history-congruence: 0.72) as compared to a linear function (adjusted  $R^2$  for stimulus-congruence: 0.53; history-congruence: 0.51), decaying at a rate of  $\gamma = -1.92 \times 10^{-3} \pm 4.5 \times 10^{-4}$  ( $T(6.88 \times 10^4)$ )

<sub>1058</sub>  $= -4.27$ ,  $p = 1.98 \times 10^{-5}$ ) for stimulus-congruence and at a rate of  $\gamma = -6.11 \times 10^{-3} \pm$   
<sub>1059</sub>  $5.69 \times 10^{-4}$  ( $T(6.75 \times 10^4) = -10.74$ ,  $p = 7.18 \times 10^{-27}$ ) for history-congruence.

<sub>1060</sub> C. Here, we depict the number of consecutive trials at which autocorrelation coefficients  
<sub>1061</sub> exceeded the respective autocorrelation of randomly permuted data within individual partici-  
<sub>1062</sub> pants. For stimulus-congruence (upper panel), the lag of positive autocorrelation amounted  
<sub>1063</sub> to  $3.24 \pm 2.39 \times 10^{-3}$  on average, showing a peak at trial  $t+1$  after the index trial. For  
<sub>1064</sub> history-congruence (lower panel), the lag of positive autocorrelation amounted to  $4.87 \pm$   
<sub>1065</sub>  $3.36 \times 10^{-3}$  on average, peaking at trial  $t+2$  after the index trial.

<sub>1066</sub> D. The smoothed probabilities of stimulus- and history-congruence (sliding windows of  $\pm 5$   
<sub>1067</sub> trials) fluctuated as a **scale-invariant process with a 1/f power law**, i.e., at power  
<sub>1068</sub> densities that were inversely proportional to the frequency.

<sub>1069</sub> E. The distribution of phase shift between fluctuations in stimulus- and history-congruence  
<sub>1070</sub> peaked at half a cycle ( $\pi$  denoted by dotted line).

<sub>1071</sub> F. The average squared coherence between fluctuations in stimulus- and history-congruence  
<sub>1072</sub> (black dotted line) amounted to  $6.49 \pm 2.07 \times 10^{-3}\%$

<sub>1073</sub> G. We observed faster RTs for both stimulus-congruence (as opposed to stimulus-incongruence,  
<sub>1074</sub>  $\beta = -0.14 \pm 1.6 \times 10^{-3}$ ,  $T(1.99 \times 10^6) = -85.84$ ,  $p < 2.2 \times 10^{-308}$ ) and history-congruence  
<sub>1075</sub> ( $\beta = -9.56 \times 10^{-3} \pm 1.37 \times 10^{-3}$ ,  $T(1.98 \times 10^6) = -6.97$ ,  $p = 3.15 \times 10^{-12}$ ).

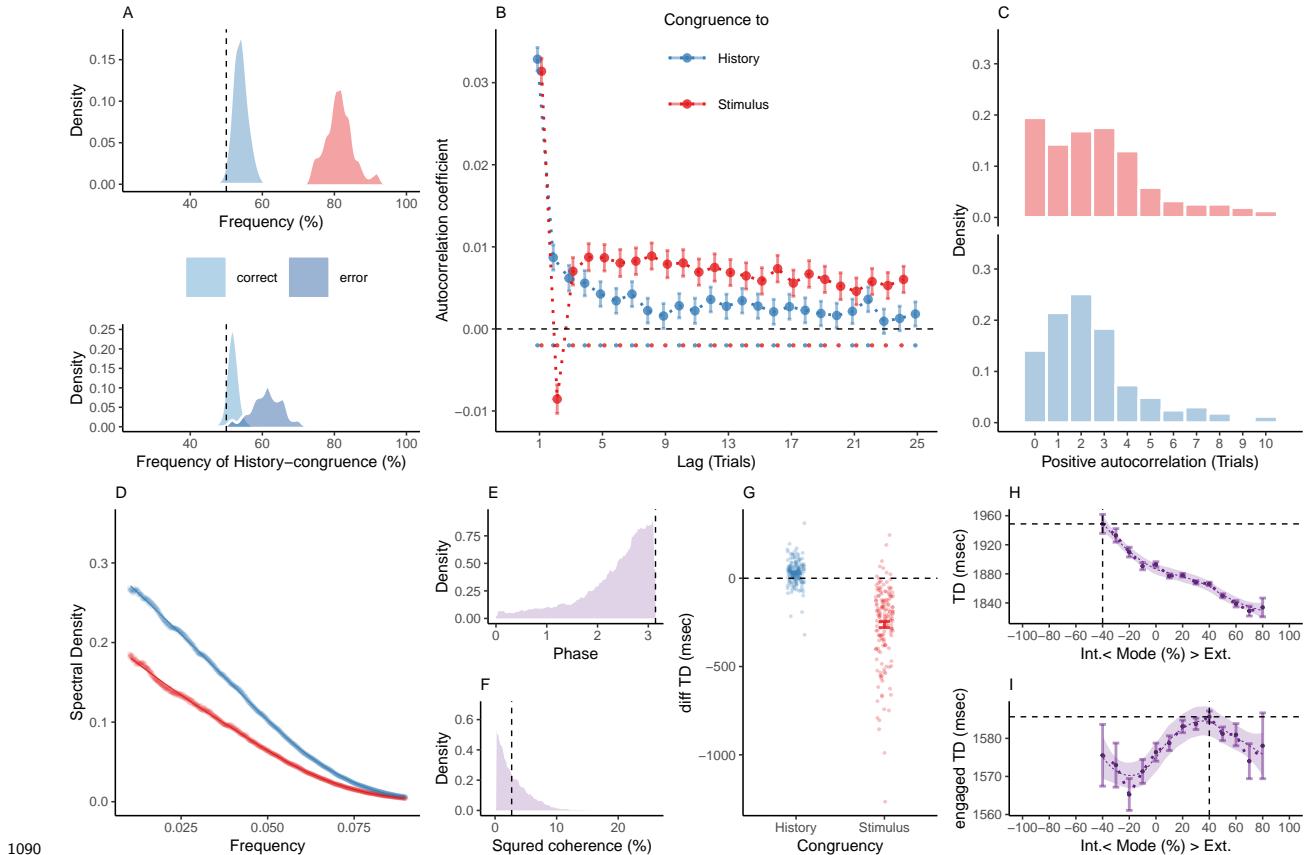
<sub>1076</sub> H. The mode of perceptual processing (i.e., the difference between the smoothed probability  
<sub>1077</sub> of stimulus- vs. history-congruence) showed a quadratic relationship to RTs, with faster  
<sub>1078</sub> RTs for stronger biases toward both external sensory information and internal predictions  
<sub>1079</sub> provided by perceptual history ( $\beta_2 = -19.86 \pm 0.52$ ,  $T(1.98 \times 10^6) = -38.43$ ,  $p = 5 \times 10^{-323}$ ).  
<sub>1080</sub> The horizontal and vertical dotted lines indicate maximum RT and the associated mode,  
<sub>1081</sub> respectively.

<sub>1082</sub> I. Confidence was enhanced for both stimulus-congruence (as opposed to stimulus-

1083 incongruence,  $\beta = 0.48 \pm 1.38 \times 10^{-3}$ ,  $T(2.06 \times 10^6) = 351.54$ ,  $p < 2.2 \times 10^{-308}$ ) and  
 1084 history-congruence ( $\beta = 0.04 \pm 1.18 \times 10^{-3}$ ,  $T(2.06 \times 10^6) = 36.85$ ,  $p = 3.25 \times 10^{-297}$ ).

1085 J. In analogy to RTs, we found a quadratic relationship between the mode of perceptual  
 1086 processing and confidence, which increased when both externally- and internally-biased modes  
 1087 grew stronger ( $\beta_2 = 39.3 \pm 0.94$ ,  $T(2.06 \times 10^6) = 41.95$ ,  $p < 2.2 \times 10^{-308}$ ). The horizontal  
 1088 and vertical dotted lines indicate minimum confidence and the associated mode, respectively.

### 1089 8.3 Figure 3



1091 **Figure 3. Internal and external modes in mouse perceptual decision-making.**

1092 A. In mice,  $81.37\% \pm 0.3\%$  of trials were stimulus-congruent (in red) and  $54.03\% \pm 0.17\%$  of  
 1093 trials were history-congruent (in blue; upper panel). History-congruent perceptual choices  
 1094 were not a consequence of the experimental design, but a source of error, as they were more  
 1095 frequent on stimulus-incongruent trials (lower panel).

1096 B. Relative to randomly permuted data, we found highly significant autocorrelations of  
1097 stimulus-congruence and history-congruence (dots indicate intercepts  $\neq 0$  in trial-wise linear  
1098 mixed effects modeling at  $p < 0.05$ ). Please note that the negative autocorrelation of  
1099 stimulus-congruence at trial 2 was a consequence of the experimental design (Supplemental  
1100 Figure 2D-F). As in humans, autocorrelation coefficients were best fit by an exponential  
1101 function (adjusted  $R^2$  for stimulus-congruence: 0.44; history-congruence: 0.52) as compared  
1102 to a linear function (adjusted  $R^2$  for stimulus-congruence:  $3.16 \times 10^{-3}$ ; history-congruence:  
1103 0.26), decaying at a rate of  $\gamma = -6.2 \times 10^{-4} \pm 5.93 \times 10^{-4}$  ( $T(3.55 \times 10^4) = -1.05$ ,  $p = 0.3$ )  
1104 for stimulus-congruence and at a rate of  $\gamma = -6.7 \times 10^{-3} \pm 5.94 \times 10^{-4}$  ( $T(3.69 \times 10^4) =$   
1105  $-11.27$ ,  $p = 2.07 \times 10^{-29}$ ) for history-congruence.

1106 C. For stimulus-congruence (upper panel), the lag of positive autocorrelation was longer in  
1107 comparison to humans ( $4.59 \pm 0.06$  on average). For history-congruence (lower panel), the  
1108 lag of positive autocorrelation was slightly shorter relative to humans ( $2.58 \pm 0.01$  on average,  
1109 peaking at trial  $t+2$  after the index trial).

1110 D. In mice, the dynamic probabilities of stimulus- and history-congruence (sliding windows  
1111 of  $\pm 5$  trials) fluctuated as **a scale-invariant process with a 1/f power law**.

1112 E. The distribution of phase shift between fluctuations in stimulus- and history-congruence  
1113 peaked at half a cycle ( $\pi$  denoted by dotted line).

1114 F. The average squared coherence between fluctuations in stimulus- and history-congruence  
1115 (black dotted line) amounted to  $3.45 \pm 0.01\%$ .

1116 G. We observed shorter trial durations (TDs) for stimulus-congruence (as opposed to stimulus-  
1117 incongruence,  $\beta = -1.12 \pm 8.53 \times 10^{-3}$ ,  $T(1.34 \times 10^6) = -131.78$ ,  $p < 2.2 \times 10^{-308}$ ), but  
1118 longer TDs for history-congruence ( $\beta = 0.06 \pm 6.76 \times 10^{-3}$ ,  $T(1.34 \times 10^6) = 8.52$ ,  $p =$   
1119  $1.58 \times 10^{-17}$ ).

1120 H. TDs decreased monotonically for stronger biases toward external mode ( $\beta_1 = -4.16 \times 10^4$   
1121  $\pm 1.29 \times 10^3$ ,  $T(1.35 \times 10^6) = -32.31$ ,  $p = 6.03 \times 10^{-229}$ ). The horizontal and vertical dotted

<sub>1122</sub> lines indicate maximum TD and the associated mode, respectively.

<sub>1123</sub> I. For TDs that differed from the median TD by no more than  $1.5 \times$  MAD (median absolute

<sub>1124</sub> distance<sup>49</sup>), mice exhibited a quadratic component in the relationship between the mode of

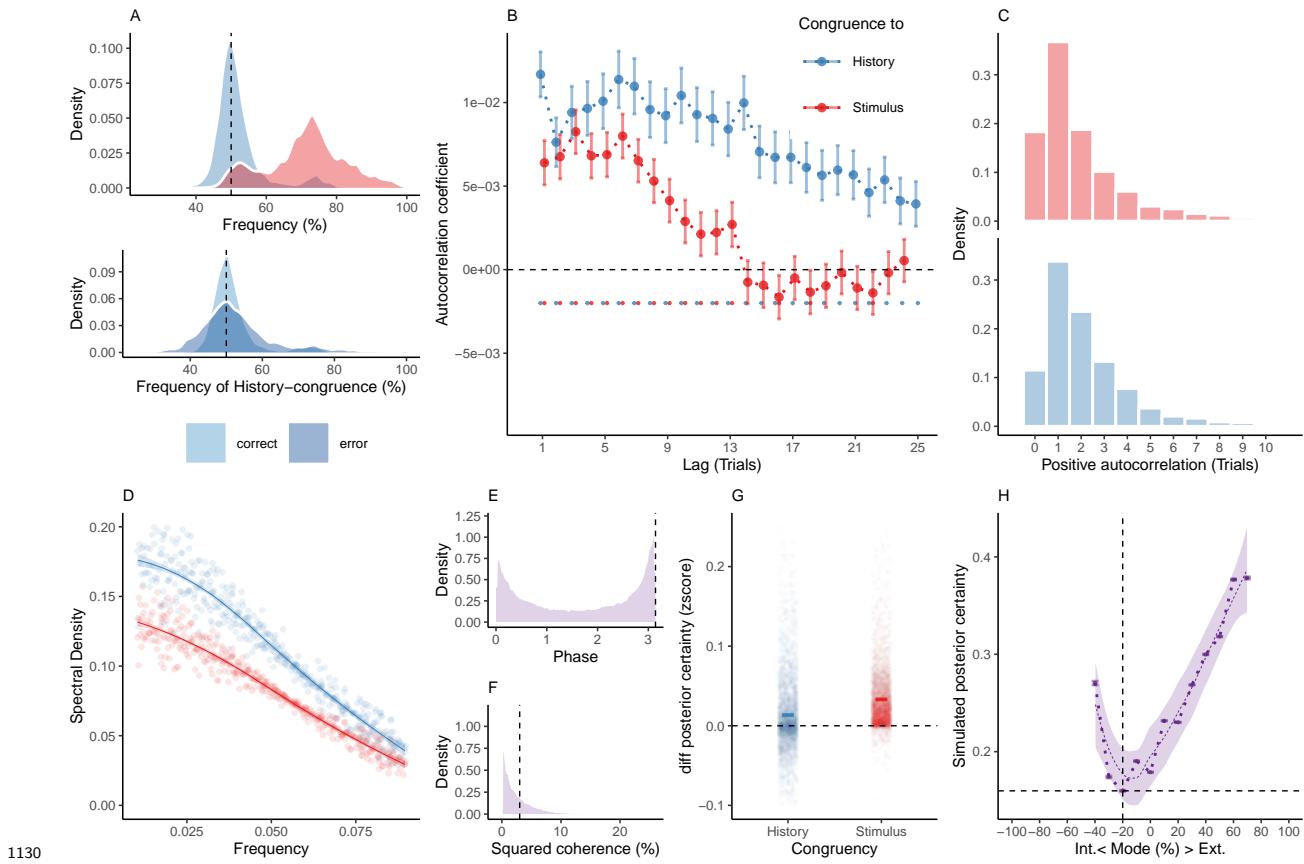
<sub>1125</sub> sensory processing and TDs ( $\beta_2 = -1.97 \times 10^3 \pm 843.74$ ,  $T(1.19 \times 10^6) = -2.34$ ,  $p = 0.02$ ).

<sub>1126</sub> This explorative post-hoc analysis focuses on trials at which mice engage more swiftly with

<sub>1127</sub> the experimental task. The horizontal and vertical dotted lines indicate maximum TD and

<sub>1128</sub> the associated mode, respectively.

1129 **8.4 Figure 4**



1130 **Figure 4. Internal and external modes in simulated perceptual decision-making.**

1131 A. Simulated perceptual choices were stimulus-congruent in  $71.36\% \pm 0.17\%$  (in red) and  
 1132 history-congruent in  $51.99\% \pm 0.11\%$  of trials (in blue;  $T(4.32 \times 10^3) = 17.42$ ,  $p = 9.89 \times 10^{-66}$ ;  
 1133 upper panel). Due to the competition between stimulus- and history-congruence, history-  
 1134 congruent perceptual choices were more frequent when perception was stimulus-incongruent  
 1135 (i.e., on *error* trials;  $T(4.32 \times 10^3) = 11.19$ ,  $p = 1.17 \times 10^{-28}$ ; lower panel) and thus impaired  
 1136 performance in the randomized psychophysical design simulated here.  
 1137

1138 B. At the simulated group level, we found significant autocorrelations in both stimulus-  
 1139 congruence (13 consecutive trials) and history-congruence (30 consecutive trials).

1140 C. On the level of individual simulated participants, autocorrelation coefficients exceeded the  
 1141 autocorrelation coefficients of randomly permuted data within a lag of  $2.46 \pm 1.17 \times 10^{-3}$

<sub>1142</sub> trials for stimulus-congruence and  $4.24 \pm 1.85 \times 10^{-3}$  trials for history-congruence.

<sub>1143</sub> D. The smoothed probabilities of stimulus- and history-congruence (sliding windows of  $\pm 5$   
<sub>1144</sub> trials) fluctuated as a **scale-invariant process with a  $1/f$  power law**, i.e., at power  
<sub>1145</sub> densities that were inversely proportional to the frequency (power  $\sim 1/f^\beta$ ; stimulus-congruence:  
<sub>1146</sub>  $\beta = -0.81 \pm 1.18 \times 10^{-3}$ ,  $T(1.92 \times 10^5) = -687.58$ ,  $p < 2.2 \times 10^{-308}$ ; history-congruence:  $\beta$   
<sub>1147</sub>  $= -0.83 \pm 1.27 \times 10^{-3}$ ,  $T(1.92 \times 10^5) = -652.11$ ,  $p < 2.2 \times 10^{-308}$ ).

<sub>1148</sub> E. The distribution of phase shift between fluctuations in simulated stimulus- and history-  
<sub>1149</sub> congruence peaked at half a cycle ( $\pi$  denoted by dotted line). The dynamic probabilities of  
<sub>1150</sub> simulated stimulus- and history-congruence were therefore were strongly anti-correlated ( $\beta =$   
<sub>1151</sub>  $-0.03 \pm 8.22 \times 10^{-4}$ ,  $T(2.12 \times 10^6) = -40.52$ ,  $p < 2.2 \times 10^{-308}$ ).

<sub>1152</sub> F. The average squared coherence between fluctuations in simulated stimulus- and history-  
<sub>1153</sub> congruence (black dotted line) amounted to  $6.49 \pm 2.07 \times 10^{-3}\%$ .

<sub>1154</sub> G. Simulated confidence was enhanced for stimulus-congruence ( $\beta = 0.03 \pm 1.71 \times 10^{-4}$ ,  
<sub>1155</sub>  $T(2.03 \times 10^6) = 178.39$ ,  $p < 2.2 \times 10^{-308}$ ) and history-congruence ( $\beta = 0.01 \pm 1.5 \times 10^{-4}$ ,  
<sub>1156</sub>  $T(2.03 \times 10^6) = 74.18$ ,  $p < 2.2 \times 10^{-308}$ ).

<sub>1157</sub> H. In analogy to humans, the simulated data showed a quadratic relationship between the  
<sub>1158</sub> mode of perceptual processing and posterior certainty, which increased for stronger external  
<sub>1159</sub> and internal biases ( $\beta_2 = 31.03 \pm 0.15$ ,  $T(2.04 \times 10^6) = 205.95$ ,  $p < 2.2 \times 10^{-308}$ ). The  
<sub>1160</sub> horizontal and vertical dotted lines indicate minimum posterior certainty and the associated  
<sub>1161</sub> mode, respectively.

<sub>1162</sub> 9 Supplemental Items

<sub>1163</sub> 9.1 Internal mode processing is driven by choice history as opposed  
<sub>1164</sub> to stimulus history

<sub>1165</sub> The main manuscript reports the effects of perceptual history, which we defined  
<sub>1166</sub> as the impact of the choice at the preceding trial on the choice at the current trial  
<sub>1167</sub> (henceforth *choice history*). *Stimulus history*, which is defined as the impact of  
<sub>1168</sub> the stimulus presented at the preceding trial on the choice at the present trial,  
<sub>1169</sub> represents an alternative approach to this. Here, we compare the effects of choice  
<sub>1170</sub> history to the effects of stimulus history.

<sub>1171</sub> We observed a significant bias toward stimulus history (humans:  $49.76\% \pm 0.1\%$   
<sub>1172</sub> of trials,  $\beta = 1.26 \pm 0.94$ ,  $T(373.62) = 1.34$ ,  $p = 0.18$ ; mice:  $51.11\% \pm 0.08\%$  of  
<sub>1173</sub> trials,  $T(164) = 13.4$ ,  $p = 3.86 \times 10^{-28}$ ). The bias toward stimulus history was  
<sub>1174</sub> smaller than the bias toward choice history (humans:  $\beta = -3.53 \pm 0.5$ ,  $T(66.53)$   
<sub>1175</sub>  $= -7.01$ ,  $p = 1.48 \times 10^{-9}$ ; mice:  $T(164) = -17.21$ ,  $p = 1.43 \times 10^{-38}$ ).

<sub>1176</sub> The attraction of choices toward both preceding choices and stimuli is expected,  
<sub>1177</sub> as perception was *stimulus-congruent* on approximately 75% of trials, causing  
<sub>1178</sub> choices and stimuli to be highly correlated. We therefore compared the effects  
<sub>1179</sub> of choice history and stimulus history after *stimulus-incongruent* (i.e., *error*)  
<sub>1180</sub> trials, since those trials lead to opposite predictions regarding the perceptual  
<sub>1181</sub> choice at the subsequent trial.

<sub>1182</sub> As expected from the findings presented in the main manuscript, perceptual  
<sub>1183</sub> choices were attracted toward perceptual choices when the inducing trial was  
<sub>1184</sub> stimulus-incongruent (i.e., a positive effect of choice history; humans:  $\beta = 0.19 \pm$   
<sub>1185</sub>  $1.4 \times 10^{-4}$ ,  $z = 1.36 \times 10^3$ ,  $p < 2.2 \times 10^{-308}$ ; mice:  $\beta = 0.92 \pm 0.01$ ,  $z = 88.82$ ,  $p <$   
<sub>1186</sub>  $2.2 \times 10^{-308}$ ). By contrast, perceptual choices tended to be repelled away from

1187 the stimulus presented at preceding stimulus-incongruent trial (i.e., a negative  
1188 effect of stimulus history; humans:  $\beta = -0.19 \pm 0.01$ ,  $z = -16.47$ ,  $p = 5.99 \times 10^{-61}$ :  
1189 mice:  $\beta = -0.92 \pm 0.01$ ,  $z = -88.76$ ,  $p < 2.2 \times 10^{-308}$ ). This repulsion of choices  
1190 away from stimuli presented at stimulus-incongruent trials confirmed that choices  
1191 (which are anti-correlated to stimuli at stimulus-incongruent trials) were the  
1192 primary driver of attracting serial effects in perception.

1193 In sum, the above results suggest that, in both humans and mice, serial depen-  
1194 dencies were better explained by the effects of choice history as opposed to the  
1195 effects of stimulus history. This aligns with a result recently published for the  
1196 IBL database, where mice were shown to follow an *action-kernel* as opposed to a  
1197 *stimulus-kernel* model when integrating information across trials<sup>81</sup>.

## 1198 9.2 Fluctuations between internal and external mode modulate 1199 perceptual performance beyond the effect of general response 1200 biases

1201 The hypothesis that perception cycles through opposing internally- and externally-biased  
1202 modes is motivated by the assumption that recurring intervals of stronger perceptual history  
1203 temporally reduce the participants' sensitivity to external information. Importantly, the  
1204 history-dependent biases that characterize internal mode processing must be differentiated  
1205 from general response biases. In binary perceptual decision-making, general response biases  
1206 are defined by a propensity to choose one of the two outcomes more often than the alternative.  
1207 Indeed, human participants selected the more frequent of the two possible outcomes in 58.71%  
1208  $\pm 0.22\%$  of trials, and mice selected the more frequent of the two possible outcomes in 54.6%  
1209  $\pm 0.3\%$  of trials.

1210 Two caveats have to be considered to make sure that the effect of history-congruence is  
1211 distinct from the effect of general response biases. First, history-congruent states become

more likely for larger response biases that cause an increasing imbalance in the likelihood of the two outcomes (humans:  $\beta = 0.24 \pm 6.93 \times 10^{-4}$ ,  $T(2.09 \times 10^6) = 342.43$ ,  $p < 2.2 \times 10^{-308}$ ; mice:  $\beta = 0.15 \pm 8.25 \times 10^{-4}$ ,  $T(1.32 \times 10^6) = 181.93$ ,  $p < 2.2 \times 10^{-308}$ ). One may thus ask whether the autocorrelation of history-congruence could be entirely driven by general response biases.

Importantly, our autocorrelation analyses account for general response biases by computing group-level autocorrelations (Figure 2-4B) relative to randomly permuted data (i.e., by subtracting the autocorrelation of randomly permuted data from the raw autocorrelation curve). This precludes that general response biases contribute to the observed autocorrelation of history-congruence (see Supplemental Figure S5 for a visualization of the correction procedure for simulated data with general response biases ranging from 60 to 90%).

Second, it may be argued that fluctuations in perceptual performance may be solely driven by ongoing changes in the strength of general response biases. To assess the links between dynamic fluctuations in stimulus-congruence on the one hand and history-congruence as well as general response bias on the other hand, we computed all variables as dynamic probabilities in sliding windows of  $\pm 5$  trials (Figure 1C). Linear mixed effects modeling indicated that fluctuations in history-congruent biases were larger in amplitude than the corresponding fluctuations in general response biases in humans ( $\beta_0 = 0.03 \pm 7.34 \times 10^{-3}$ ,  $T(64.94) = 4.46$ ,  $p = 3.28 \times 10^{-5}$ ), but slightly smaller in mice ( $\beta_0 = -5.26 \times 10^{-3} \pm 4.67 \times 10^{-4}$ ,  $T(2.12 \times 10^3) = -11.28$ ,  $p = 1.02 \times 10^{-28}$ ).

Crucially, ongoing fluctuations in history-congruence had a significant negative effect on stimulus-congruence (humans:  $\beta_1 = -0.05 \pm 5.63 \times 10^{-4}$ ,  $T(2.1 \times 10^6) = -84.21$ ,  $p < 2.2 \times 10^{-308}$ ; mice:  $\beta_1 = -0.12 \pm 7.17 \times 10^{-4}$ ,  $T(1.34 \times 10^6) = -168.39$ ,  $p < 2.2 \times 10^{-308}$ ) beyond the effect of ongoing changes in general response biases (humans:  $\beta_2 = -0.06 \pm 5.82 \times 10^{-4}$ ,  $T(2.1 \times 10^6) = -103.51$ ,  $p < 2.2 \times 10^{-308}$ ; mice:  $\beta_2 = -0.03 \pm 6.94 \times 10^{-4}$ ,  $T(1.34 \times 10^6) = -48.14$ ,  $p < 2.2 \times 10^{-308}$ ). In sum, the above control analyses confirmed

1238 that, in both humans and mice, the observed influence of preceding choices on perceptual  
1239 decision-making cannot be reduced to general response biases.

1240 **9.3 Internal mode is characterized by lower thresholds as well as**  
1241 **by history-dependent changes in biases and lapses**

1242 Random or stereotypical responses may provide an alternative explanation for the reduced  
1243 sensitivity to external sensory information that we attribute to internal mode processing. To  
1244 test this hypothesis, we asked whether history-independent changes in biases and lapses may  
1245 provide an alternative explanation of the reduced sensitivity during internal mode.

1246 To this end, we estimated full and history-conditioned psychometric curves to investigate how  
1247 internal and external mode relate to biases (i.e., the horizontal position of the psychometric  
1248 curve), lapses (i.e., the asymptotes of the psychometric curve) and thresholds (i.e., 1/sensitivity,  
1249 estimated from the slope of the psychometric curve). We used a maximum likelihood procedure  
1250 to predict trial-wise choices  $y$  ( $y = 0$  and  $y = 1$  for outcomes A and B respectively) from  
1251 the choice probabilities  $y_p$ .  $y_p$  was computed from the difficulty-weighted inputs  $s_w$  via a  
1252 parametric error function defined by the parameters  $\gamma$  (lower lapse),  $\delta$  (upper lapse),  $\mu$  (bias)  
1253 and  $t$  (threshold; see Methods for details):

$$y_p = \gamma + (1 - \gamma - \delta) * (\text{erf}(\frac{s_w + \mu}{t}) + 1)/2 \quad (18)$$

1254 Under our main hypothesis that periodic reductions in sensitivity to external information  
1255 are driven by increases in the impact of perceptual history, one would expect (i) a history-  
1256 dependent increase in biases and lapses (effects of perceptual history), and (ii), a history-  
1257 independent increase in threshold (reduced sensitivity to external information). Conversely,  
1258 if what we identified as internal mode processing was in fact driven by random choices, one  
1259 would expect (i), a history-independent increase in lapses (choice randomness), (ii), no change

1260 in bias (no effect of perceptual history), and (iii), reduced thresholds (reduced sensitivity to  
1261 external information).

1262 **9.3.1 Humans**

1263 Across all data provided by the Confidence database<sup>20</sup> (i.e., irrespective of the preceding  
1264 perceptual choice  $y_{t-1}$ ), biases  $\mu$  were distributed around zero ( $-0.05 \pm 0.03$ ;  $\beta_0 = 7.37 \times 10^{-3}$   
1265  $\pm 0.09$ ,  $T(36.8) = 0.08$ ,  $p = 0.94$ ; Supplemental Figure 6A-B, upper panel). When conditioned  
1266 on perceptual history, biases  $\mu$  varied according to the preceding perceptual choice, with  
1267 negative biases for  $y_{t-1} = 0$  ( $-0.22 \pm 0.04$ ;  $\beta_0 = 0.56 \pm 0.12$ ,  $T(43.39) = 4.6$ ,  $p = 3.64 \times 10^{-5}$ ;  
1268 Supplemental Figure 6A-B, upper panel) and positive biases for  $y_{t-1} = 1$  ( $0.29 \pm 0.03$ ;  $\beta_0$   
1269  $= 0.56 \pm 0.12$ ,  $T(43.39) = 4.6$ ,  $p = 3.64 \times 10^{-5}$ ; Supplemental Figure 6A-B, lower panel).  
1270 Absolute biases  $|\mu|$  were larger in internal mode ( $1.84 \pm 0.03$ ) as compared to external  
1271 mode ( $0.86 \pm 0.02$ ;  $\beta_0 = -0.62 \pm 0.07$ ,  $T(45.62) = -8.38$ ,  $p = 8.59 \times 10^{-11}$ ; controlling for  
1272 differences in lapses and thresholds).

1273 Lower and upper lapses amounted to  $\gamma = 0.13 \pm 2.83 \times 10^{-3}$  and  $\delta = 0.1 \pm 2.45 \times 10^{-3}$   
1274 (Supplemental Figure 6A, C and D). Lapses were larger in internal mode ( $\gamma = 0.17 \pm$   
1275  $3.52 \times 10^{-3}$ ,  $\delta = 0.14 \pm 3.18 \times 10^{-3}$ ) as compared to external mode ( $\gamma = 0.1 \pm 2.2 \times 10^{-3}$ ,  $\delta =$   
1276  $0.08 \pm 2 \times 10^{-3}$ ;  $\beta_0 = -0.05 \pm 5.73 \times 10^{-3}$ ,  $T(47.03) = -9.11$ ,  $p = 5.94 \times 10^{-12}$ ; controlling  
1277 for differences in biases and thresholds).

1278 Conditioning on the previous perceptual choice revealed that the between-mode difference in  
1279 lapse was not general, but depended on perceptual history: For  $y_{t-1} = 0$ , only higher lapses  $\delta$   
1280 differed between internal and external mode ( $\beta_0 = -0.1 \pm 9.58 \times 10^{-3}$ ,  $T(36.87) = -10.16$ ,  $p$   
1281  $= 3.06 \times 10^{-12}$ ), whereas lower lapses  $\gamma$  did not ( $\beta_0 = 0.01 \pm 7.77 \times 10^{-3}$ ,  $T(33.1) = 1.61$ ,  $p$   
1282  $= 0.12$ ). Vice versa, for  $y_{t-1} = 1$ , lower lapses  $\gamma$  differed between internal and external mode  
1283 ( $\beta_0 = -0.11 \pm 0.01$ ,  $T(40.11) = -9.59$ ,  $p = 6.14 \times 10^{-12}$ ), whereas higher lapses  $\delta$  did not  
1284 ( $\beta_0 = 0.01 \pm 7.74 \times 10^{-3}$ ,  $T(33.66) = 1.58$ ,  $p = 0.12$ ).

1285 Thresholds  $t$  were estimated at  $3 \pm 0.06$  (Supplemental Figure 6A and E). Thresholds  $t$  were  
1286 larger in internal mode ( $3.66 \pm 0.09$ ) as compared to external mode ( $2.02 \pm 0.03$ ;  $\beta_0 = -1.77$   
1287  $\pm 0.25$ ,  $T(50.45) = -7.14$ ,  $p = 3.48 \times 10^{-9}$ ; controlling for differences in biases and lapses).  
1288 In contrast to the bias  $\mu$  and the lapse rates  $\gamma$  and  $\delta$ , thresholds  $t$  were not modulated by  
1289 perceptual history ( $\beta_0 = 0.04 \pm 0.06$ ,  $T(2.97 \times 10^3) = 0.73$ ,  $p = 0.47$ ).

1290 **9.3.2 Mice**

1291 When estimated based on the full dataset provided in the IBL database<sup>21</sup> (i.e., irrespective  
1292 of the preceding perceptual choice  $y_{t-1}$ ), biases  $\mu$  were distributed around zero ( $3.87 \times 10^{-3}$   
1293  $\pm 9.81 \times 10^{-3}$ ;  $T(164) = 0.39$ ,  $p = 0.69$ ; Supplemental Figure 7A-B, upper panel). When  
1294 conditioned on the preceding perceptual choice, biases were negative for  $y_{t-1} = 0$  ( $-0.02$   
1295  $\pm 8.7 \times 10^{-3}$ ;  $T(164) = -1.99$ ,  $p = 0.05$ ; Supplemental Figure 7A-B, middle panel) and  
1296 positive for  $y_{t-1} = 1$  ( $0.02 \pm 9.63 \times 10^{-3}$ ;  $T(164) = 1.91$ ,  $p = 0.06$ ; Supplemental Figure  
1297 7A-B, lower panel). As in humans, mice showed larger biases during internal mode ( $0.14$   
1298  $\pm 7.96 \times 10^{-3}$ ) as compared to external mode ( $0.07 \pm 8.7 \times 10^{-3}$ ;  $\beta_0 = -0.18 \pm 0.03$ ,  $T =$   
1299  $-6.38$ ,  $p = 1.77 \times 10^{-9}$ ; controlling for differences in lapses and thresholds).

1300 Lower and upper lapses amounted to  $\gamma = 0.1 \pm 4.35 \times 10^{-3}$  and  $\delta = 0.11 \pm 4.65 \times 10^{-3}$   
1301 (Supplemental Figure 7A, C and D). Lapse rates were higher in internal mode ( $\gamma = 0.15 \pm$   
1302  $5.14 \times 10^{-3}$ ,  $\delta = 0.16 \pm 5.79 \times 10^{-3}$ ) as compared to external mode ( $\gamma = 0.06 \pm 3.11 \times 10^{-3}$ ,  
1303  $\delta = 0.07 \pm 3.34 \times 10^{-3}$ ;  $\beta_0 = -0.11 \pm 4.39 \times 10^{-3}$ ,  $T = -24.8$ ,  $p = 4.91 \times 10^{-57}$ ; controlling  
1304 for differences in biases and thresholds).

1305 For  $y_{t-1} = 0$ , the difference between internal and external mode was more pronounced for  
1306 higher lapses  $\delta$  ( $T(164) = 21.44$ ,  $p = 1.93 \times 10^{-49}$ ). Conversely, for  $y_{t-1} = 1$ , the difference  
1307 between internal and external mode was more pronounced for lower lapses  $\gamma$  ( $T(164) =$   
1308  $-18.24$ ,  $p = 2.68 \times 10^{-41}$ ). In contrast to the human data, higher lapses  $\delta$  and lower lapses  
1309  $\gamma$  were significantly elevated during internal mode irrespective of the preceding perceptual  
1310 choice (higher lapses  $\delta$  for  $y_{t-1} = 1$ :  $T(164) = -2.65$ ,  $p = 8.91 \times 10^{-3}$ ; higher lapses  $\delta$  for

<sub>1311</sub>  $y_{t-1} = 0$ :  $T(164) = -28.29$ ,  $p = 5.62 \times 10^{-65}$ ; lower lapses  $\gamma$  for  $y_{t-1} = 1$ :  $T(164) = -32.44$ ,  $p$   
<sub>1312</sub>  $= 2.92 \times 10^{-73}$ ; lower lapses  $\gamma$  for  $y_{t-1} = 0$ :  $T(164) = -2.5$ ,  $p = 0.01$ .

<sub>1313</sub> In mice, thresholds  $t$  amounted to  $0.15 \pm 6.52 \times 10^{-3}$  (Supplemental Figure 7A and E) and  
<sub>1314</sub> were higher in internal mode ( $0.27 \pm 0.01$ ) as compared to external mode ( $0.09 \pm 4.44 \times 10^{-3}$ ;  
<sub>1315</sub>  $\beta_0 = -0.28 \pm 0.04$ ,  $T = -7.26$ ,  $p = 1.53 \times 10^{-11}$ ; controlling for differences in biases and  
<sub>1316</sub> lapses). Thresholds  $t$  were not modulated by perceptual history ( $T(164) = 0.94$ ,  $p = 0.35$ ).

<sub>1317</sub> In sum, the above analyses showed that, in both humans and mice, internal and external  
<sub>1318</sub> mode differ with respect to biases, lapses and thresholds. Internally-biased processing was  
<sub>1319</sub> characterized by higher thresholds, indicating a reduced sensitivity to sensory information,  
<sub>1320</sub> as well as by larger biases and lapses. Importantly, between-mode differences in biases and  
<sub>1321</sub> lapses strongly depended on perceptual history. This confirmed that internal mode processing  
<sub>1322</sub> cannot be explained solely on the ground of a general (i.e., history-independent) increase in  
<sub>1323</sub> lapses or bias indicative of random or stereotypical responses.

## <sub>1324</sub> **9.4 Internal mode processing can not be reduced to insufficient 1325 task familiarity**

<sub>1326</sub> It may be assumed that participants tend to repeat preceding choices when they are not yet  
<sub>1327</sub> familiar with the experimental task, leading to history-congruent choices that are caused by  
<sub>1328</sub> insufficient training. To assess this alternative explanation, we contrasted the correlates of  
<sub>1329</sub> bimodal inference with training effects in humans and mice.

### <sub>1330</sub> **9.4.1 Humans**

<sub>1331</sub> In the Confidence database<sup>20</sup>, training effects were visible from RTs that were shortened by  
<sub>1332</sub> increasing exposure to the task ( $\beta = -7.53 \times 10^{-5} \pm 6.32 \times 10^{-7}$ ,  $T(1.81 \times 10^6) = -119.15$ ,  $p$   
<sub>1333</sub>  $< 2.2 \times 10^{-308}$ ). Intriguingly, however, history-congruent choices became more frequent with  
<sub>1334</sub> increased exposure to the task ( $\beta = 3.6 \times 10^{-5} \pm 2.54 \times 10^{-6}$ ,  $z = 14.19$ ,  $p = 10^{-45}$ ), speaking

<sub>1335</sub> against the proposition that insufficient training induces seriality in response behavior.

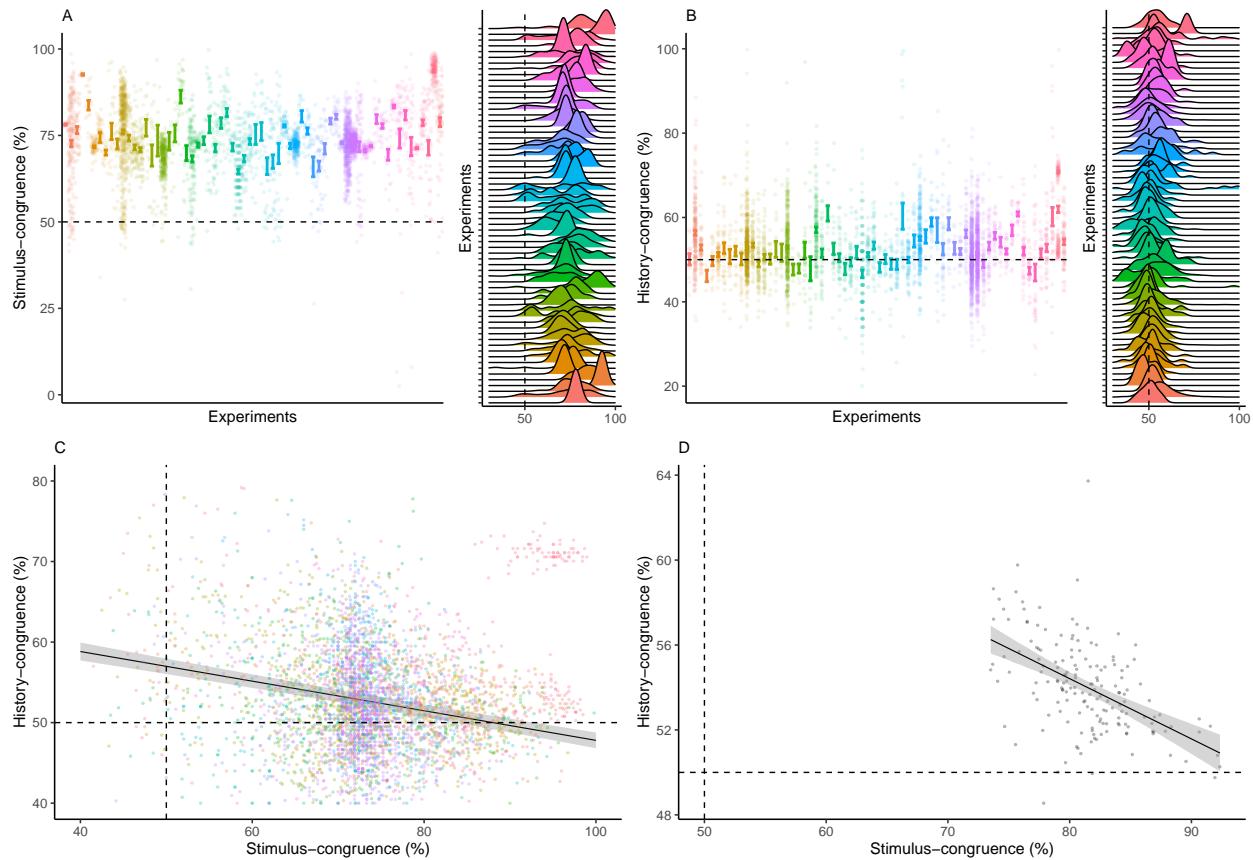
<sub>1336</sub> **9.4.2 Mice**

<sub>1337</sub> As in humans, it is an important caveat to consider whether the observed serial dependencies  
<sub>1338</sub> in mice reflect a phenomenon of perceptual inference, or, alternatively, an unspecific strategy  
<sub>1339</sub> that occurs at the level of reporting behavior. We reasoned that, if mice indeed tended to  
<sub>1340</sub> repeat previous choices as a general response pattern, history effects should decrease during  
<sub>1341</sub> training of the perceptual task. We therefore analyzed how stimulus- and history-congruent  
<sub>1342</sub> perceptual choices evolved across sessions in mice that, by the end of training, achieved  
<sub>1343</sub> proficiency (i.e., stimulus-congruence  $\geq 80\%$ ) in the *basic* task of the IBL dataset<sup>21</sup>.

<sub>1344</sub> Across sessions, we found that stimulus-congruent perceptual choices became more frequent  
<sub>1345</sub> ( $\beta = 0.34 \pm 7.13 \times 10^{-3}$ ,  $T(8.51 \times 10^3) = 47.66$ ,  $p < 2.2 \times 10^{-308}$ ) and TDs were progressively  
<sub>1346</sub> shortened ( $\beta = -22.14 \pm 17.06$ ,  $T(1.14 \times 10^3) = -1.3$ ,  $p < 2.2 \times 10^{-308}$ ). Crucially, the  
<sub>1347</sub> frequency of history-congruent perceptual choices also increased during training ( $\beta = 0.13 \pm$   
<sub>1348</sub>  $4.67 \times 10^{-3}$ ,  $T(8.4 \times 10^3) = 27.04$ ,  $p = 1.96 \times 10^{-154}$ ; Supplemental Figure S8).

<sub>1349</sub> Within individual session, longer task exposure was associated with an increase in history-  
<sub>1350</sub> congruence ( $\beta = 3.6 \times 10^{-5} \pm 2.54 \times 10^{-6}$ ,  $z = 14.19$ ,  $p = 10^{-45}$ ) and a decrease in TDs ( $\beta$   
<sub>1351</sub>  $= -0.1 \pm 3.96 \times 10^{-3}$ ,  $T(1.34 \times 10^6) = -24.99$ ,  $p = 9.45 \times 10^{-138}$ ). In sum, these findings  
<sub>1352</sub> strongly argue against the proposition that mice show biases toward perceptual history due  
<sub>1353</sub> to an unspecific response strategy.

1354 **9.5 Supplemental Figure S1**



1355 **1356 Supplemental Figure S1. Stimulus- and history-congruence.**

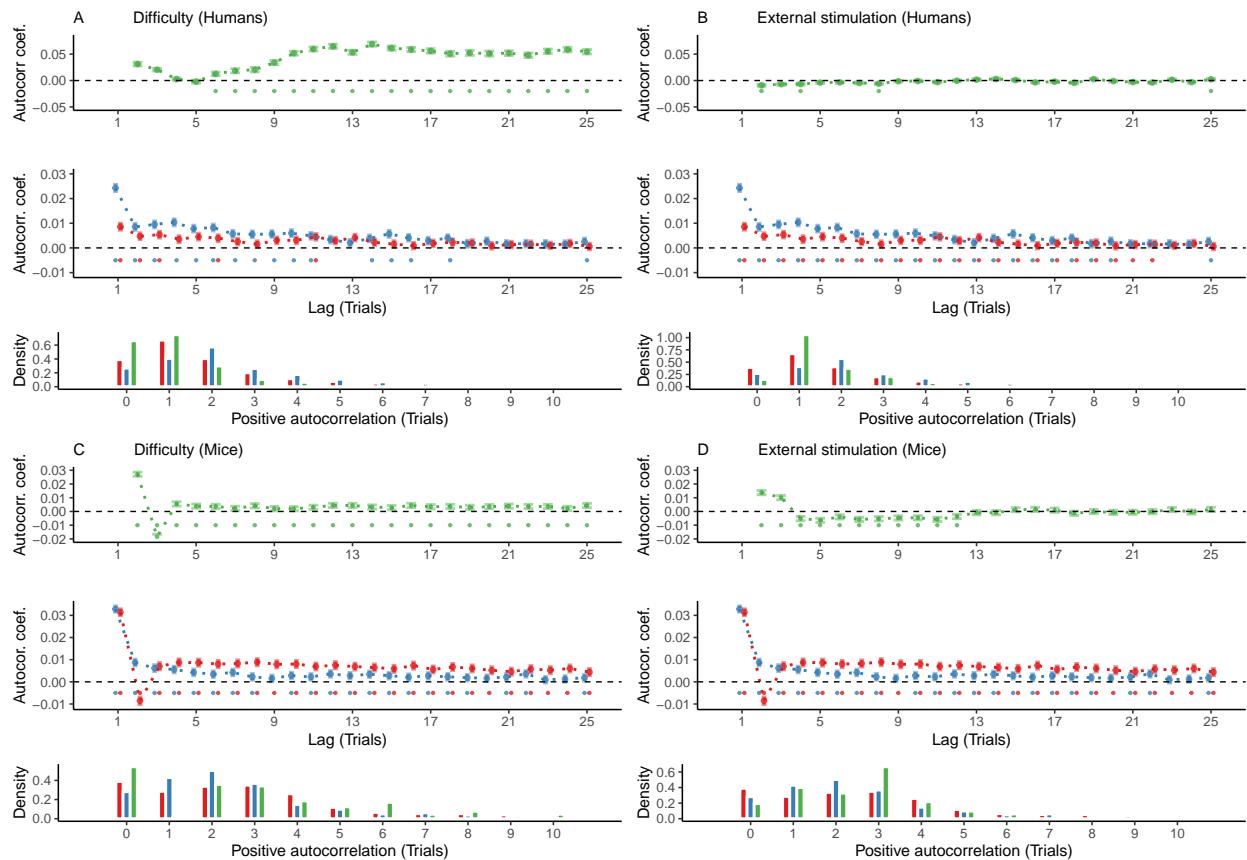
1357 A. Stimulus-congruent choices in humans amounted to  $73.46\% \pm 0.15\%$  of trials and were  
1358 highly consistent across the experiments selected from the Confidence Database.

1359 B. History-congruent choices in humans amounted to  $52.7\% \pm 0.12\%$  of trials. In analogy  
1360 to stimulus-congruence, the prevalence of history-congruence was highly consistent across  
1361 the experiments selected from the Confidence Database. 48.48% of experiments showed  
1362 significant ( $p < 0.05$ ) biases toward preceding choices, whereas 2 of the 66 of the included  
1363 experiments showed significant repelling biases.

1364 C. In humans, we found an enhanced impact of perceptual history in participants who were  
1365 less sensitive to external sensory information ( $T(4.3 \times 10^3) = -14.27$ ,  $p = 3.78 \times 10^{-45}$ ),  
1366 suggesting that perception results from the competition of external with internal information.

<sub>1367</sub> D. In analogy to humans, mice that were less sensitive to external sensory information  
<sub>1368</sub> showed stronger biases toward perceptual history ( $T(163) = -7.52$ ,  $p = 3.44 \times 10^{-12}$ , Pearson  
<sub>1369</sub> correlation).

1370 **9.6 Supplemental Figure S2**



1371

1372 **Supplemental Figure S2. Controlling for task difficulty and external stimulation.**

1373 In this study, we found highly significant autocorrelations of stimulus- and history-congruence  
 1374 in humans as well as in mice, while controlling for task difficulty and the sequence of external  
 1375 stimulation. **Here, we confirm that the autocorrelations of stimulus- and history-**  
 1376 **congruence were not a trivial consequence of the experimental design or the**  
 1377 **addition of task difficulty and external stimulation as control variables in the**  
 1378 **computation of group-level autocorrelations.**

1379 A. In humans, task difficulty (in green) showed a significant autocorrelation starting at the  
 1380 5th trial (upper panel, dots at the bottom indicate intercepts  $\neq 0$  in trial-wise linear mixed  
 1381 effects modeling at  $p < 0.05$ ). When controlling for task difficulty only, linear mixed effects  
 1382 modeling indicated a significant autocorrelation of stimulus-congruence (in red) for the first 3  
 1383 consecutive trials (middle panel). 20% of trials within the displayed time window remained

1384 significantly autocorrelated. The autocorrelation of history-congruence (in blue) remained  
1385 significant for the first 11 consecutive trials (64% significantly autocorrelated trials within  
1386 the displayed time window). At the level of individual participants, the autocorrelation of  
1387 task difficulty exceeded the respective autocorrelation of randomly permuted within a lag of  
1388  $21.66 \pm 8.37 \times 10^{-3}$  trials (lower panel).

1389 B. In humans, the sequence of external stimulation (i.e., which of the two binary outcomes  
1390 was supported by the presented stimuli; depicted in green) was negatively autocorrelated  
1391 for 1 trial. When controlling for the autocorrelation of external stimulation only, stimulus-  
1392 congruence remained significantly autocorrelated for 22 consecutive trials (88% of trials  
1393 within the displayed time window; lower panel) and history-congruence remained significantly  
1394 autocorrelated for 20 consecutive trials (84% of trials within the displayed time window). At  
1395 the level of individual participants, the autocorrelation of external stimulation exceeded the  
1396 respective autocorrelation of randomly permuted within a lag of  $2.94 \pm 4.4 \times 10^{-3}$  consecutive  
1397 trials (lower panel).

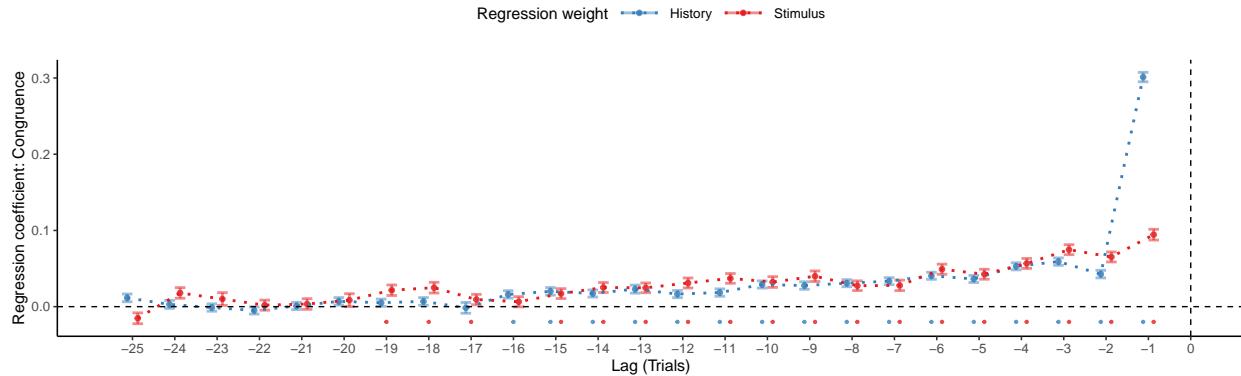
1398 C. In mice, task difficulty showed a significant autocorrelation for the first 25 consecutive trials  
1399 (upper panel). When controlling only for task difficulty only, linear mixed effects modeling  
1400 indicated a significant autocorrelation of stimulus-congruence for the first 36 consecutive trials  
1401 (middle panel). In total, 100% of trials within the displayed time window remained significantly  
1402 autocorrelated. The autocorrelation of history-congruence remained significant for the first  
1403 8 consecutive trials, with 84% significantly autocorrelated trials within the displayed time  
1404 window. At the level of individual mice, autocorrelation coefficients for difficulty were elevated  
1405 above randomly permuted data within a lag of  $15.13 \pm 0.19$  consecutive trials (lower panel).

1406 D. In mice, the sequence of external stimulation (i.e., which of the two binary outcomes was  
1407 supported by the presented stimuli) was negatively autocorrelated for 11 consecutive trials  
1408 (upper panel). When controlling only for the autocorrelation of external stimulation, stimulus-  
1409 congruence remained significantly autocorrelated for 86 consecutive trials (100% of trials

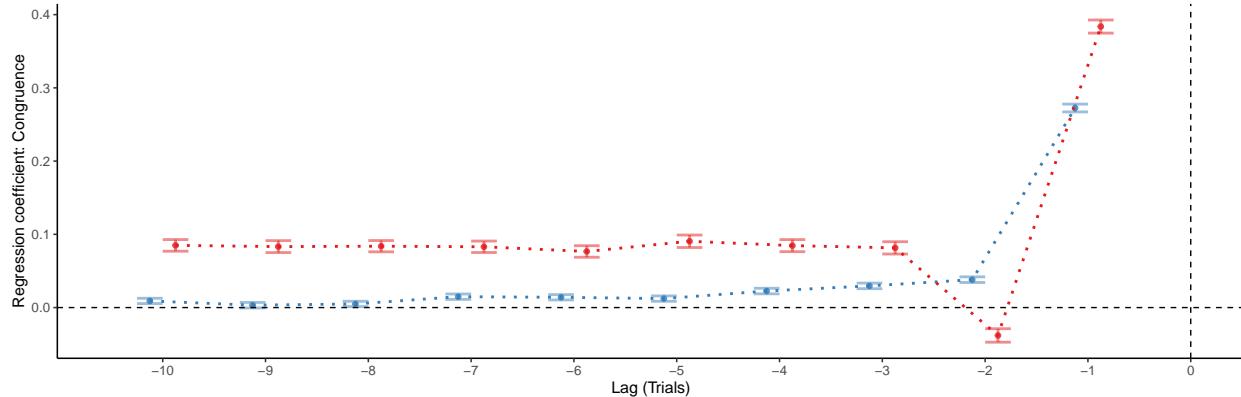
<sup>1410</sup> within the displayed time window; middle) and history-congruence remained significantly  
<sup>1411</sup> autocorrelated for 8 consecutive trials (84% of trials within the displayed time window). At  
<sup>1412</sup> the level of individual mice, autocorrelation coefficients for external stimulation were elevated  
<sup>1413</sup> above randomly permuted data within a lag of  $2.53 \pm 9.8 \times 10^{-3}$  consecutive trials (lower  
<sup>1414</sup> panel).

1415 **9.7 Supplemental Figure S3**

A



B



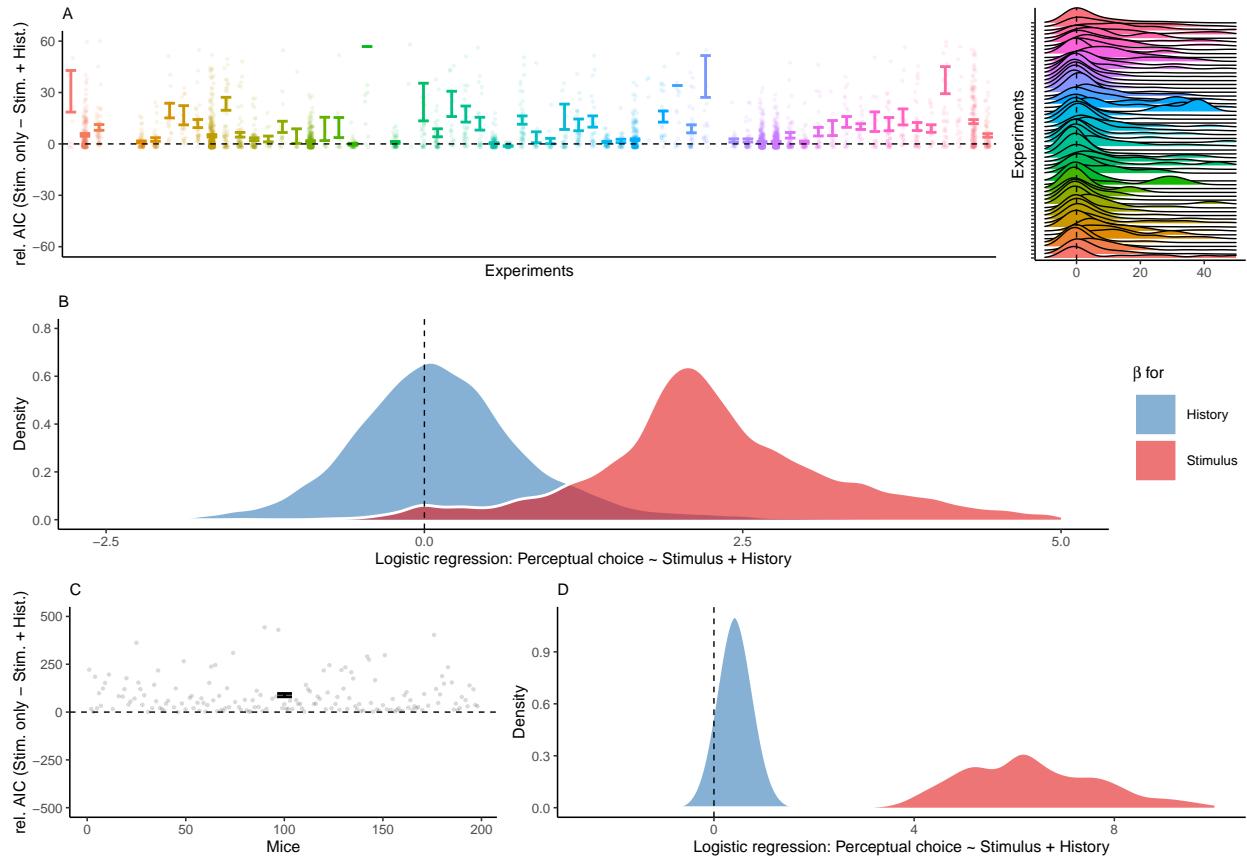
1416 **Supplemental Figure S3. Reproducing group-level autocorrelations using logistic  
1417 regression.**

1419 A. As an alternative to group-level autocorrelation coefficients, we used trial-wise logistic  
1420 regression to quantify serial dependencies in stimulus- and history-congruence. This analysis  
1421 predicted stimulus- and history-congruence at the index trial (trial  $t = 0$ , vertical line) based  
1422 on stimulus- and history-congruence at the 100 preceding trials. Mirroring the shape of the  
1423 group-level autocorrelations, trial-wise regression coefficients (depicted as mean  $\pm$  SEM, dots  
1424 mark trials with regression weights significantly greater than zero at  $p < 0.05$ ) increased  
1425 toward the index trial  $t = 0$  for the human data.

1426 B. Following our results in human data, regression coefficients that predicted history-  
1427 congruence at the index trial (trial  $t = 0$ , vertical line) increased exponentially for trials  
1428 closer to the index trial in mice. In contrast to history-congruence, stimulus-congruence

<sup>1429</sup> showed a negative regression weight (or autocorrelation coefficient; Figure 3B) at trial -2.  
<sup>1430</sup> This was due to the experimental design (see also the autocorrelations of difficulty and  
<sup>1431</sup> external stimulation in Supplemental Figure S2C and D): When mice made errors at easy  
<sup>1432</sup> trials (contrast  $\geq 50\%$ ), the upcoming stimulus was shown at the same spatial location and at  
<sup>1433</sup> high contrast. This increased the probability of stimulus-congruent perceptual choices after  
<sup>1434</sup> stimulus-incongruent perceptual choices at easy trials, thereby creating a negative regression  
<sup>1435</sup> weight (or autocorrelation coefficient) of stimulus-congruence at trial -2.

1436 **9.8 Supplemental Figure S4**



1437 **1438 Supplemental Figure S4. History-congruence in logistic regression.**

1439 A. To ensure that perceptual history played a significant role in perception despite the ongoing  
 1440 stream of external information, we tested whether human perceptual decision-making was  
 1441 better explained by the combination of external and internal information or, alternatively,  
 1442 by external information alone. To this end, we compared AIC between logistic regression  
 1443 models that predicted trial-wise perceptual responses either by both current external sensory  
 1444 information and the preceding percept, or by external sensory information alone (values above  
 1445 zero indicate a superiority of the full model). With high consistency across the experiments  
 1446 selected from the Confidence Database, this model-comparison confirmed that perceptual  
 1447 history contributed significantly to perception (difference in AIC =  $8.07 \pm 0.53$ ,  $T(57.22) =$   
 1448  $4.1$ ,  $p = 1.31 \times 10^{-4}$ ).

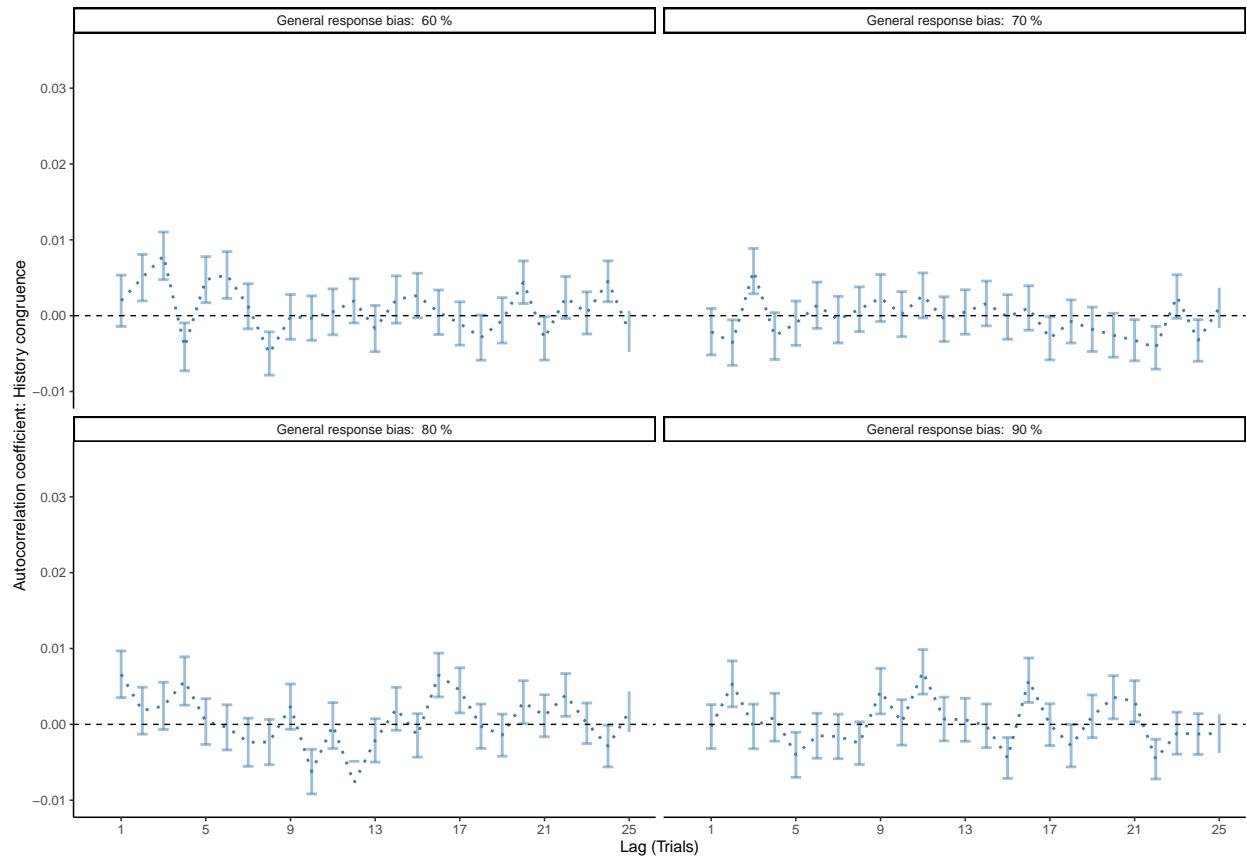
1449 B. Participant-wise regression coefficients amount to  $0.18 \pm 0.02$  for the effect of perceptual

<sub>1450</sub> history and  $2.51 \pm 0.03$  for external sensory stimulation.

<sub>1451</sub> C. In mice, an AIC-based model comparison indicated that perception was better explained  
<sub>1452</sub> by logistic regression models that predicted trial-wise perceptual responses based on both  
<sub>1453</sub> current external sensory information and the preceding percept (difference in AIC =  $88.62 \pm$   
<sub>1454</sub>  $8.57$ ,  $T(164) = -10.34$ ,  $p = 1.29 \times 10^{-19}$ ).

<sub>1455</sub> D. In mice, individual regression coefficients amounted to  $0.42 \pm 0.02$  for the effect of  
<sub>1456</sub> perceptual history and  $6.91 \pm 0.21$  for external sensory stimulation.

1457 **9.9 Supplemental Figure S5**



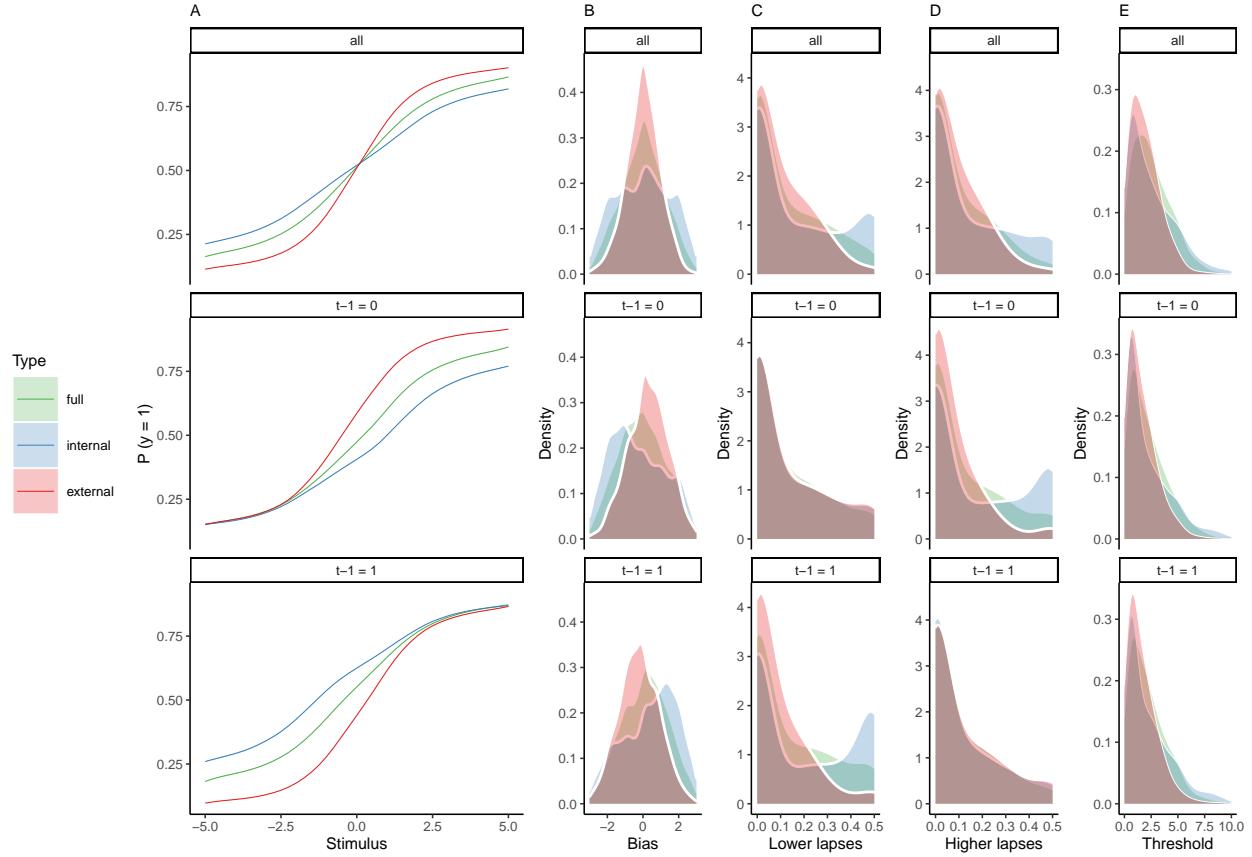
1458 **1459 Supplemental Figure S5. Correcting for general response biases.**

1460 Here, we ask whether the autocorrelation of history-congruence (as shown in Figure 2-3C)  
1461 may be driven by general response biases (i.e., a general propensity to choose one of the two  
1462 possible outcomes more frequently than the alternative). To this end, we generated sequences  
1463 of 100 perceptual choices with general response biases ranging from 60 to 90% for 1000  
1464 simulated participants each. We then computed the autocorrelation of history-congruence  
1465 for these simulated data. Crucially, we used the correction procedure that is applied to the  
1466 autocorrelation curves shown in this manuscript: All reported autocorrelation coefficients are  
1467 computed relative to the average autocorrelation coefficients obtained for 100 iterations of  
1468 randomly permuted trial sequences. The above simulation show that this correction procedure  
1469 removes any potential contribution of general response biases to the autocorrelation of history-  
1470 congruence. This indicates that the autocorrelation of history-congruence (as shown in Figure

<sub>1471</sub> 2-3C) is not driven by general response biases that were present in the empirical data at a

<sub>1472</sub> level of  $58.71\% \pm 0.22\%$  in humans and  $54.6\% \pm 0.3\%$  in mice.

1473 **9.10 Supplemental Figure S6**



1474

1475 **Supplemental Figure S6. Full and history-conditioned psychometric functions**  
1476 **across modes in humans.**

1477 A. Here, we show average psychometric functions for the full dataset (upper panel) and  
1478 conditioned on perceptual history ( $y_{t-1} = 1$  and  $y_{t-1} = 0$ ; middle and lower panel) across  
1479 modes (green line) and for internal mode (blue line) and external mode (red line) separately.

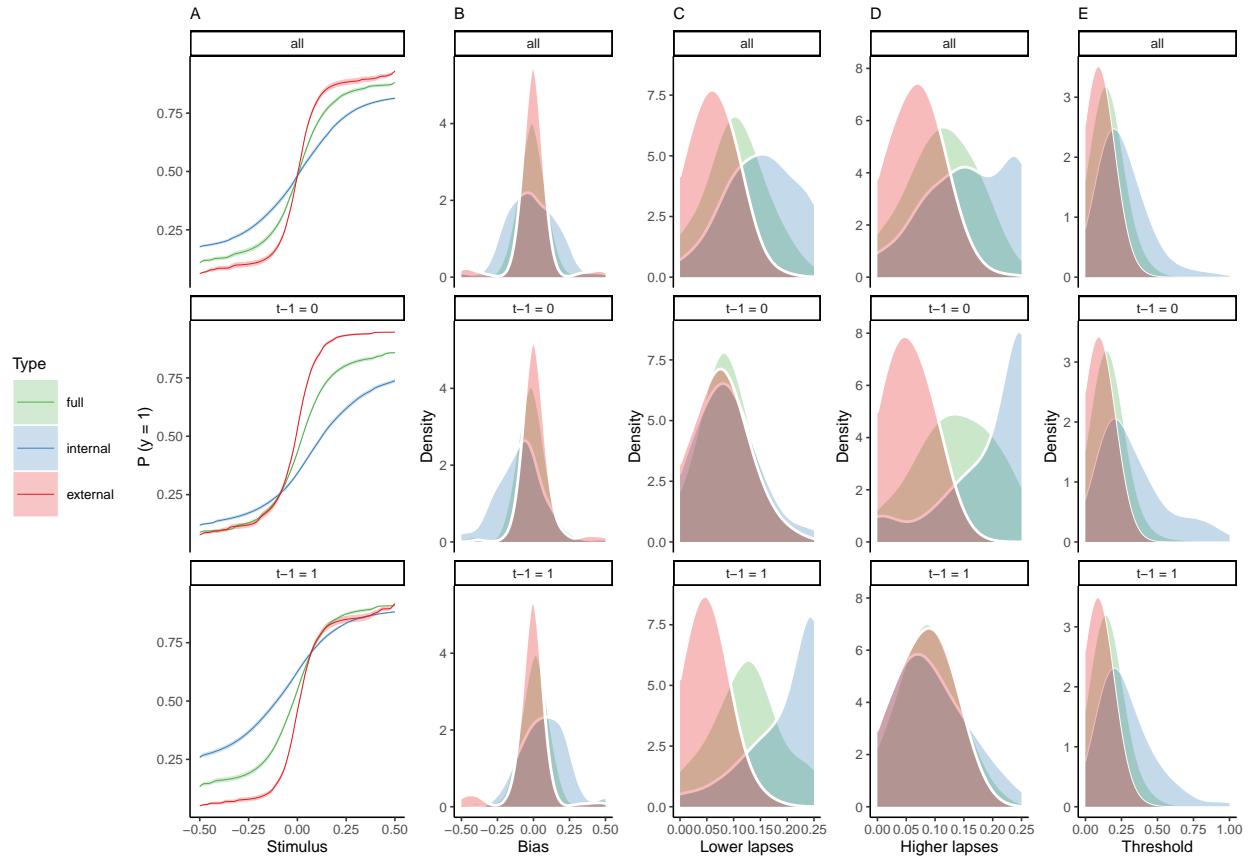
1480 B. Across the full dataset, biases  $\mu$  were distributed around zero ( $\beta_0 = 7.37 \times 10^{-3} \pm 0.09$ ,  
1481  $T(36.8) = 0.08$ ,  $p = 0.94$ ; upper panel), with larger absolute biases  $|\mu|$  for internal as compared  
1482 to external mode ( $\beta_0 = -0.62 \pm 0.07$ ,  $T(45.62) = -8.38$ ,  $p = 8.59 \times 10^{-11}$ ; controlling for  
1483 differences in lapses and thresholds). When conditioned on perceptual history, we observed  
1484 negative biases for  $y_{t-1} = 0$  ( $\beta_0 = 0.56 \pm 0.12$ ,  $T(43.39) = 4.6$ ,  $p = 3.64 \times 10^{-5}$ ; middle  
1485 panel) and positive biases for  $y_{t-1} = 1$  ( $\beta_0 = 0.56 \pm 0.12$ ,  $T(43.39) = 4.6$ ,  $p = 3.64 \times 10^{-5}$ ;  
1486 lower panel).

<sub>1487</sub> C. Lapse rates were higher in internal mode as compared to external mode ( $\beta_0 = -0.05 \pm$   
<sub>1488</sub>  $5.73 \times 10^{-3}$ ,  $T(47.03) = -9.11$ ,  $p = 5.94 \times 10^{-12}$ ; controlling for differences in biases and  
<sub>1489</sub> thresholds; see upper panel and subplot D). Importantly, the between-mode difference in  
<sub>1490</sub> lapses depended on perceptual history: We found no significant difference in lower lapses  
<sub>1491</sub>  $\gamma$  for  $y_{t-1} = 0$  ( $\beta_0 = 0.01 \pm 7.77 \times 10^{-3}$ ,  $T(33.1) = 1.61$ ,  $p = 0.12$ ; middle panel), but a  
<sub>1492</sub> significant difference for  $y_{t-1} = 1$  ( $\beta_0 = -0.11 \pm 0.01$ ,  $T(40.11) = -9.59$ ,  $p = 6.14 \times 10^{-12}$ ;  
<sub>1493</sub> lower panel).

<sub>1494</sub> D. Conversely, higher lapses  $\delta$  were significantly increased for  $y_{t-1} = 0$  ( $\beta_0 = -0.1 \pm$   
<sub>1495</sub>  $9.58 \times 10^{-3}$ ,  $T(36.87) = -10.16$ ,  $p = 3.06 \times 10^{-12}$ ; middle panel), but not for  $y_{t-1} = 1$  ( $\beta_0 =$   
<sub>1496</sub>  $0.01 \pm 7.74 \times 10^{-3}$ ,  $T(33.66) = 1.58$ ,  $p = 0.12$ ; lower panel).

<sub>1497</sub> E. The thresholds  $t$  were larger in internal as compared to external mode ( $\beta_0 = -1.77 \pm 0.25$ ,  
<sub>1498</sub>  $T(50.45) = -7.14$ ,  $p = 3.48 \times 10^{-9}$ ; controlling for differences in biases and lapses) and were  
<sub>1499</sub> not modulated by perceptual history ( $\beta_0 = 0.04 \pm 0.06$ ,  $T(2.97 \times 10^3) = 0.73$ ,  $p = 0.47$ ).

1500 **9.11 Supplemental Figure S7**



1501 **Supplemental Figure S7. Full and history-conditioned psychometric functions**  
1502 **across modes in mice.**

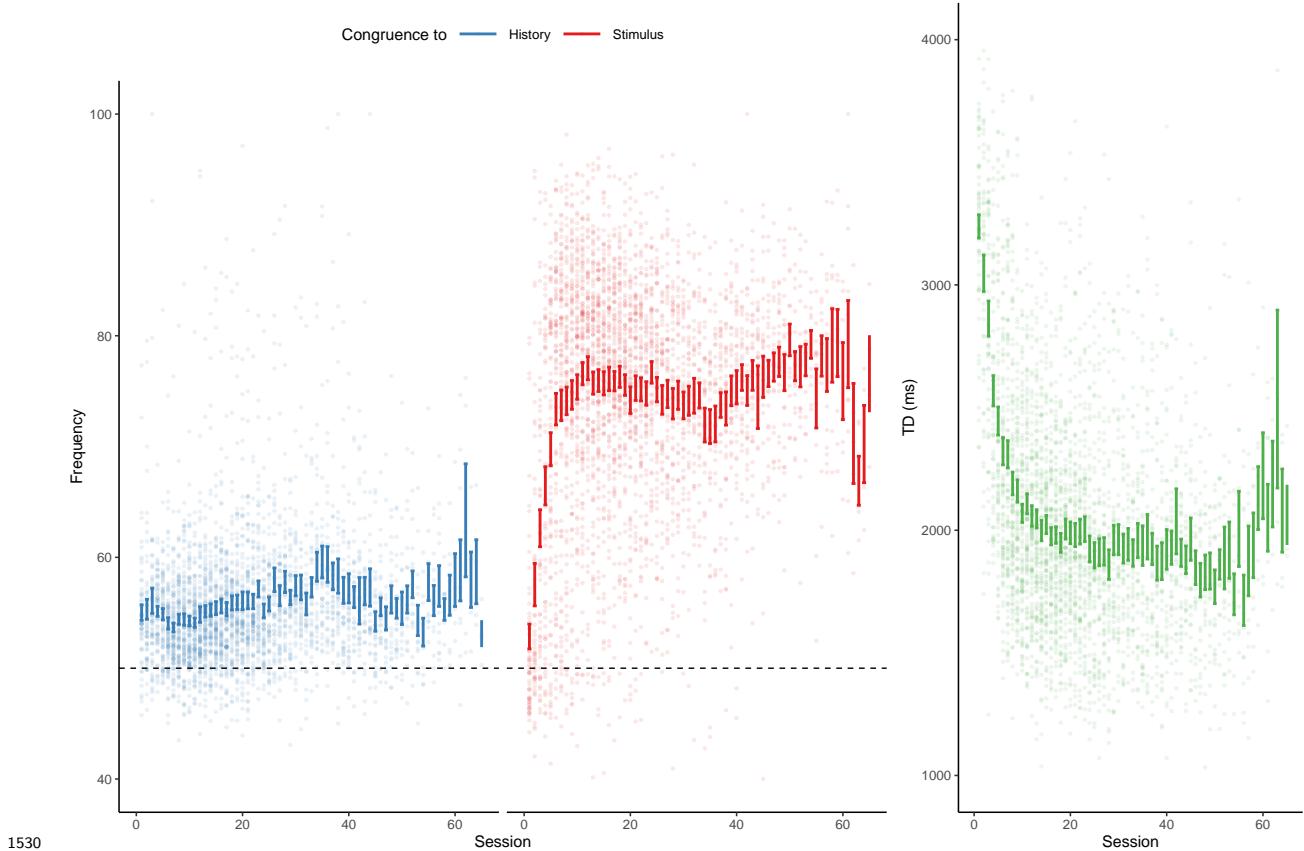
1503 A. Here, we show average psychometric functions for the full IBL dataset (upper panel) and  
1504 conditioned on perceptual history ( $y_{t-1} = 1$  and  $y_{t-1} = 0$ ; middle and lower panel) across  
1505 modes (green line) and for internal mode (blue line) and external mode (red line) separately.  
1506  
1507 B. Across the full dataset, biases  $\mu$  were distributed around zero ( $T(164) = 0.39$ ,  $p = 0.69$ ;  
1508 upper panel), with larger absolute biases  $|\mu|$  for internal as compared to external mode ( $\beta_0 =$   
1509  $-0.18 \pm 0.03$ ,  $T = -6.38$ ,  $p = 1.77 \times 10^{-9}$ ; controlling for differences in lapses and thresholds).  
1510 When conditioned on perceptual history, we observed negative biases for  $y_{t-1} = 0$  ( $T(164)$   
1511  $= -1.99$ ,  $p = 0.05$ ; middle panel) and positive biases for  $y_{t-1} = 1$  ( $T(164) = 1.91$ ,  $p = 0.06$ ;  
1512 lower panel).

1513 C. Lapse rates were higher in internal as compared to external mode ( $\beta_0 = -0.11 \pm 4.39 \times 10^{-3}$ ,  
1514  $T = -24.8$ ,  $p = 4.91 \times 10^{-57}$ ; controlling for differences in biases and thresholds; upper  
1515 panel, see subplot D). For  $y_{t-1} = 1$ , the difference between internal and external mode was  
1516 more pronounced for lower lapses  $\gamma$  ( $T(164) = -18.24$ ,  $p = 2.68 \times 10^{-41}$ ) as compared to  
1517 higher lapses  $\delta$  (see subplot D). In mice, lower lapses  $\gamma$  were significantly elevated during  
1518 internal mode irrespective of the preceding perceptual choice (middle panel: lower lapses  $\gamma$   
1519 for  $y_{t-1} = 0$ ;  $T(164) = -2.5$ ,  $p = 0.01$ , lower panel: lower lapses  $\gamma$  for  $y_{t-1} = 1$ ;  $T(164) =$   
1520  $-32.44$ ,  $p = 2.92 \times 10^{-73}$ ).

1521 D. For  $y_{t-1} = 0$ , the difference between internal and external mode was more pronounced  
1522 for higher lapses  $\delta$  ( $T(164) = 21.44$ ,  $p = 1.93 \times 10^{-49}$ , see subplot C). Higher lapses were  
1523 significantly elevated during internal mode irrespective of the preceding perceptual choice  
1524 (middle panel: higher lapses  $\delta$  for  $y_{t-1} = 0$ ;  $T(164) = -28.29$ ,  $p = 5.62 \times 10^{-65}$  lower panel:  
1525 higher lapses  $\delta$  for  $y_{t-1} = 1$ ;  $T(164) = -2.65$ ,  $p = 8.91 \times 10^{-3}$ ; ).

1526 E. Thresholds  $t$  were higher in internal as compared to external mode ( $\beta_0 = -0.28 \pm 0.04$ ,  
1527  $T = -7.26$ ,  $p = 1.53 \times 10^{-11}$ ; controlling for differences in biases and lapses) and were not  
1528 modulated by perceptual history ( $T(164) = 0.94$ ,  $p = 0.35$ ).

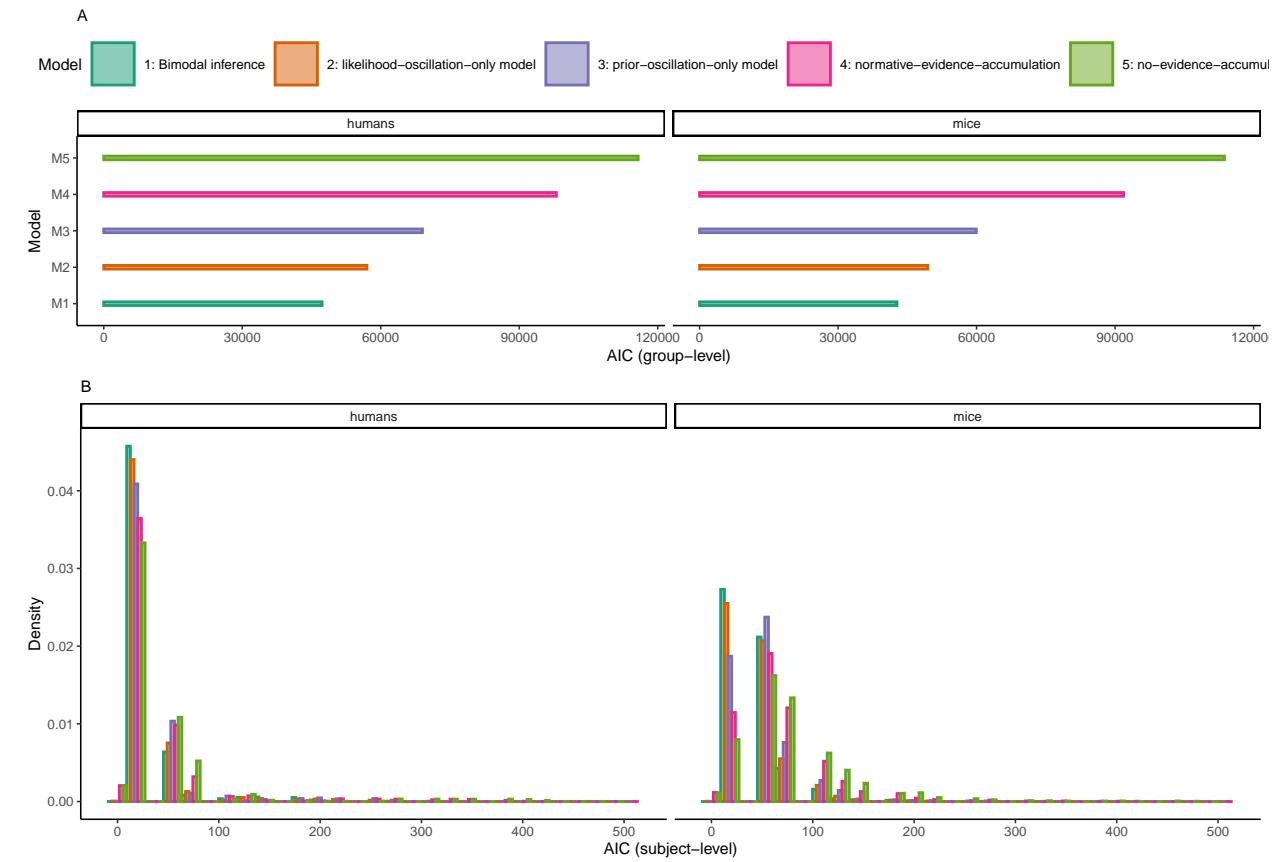
1529 **9.12 Supplemental Figure S8**



1531 **Supplemental Figure S8. History-/stimulus-congruence and TDs during training  
1532 of the basic task.**

1533 Here, we depict the progression of history- and stimulus-congruence (depicted in blue and  
1534 red, respectively; left panel) as well as TDs (in green; right panel) across training sessions in  
1535 mice that achieved proficiency (i.e., stimulus-congruence  $\geq 80\%$ ) in the *basic* task of the IBL  
1536 dataset. We found that both history-congruent perceptual choices ( $\beta = 0.13 \pm 4.67 \times 10^{-3}$ ,  
1537  $T(8.4 \times 10^3) = 27.04$ ,  $p = 1.96 \times 10^{-154}$ ) and stimulus-congruent perceptual choices ( $\beta =$   
1538  $0.34 \pm 7.13 \times 10^{-3}$ ,  $T(8.51 \times 10^3) = 47.66$ ,  $p < 2.2 \times 10^{-308}$ ) became more frequent with  
1539 training. As in humans, mice showed shorter TDs with increased exposure to the task ( $\beta =$   
1540  $-22.14 \pm 17.06$ ,  $T(1.14 \times 10^3) = -1.3$ ,  $p < 2.2 \times 10^{-308}$ ).

1541 **9.13 Supplemental Figure S9**



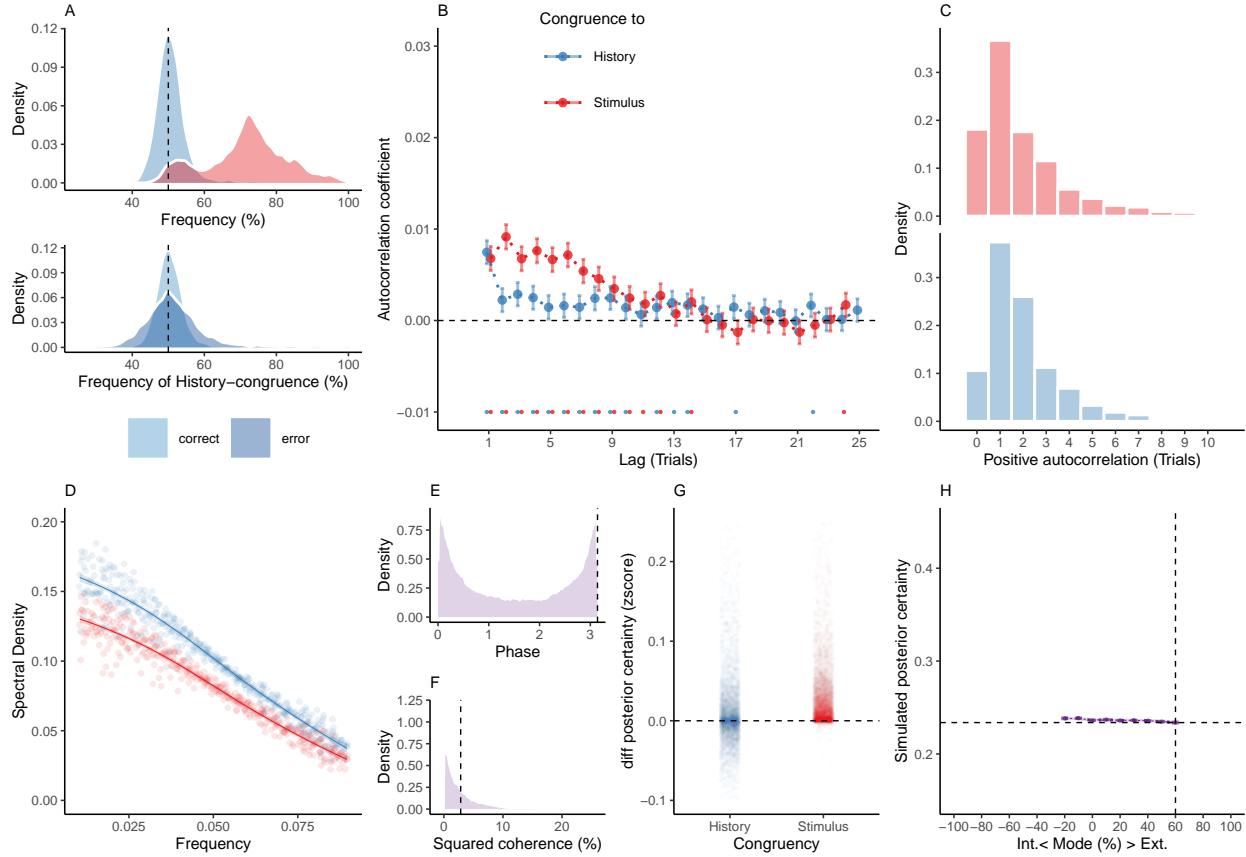
1542 **Supplemental Figure S9. Comparison of the bimodal inference model against reduced control models.**

1543 **A. Group-level AIC.** The bimodal inference model (M1) achieved the lowest AIC across the full model space ( $AIC_1 = 4.73 \times 10^4$  in humans and  $4.28 \times 10^4$  in mice).

1544 Model M2 ( $AIC_2 = 5.7 \times 10^4$  in humans and  $4.94 \times 10^4$  in mice) and Model M3 ( $AIC_3 = 6.9 \times 10^4$  in humans and  $5.99 \times 10^4$  in mice) incorporated only oscillations of either likelihood or prior precision. Model M4 ( $AIC_4 = 9.8 \times 10^4$  in humans and  $9.19 \times 10^4$  in mice) lacked any oscillations of likelihood and prior precision and corresponded to the normative model proposed by Glaze et al.<sup>51</sup>. In model M5 ( $AIC_5 = 1.16 \times 10^5$  in humans and  $1.14 \times 10^5$  in mice), we furthermore removed the integration of information across trials, such that perception depended only in incoming sensory information.

1555 **B. Subject-level AIC.** Here, we show the distribution of AIC values at the subject-  
1556 level. AIC for the bimodal inference model tended to be smaller than AIC for  
1557 the comparator models (statistical comparison to the second-best model M2 in  
1558 humans:  $\beta = -1.81 \pm 0.27$ ,  $T(5.07 \times 10^3) = -6.82$ ,  $p = 1.02 \times 10^{-11}$ ; mice:  $T(1.5 \times 10^3)$   
1559 = **-6.28**,  $p = 4.38 \times 10^{-10}$ ).

1560 **9.14 Supplemental Figure S10**



1561 **Supplemental Figure S10. Reduced Control Model M2: Only oscillation of the likelihood.** When simulating data for the *likelihood-oscillation-only model*, we removed the oscillation from the prior term by setting the amplitude  $a_\psi$  to zero. Simulated data thus depended only on the participant-wise estimates for hazard rate  $H$ , amplitude  $a_{LLR}$ , frequency  $f$ , phase  $p$  and inverse decision temperature  $\zeta$ .

1562 A. Similar to the full model M1 (Figure 1F and Figure 4), simulated perceptual choices  
 1563 were stimulus-congruent in  $71.97\% \pm 0.17\%$  of trials (in red). History-congruent amounted  
 1564 to  $50.76\% \pm 0.07\%$  of trials (in blue). As in the full model, the likelihood-oscillation-only  
 1565 model showed a significant bias toward perceptual history  $T(4.32 \times 10^3) = 10.29$ ,  $p =$   
 1566  $1.54 \times 10^{-24}$ ; upper panel). Similarly, history-congruent choices were more frequent at error  
 1567 trials ( $T(4.32 \times 10^3) = 9.71$ ,  $p = 4.6 \times 10^{-22}$ ; lower panel).

1568 B. In the likelihood-oscillation-only model, we observed that the autocorrelation coefficients for

1574 history-congruence were reduced below the autocorrelation coefficients of stimulus-congruence.

1575 This is an approximately five-fold reduction relative to the empirical results observed in humans

1576 (Figure 2B), where the autocorrelation of history-congruence was above the autocorrelation of

1577 stimulus-congruence. Moreover, in the reduced model shown here, the number of consecutive

1578 trials that showed significant autocorrelation of history-congruence was reduced to 11.

1579 C. In the likelihood-oscillation-only model, the number of consecutive trials at which true

1580 autocorrelation coefficients exceeded the autocorrelation coefficients for randomly permuted

1581 data did not differ with respect to stimulus-congruence ( $2.62 \pm 1.39 \times 10^{-3}$  trials;  $T(4.32 \times 10^3)$

1582 = 1.85,  $p = 0.06$ ), but decreased with respect to history-congruence ( $2.4 \pm 8.45 \times 10^{-4}$  trials;

1583  $T(4.32 \times 10^3) = -15.26$ ,  $p = 3.11 \times 10^{-51}$ ) relative to the full model.

1584 D. In the likelihood-oscillation-only model, the smoothed probabilities of stimulus- and

1585 history-congruence (sliding windows of  $\pm 5$  trials) fluctuated as **a scale-invariant process**

1586 **with a 1/f power law**, i.e., at power densities that were inversely proportional to the

1587 frequency (power  $\sim 1/f^\beta$ ; stimulus-congruence:  $\beta = -0.81 \pm 1.17 \times 10^{-3}$ ,  $T(1.92 \times 10^5) =$

1588  $-688.65$ ,  $p < 2.2 \times 10^{-308}$ ; history-congruence:  $\beta = -0.79 \pm 1.14 \times 10^{-3}$ ,  $T(1.92 \times 10^5) =$

1589  $-698.13$ ,  $p < 2.2 \times 10^{-308}$ ).

1590 E. In the likelihood-oscillation-only model, the distribution of phase shift between fluctuations

1591 in simulated stimulus- and history-congruence peaked at half a cycle ( $\pi$  denoted by dotted

1592 line). In contrast to the full model, the dynamic probabilities of simulated stimulus- and

1593 history-congruence were positively correlated ( $\beta = 2.7 \times 10^{-3} \pm 7.6 \times 10^{-4}$ ,  $T(2.02 \times 10^6) =$

1594  $3.55$ ,  $p = 3.8 \times 10^{-4}$ ).

1595 F. In the likelihood-oscillation-only model, the average squared coherence between fluctuations

1596 in simulated stimulus- and history-congruence (black dotted line) was reduced in comparison

1597 to the full model ( $T(3.51 \times 10^3) = -4.56$ ,  $p = 5.27 \times 10^{-6}$ ) and amounted to  $3.43 \pm 1.02 \times 10^{-3}\%$ .

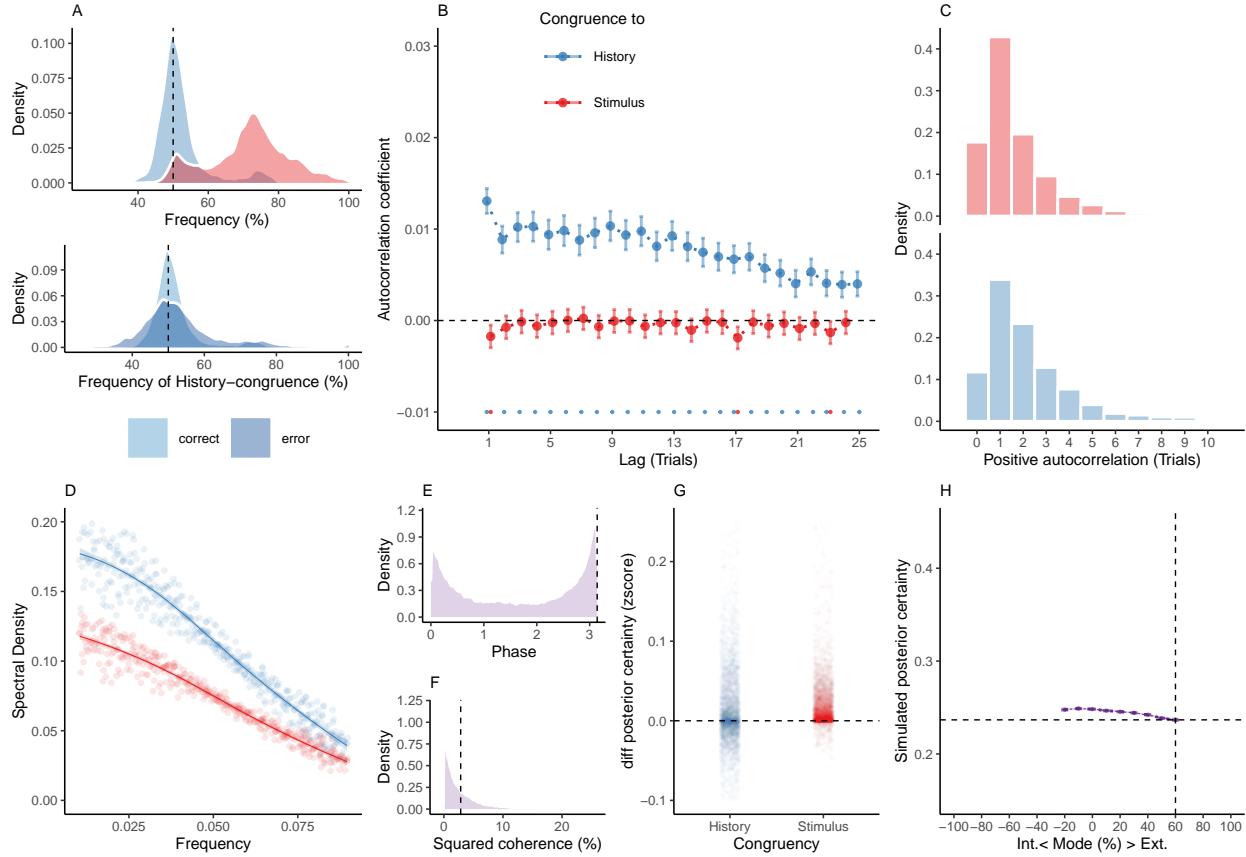
1598 G. Similar to the full bimodal inference model, confidence simulated from the likelihood-

1599 oscillation-only model was enhanced for stimulus-congruent choices ( $\beta = 0.03 \pm 1.42 \times 10^{-4}$ ,

<sub>1600</sub>  $T(2.1 \times 10^6) = 191.78$ ,  $p < 2.2 \times 10^{-308}$ ) and history-congruent choices ( $\beta = 9.1 \times 10^{-3} \pm$   
<sub>1601</sub>  $1.25 \times 10^{-4}$ ,  $T(2.1 \times 10^6) = 72.51$ ,  $p < 2.2 \times 10^{-308}$ ).

<sub>1602</sub> H. In the likelihood-oscillation-only model, the positive quadratic relationship between the  
<sub>1603</sub> mode of perceptual processing and confidence was markedly reduced in comparison to the full  
<sub>1604</sub> model ( $\beta_2 = 0.34 \pm 0.1$ ,  $T(2.1 \times 10^6) = 3.49$ ,  $p = 4.78 \times 10^{-4}$ ). The horizontal and vertical  
<sub>1605</sub> dotted lines indicate minimum posterior certainty and the associated mode, respectively.

1606 **9.15 Supplemental Figure S11**



1607 **Supplemental Figure S11. Reduced Control Model M3: Only oscillation of the prior.** When simulating data for the *prior-oscillation-only model*, we removed the oscillation from the prior term by setting the amplitude  $a_{LLR}$  to zero. Simulated data thus depended only on the participant-wise estimates for hazard rate  $H$ , amplitude  $a_\psi$ , frequency  $f$ , phase  $p$  and inverse decision temperature  $\zeta$ .

1613 A. Similar to the full model (Figure 1F and Figure 4), simulated perceptual choices were  
 1614 stimulus-congruent in  $71.97\% \pm 0.17\%$  of trials (in red). History-congruent amounted to  
 1615  $52.1\% \pm 0.11\%$  of trials (in blue). As in the full model, the prior-oscillation-only showed a  
 1616 significant bias toward perceptual history  $T(4.32 \times 10^3) = 18.34$ ,  $p = 1.98 \times 10^{-72}$ ; upper  
 1617 panel). Similarly, history-congruent choices were more frequent at error trials ( $T(4.31 \times 10^3)$   
 1618  $= 12.35$ ,  $p = 1.88 \times 10^{-34}$ ; lower panel).

1619 B. In the prior-oscillation-only model, we did not observe any significant positive autocor-

<sub>1620</sub> relation of stimulus-congruence , whereas the autocorrelation of history-congruence was  
<sub>1621</sub> preserved.

<sub>1622</sub> C. In the prior-oscillation-only model, the number of consecutive trials at which true au-  
<sub>1623</sub> tocorrelation coefficients exceeded the autocorrelation coefficients for randomly permuted  
<sub>1624</sub> data did was decreased with respect to stimulus-congruence relative to the full model ( $1.8 \pm$   
<sub>1625</sub>  $1.01 \times 10^{-3}$  trials;  $T(4.31 \times 10^3) = -6.48$ ,  $p = 1.03 \times 10^{-10}$ ), but did not differ from the full  
<sub>1626</sub> model with respect to history-congruence ( $4.25 \pm 1.84 \times 10^{-3}$  trials;  $T(4.32 \times 10^3) = 0.07$ ,  $p$   
<sub>1627</sub> = 0.95).

<sub>1628</sub> D. In the prior-oscillation-only model, the smoothed probabilities of stimulus- and history-  
<sub>1629</sub> congruence (sliding windows of  $\pm 5$  trials) fluctuated as **a scale-invariant process with a**  
<sub>1630</sub> **1/f power law**, i.e., at power densities that were inversely proportional to the frequency  
<sub>1631</sub> (power  $\sim 1/f^\beta$ ; stimulus-congruence:  $\beta = -0.78 \pm 1.11 \times 10^{-3}$ ,  $T(1.92 \times 10^5) = -706.62$ ,  $p$   
<sub>1632</sub>  $< 2.2 \times 10^{-308}$ ; history-congruence:  $\beta = -0.83 \pm 1.27 \times 10^{-3}$ ,  $T(1.92 \times 10^5) = -651.6$ ,  $p <$   
<sub>1633</sub>  $2.2 \times 10^{-308}$ ).

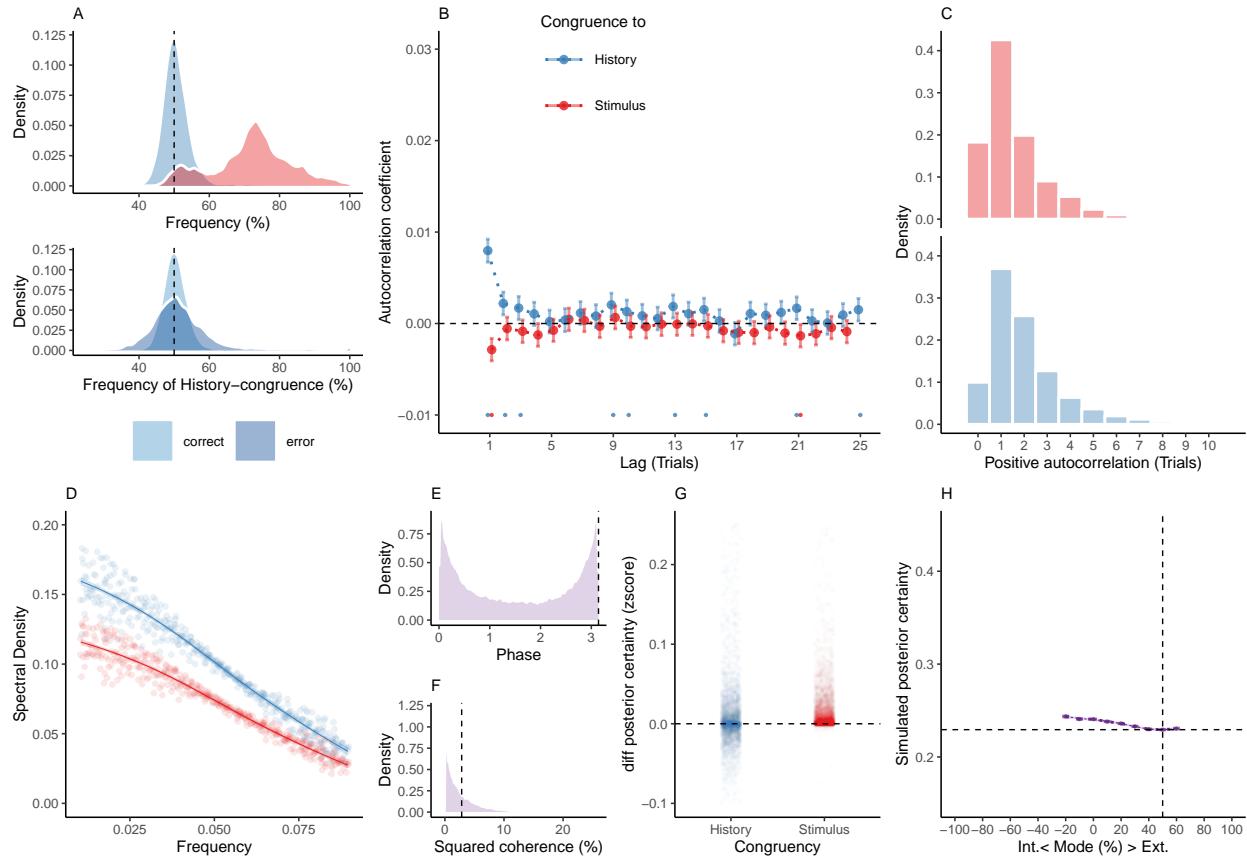
<sub>1634</sub> E. In the prior-oscillation-only model, the distribution of phase shift between fluctuations  
<sub>1635</sub> in simulated stimulus- and history-congruence peaked at half a cycle ( $\pi$  denoted by dotted  
<sub>1636</sub> line). Similar to the full model, the dynamic probabilities of simulated stimulus- and history-  
<sub>1637</sub> congruence were anti-correlated ( $\beta = -0.03 \pm 8.61 \times 10^{-4}$ ,  $T(2.12 \times 10^6) = -34.03$ ,  $p =$   
<sub>1638</sub>  $8.17 \times 10^{-254}$ ).

<sub>1639</sub> F. In the prior-oscillation-only model, the average squared coherence between fluctuations in  
<sub>1640</sub> simulated stimulus- and history-congruence (black dotted line) was reduced in comparison to  
<sub>1641</sub> the full model ( $T(3.54 \times 10^3) = -3.22$ ,  $p = 1.28 \times 10^{-3}$ ) and amounted to  $3.52 \pm 1.04 \times 10^{-3}\%$ .

<sub>1642</sub> G. Similar to the full bimodal inference model, confidence simulated from the prior-oscillation-  
<sub>1643</sub> only model was enhanced for stimulus-congruent choices ( $\beta = 0.02 \pm 1.44 \times 10^{-4}$ ,  $T(2.03 \times 10^6)$   
<sub>1644</sub> = 128.53,  $p < 2.2 \times 10^{-308}$ ) and history-congruent choices ( $\beta = 0.01 \pm 1.26 \times 10^{-4}$ ,  $T(2.03 \times 10^6)$   
<sub>1645</sub> = 88.24,  $p < 2.2 \times 10^{-308}$ ).

<sub>1646</sub> H. In contrast to the full bimodal inference model, the prior-oscillation-only model did  
<sub>1647</sub> not yield a positive quadratic relationship between the mode of perceptual processing and  
<sub>1648</sub> confidence ( $\beta_2 = -0.17 \pm 0.1$ ,  $T(2.04 \times 10^6) = -1.66$ ,  $p = 0.1$ ). The horizontal and vertical  
<sub>1649</sub> dotted lines indicate minimum posterior certainty and the associated mode, respectively.

1650 **9.16 Supplemental Figure S12**



1651 **1652 Supplemental Figure S12. Reduced Control Model M4: Normative evidence**

1653 **accumulation.** When simulating data for the *normative-evidence-accumulation model*, we  
 1654 removed the oscillation from the likelihood and prior terms by setting the amplitudes  $a_{LLR}$   
 1655 and  $a_\psi$  to zero. Simulated data thus depended only on the participant-wise estimates for  
 1656 hazard rate  $H$  and inverse decision temperature  $\zeta$ .

1657 A. Similar to the full model (Figure 1F and Figure 4), simulated perceptual choices were  
 1658 stimulus-congruent in  $71.97\% \pm 0.17\%$  of trials (in red). History-congruent amounted to  
 1659  $50.73\% \pm 0.07\%$  of trials (in blue). As in the full model, the no-oscillation model showed  
 1660 a significant bias toward perceptual history  $T(4.32 \times 10^3) = 9.94$ ,  $p = 4.88 \times 10^{-23}$ ; upper  
 1661 panel). Similarly, history-congruent choices were more frequent at error trials ( $T(4.31 \times 10^3)$   
 1662  $= 10.59$ ,  $p = 7.02 \times 10^{-26}$ ; lower panel).

1663 B. In the normative-evidence-accumulation model, we did not find significant autocor-

<sub>1664</sub> relations for stimulus-congruence. Likewise, we did not observe any autocorrelation of  
<sub>1665</sub> history-congruence beyond the first three consecutive trials.

<sub>1666</sub> C. In the normative-evidence-accumulation model, the number of consecutive trials at  
<sub>1667</sub> which true autocorrelation coefficients exceeded the autocorrelation coefficients for randomly  
<sub>1668</sub> permuted data decreased with respect to both stimulus-congruence ( $1.8 \pm 1.59 \times 10^{-3}$  trials;  
<sub>1669</sub>  $T(4.31 \times 10^3) = -5.21$ ,  $p = 2 \times 10^{-7}$ ) and history-congruence ( $2.18 \pm 5.48 \times 10^{-4}$  trials;  
<sub>1670</sub>  $T(4.32 \times 10^3) = -17.1$ ,  $p = 1.75 \times 10^{-63}$ ) relative to the full model.

<sub>1671</sub> D. In the normative-evidence-accumulation model, the smoothed probabilities of stimulus- and  
<sub>1672</sub> history-congruence (sliding windows of  $\pm 5$  trials) fluctuated as **a scale-invariant process**  
<sub>1673</sub> **with a  $1/f$  power law**, i.e., at power densities that were inversely proportional to the  
<sub>1674</sub> frequency (power  $\sim 1/f^\beta$ ; stimulus-congruence:  $\beta = -0.78 \pm 1.1 \times 10^{-3}$ ,  $T(1.92 \times 10^5) =$   
<sub>1675</sub>  $-706.93$ ,  $p < 2.2 \times 10^{-308}$ ; history-congruence:  $\beta = -0.79 \pm 1.12 \times 10^{-3}$ ,  $T(1.92 \times 10^5) =$   
<sub>1676</sub>  $-702.46$ ,  $p < 2.2 \times 10^{-308}$ ).

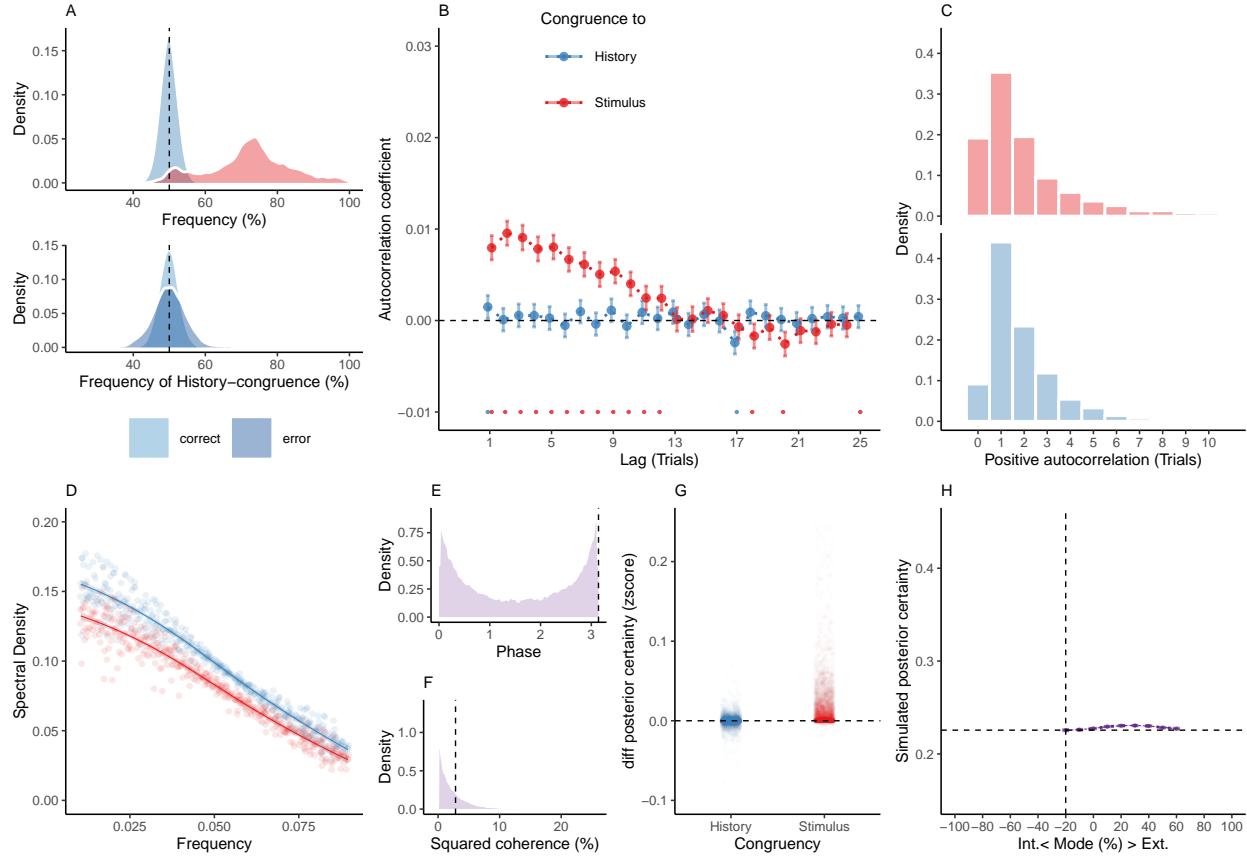
<sub>1677</sub> E. In the normative-evidence-accumulation model, the distribution of phase shift between  
<sub>1678</sub> fluctuations in simulated stimulus- and history-congruence peaked at half a cycle ( $\pi$  denoted  
<sub>1679</sub> by dotted line). In contrast to the full model, the dynamic probabilities of simulated stimulus-  
<sub>1680</sub> and history-congruence were positively correlated ( $\beta = 4.3 \times 10^{-3} \pm 7.97 \times 10^{-4}$ ,  $T(1.98 \times 10^6)$   
<sub>1681</sub>  $= 5.4$ ,  $p = 6.59 \times 10^{-8}$ ).

<sub>1682</sub> F. In the normative-evidence-accumulation model, the average squared coherence between  
<sub>1683</sub> fluctuations in simulated stimulus- and history-congruence (black dotted line) was reduced in  
<sub>1684</sub> comparison to the full model ( $T(3.52 \times 10^3) = -6.27$ ,  $p = 3.97 \times 10^{-10}$ ) and amounted to  
<sub>1685</sub>  $3.26 \pm 8.88 \times 10^{-4}\%$ .

<sub>1686</sub> G. Similar to the full bimodal inference model, confidence simulated from the no-oscillation  
<sub>1687</sub> model was enhanced for stimulus-congruent choices ( $\beta = 0.01 \pm 1.05 \times 10^{-4}$ ,  $T(2.1 \times 10^6)$   
<sub>1688</sub>  $= 139.17$ ,  $p < 2.2 \times 10^{-308}$ ) and history-congruent choices ( $\beta = 8.05 \times 10^{-3} \pm 9.2 \times 10^{-5}$ ,  
<sub>1689</sub>  $T(2.1 \times 10^6) = 87.54$ ,  $p < 2.2 \times 10^{-308}$ ).

<sub>1690</sub> H. In the normative-evidence-accumulation model, the positive quadratic relationship between  
<sub>1691</sub> the mode of perceptual processing and confidence was markedly reduced in comparison to  
<sub>1692</sub> the full model ( $\beta_2 = 0.14 \pm 0.07$ ,  $T(2.1 \times 10^6) = 1.95$ ,  $p = 0.05$ ). The horizontal and vertical  
<sub>1693</sub> dotted lines indicate minimum posterior certainty and the associated mode, respectively.

1694 **9.17 Supplemental Figure S13**



1695 **1696 Supplemental Figure S13. Reduced Control Model M5: No accumulation of  
1697 information across trials.** When simulating data for the *no-evidence-accumulation model*,  
1698 we removed the accumulation of information across trials by setting the Hazard rate  $H$  to  
1699 0.5. Simulated data thus depended only on the participant-wise estimates for the amplitudes  
1700  $a_{LLR/\psi}$ , frequency  $f$ , phase  $p$  and inverse decision temperature  $\zeta$ .

1701 A. Similar to the full model (Figure 1F and Figure 4), simulated perceptual choices were  
1702 stimulus-congruent in  $72.14\% \pm 0.17\%$  of trials (in red). History-congruent amounted to  
1703  $49.89\% \pm 0.03\%$  of trials (in blue). In contrast to the full model, the no-accumulation model  
1704 showed a significant bias against perceptual history  $T(4.32 \times 10^3) = -3.28$ ,  $p = 1.06 \times 10^{-3}$ ;  
1705 upper panel). In contrast to the full model, there was no difference in the frequency of  
1706 history-congruent choices between correct and error trials ( $T(4.31 \times 10^3) = 0.76$ ,  $p = 0.44$ ;  
1707 lower panel).

1708 B. In the no-evidence-accumulation model, we found no significant autocorrelation of history-  
1709 congruence beyond the first trial, whereas the autocorrelation of stimulus-congruence was  
1710 preserved.

1711 C. In the no-evidence-accumulation model, the number of consecutive trials at which true  
1712 autocorrelation coefficients exceeded the autocorrelation coefficients for randomly permuted  
1713 data increased with respect to stimulus-congruence ( $2.83 \pm 1.49 \times 10^{-3}$  trials;  $T(4.31 \times 10^3) =$   
1714  $3.45$ ,  $p = 5.73 \times 10^{-4}$ ) and decreased with respect to history-congruence ( $1.85 \pm 3.49 \times 10^{-4}$   
1715 trials;  $T(4.32 \times 10^3) = -19.37$ ,  $p = 3.49 \times 10^{-80}$ ) relative to the full model.

1716 D. In the no-evidence-accumulation model, the smoothed probabilities of stimulus- and  
1717 history-congruence (sliding windows of  $\pm 5$  trials) fluctuated as **a scale-invariant process**  
1718 **with a 1/f power law**, i.e., at power densities that were inversely proportional to the  
1719 frequency (power  $\sim 1/f^\beta$ ; stimulus-congruence:  $\beta = -0.82 \pm 1.2 \times 10^{-3}$ ,  $T(1.92 \times 10^5) =$   
1720  $-681.98$ ,  $p < 2.2 \times 10^{-308}$ ; history-congruence:  $\beta = -0.78 \pm 1.11 \times 10^{-3}$ ,  $T(1.92 \times 10^5) =$   
1721  $-706.57$ ,  $p < 2.2 \times 10^{-308}$ ).

1722 E. In the no-evidence-accumulation model, the distribution of phase shift between fluctuations  
1723 in simulated stimulus- and history-congruence peaked at half a cycle ( $\pi$  denoted by dotted  
1724 line). In contrast to the full model, the dynamic probabilities of simulated stimulus- and  
1725 history-congruence were not significantly anti-correlated ( $\beta = 6.39 \times 10^{-4} \pm 7.22 \times 10^{-4}$ ,  
1726  $T(8.89 \times 10^5) = 0.89$ ,  $p = 0.38$ ).

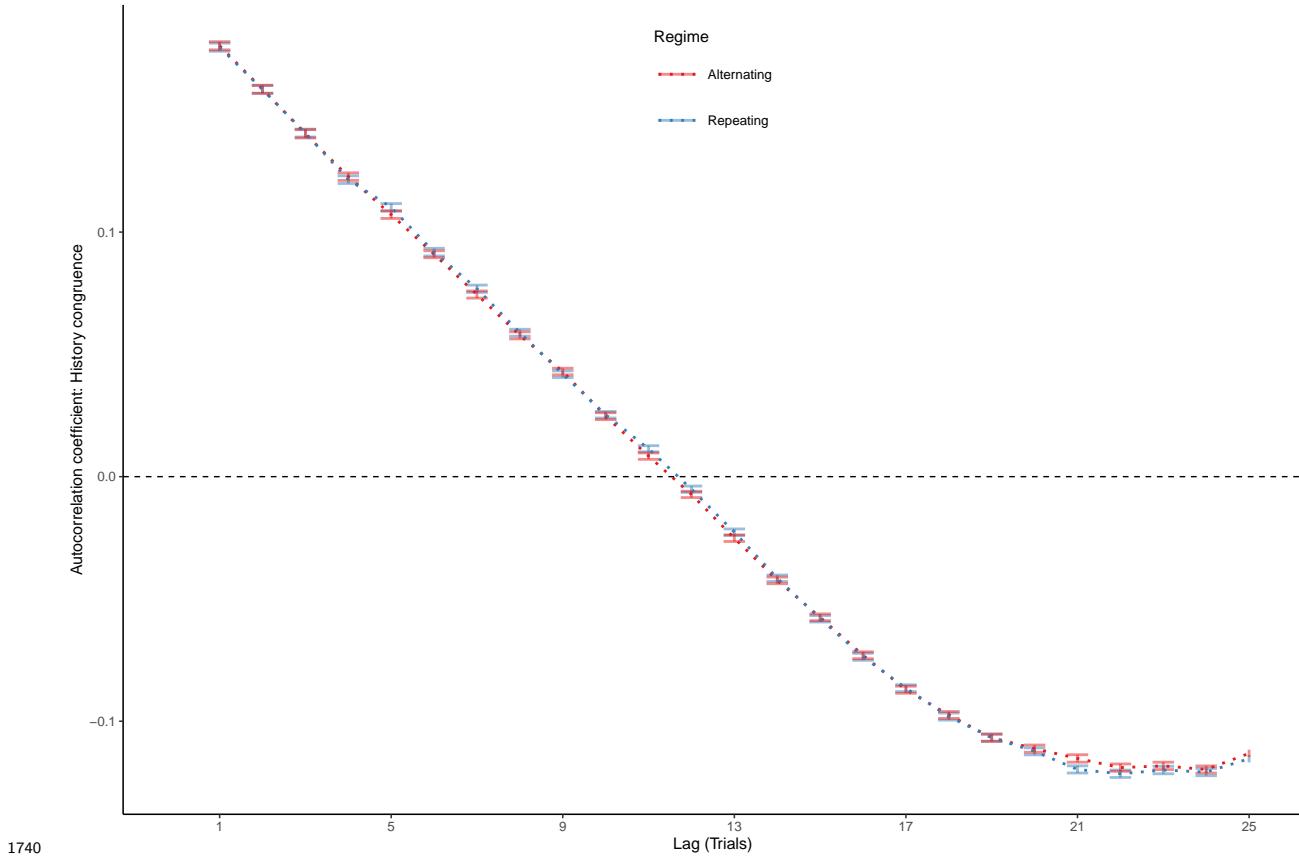
1727 F. In the no-evidence-accumulation model, the average squared coherence between fluctuations  
1728 in simulated stimulus- and history-congruence (black dotted line) was reduced in comparison  
1729 to the full model ( $T(3.56 \times 10^3) = -9.96$ ,  $p = 4.63 \times 10^{-23}$ ) and amounted to  $2.8 \pm 7.29 \times 10^{-4}\%$ .

1730 G. Similar to the full bimodal inference model, confidence simulated from the no-evidence-  
1731 accumulation model was enhanced for stimulus-congruent choices ( $\beta = 0.01 \pm 9.4 \times 10^{-5}$ ,  
1732  $T(2.11 \times 10^6) = 158.1$ ,  $p < 2.2 \times 10^{-308}$ ). In contrast to the full bimodal inference model,  
1733 history-congruent choices were not characterized by enhanced confidence ( $\beta = 8.78 \times 10^{-5} \pm$

<sub>1734</sub>  $8.21 \times 10^{-5}$ ,  $T(2.11 \times 10^6) = 1.07$ ,  $p = 0.29$ ).

<sub>1735</sub> H. In the no-evidence-accumulation model, the positive quadratic relationship between the  
<sub>1736</sub> mode of perceptual processing and confidence was markedly reduced in comparison to the full  
<sub>1737</sub> model ( $\beta_2 = 0.19 \pm 0.06$ ,  $T(2.11 \times 10^6) = 3$ ,  $p = 2.69 \times 10^{-3}$ ). The horizontal and vertical  
<sub>1738</sub> dotted lines indicate minimum posterior certainty and the associated mode, respectively.

1739 **9.18 Supplemental Figure S14**



1740 **Supplemental Figure S14. Autocorrelation of history-congruence of alternating  
1741 and repeating biases.** Here, we simulate the autocorrelation of history-congruence in  $10^3$   
1742 synthetic participants. In the repeating regime (blue), history-congruence fluctuated between  
1743 50% and 80% (blue) in interleaved blocks (10 blocks per condition with a random duration  
1744 between 15 and 30 trials). In the alternation regime (red), history-congruence fluctuated  
1745 between 50% and 20%. The resulting autocorrelation curves for history-congruence overlap,  
1746 indicating that our analysis is able to accommodate both repeating and alternating biases.  
1747

<sup>1748</sup> **9.19 Supplemental Table T1**

Authors	Journal	Year
Bang, Shekhar, Rahnev	JEP:General	2019
Bang, Shekhar, Rahnev	JEP:General	2019
Calder-Travis, Charles, Bogacz, Yeung	Unpublished	NA
Clark & Merfeld	Journal of Neurophysiology	2018
Clark	Unpublished	NA
Faivre, Filevich, Solovey, Kuhn, Blanke	Journal of Neuroscience	2018
Faivre, Vuillaume, Blanke, Cleeremans	bioRxiv	2018
Filevich & Fandakova	Unplublished	NA
Gajdos, Fleming, Saez Garcia, Weindel, Davranche	Neuroscience of Consciousness	2019
Gherman & Philiastides	eLife	2018
Haddara & Rahnev	PsyArXiv	2020
Haddara & Rahnev	PsyArXiv	2020
Hainguerlot, Vergnaud, & de Gardelle	Scientific Reports	2018
Hainguerlot, Gajdos, Vergnaud, & de Gardelle	Unpublished	NA
Jachs, Blanco, Grantham-Hill, Soto	JEP:HPP	2015
Jachs, Blanco, Grantham-Hill, Soto	JEP:HPP	2015
Jachs, Blanco, Grantham-Hill, Soto	JEP:HPP	2015
Jaquiere, Yeung	Unpublished	NA
Kvam, Pleskac, Yu, Busemeyer	PNAS	2015
Kvam, Pleskac, Yu, Busemeyer	PNAS	2015
Kvam and Pleskac	Cognition	2016
Law, Lee	Unpublished	NA
Lebreton, et al.	Sci. Advances	2018
Lempert, Chen, & Fleming	PlosOne	2015
Locke*, Gaffin-Cahn*, Hosseiniaveh, Mamassian, & Landy	Attention, Perception, & Psychophysics	2020
Maniscalco, McCurdy,Odegaard, & Lau	J Neurosci	2017
Maniscalco, McCurdy,Odegaard, & Lau	J Neurosci	2017
Maniscalco, McCurdy,Odegaard, & Lau	J Neurosci	2017
Maniscalco, McCurdy,Odegaard, & Lau	J Neurosci	2017
Martin, Hsu	Unpublished	NA
Massoni & Roux	Journal of Mathematical Psychology	2017
Massoni	Unpublished	NA
Mazor, Friston & Fleming	eLife	2020
Mei, Rankine,Olafsson, Soto	bioRxiv	2019
Mei, Rankine,Olafsson, Soto	bioRxiv	2019
O'Hora, Zgonnikov, Kenny, Wong-Lin	Fechner Day proceedings	2017
O'Hora, Zgonnikov, CiChocki	Unpublished	NA

(continued)

Authors	Journal	Year
O'Hora, Zgonnikov, Neverauskaite	Unpublished	NA
Palser et al	Consciousness & Cognition	2018
Pereira, Faivre, Iturrate et al.	bioRxiv	2018
Prieto et al.	Submitted	NA
Rahnev et al	J Neurophysiol	2013
Rausch & Zehetleitner	Front Psychol	2016
Rausch et al	Attention, Perception, & Psychophysics	2018
Rausch et al	Attention, Perception, & Psychophysics	2018
Rausch, Zehetleitner, Steinhauser, & Maier	NeuroImage	2020
Recht, de Gardelle & Mamassian	Unpublished	NA
Reyes et al.	PlosOne	2015
Reyes et al.	Submitted	NA
Rouault, Seow, Gillan, Fleming	Biol. Psychiatry	2018
Rouault, Seow, Gillan, Fleming	Biol. Psychiatry	2018
Rouault, Dayan, Fleming	Nat Commun	2019
Sadeghi et al	Scientific Reports	2017
Schmidt et al.	Consc Cog	2019
Shekhar & Rahnev	J Neuroscience	2018
Shekhar & Rahnev	PsyArXiv	2020
Sherman et al	Journal of Neuroscience	2016
Sherman et al	Journal of Cognitive Neuroscience	2016
Sherman et al	Unpublished	NA
Sherman et al	Unpublished	NA
Siedlecka, Wereszczyski, Paulewicz, Wierzchon	bioRxiv	2019
Song et al	Consciousness & Cognition	2011
van Boxtel, Orchard, Tsuchiya	bioRxiv	2019
van Boxtel, Orchard, Tsuchiya	bioRxiv	2019
Wierzchon, Paulewicz, Asanowicz, Timmermans & Cleeremans	Consciousness and Cognition	2014
Wierzchon, Anzulewicz, Hobot, Paulewicz & Sackur	Consciousness and Cognition	2019

<sup>1749</sup> **9.20 Supplemental Table T2**

Parameters	Interpretation
$\alpha$	Sensitivity to sensory information
H	Expected probability of a switch in the cause of sensory information (Hazard)
$a_{LLR}$	Amplitude of fluctuations in likelihood precision $\omega_{LLR}$
$a_\psi$	Amplitude of fluctuations in prior precision $\omega_\psi$
f	Frequency of $\omega_{LLR}$ and $\omega_\psi$
p	Phase (p for $\omega_{LLR}$ ; p + $\pi$ for $\omega_\psi$ )
$\zeta$	Inverse decision temperature

1750 **10 Response to Reviewers**

1751 **10.1 Reviewer 1**

1752 This was an interesting and thought-provoking submission. I note that it is  
1753 a revision: I am therefore supposing that the authors have already responded  
1754 to one round of reviewer comments and that you are potentially interested in  
1755 publishing this work. In brief, I think there are many elements of this report that  
1756 warrant publication; however, there are some parts that are less compelling and  
1757 could be deferred to a subsequent paper. The paper is far too long and would  
1758 benefit greatly from being streamlined. Furthermore, some of the modeling is  
1759 overengineered and is difficult to follow. I have tried to suggest how the authors  
1760 might improve the presentation of their work in my comments to authors.

1761 I enjoyed reading this long but thought-provoking report of fluctuations in the  
1762 sensitivity to sensory evidence in perceptual decision-making tasks. There were  
1763 some parts of this report that were compelling and interesting. Other parts were  
1764 less convincing and difficult to understand. Overall, this paper is far too long. An  
1765 analogy that might help here is that a dinner guest is very entertaining for the  
1766 first hour or so - and then overstays their welcome; until you start wishing they  
1767 would leave. Another analogy, which came to mind, was that the modeling—and  
1768 its interpretation—was a bit autistic (i.e., lots of fascinating if questionable detail  
1769 with a lack of central coherence).

1770 I think that both issues could be resolved by shortening the paper and removing  
1771 (or, at least, greatly simplifying) the final simulation studies of metacognition. I  
1772 try to unpack this suggestion in the following.

1773 We would like to thank Prof. Friston for the very insightful and helpful comments on our  
1774 manuscript. We fully agree that our ideas about the computational function of between-mode

1775 fluctuations and the associated simulations may be presented in a more accessible form in a  
1776 standalone paper. As we outlined in more detail below, we have streamlined our findings  
1777 and rewrote the paper and reduced it's length by shortening the sections on computational  
1778 modeling. We have also followed Prof. Friston's suggestion to interpret the effects of mode  
1779 on RT and confidence in the context of predictive processing definitions of attention, namely  
1780 the allocation of precision between prior and likelihood.

1781 **Major points:**

1782 **As I understand it, you have used publicly available data on perceptual decision-**  
1783 **making to demonstrate slow fluctuations in the tendency to predicate perceptual**  
1784 **decisions on the stimuli and on the history of recent decisions. You find scale-free**  
1785 **fluctuations in this tendency — that are anti-correlated — and interpret this as**  
1786 **fluctuations in the precision afforded sensory evidence, relative to prior beliefs.**  
1787 **This interpretation is based upon a model of serial dependencies (parameterised**  
1788 **with a hazard function).**

1789 **The stimulus and history (i.e., likelihood and prior) sensitivities are anti-correlated**  
1790 **and both show scale free behavior. This is reproduced in men and mice. You**  
1791 **then proceed to model this with periodic fluctuations in the precisions or weights**  
1792 **applied to the likelihood and prior that are in anti-phase - and then estimate the**  
1793 **parameters of the ensuing model. Finally, you then simulate the learning of the**  
1794 **hazard parameter — and something called metacognition - to show that periodic**  
1795 **fluctuations improve estimates of metacognition (based upon a Rescorla-Wagner**  
1796 **model of learning). You motivate this by suggesting that the fluctuations in**  
1797 **sensitivity are somehow necessary to elude circular inference and provide better**  
1798 **estimates of precision.**

1799 **Note that I am reading the parameters omega\_LL and omega\_psi as the**  
1800 **precision of the likelihood and prior, where the precision of the likelihood is**

1801 called sensory precision. This contrasts with your use of sensory precision, which  
1802 seems to be attributed to a metacognitive construct M.

1803 As noted above, all of this is fascinating but there are too many moving parts  
1804 that do not fit together comfortably. I will list a few examples:

1805 **10.1.1 Comment 1**

1806 If, empirically, the fluctuations in sensitivity are scale-free with a 1/f power law,  
1807 why did you elect to model fluctuations in precision as a periodic function with  
1808 one unique timescale (i.e., f).?

1809 The reason for choosing a unique timescale  $f$  was to enable our model to depict the dominant  
1810 timescale at which prior and likelihood precision fluctuate in their impact on perceptual  
1811 decision-making, giving rise to between-mode fluctuations. We think that identifying this  
1812 timescale is important for planning future experiments targeted at between-mode fluctuations  
1813 and their manipulation by causal interventions (e.g., pharmacology or TMS). The posterior  
1814 value for  $f$  lies at approximately  $0.11 \frac{1}{N_{trials}}$  in both humans and mice. The value of  $f$   
1815 approximately matches the transition probabilities between *engaged* and *disengaged* states in  
1816 work assessing fluctuations in perceptual decision-making using Hidden Markov models (stay  
1817 probabilities ranged between 0.94 and 0.98, see Ashwood et al., Nature Neuroscience 2022).  
1818 Simulating from our model (Figure 4) replicates the 1/f feature of the empirical data. Please  
1819 note that the individual trial is the smallest unit of *measurement* for these fluctuations, such  
1820 that our analysis is limited by definition to frequencies below 1 ( $1/N_{trials}$ ).

1821 We now provide a rationale for choosing one value for  $f$  - identifying the dominant timescale  
1822 for fluctuations in mode - in the results section:

1823 • To allow for *bimodal inference*, i.e., alternating periods of internally- and externally-  
1824 biased modes of perceptual processing that occur irrespective of the sequence of preceding  
1825 experiences, we assumed that likelihood and prior vary in their influence on the perceptual

1826 decision according to fluctuations governed by  $\omega_{LLR}$  and  $\omega_\psi$ . These anti-phase sine  
1827 functions (defined by amplitudes  $a_{LLR/\psi}$ , frequency  $f$  and phase  $p$ ) determine the  
1828 precision afforded to the likelihood and prior<sup>53</sup>. The implicit anti-phase fluctuations  
1829 are mandated by Bayes-optimal formulations in which inference depends only on the  
1830 relative values of prior and likelihood precision (i.e., the Kalman gain<sup>54</sup>). As such,  $\omega_{LLR}$   
1831 and  $\omega_\psi$  implement a hyperprior<sup>55</sup> in which the likelihood and prior precisions are shifted  
1832 against each other at a dominant timescale defined by  $f$ : (...)

- 1833 • (...) The parameter  $f$  captures the dominant time scale at which likelihood (amplitude  
1834 humans:  $a_{LLR} = 0.5 \pm 2.02 \times 10^{-4}$ ; mice:  $a_{LLR} = 0.39 \pm 1.08 \times 10^{-3}$  and prior precision  
1835 (amplitude humans:  $a_\psi = 1.44 \pm 5.27 \times 10^{-4}$ ; mice:  $a_\psi = 1.71 \pm 7.15 \times 10^{-3}$  were shifted  
1836 against each other and was estimated at  $0.11 \pm 1.68 \times 10^{-5} 1/N_{trials}$  and  $0.11 \pm 1.63 \times 10^{-4}$   
1837  $1/N_{trials}$  in mice.
- 1838 • Table 2 (see response to Comment 22 by Reviewer 1) contains an additional definition  
1839 for all model parameters, including  $f$ .

1840 **10.1.2 Comment 2**

1841 **At present, the estimates of meta-cognition (M) play the role of accumulated  
1842 estimates of (sensory or prior) precision. Why are these not used in your model  
1843 of perceptual decisions in Equation 2.**

1844 In our model, the parameter  $\alpha$  controls the encoding precision by governing the transformation  
1845 from sensory stimuli to the log likelihood ratio (LLR) via the equations (13-16) (the LLR  
1846 ends up closer to zero when  $\alpha$  is low). Our simulations on the adaptive benefits of bimodal  
1847 inference rest on the assumption that  $\alpha$  may change unpredictably. The construct  $M$  is a  
1848 belief about  $\alpha$  that may be useful for, e.g., communicating the precision of sensory encoding  
1849 to other cognitive domains or agents. To our mind,  $\alpha$  is a feature of low-level sensory encoding  
1850 that cannot be modulated by top-down beliefs such as  $M$ . This is why we did not include

<sub>1851</sub>  $M$  in equation (2). Please note that we have removed this section following Comment 9 of  
<sub>1852</sub> Reviewer 1.

<sub>1853</sub> **10.1.3 Comment 3**

<sub>1854</sub> **Why do you assume that non-specific increases in attention and arousal will**  
<sub>1855</sub> **increase reaction times? If one has very precise prior beliefs (and is not attending**  
<sub>1856</sub> **to stimuli), would you not expect a decrease in reaction time?**

<sub>1857</sub> Thanks a lot for pointing this out (see also the Comment below and Comment 6 by Reviewer  
<sub>1858</sub> 3). Both high prior and high likelihood precision lead to higher absolute values of the log  
<sub>1859</sub> posterior ratio (reflecting certainty encoded by the decision variable), and thus faster RTs.  
<sub>1860</sub> This is reflected empirically by RTs in humans (Figure 2) and to a lesser degree in mice  
<sub>1861</sub> (Figure 3): RTs tended to be shorter for stronger biases toward both external and internal  
<sub>1862</sub> mode. Our model, which incorporates (i), the accumulation of information across trials, and  
<sub>1863</sub> (ii), fluctuations in the likelihood precision relative to the prior precision, recapitulates this  
<sub>1864</sub> feature of the data, which is lost or greatly attenuated when eliminating process (i) and/or  
<sub>1865</sub> (ii) (see model comparison and simulations below). Our data thus confirm the hypothesis  
<sub>1866</sub> that both high prior and likelihood precision lead to faster RTs.

<sub>1867</sub> In the previous version of the manuscript, we had included the relation between mode and  
<sub>1868</sub> RTs and confidence primarily as a defensive analysis against the proposition that what we  
<sub>1869</sub> call between-mode fluctuations is not a perceptual phenomenon, but occurs downstream of  
<sub>1870</sub> perception. One may imagine that fluctuations in perceptual performance are not influenced  
<sub>1871</sub> by periods of relative increases in prior precision (which decrease performance in fully  
<sub>1872</sub> randomized designs), but by periods when participants do not attend to the task at all, i.e.,  
<sub>1873</sub> neither to sensory information nor to prior precision. We propose that the analyses of RTs  
<sub>1874</sub> and confidence can give some insight into whether such alternative mechanisms may be at  
<sub>1875</sub> play, as we would assume longer RTs and lower confidence if participants failed to attend to  
<sub>1876</sub> the task at all.

1877 That being said, we realize that, due to the potential non-linearity in their relation to arousal  
1878 (see also Comment 6 by Reviewer 3), RTs and confidence cannot provide a definitive map  
1879 of where fluctuations in mode are situated in relation to arousal. Such a delineation may  
1880 potentially be provided by tracking of pupil size, response behavior or by neural data (e.g.,  
1881 noise correlations of fluctuations in LFP). These data are not available for the studies in  
1882 the Confidence Database, but were very recently published for the IBL database (after this  
1883 manuscript was submitted). While we believe that this is beyond the scope of this manuscript,  
1884 we will assess the relation of pupil diameter, motor behavior (turning of the response wheel)  
1885 and LFPs to between-mode fluctuations in a future publication using the IBL dataset.

1886 In light of the considerations above and our response to Comment 6 by Reviewer 3, we now  
1887 refer to attention in the predictive processing sense. We use the term “task engagement”  
1888 instead of “on-task attention” to refer to situation in which participants may not attend to  
1889 the task at all, e.g. due to low arousal or fatigue, and discuss these as alternative explanations  
1890 for between-mode fluctuations. We have made three sets of changes to our manuscript:

1891 First, we present our results on the relation of mode to RT and Confidence in a more  
1892 descriptive way, and do not use it as a strong defensive analysis against arousal:

1893 • The above results point to systematic fluctuations in the *decision variable*<sup>44</sup> that deter-  
1894 mines perceptual choices, causing enhanced sensitivity to external stimulus information  
1895 during external mode and increased biases toward preceding choices during internal  
1896 mode. As such, fluctuations in mode should influence downstream aspects of behavior  
1897 and cognition that operate on the perceptual decision variable<sup>44</sup>. To test this hypothesis  
1898 with respect to motor behavior and metacognition, we asked how bimodal inference  
1899 relates to response times (RTs) and confidence reports. (...)

1900 • (...) In sum, the above results indicate that reporting behavior and metacognition do  
1901 not map linearly onto the mode of sensory processing. Rather, they suggest that slow  
1902 fluctuations in the respective impact of external and internal information are most likely

1903 to affect perception at an early level of sensory analysis<sup>46,47</sup>. Such low-level processing  
1904 may thus integrate perceptual history with external inputs into a decision variable<sup>44</sup>  
1905 that influences not only perceptual choices, but also the speed and confidence at which  
1906 they are made.

- 1907 • In what follows, we probe alternative explanations for between-mode fluctuations, test  
1908 for the existence of modes in mice, and propose a predictive processing model that  
1909 explains fluctuations in mode by ongoing shifts in the precision afforded to external  
1910 sensory information relative to internal predictions driven by perceptual history.

1911 Second, we have re-written our discussion of the quadratic relationship of mode to RTs  
1912 and Confidence, focusing on predictive processing models of attention: - As a functional  
1913 explanation for bimodal inference, we propose that perception temporarily disengages from  
1914 internal predictions to form stable inferences about the statistical properties of the sensory  
1915 environment. Between-mode fluctuations may thus elude circular inferences that occur when  
1916 both the causes and the encoding of sensory stimuli are volatile<sup>19,57</sup>. By the same token, we  
1917 suggest that fluctuations in mode occur at the level of perceptual processing<sup>26,30,46,47</sup>, and are  
1918 not a passive phenomenon that is primarily driven by factors situated up- or downstream of  
1919 sensory analysis.

- 1920 • How does attention relate to between-mode fluctuations? According to predictive  
1921 processing, attention corresponds to the precision afforded to the probability distributions  
1922 that underlie perceptual inference<sup>53</sup>. From this perspective, fluctuations between external  
1923 and internal mode can be understood as ongoing shifts in the attention afforded to either  
1924 external sensory information (regulated via likelihood precision) or internal predictions  
1925 (regulated via prior precision). When the precision of either likelihood or prior increases,  
1926 posterior precision increases, which leads to faster RTs and higher confidence. Therefore,  
1927 when defined from the perspective of predictive processing as the precision afforded to

1928 likelihood and prior<sup>53</sup>, fluctuations in attention may provide a plausible explanation for  
1929 the quadratic relationship of mode to RTs and confidence (Figure 2H and J; Figure 3I;  
1930 Figure 3I).

1931 Third, we have added a more general discussion of our findings in the light of fluctuations in  
1932 task engagement:

1933 • Outside of the predictive processing field, attention is often understood in the context of  
1934 task engagement<sup>63</sup>, which varies according to the availability of cognitive resources that  
1935 are modulated by factors such as tonic arousal, familiarity with the task, or fatigue<sup>63</sup>. Our  
1936 results suggest that internal mode processing cannot be completely reduced to intervals  
1937 of low task engagement: In addition to shorter RTs and elevated confidence, choices  
1938 during internal mode were not random or globally biased, but driven by perceptual  
1939 history (Supplemental Figures S6-7). Moreover, our computational model identified  
1940 the dominant timescale of between-mode fluctuations at  $0.11 \text{ } 1/N_{trials}$ , which may be  
1941 compatible with fluctuations in arousal<sup>64</sup>, but is faster than to be expected for the  
1942 development of task familiarity or fatigue.

1943 • However, in interpreting the impact of between-mode fluctuations on perceptual accuracy,  
1944 speed of response and confidence, it is important to consider that global modulators  
1945 such as tonic arousal are known to have non-linear effects on task performance<sup>65</sup>: In  
1946 perceptual tasks, performance seems to be highest during mid-level arousal, whereas low-  
1947 and high-level arousal lead to reduced accuracy and slower responses<sup>65</sup>. This contrasts  
1948 with the effects of bimodal inference, where accuracy increases linearly as one moves  
1949 from internal to external mode, and responses become faster at both ends of the mode  
1950 spectrum.

1951 • Of note, high phasic arousal has been shown to suppress multi-domain biases in decision-  
1952 making in humans and mice<sup>66-68</sup>, including the biases toward perceptual history<sup>28</sup> that

1953 we implicate in internal mode processing. The increase in response speed and history  
1954 congruence over time (Supplemental Section 9.4) may argue against insufficient training  
1955 as an alternative explanation for internal mode processing, but may also taken as a  
1956 sign of waning arousal. The multiple mechanistic mappings to RTs and confidence  
1957 therefore warrant more direct measures of arousal (such as pupil size<sup>28,65,66,68–70</sup>, motor  
1958 behavior<sup>69,70</sup>, or neural data<sup>71</sup>) to better delineate bimodal inference from fluctuations  
1959 in global modulators of task performance.

1960 **10.1.4 Comment 4**

1961 **In the predictive processing literature, attention is thought to correspond to**  
1962 **fluctuations in sensory and prior precision. Why did you then consider attention**  
1963 **as some additional or unrelated confound?**

1964 This point is closely related to the comment above. We realize that, in the predictive  
1965 processing field, attention is equated with the precision of probability distributions that  
1966 contribute to the perceptual decision, such that an observer can attend strongly to sensory  
1967 information (high likelihood precision) or to internal predictions derived from the sequence of  
1968 preceding percepts (high prior precision). Therefore, when following the above predictive  
1969 processing definition, fluctuations in attention can be equated with fluctuations in mode.

1970 However, we feel that outside of the predictive processing field, attention is not always  
1971 conceived in that way, such that low attention is often considered as low engagement with  
1972 the task, i.e., relating to low likelihood and low prior precision in the predictive processing  
1973 sense. It is against these caveats that our control analysis (based on psychometric functions,  
1974 training effects, RTs and confidence) defend our conclusions on bimodal inference.

1975 We now provide a more nuanced interpretation of our findings of RTs and confidence in  
1976 relation to attention, with a specific focus on predictive processing and precision. We hope  
1977 that our responses to the comment above resolve the points raised in this comment.

1978 **10.1.5 Comment 5**

1979 **What licences the assumption that “agents depend upon internal confidence**  
1980 **signals” in the absence of feedback?**

1981 In the absence of feedback, observers can only rely on internal estimates of performance to  
1982 guide updates to their model of the reliability of their sensory apparatus (inferences about  
1983  $M$ ). Previous work (e.g. Guggenmos et al., Elife 2106, <https://doi.org/10.7554/eLife.13388>)  
1984 has shown that confidence signals can provide signals that drive perceptual learning in the  
1985 absence of feedback. This has motivated our model simulation on the adaptive benefits of  
1986 bimodal inference for metacognition, where the learning signal  $\epsilon_M$  (i.e., the difference between  
1987 the choice and its probability) drives inferences about  $M$ . Please note that we have removed  
1988 this section following Comment 9 of Reviewer 1.

1989 **10.1.6 Comment 6**

1990 **And what licences the assumption that internal confidence feedback corresponds**  
1991 **to “the absolute of the posterior log ratio” (did you mean the log of the posterior**  
1992 **ratio)?**

1993 We mean the absolute of the log of the posterior ratio. Following first order models (see  
1994 e.g., Fleming & Daw, Self-evaluation of decision-making: A general Bayesian framework for  
1995 metacognitive computation, Psychol. Rev. 2017, <https://doi.org/10.1037/rev0000045>), the  
1996 perceptual decision and the confidence report rely on the posterior. The distance of the log  
1997 of the posterior ratio  $L_t$  from zero becomes a measure of decision-certainty or confidence.

1998 **10.1.7 Comment 7**

1999 **I got a bit lost here when you say that “the precision of sensory coding M a**  
2000 **function of u\_t. This is largely because I couldn’t find a definition of u\_t.**

2001 We apologize for this lack of clarity. In the model simulations on the adaptive benefits of

2002 bimodal inference, we generated stimuli  $s_t$  from a Bernoulli-distribution with  $p = q = 0.5$ .  
2003 The value of  $u_t$  was then defined via equation (13), following our modeling of the human  
2004 data. Please note that we have removed this section following Comment 9 of Reviewer 1.

2005 **10.1.8 Comment 8**

2006 **What licences an application of Rescorla-Wagner to learning the parameters (as**  
2007 **in Equation 11) and, learning sensory precision as described by M\_T (Equation**  
2008 **13). Are you moving from a Bayesian framework to a reinforcement learning**  
2009 **framework?**

2010 We would like to thank the reviewer for pointing out this inconsistency. We have chosen the  
2011 Rescorla-Wagner learning rule for simplicity: In our model, the speed of learning about  $H$   
2012 and  $M$  varied according to the current mode of perceptual processing and a constant learning  
2013 rate. Allowing the learning rate itself to vary as a function of preceding experiences would  
2014 add an additional level of complexity that we sought to omit in this analysis. However, we  
2015 fully agree that choosing a Bayesian framework (e.g., a three-level HGF) would indeed be  
2016 more consistent. Please note that we have removed this section following Comment 9 of  
2017 Reviewer 1.

2018 **10.1.9 Comment 9**

2019 **I am sure you have answers to these questions - but with each new question**  
2020 **the reader is left more and more skeptical that there is a coherent story behind**  
2021 **your analyses. It would have been more convincing had you just committed to**  
2022 **a Bayesian filter and made your points using one update scheme, under ideal**  
2023 **Bayesian observer assumptions.**

2024 **Unlike your piecemeal scheme, things like the hierarchical Gaussian filter estimates**  
2025 **the sensory and prior decisions explicitly and these estimates underwrite posterior**  
2026 **inference. In your scheme, the sensory precision M appears to have no influence**

2027 on perceptual inference (which is why, presumably you call it metacognition).  
2028 The problem with this is that your motivation for systematic fluctuations in  
2029 precision is weakened. This is because improved metacognition does not improve  
2030 perception — it only improves the perception of perception.

2031 In light of the above, can I suggest that you remove Section 5.8 and use your  
2032 model in the preceding section to endorse your hypothesis along the following  
2033 lines:

2034 “In summary, we hypothesized that subjects have certain hyperpriors that are  
2035 apt for accommodating fluctuations in the predictability of their environment;  
2036 i.e., people believe that their world is inherently volatile. This means that to be  
2037 Bayes optimal it is necessary to periodically re-evaluate posterior beliefs about  
2038 model parameters. One way to do this is to periodically suspend the precision  
2039 of prior beliefs and increase the precision afforded to sensory evidence that  
2040 updates (Bayesian) beliefs about model parameters. The empirical evidence above  
2041 suggests that the timescale of this periodic scheduling of evidence accumulation  
2042 may be scale-invariant. This means that there may exist a timescale of periodic  
2043 fluctuations in precision over every window or length of perceptual decision-  
2044 making. In what follows, we model perceptual decisions under a generative model  
2045 (based upon a hazard function to model historical or serial dependencies) with, a  
2046 periodic fluctuation in the precision of sensory evidence relative to prior beliefs  
2047 at a particular timescale. Remarkably—using Bayesian model comparison—we  
2048 find that a model with fluctuating precisions has much greater evidence, relative  
2049 to a model in the absence of fluctuating precisions. Furthermore, we were able  
2050 to quantify the dominant timescale of periodic fluctuations; appropriate for these  
2051 kinds of paradigm.”

2052 Note, again, I am reading your omega\_LL and omega\_psi as precisions and

2053 that the periodic modulation is the hyperprior that you are characterizing—and  
2054 have discovered.

2055 We would like to thank Prof. Friston for these very helpful and precise suggestions. In brief,  
2056 we now provide a quantitative assessment of model space based on AIC (i) and have followed  
2057 the suggestion of omitting section 5.8 (ii).

2058 In addition to the qualitative assessment of our models in the initial version of our manuscript,  
2059 we have conducted a formal model comparison (i). Following the model comparisons in  
2060 other sections of the manuscript, we based the model comparison on AIC. We furthermore  
2061 show that the winning *bimodal inference model* predicts out-of-training variables (RT and  
2062 confidence) and use simulations from posterior model parameters to show that, in contrast to  
2063 reduced models, the bimodal inference model neither over- nor underfits the empirical data.

2064 We have added a description of our model comparison to the Method section:

2065 • We validated the bimodal inference model in three steps: a formal model comparison to  
2066 reduced models based on AIC (Figure 1F-G; Supplemental Figure S9), the prediction of  
2067 within-training (stimulus- and history-congruence) as well as out-of-training variables  
2068 (RT and confidence), and a qualitative reproduction of the empirical data from model  
2069 simulations based on estimated parameters (Figure 4).

2070 • **Model comparison.** We assessed the following model space based on AIC:

2071 • The full *bimodal inference model* (M1; Figure 1F) incorporates the influence of sensory  
2072 information according to the parameter  $\alpha$  (likelihood); the integration of evidence across  
2073 trials according to the parameter  $H$  (prior); anti-phase oscillations in between likelihood  
2074 and prior precision according to  $\omega_{LLR}$  and  $\omega_\psi$  with parameters  $a_{LLR}$  (amplitude likelihood  
2075 fluctuation),  $a_\psi$  (amplitude prior fluctuation),  $f$  (frequency) and  $p$  (phase).

2076 • The *likelihood-oscillation-only model* (M2; Figure 1G) incorporates the influence of sen-  
2077 sory information according to parameter  $\alpha$  (likelihood); the integration of evidence across

2078 trials according to parameter  $H$  (prior); oscillations in likelihood precision according  
2079 to  $\omega_{LLR}$  with parameters  $a_{LLR}$  (amplitude likelihood fluctuation),  $f$  (frequency) and  $p$   
2080 (phase).

- 2081 • The *prior-oscillation-only model* (M3; Figure 1G) incorporates the influence of sensory  
2082 information according to parameter  $\alpha$  (likelihood); the integration of evidence across  
2083 trials according to parameter  $H$  (prior); oscillations in the prior precision according  
2084 to  $\omega_\psi$  with parameters  $a_\psi$  (amplitude prior fluctuation),  $f$  (frequency) and  $p$  (phase).  
2085 Please note that all models M1-3 lead to shifts in the relative precision of likelihood and  
2086 prior.
- 2087 • The *normative-evidence-accumulation* (M4; Figure 1G) incorporates the influence of  
2088 sensory information according to parameter  $\alpha$  (likelihood); the integration of evidence  
2089 across trials according to parameter  $H$  (prior), There are no additional oscillations.  
2090 Model M4 thus corresponds to the model proposed by Glaze et al. and captures normative  
2091 evidence accumulation in unpredictable environments using a Bayesian update scheme<sup>51</sup>.  
2092 The comparison against M4 tests the null hypothesis that fluctuations in mode emerge  
2093 from a normative Bayesian model without the ad-hoc addition of oscillations as in models  
2094 M1-3.
- 2095 • The *no-evidence-accumulation* (M5; Figure 1G) incorporates the influence of sensory  
2096 information according to parameter  $\alpha$  (likelihood). The model lacks integration of  
2097 evidence across trials (flat prior) and oscillations. The comparison against M5 tests  
2098 the null hypothesis that observers do not use prior information derived from serial  
2099 dependency in perception.

- 2100 • **Prediction of within-training and out-of-training variables.** To validate our  
2101 model, we correlated individual posterior parameter estimates with the respective  
2102 conventional variables. As a sanity check, we tested (i), whether the estimated hazard  
2103 rate  $H$  correlated negatively with the frequency of history-congruent choices and, (ii),

whether the estimated sensitivity to sensory information  $\alpha$  correlated positively with the frequency of stimulus-congruent choices. In addition, we tested whether the posterior decision certainty (i.e., the absolute of the log posterior ratio) correlated negatively with RTs and positively with confidence. This allowed us to assess whether our model could explain aspects of the data it was not fitted to (i.e., RTs and confidence).

- **Simulations.** Finally, we used simulations (Figure 4, Supplemental Figures S10-13) to show that all model components, including the anti-phase oscillations governed by  $a_\psi$ ,  $a_{LLR}$ ,  $f$  and  $p$ , were necessary for our model to reproduce the characteristics of the empirical data. This enabled us to assess over- or under-fitting in the bimodal inference model and all reduced models M2-M5. We used the posterior model parameters observed for humans ( $H$ ,  $\alpha$ ,  $a_\psi$ ,  $a_{LLR}$ ,  $f$ ,  $p$  and  $\zeta$ ) to define individual parameters for simulation in 4317 simulated participants (i.e., equivalent to the number of human participants). For each participant, the number of simulated trials was drawn at random between 300 to 700. Inputs  $s$  were drawn at random for each trial, such that the sequence of inputs to the simulation did not contain any systematic seriality. Noisy observations  $u$  were generated by applying the posterior parameter  $\alpha$  to inputs  $s$ , thus generating stimulus-congruent choices in  $71.36 \pm 2.6 \times 10^{-3}\%$  of trials. Choices were simulated based on the trial-wise choice probabilities  $y_p$  obtained from our model. Simulated data were analyzed in analogy to the human and mouse data. As a substitute of subjective confidence, we computed the absolute of the trial-wise log posterior ratio  $|L|$  (i.e., the posterior decision certainty).

We have also added a graphical depiction of the model space to Figure 1 (subpanels F and G):

- F. The bimodal inference model (M1) explains fluctuations between externally- and externally-biased modes (left panel) by two interacting factors: a normative accumulation

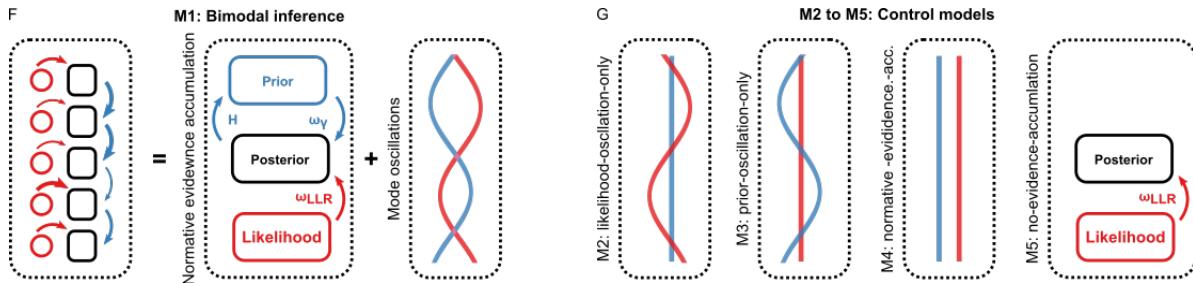


Figure 1 F-G

of evidence according to parameters  $H$  (middle panel), and anti-phase oscillations in the precision terms  $\omega_{LLR}$  and  $\omega_\psi$  (right panel).

- G. The control models M2-M5 were constructed by successively removing the anti-phase oscillations and the integration of information from the bimodal inference model. Please note that the normative-evidence-accumulation-model (M4) corresponds to the model proposed by Glaze et al.<sup>51</sup>. In the no-evidence-accumulation model (M5), perceptual decisions depend only on likelihood information (flat priors).

The formal model comparison yielded clear evidence for a superiority of the bimodal inference model, in particular over the normative Bayesian model of evidence accumulation. The model successfully predicted both within-training variables (as a sanity-check) and out-of-training variables. Simulations from posterior model parameters closely followed the empirical data (Figure 4), which was not the case for reduced models (Supplemental Figures S10-13). We summarize these findings in the Results section and have added a Supplemental Figure S9 to show the distribution of observer-level AIC at the session-level (see below):

- We used a maximum likelihood procedure to fit the bimodal inference model (M1, Figure 1F) to the behavioral data from the Confidence database<sup>20</sup> and the IBL database<sup>21</sup>, optimizing the parameters  $\alpha$ ,  $H$ ,  $\omega_{LLR}$ ,  $\omega_\psi$ ,  $f$ ,  $p$ , and  $\zeta$  (see Methods for details and Supplemental Table T2 for a summary of the parameters of the bimodal inference model). We validated our model in three steps: First, to show that bimodal inference does not

2148 emerge spontaneously in normative Bayesian models of evidence accumulation, but  
2149 requires the ad-hoc addition of anti-phase oscillations in prior and likelihood precision,  
2150 we compared the bimodal inference model to four control models (M2-5, Figure 1G).  
2151 In these models, we successively removed the anti-phase oscillations (M2-M4) and the  
2152 integration of information across trials (M5) from the bimodal inference model and  
2153 performed a model comparison based on AIC.

- 2154 • Model M2 ( $AIC_2 = 5.7 \times 10^4$  in humans and  $4.94 \times 10^4$  in mice) and Model M3 ( $AIC_3$   
2155  $= 6.9 \times 10^4$  in humans and  $5.99 \times 10^4$  in mice) incorporated only oscillations of either  
2156 likelihood or prior precision. Model M4 ( $AIC_4 = 9.8 \times 10^4$  in humans and  $9.19 \times 10^4$  in  
2157 mice) lacked any oscillations of likelihood and prior precision and corresponded to the  
2158 normative model proposed by Glaze et al.<sup>51</sup>. In model M5 ( $AIC_4 = 1.16 \times 10^5$  in humans  
2159 and  $1.14 \times 10^5$  in mice), we furthermore removed the integration of information across  
2160 trials, such that perception depended only in incoming sensory information (Figure 1G).
- 2161 • The bimodal inference model achieved the lowest AIC across the full model space ( $AIC_1$   
2162  $= 4.73 \times 10^4$  in humans and  $4.28 \times 10^4$  in mice) and was clearly superior to the normative  
2163 Bayesian model of evidence accumulation ( $\delta_{AIC} = -5.08 \times 10^4$  in humans and  $-4.91 \times 10^4$   
2164 in mice; Supplemental Figure S9).
- 2165 • As a second validation of the bimodal inference model, we tested whether the posterior  
2166 model predicted within-training and out-of-training variables. The bimodal inference  
2167 model characterizes each subject by a sensitivity parameter  $\alpha$  (humans:  $\alpha = 0.5 \pm$   
2168  $1.12 \times 10^{-4}$ ; mice:  $\alpha = 1.06 \pm 2.88 \times 10^{-3}$ ) that captures how strongly perception is  
2169 driven by the available sensory information, and a hazard rate parameter  $H$  (humans:  $H$   
2170  $= 0.45 \pm 4.8 \times 10^{-5}$ ; mice:  $H = 0.46 \pm 2.97 \times 10^{-4}$ ) that controls how heavily perception  
2171 is biased by perceptual history. The parameter  $f$  captures the dominant time scale at  
2172 which likelihood (amplitude humans:  $a_{LLR} = 0.5 \pm 2.02 \times 10^{-4}$ ; mice:  $a_{LLR} = 0.39 \pm$   
2173  $1.08 \times 10^{-3}$ ) and prior precision (amplitude humans:  $a_\psi = 1.44 \pm 5.27 \times 10^{-4}$ ; mice:  $a_\psi$

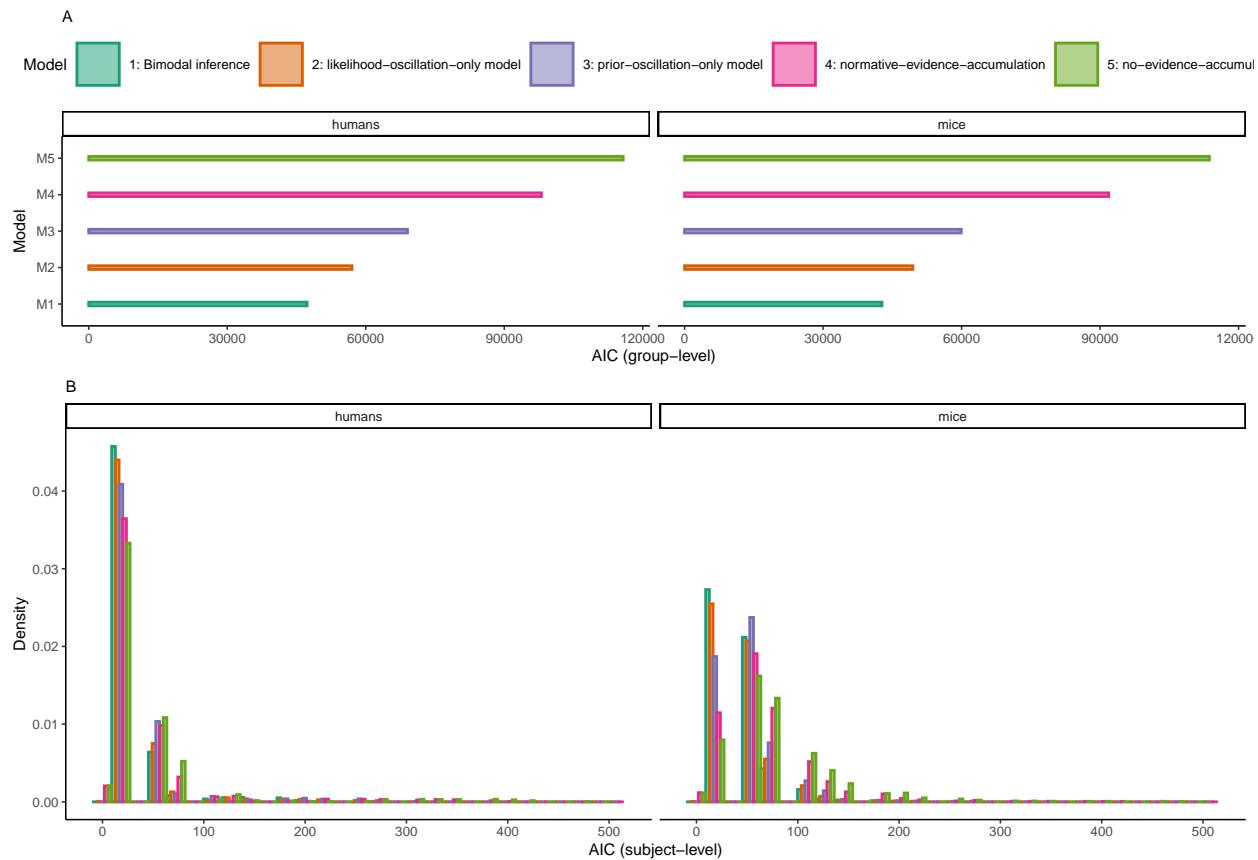
2174  $= 1.71 \pm 7.15 \times 10^{-3}$ ) fluctuated and was estimated at  $0.11 \pm 1.68 \times 10^{-5} 1/N_{trials}$  and  
2175  $0.11 \pm 1.63 \times 10^{-4} 1/N_{trials}$  in mice.

- 2176 • As a sanity check for model fit, we tested whether the frequency of stimulus- and  
2177 history-congruent trials in the Confidence database<sup>20</sup> and IBL database<sup>21</sup> correlate with  
2178 the estimated parameters  $\alpha$  and  $H$ , respectively. As expected, the estimated sensitivity  
2179 toward stimulus information  $\alpha$  was positively correlated with the frequency of stimulus-  
2180 congruent perceptual choices (humans:  $\beta = 8.4 \pm 0.26$ ,  $T(4.31 \times 10^3) = 32.87$ ,  $p =$   
2181  $1.3 \times 10^{-211}$ ; mice:  $\beta = 1.93 \pm 0.12$ ,  $T(2.07 \times 10^3) = 16.21$ ,  $p = 9.37 \times 10^{-56}$ ). Likewise,  
2182  $H$  was negatively correlated with the frequency of history-congruent perceptual choices  
2183 (humans:  $\beta = -11.84 \pm 0.5$ ,  $T(4.29 \times 10^3) = -23.5$ ,  $p = 5.16 \times 10^{-115}$ ; mice:  $\beta = -6.18$   
2184  $\pm 0.66$ ,  $T(2.08 \times 10^3) = -9.37$ ,  $p = 1.85 \times 10^{-20}$ ).
- 2185 • Our behavioral analyses reveal that humans and mice show significant effects of perceptual  
2186 history that impaired performance in randomized psychophysical experiments<sup>24,28,30,31,43</sup>  
2187 (Figure 2A and 3A). We therefore expected that humans and mice underestimated the  
2188 true hazard rate  $\hat{H}$  of the experimental environments (Confidence database<sup>20</sup>:  $\hat{H}_{Humans}$   
2189  $= 0.5 \pm 1.58 \times 10^{-5}$ ); IBL database<sup>21</sup>:  $\hat{H}_{Mice} = 0.49 \pm 6.47 \times 10^{-5}$ ). Indeed, when  
2190 fitting the bimodal inference model to the trial-wise perceptual choices, we found that  
2191 the estimated (i.e., subjective) hazard rate  $H$  was lower than  $\hat{H}$  for both humans ( $\beta$   
2192  $= -6.87 \pm 0.94$ ,  $T(61.87) = -7.33$ ,  $p = 5.76 \times 10^{-10}$ ) and mice ( $\beta = -2.91 \pm 0.34$ ,  
2193  $T(112.57) = -8.51$ ,  $p = 8.65 \times 10^{-14}$ ).
- 2194 • To further probe the validity of the bimodal inference model, we tested whether posterior  
2195 model quantities could explain aspects of the behavioral data that the model was not  
2196 fitted to. We predicted that the posterior decision variable  $L_t$  not only encodes perceptual  
2197 choices (i.e., the variable used for model estimation), but should also predict the speed  
2198 of response and subjective confidence<sup>30,44</sup>. Indeed, the estimated trial-wise posterior  
2199 decision certainty  $|L_t|$  correlated negatively with RTs in humans ( $\beta = -4.36 \times 10^{-3} \pm$

2200         $4.64 \times 10^{-4}$ ,  $T(1.98 \times 10^6) = -9.41$ ,  $p = 5.19 \times 10^{-21}$ ) and TDs mice ( $\beta = -35.45 \pm$   
2201         $0.86$ ,  $T(1.28 \times 10^6) = -41.13$ ,  $p < 2.2 \times 10^{-308}$ ). Likewise, subjective confidence reports  
2202        were positively correlated with the estimated posterior decision certainty in humans ( $\beta$   
2203         $= 7.63 \times 10^{-3} \pm 8.32 \times 10^{-4}$ ,  $T(2.06 \times 10^6) = 9.18$ ,  $p = 4.48 \times 10^{-20}$ ).

- 2204        • The dynamic accumulation of information inherent to our model entails that biases  
2205        toward perceptual history are stronger when the posterior decision certainty at the  
2206        preceding trial is high<sup>30,31,51</sup>. Due to the link between posterior decision certainty and  
2207        confidence, we reasoned that confident perceptual choices should be more likely to induce  
2208        history-congruent perception at the subsequent trial<sup>30,31</sup>. Indeed, logistic regression  
2209        indicated that history-congruence was predicted by the posterior decision certainty  
2210         $|L_{t-1}|$  (humans:  $\beta = 8.22 \times 10^{-3} \pm 1.94 \times 10^{-3}$ ,  $z = 4.25$ ,  $p = 2.17 \times 10^{-5}$ ; mice:  $\beta =$   
2211         $-3.72 \times 10^{-3} \pm 1.83 \times 10^{-3}$ ,  $z = -2.03$ ,  $p = 0.04$ ) and subjective confidence (humans:  
2212         $\beta = 0.04 \pm 1.62 \times 10^{-3}$ ,  $z = 27.21$ ,  $p = 4.56 \times 10^{-163}$ ) at the preceding trial.
- 2213        • As a third validation of the bimodal inference model, we used the posterior model  
2214        parameters to simulate synthetic perceptual choices and repeated the behavioral analyses  
2215        conducted for the empirical data. Simulations from the bimodal inference model  
2216        closely replicated our empirical results: Simulated perceptual decisions resulted from a  
2217        competition of perceptual history with incoming sensory signals (Figure 4A). Stimulus-  
2218        and history-congruence were significantly autocorrelated (Figure 4B-C), fluctuating in  
2219        anti-phase as a scale-invariant process with a 1/f power law (Figure 4D-F). Simulated  
2220        posterior certainty<sup>28,30,44</sup> (i.e., the absolute of the log posterior ratio  $|L_t|$ ) showed a  
2221        quadratic relationship to the mode of sensory processing (Figure 4H), mirroring the  
2222        relation of RTs and confidence reports to external and internal biases in perception  
2223        (Figure 2G-H and Figure 3G-H). Crucially, the overlap between empirical and simulated  
2224        data broke down when we removed the anti-phase oscillations or the accumulation of  
2225        evidence over time from the bimodal inference model (Supplemental Figure S10-13).

2226 • In sum, computational modeling suggested that between-mode fluctuations are best  
 2227 explained by two interlinked processes (Figure 1E): (i), the dynamic accumulation of  
 2228 information across successive trials mandated by normative Bayesians model of evidence  
 2229 accumulation and, (ii), ongoing anti-phase oscillations in the impact of external and  
 2230 internal information.



2231

- 2232 • **Supplemental Figure S9.** Comparison of the bimodal inference model against reduced  
 2233 control models.
- 2234 • A. Group-level AIC. The bimodal inference model (M1) achieved the lowest AIC across  
 2235 the full model space ( $AIC_1 = 4.73 \times 10^4$  in humans and  $4.28 \times 10^4$  in mice). Model M2  
 2236 ( $AIC_2 = 5.7 \times 10^4$  in humans and  $4.94 \times 10^4$  in mice) and Model M3 ( $AIC_3 = 6.9 \times 10^4$   
 2237 in humans and  $5.99 \times 10^4$  in mice) incorporated only oscillations of either likelihood or  
 2238 prior precision. Model M4 ( $AIC_4 = 9.8 \times 10^4$  in humans and  $9.19 \times 10^4$  in mice) lacked

any oscillations of likelihood and prior precision and corresponded to the normative model proposed by Glaze et al.<sup>51</sup>. In model M5 ( $AIC_4 = 1.16 \times 10^5$  in humans and  $1.14 \times 10^5$  in mice), we furthermore removed the integration of information across trials, such that perception depended only in incoming sensory information.

- B. Subject-level AIC. Here, we show the distribution of AIC values at the subject-level. AIC for the bimodal inference model tended to be smaller than AIC for the comparator models (statistical comparison to the second-best model M2 in humans:  $\beta = -1.81 \pm 0.27$ ,  $T(5.07 \times 10^3) = -6.82$ ,  $p = 1.02 \times 10^{-11}$ ; mice:  $T(1.5 \times 10^3) = -6.28$ ,  $p = 4.38 \times 10^{-10}$ ).

In light of our response to Comments 1 - 9 of Reviewer 1, we agree that a complete and extensive investigation of the relation between bimodal inference, learning about changes in the environment and the relation to metacognition may be beyond the scope of the current manuscript: Both Reviewer 1 and 3 (see below) have shared that the manuscript is too long and should be streamlined. Yet evaluating the full model space (e.g., comparing update rules for inferences about  $H$  and  $M$ , testing for an influence of beliefs about  $M$  on learning about  $H$  etc.) would make the manuscript even longer. We are therefore happy to follow Prof. Fristons suggestions to omit section 5.8. We have changed the manuscript in the following ways:

When introducing  $\omega_{LLR}$ , we identify it as the precision afforded to the likelihood, referring to the Bayesian framework, and refer to fluctuations in mode as a hyperprior.

- To allow for *bimodal inference*, i.e., alternating periods of internally- and externally-biased modes of perceptual processing that occur irrespective of the sequence of preceding experiences, we assumed that likelihood and prior vary in their influence on the perceptual decision according to fluctuations governed by  $\omega_{LLR}$  and  $\omega_\psi$ . These anti-phase sine functions (defined by amplitudes  $a_{LLR/\psi}$ , frequency  $f$  and phase  $p$ ) determine the precision afforded to the likelihood and prior<sup>53</sup>. The implicit anti-phase fluctuations

2264 are mandated by Bayes-optimal formulations in which inference depends only on the  
2265 relative values of prior and likelihood precision (i.e., the Kalman gain<sup>54</sup>). As such,  $\omega_{LLR}$   
2266 and  $\omega_\psi$  implement a hyperprior<sup>55</sup> in which the likelihood and prior precisions are shifted  
2267 against each other at a dominant timescale defined by  $f$ .

2268 We have deleted the section 5.8 and added a summary of our modeling approach to the  
2269 discussion, closely following the text recommended by Prof. Friston:

2270 • (...) Yet relying too strongly on serial dependencies may come at a cost: When  
2271 accumulating over time, internal predictions may eventually override external information,  
2272 leading to circular and false inferences about the state of the environment<sup>57</sup>. Akin to the  
2273 wake-sleep-algorithm in machine learning<sup>58</sup>, bimodal inference may help to determine  
2274 whether errors result from external input or from internally-stored predictions: During  
2275 internal mode, sensory processing is more strongly constrained by predictive processes  
2276 that auto-encode the agent’s environment. Conversely, during external mode, the  
2277 network is driven predominantly by sensory inputs<sup>18</sup>. Between-mode fluctuations may  
2278 thus generate an unambiguous error signal that aligns internal predictions with the  
2279 current state of the environment in iterative test-update-cycles<sup>58</sup>. On a broader scale,  
2280 between-mode fluctuations may thus regulate the balance between feedforward versus  
2281 feedback contributions to perception and thereby play a adaptive role in metacognition  
2282 and reality monitoring<sup>59</sup>.

2283 • From the perspective of the Bayesian brain hypothesis, we hypothesized that observers  
2284 have certain hyperpriors that are apt for accommodating fluctuations in the predictability  
2285 of their environment, i.e., people believe that their world is inherently volatile. To be  
2286 Bayes optimal, it is therefore necessary to periodically re-evaluate posterior beliefs  
2287 about the parameters that define an internal generative model of the external sensory  
2288 environment. One way to do this is to periodically suspend the precision of prior beliefs

2289 and increase the precision afforded to sensory evidence, thus updating Bayesian beliefs  
2290 about model parameters.

- 2291 • The empirical evidence above suggests that the timescale of this periodic scheduling  
2292 of evidence accumulation may be scale-invariant. This means that there may exist a  
2293 timescale of periodic fluctuations in precision over every window or length of perceptual  
2294 decision-making. Bimodal inference predicts perceptual decisions under a generative  
2295 model (based upon a hazard function to model serial dependencies between subsequent  
2296 trials) with periodic fluctuations in the precision of sensory evidence relative to prior  
2297 beliefs at a particular timescale. Remarkably, a systematic model comparison based  
2298 on AIC indicated that a model with fluctuating precisions has much greater evidence,  
2299 relative to a model in the absence of fluctuating precisions. This ad-hoc addition of  
2300 oscillations to a normative Bayesian model of evidence accumulation<sup>51</sup> allowed us to  
2301 quantify the dominant timescale of periodic fluctuations mode at approximately 0.11  
2302  $1/N_{trials}$  in humans and mice that is appropriate for these kinds of paradigms.

2303 Following the deletion of section 5.8, we have adapted the last sentence of the abstract and  
2304 the last paragraph of the introduction:

- 2305 • (...) We propose that between-mode fluctuations generate unambiguous error signals  
2306 that enable optimal inference in volatile environments.
- 2307 • When less sensitive to external stimulus information, humans and mice did not behave  
2308 more randomly, but showed stronger serial dependencies in their perceptual choices<sup>22–33</sup>.  
2309 These serial dependencies may be understood as driven by internal predictions that reflect  
2310 the autocorrelation of natural environments<sup>34</sup> and bias perception toward preceding  
2311 experiences<sup>30,31,35</sup>. Computational modeling indicated that ongoing changes in perceptual  
2312 performance may be driven by systematic fluctuations between externally- and internally-  
2313 oriented modes of sensory analysis. We suggest that such *bimodal inference* may help

2314 to build stable internal representations of the sensory environment despite an ongoing  
2315 stream of sensory information.

2316 **10.1.10 Comment 11**

2317 This begs the question as to whether you want to pursue the  $1/f$  story. You  
2318 refer to this as “noise”. However, there is no noise in this setup. I think what  
2319 you meant was that the fluctuations are scale free, because they evinced a power  
2320 law. I am sure that there are scale free aspects of these kinds of hyperpriors;  
2321 however, in the context of your paradigm I wonder whether you should just  
2322 ignore the scale free aspect and focus on your estimated temporal scale implicit  
2323 in  $f$ . This means you don’t have to hand wave about self-organized criticality in  
2324 the discussion and focus upon your hypothesis.

2325 We would like to thank the reviewer for this suggestion. We agree that the discussion  
2326 of self-organized criticality is far from the data. We have omitted this section from the  
2327 discussion. With respect to  $f$ , we have adapted the manuscript to make clear that it captures  
2328 the dominant timescale of fluctuations in mode:

- 2329 • (...) This implements a hyperprior<sup>55</sup> in which the likelihood and prior precisions are  
2330 shifted against each other at a dominant timescale defined by  $f$ : (...)
- 2331 • (...) The parameter  $f$  captured the dominant time scale at which likelihood and prior  
2332 precision were shifted against each other and was estimated at  $0.11 \text{ } 1/N_{trials}$  in both  
2333 humans and mice.
- 2334 • Remarkably, a systematic model comparison based on AIC indicated that a model with  
2335 fluctuating precisions has much greater evidence, relative to a model in the absence  
2336 of fluctuating precisions. The ad-hoc addition of oscillations to a normative Bayesian  
2337 model of evidence accumulation<sup>51</sup> allowed us to quantify the dominant timescale of

2338 periodic fluctuations mode at approximately  $0.11\ 1/N_{trials}$  in humans and mice that is  
2339 appropriate for these kinds of paradigms.

2340 **10.1.11 Comment 12**

2341 **A final move—to make the paper more focused and digestible—would be to**  
2342 **put a lot of your defensive analyses (e.g. about general arousal et cetera) in**  
2343 **supplementary material. You have to be careful not to exhaust the reader by**  
2344 **putting up a lot of auxiliary material before the important messages in your**  
2345 **report.**

2346 We have followed this suggestion and move the following sections to the Supplement: section  
2347 5.3 (Internal and external modes of processing facilitate response behavior and enhance  
2348 confidence in human perceptual decision-making), section 5.4 (Fluctuations between internal  
2349 and external mode modulate perceptual performance beyond the effect of general response  
2350 biases), section 5.5 (Internal mode is characterized by lower thresholds as well as by history-  
2351 dependent changes in biases and lapses). We have also moved secondary statistics to the  
2352 figure legends and to the Supplement.

2353 **Minor points**

2354 **10.1.12 Comment 13**

2355 **I cannot resist suggesting that you change your title to “Bimodal Inference in**  
2356 **Mice and Men”**

2357 We would like to thank the Reviewer for this suggestion and agree that this would indeed  
2358 sound great. However, we are worried that changing the title to *mice and men* would not  
2359 be as gender-neutral as *humans and mice*. We would therefore propose to stay with the  
2360 current title. If we are mistaken and *mice and men* can be considered gender-neutral (we are  
2361 non-native speakers), we would be happy to change the title.

<sub>2362</sub> **10.1.13 Comment 14**

<sub>2363</sub> Please replace “infra-slow fluctuations” with “slow fluctuations”. Slow has some  
<sub>2364</sub> colloquial meaning in fMRI studies but not in any scale free context.

<sub>2365</sub> Done.

<sub>2366</sub> **10.1.14 Comment 15**

<sub>2367</sub> Please replace “simulated data” with “simulations” in the abstract. Finally,  
<sub>2368</sub> please replace “robust learning and metacognition in volatile environments” with  
<sub>2369</sub> “enable optimal inference and learning in volatile environments.”

<sub>2370</sub> Done. Since we have followed the suggestion to delete section 5.8, we have rephrased the last  
<sub>2371</sub> paragraph of the abstract into:

<sub>2372</sub> • (...) We propose that between-mode fluctuations generate unambiguous error signals  
<sub>2373</sub> that enable optimal inference in volatile environments.

<sub>2374</sub> **10.1.15 Comment 16**

<sub>2375</sub> Line 50, please replace “about the degree of noise inherent in encoding of  
<sub>2376</sub> sensory information” with “the precision of sensory information relative to prior  
<sub>2377</sub> (Bayesian) beliefs.”

<sub>2378</sub> Done.

<sub>2379</sub> **10.1.16 Comment 17**

<sub>2380</sub> Line 125: please replace “a source of error” with “a source of bias”

<sub>2381</sub> Done.

2382 10.1.17 Comment 18

2383 Line 141: please replace “one 1/f noise” with a scale-invariant process with a 1/f  
2384 power law” (here and throughout) this is not “noise” it is a particular kind of  
2385 fluctuation.

2386 Done.

2387 10.1.18 Comment 19

2388 Line 178, when you say that the fluctuations may arise due to “changes in level of  
2389 tonic arousal or on-task attention”, I think you need to qualify this. In predictive  
2390 processing, on-task attention is exactly the modulation of sensory precision,  
2391 relative to prior precision that you are characterizing here. Tonic arousal may be  
2392 another thing may or may not confound your current results.

2393 Thank you very much for pointing this out. We have adapted the discussion to make the  
2394 distinction between attention in the predictive processing sense and the broader issue of task  
2395 engagement (reflecting fluctuations in arousal, fatigue etc.) clearer (see also our responses  
2396 above):

- 2397 • As a functional explanation for bimodal inference, we propose that perception temporarily  
2398 disengages from internal predictions to form stable inferences about the statistical  
2399 properties of the sensory environment. Between-mode fluctuations may thus elude  
2400 circular inferences that occur when both the causes and the encoding of sensory stimuli  
2401 are volatile<sup>19,57</sup>). By the same token, we suggest that fluctuations in mode occur at  
2402 the level of perceptual processing<sup>26,30,46,47</sup>, and are not a passive phenomenon that is  
2403 primarily driven by factors situated up- or downstream of sensory analysis.
- 2404 • How does attention relate to between-mode fluctuations? According to predictive  
2405 processing, attention corresponds to the precision afforded to the probability distributions

2406 that underlie perceptual inference<sup>53</sup>. As outlined above, between-mode fluctuations  
2407 can be understood as ongoing shifts in the precision afforded to likelihood (*external*  
2408 *mode*) and prior (*internal mode*), respectively. When the precision afforded to prior or  
2409 likelihood increases, posterior precision increases, which leads to faster RTs and higher  
2410 confidence. When defined from the perspective of predictive processing as the precision  
2411 afforded to likelihood and prior<sup>53</sup>, fluctuations in attention may thus provide a plausible  
2412 explanation for the quadratic relationship between mode and RTs and confidence (Figure  
2413 2H and J; Figure 3I; Figure 3I).

- 2414 • Outside of the predictive processing field, attention is often understood in the context of  
2415 task engagement<sup>63</sup>, which varies according to the availability of cognitive resources that  
2416 are modulated by factors such as tonic arousal, familiarity with the task, or fatigue<sup>63</sup>. Our  
2417 results suggest that internal mode processing cannot be completely reduced to intervals  
2418 of low task engagement: In addition to shorter RTs and elevated confidence, choices  
2419 during internal mode were not random or globally biased, but driven by perceptual  
2420 history (Supplemental Figures S6-7). Moreover, our computational model identified  
2421 the dominant timescale of between-mode fluctuations at  $0.11\ 1/N_{trials}$ , which may be  
2422 compatible with fluctuations in arousal<sup>64</sup>, but is faster than to be expected for the  
2423 development of task familiarity or fatigue.
- 2424 • However, in interpreting the impact of between-mode fluctuations on perceptual accuracy,  
2425 speed of response and confidence, it is important to consider that global modulators  
2426 such as tonic arousal are known to have non-linear effects on task performance<sup>65</sup>: In  
2427 perceptual tasks, performance seems so be highest during mid-level arousal, whereas low-  
2428 and high-level arousal lead to reduced accuracy and slower responses<sup>65</sup>. This contrasts  
2429 with the effects of bimodal inference, where accuracy increases linearly as one moves  
2430 from internal to external mode, and responses become faster at both ends of the mode  
2431 spectrum.

2432 • Of note, high phasic arousal has been shown to suppress multi-domain biases in decision-  
2433 making in humans and mice<sup>66–68</sup>, including the biases toward perceptual history<sup>28</sup> that  
2434 we implicate in internal mode processing. The increase in response speed and history  
2435 congruence over time (Supplemental Section 9.4) may argue against insufficient training  
2436 as an alternative explanation for internal mode processing, but may also taken as a  
2437 sign of waning arousal. The multiple mechanistic mappings to RTs and confidence  
2438 therefore warrant more direct measures of arousal (such as pupil size<sup>28,65,66,68–70</sup>, motor  
2439 behavior<sup>69,70</sup>, or neural data<sup>71</sup>) to better delineate bimodal inference from fluctuations  
2440 in global modulators of task performance.

2441 **10.1.19 Comment 20**

2442 When introducing Equation 2, please make it clear that the omega terms stand in  
2443 for the precisions afforded to the likelihood (omega\_LL) and prior (omega\_psi)  
2444 that constitute the log posterior.

2445 We have modified the introduction of equation 2 as follows:

2446 • Following Bayes' theorem, we reasoned that binary perceptual decisions depend on the  
2447 log posterior ratio  $L$  of the two alternative states of the environment that participants  
2448 learn about via noisy sensory information<sup>51</sup>. We computed the posterior by combining  
2449 the sensory evidence available at time-point  $t$  (i.e., the log likelihood ratio  $LLR$ ) with  
2450 the prior probability  $\psi$ , weighted by the respective precision terms  $\omega_{LL}$  and  $\omega_\psi$ :

2451 You can then motivate Equation 6 and 7 as implementing the hyperprior in which  
2452 the sensory and prior precisions fluctuate at a particular time scale.

2453 We would like to thank the reviewer for this suggestion, which we have added to the  
2454 introduction of equations (6) and (7):

2455 • To allow for *bimodal inference*, i.e., alternating periods of internally- and externally-  
2456 biased modes of perceptual processing that occur irrespective of the sequence of preceding  
2457 experiences, we assumed that likelihood and prior vary in their influence on the perceptual  
2458 decision according to fluctuations governed by  $\omega_{LLR}$  and  $\omega_\psi$ . These anti-phase sine  
2459 functions (defined by amplitudes  $a_{LLR/\psi}$ , frequency  $f$  and phase  $p$ ) determine the  
2460 precision afforded to the likelihood and prior<sup>53</sup>. The implicit anti-phase fluctuations  
2461 are mandated by Bayes-optimal formulations in which inference depends only on the  
2462 relative values of prior and likelihood precision (i.e., the Kalman gain<sup>54</sup>). As such,  $\omega_{LLR}$   
2463 and  $\omega_\psi$  implement a hyperprior<sup>55</sup> in which the likelihood and prior precisions are shifted  
2464 against each other at a dominant timescale defined by  $f$ : (...)

#### 2465 10.1.20 Comment 21

2466 You can also point out that the implicit anti-phase fluctuations are mandated by  
2467 Bayes optimal formulations in which it is only the relative values of the prior  
2468 and sensory precision that matter. Bayesian filters these precisions constitute  
2469 the Kalman gain. You can find a derivation of why this in treatments of the  
2470 hierarchical Gaussian filter is by Mathys et al.

2471 We would like to thank the reviewer for this suggestion. We added this information to the  
2472 description of our model in the Results section (see comment above).

#### 2473 10.1.21 Comment 22

2474 In your first model simulations, I would make it clear in the main text which  
2475 parameters you are optimizing's; namely (H, alpha, a\_likelihood, a\_prior f).  
2476 Perhaps a little table with a brief description of the meaning of these hyper  
2477 parameters would be useful?

2478 We now identify the optimized parameters at the outset of the modeling section:

2479 • (...) We used a maximum likelihood procedure to fit the bimodal inference model  
2480 (M1, Figure 1F) to the behavioral data from the Confidence database<sup>20</sup> and the IBL  
2481 database<sup>21</sup>, optimizing the parameters  $\alpha$ ,  $H$ ,  $amp_{LLR}$ ,  $amp_\psi$ ,  $f$ ,  $p$ , and  $\zeta$  (see Methods  
2482 for details and Supplemental Table T2 for a summary of the parameters of the bimodal  
2483 inference model). We validated our model in three steps: (...).

2484 We furthermore included a table summarizing the model parameters in the Supplement.

#### 2485 10.1.22 Comment 23

2486 Please remove Section 5.8. If you do not, you need to explain why — on line 586  
2487 - setting  $a = 0$  is appropriate when  $a = 0$ , the log posterior in Equation 2 is zero  
2488 because the precisions (omegas) are zero (by Equations 6 and 7).

2489 We have removed the section 5.8. When setting the amplitude parameters to zero,  $\omega_{LLR}$  and  
2490  $\omega_\psi$  are constant at 1, creating a unimodal control model that corresponds to the normative  
2491 Bayesian evidence accumulation model proposed by Glaze et al<sup>51</sup>.

#### 2492 10.2 Reviewer 2

2493 The authors elucidate whether periodicities in the sensitivity to external informa-  
2494 tion represent an epiphenomenon of limited processing capacity or, alternatively,  
2495 result from a structured and adaptive mechanism of perceptual inference. Ana-  
2496 lyzing large datasets of perceptual decision-making in humans and mice, they  
2497 investigated whether the accuracy of visual perception is constant over time  
2498 or whether it fluctuates. The authors found significant autocorrelations on the  
2499 group level and on the level of individual participants, indicating that a stimulus-  
2500 congruent response in a given trial increased the probability of stimulus-congruent  
2501 responses in the future. Furthermore, the authors addressed whether observers  
2502 cycle through periods of enhanced and reduced sensitivity to external information

2503 or whether observers rely on internal information in certain phases. This was  
2504 quantified by whether a response at a given trial was correlated with responses  
2505 in previous trials. The authors used computational modeling to infer the origin  
2506 of the different modes (internal vs. external).

2507 **Evaluation**

2508 This is a very interesting and well-written manuscript, dealing with an important  
2509 question. The findings are novel and provide an innovative account of interpreting  
2510 visual perception. I am not an expert in modeling, so I will restrict my comments  
2511 to theoretical framework and the experimental approach. I have a few minor  
2512 questions that I would like the authors to answer or clarify.

2513 We would like to thank the reviewer for the evaluation of our manuscript. We have added  
2514 the discussion of potential effects at the motor-level to our discussion.

2515 **Minor questions**

2516 **10.2.1 Comment 1**

2517 History congruent perception was defined on the basis of response repetitions.  
2518 Are we really sure that responses are repeated due to some variant of a per-  
2519 ceptual decision process (internal or external) or may arise on the motor-level -  
2520 independent of a perceptual source? For instance, a response primed by residual  
2521 activation in the motor system may represent a local effect independent from a  
2522 general response bias. If indeed, a response repetition is initiated by whatever  
2523 reasons (non-perceptual), wouldn't this imply that the repeated response is  
2524 per se more related to previous than to current visual information and would  
2525 hence signal a reduced sensitivity to current external information? The authors  
2526 are discussing the option of stereotypically repeated responses in the context  
2527 of alertness. However, a tendency to repeat responses may arise due to other

2528 **reasons. For instance, may the motor priming effects mentioned possibly explain**  
2529 **faster RTs along with a stronger bias when in internal-mode.**

2530 Thanks a lot for pointing this out. In this manuscript, we attempt to characterize the  
2531 phenomenon of bimodal inference at the level of behavior: The Confidence database consists  
2532 only of behavioral data. At the time of publishing this paper as a preprint, the IBL database  
2533 had also released only behavioral data.

2534 We realize that it is very difficult to preclude all influences from effects that occur at the  
2535 level of behavior. Not all studies in the confidence database have used a counter-balanced  
2536 mapping between the perceptual decision and the associated motor-response. In the IBL  
2537 data, the mapping between the perceptual decision and the associated motor-response is  
2538 fixed (turning a response wheel left or right depending on the perceived location of a grating).  
2539 Confidence reports also provide only indirect information on motor- vs. perceptual effects.  
2540 One may speculate that, if a response was driven by residual activity in the motor system, it  
2541 may be more likely to be a lapse and be accompanied by reduced confidence. By contrast,  
2542 we found that confidence was, on average, elevated for history-congruent choices.

2543 That being said, behavioral analyses alone are insufficient to rule out the contribution of  
2544 motor-related effects to seriality in choices. This would require analyses of additional types  
2545 of data, such as video tracking of the motor response or even neural data collected in brain  
2546 areas directly related to motor behavior. While this analysis is beyond the scope of the  
2547 present manuscript, we plan to carry out these analyses using the recent data publication of  
2548 the IBL, that contains, among others, video tracking of the motor response (turning of the  
2549 response wheel) and neuropixel recording across the whole brain, including premotor and  
2550 motor cortex<sup>71</sup>.

2551 We have added these considerations to the discussion of potential confounds:

- 2552 • Residual activation of the motor system may provide another contribution to serial biases  
2553 in perceptual choices<sup>72</sup>. Such motor-driven priming may lead to errors in randomized

psychophysical designs, resembling the phenomenon that we identify as internally-biased processing<sup>73</sup>. Moreover, residual activation of the motor system may lead to faster responses, and thus constitutes an alternative explanation for the quadratic relationship of mode with RTs<sup>72</sup>. The observation of elevated confidence for stronger biases toward internal mode speaks against the proposition that residual activation of the motor system is the primary driver of serial choice biases, since strong motor-driven priming should lead to frequent lapses that are typically associated reduced confidence<sup>74</sup>. Likewise, perceptual history effects have repeatedly been replicated in experiments with counter-balanced stimulus-response mappings<sup>82</sup>.

- No-response paradigms, in which perceptual decision are inferred from eye-movements alone, could help to better differentiate perceptual from motor-related effects. Likewise, video-tracking of response behavior and neural recording from motor- and premotor, which has recently been released for the IBL database<sup>71</sup>, may provide further insight into the relation of motor behavior to the perceptual phenomenon of between-mode fluctuations.

### 10.3 Reviewer 3

In this paper the authors propose that during perceptual decisions, humans and mice exhibit regular oscillatory fluctuations between an “external” (that places more weight on the perceptual evidence) and an “internal” (that places more weight on historical experiences) mode. In particular, the authors propose a computational scheme in which the influences of history and current stimulus on choice oscillate in anti phase, effectively implementing “bimodal inference”. The computational advantages of these scheme as well as its relation to the underlying neurophysiology are discussed.

Overall, the authors make a very interesting proposal about what drives slow

2579 fluctuations in perceptual performance during randomized two-alternative choice  
2580 tasks. This proposal relates changes in accuracy with changes in serial choice  
2581 biases, which is a timely and synthesizing contribution. Furthermore, this proposal  
2582 is backed by analyses over several human datasets and a large dataset in mice.

2583 Despite its strong empirical contribution, the paper seems limited by the fact  
2584 that alternative computational hypotheses are not adequately considered (or at  
2585 least considered in a systematic way). At the same time, and although the paper  
2586 is well written, some parts are overly technical.

2587 We would like to thank the Reviewer for the very helpful comments on our manuscript.  
2588 We fully agree that the previous version of our manuscript did not consider alternative  
2589 computational hypotheses in a systematic and adequate way. As we outline in more detail in  
2590 our point-by-point-responses below, we have addressed this issue by adding a formal model  
2591 comparison of the bimodal inference model to reduced models, including a normative models  
2592 of Bayesian evidence accumulation. We have added null-hypothesis-testing for enhanced  
2593 history-congruence during internal mode. We have also moved a number of defensive analyses  
2594 to the Supplement.

2595 **Major comments:**

### 2596 10.3.1 Comment 1

2597 The authors collapse across various datasets in which different tasks were em-  
2598 ployed. However, some details on the nature of these different tasks and a  
2599 discussion on the rationale of collapsing behavioral metrics across them is miss-  
2600 ing. The authors mention that all tasks involved binary perceptual decisions. In  
2601 some parts of the manuscript the term “false alarms” is mentioned, indicating a  
2602 detection protocol. Other terms in the methods section (e.g., “set size”) might  
2603 need further clarification. Importantly, it is not clear how reaction times were

2604 calculated in the various tasks and whether some experiments involved free  
2605 response paradigms while others interrogation/ cued paradigms (in which case  
2606 RTs can be defined as the latency between the response cue and the response).

2607 We would like to thank the Reviewer for this important point. Regarding the rationale for  
2608 collapsing across the studies in the Confidence database: Having found strong evidence of  
2609 apparent between-mode fluctuations in a study on intermittent bistable perception<sup>19</sup>, our  
2610 goal was to test whether between-mode fluctuations were a general phenomenon in perceptual  
2611 decision-making. We thus had a lenient threshold for including studies from the Confidence  
2612 database, i.e., all that addressed the domain of perception in 2AFC tasks. This has the  
2613 advantage of looking at perceptual 2AFC decisions in general and indicated that history  
2614 effects and bimodal inference are present in a wide variety of tasks.

2615 At the same time, collapsing across diverse set of experiments means that the stimuli, the  
2616 timing and the way that responses were collected differed between them. To account for this  
2617 variability, we included individual experiments as random factors in linear mixed modeling.

2618 We also made sure that perceptual performance is comparable across studies (Supplemental  
2619 Figure S1A-B). While our analysis of the IBL database was mainly motivated by investigating  
2620 bimodal inference across species, it also allowed us to replicate our results in a highly  
2621 standardized task that was collected across many individual subjects<sup>21</sup>. We have added the  
2622 rationale for collapsing across studies with its advantages and disadvantages to the *Open*  
2623 *questions and limitations* subsection of the discussion:

- 2624 • Our results suggest bimodal inference as a pervasive aspect in perceptual decision-  
2625 making in humans and mice. However, a number of limitations and open questions  
2626 have to be considered: First, this work sought to understand whether fluctuations  
2627 between internal and external mode, which we initially observed in an experiment on  
2628 bistable perception in humans<sup>19</sup>, are general phenomenon that occurs across a diverse  
2629 set of perceptual decision-making tasks. Our analysis of the Confidence database<sup>20</sup>

2630 therefore collapsed across all available experiments on binary perceptual decision-making.  
2631 Individual experiments differed with respect to the stimuli, the manipulation of difficulty,  
2632 the timing of trials, and the way responses were collected, but were highly comparable  
2633 with respect to the central variables of stimulus- and history-congruence (Supplemental  
2634 Figure S1A-B).

- 2635 • The variability across experiments, which we considered as random effects in all statistical  
2636 analyses, enabled us to assess whether bimodal inference represents a general phenomenon  
2637 in perceptual decision-making, but limited the precision at which we were able to  
2638 investigate the relation of mode to behavioral variables such as timing, task difficulty,  
2639 RT or confidence. This issue is partially resolved by our analyses of the IBL database,  
2640 which replicated our findings in an experiment that was highly standardized with respect  
2641 to timing, task difficulty, and behavioral read-out<sup>21</sup>. It will be an important task for  
2642 future research to validate our results on bimodal inference in a standardized dataset of  
2643 comparable volume in humans, which is, to our knowledge, not yet available.

2644 We apologize for the lack of clarity regarding the way we queried the Confidence database.  
2645 To select a broad variety of experiments on 2AFC perceptual decision-making, we queried  
2646 the Confidence database for studies from the *perception* category (excluding studies from the  
2647 categories *cognitive*, *motor*, *memory* and *mixed*) and selected studies with 2AFC responses.  
2648 Our previous version of the manuscript had mentioned the variable names given to the  
2649 difficulty variable in the individual experiments (i.e., the name of the column in the individual  
2650 .txt files provided for every experiment in the Confidence database). The term *false alarm*  
2651 turned up in the discussion of lapses of attention and arousal, which we have re-written in  
2652 response to Comment 19 by Reviewer 1 and Comment 6 by Reviewer 3. We now provide  
2653 more information on the experiments and variables selected in the Method section:

- 2654 • We downloaded the human data from the Confidence database<sup>20</sup> on 10/21/2020, limiting  
2655 our analyses to the category *perception*. Within this category, we selected studies in

which participants made binary perceptual decisions between two alternatives. We excluded two experiments in which the average perceptual accuracy fell below 50%. After excluding these experiments, our sample consisted of 21.05 million trials obtained from 4317 human participants and 66 individual experiments (Supplemental Table 1). Out of the 66 included experiments, 62 investigated visual, 1 auditory, 2 proprioceptive, and 1 multimodal perception. 59 experiments were based on discrimination and 6 on detection, with one investigating both.

- Out of the 58 experiments that provide information on RTs, 46 cued the response by the onset of a response screen or an additional response cue, whereas 14 allowed participants to respond at any time after stimulus onset.
- 21 of the 66 included experiments used fixed difficulty levels, whereas 45 manipulated difficulty levels within participants. Difficulty was manipulated via noise masks, contrast, luminance, presentation time, or stimulus probability for gabor, dot coherence for random dot kinematograms, difference in elements and set size for comparisons of numerosity, difference in clicks for auditory discrimination, temporal distance for meta-contrast masking, and amount of self-motion for proprioception. We treated task difficulty as a missing variable for the experiments that fixed it at the participant-level, as this precluded the computation of autocorrelation curves.

### 10.3.2 Comment 2

The key premise that when participants do not rely on the external stimulus they rely more on the previous trial needs to be more clearly (and statistically) contrasted against a null hypothesis. For instance, an null hypothesis could be that when participants place a lower weight on the stimulus they simply choose randomly. It is important to specify a null hypothesis such that the key premise does not appear self-evident or circular.

2681 We would like to thank the reviewer for highlighting this important point. Following this  
2682 suggestion, we have explicitly tested our main hypothesis ( $H1$ : periods of reduced stimulus-  
2683 congruence are periods of enhanced reliance on history-congruence) against the following null  
2684 hypotheses:

- 2685 •  $H0_1$ : Periods of reduced stimulus-congruence are periods of enhanced random choices  
2686 •  $H0_2$ : Periods of reduced stimulus-congruence are periods of enhanced general bias

2687 We present three sets of statistical analyses to test  $H1$  against  $H0_{1/2}$ :

2688 First, we used logistic regression to predict individual choices. Under  $H1$ , one would expect a  
2689 significant effect of perceptual history in a logistic regression model that predicts individual  
2690 choices from the external stimulus, perceptual history and general response bias. At the  
2691 model level, one would expect higher AIC in a model without perceptual history as a predictor  
2692 of individual choices, indicating that perceptual history influences choices beyond noise ( $H0_1$ )  
2693 and general response bias ( $H0_2$ ).

2694 In both humans and mice, we found a significant effect of perceptual history on choices  
2695 while controlling for bias. When eliminating perceptual history as a predictor of individual  
2696 choices, we found higher AIC (providing model-level evidence against  $H0_1$  and  $H0_2$ ). We  
2697 complemented this analysis by computing AIC in individual observers (Supplemental Figure  
2698 S4), and again found higher AIC in models from which perceptual history was eliminated.

2699 We have made the following changes to the main manuscript:

2700 Humans:

- 2701 • Subsection title: Fluctuations between internal and external mode cannot be reduced to  
2702 general response biases or random choices
- 2703 • The core assumption of bimodal inference - that ongoing changes in the sensitivity to  
2704 external information are driven by internal predictions induced via perceptual history

2705 - needs to be contrasted against two alternative hypotheses: When making errors,  
2706 observers may not engage with the task and respond stereotypically, i.e., exhibit stronger  
2707 general biases toward one of the two potential outcomes, or simply choose randomly.  
2708 Logistic regression confirmed that perceptual history made a significant contribution to  
2709 perception ( $\beta = 0.11 \pm 5.79 \times 10^{-3}$ ,  $z = 18.53$ ,  $p = 1.1 \times 10^{-76}$ ) over and above the  
2710 ongoing stream of external sensory information ( $\beta = 2.2 \pm 5.87 \times 10^{-3}$ ,  $z = 375.11$ ,  $p <$   
2711  $2.2 \times 10^{-308}$ ) and general response biases toward ( $\beta = 15.19 \pm 0.08$ ,  $z = 184.98$ ,  $p <$   
2712  $2.2 \times 10^{-308}$ ). When eliminating perceptual history as a predictor of individual choices  
2713 at individual trials, AIC increased by  $\delta_{AIC} = 1.64 \times 10^3$  (see Supplemental Figure S4A-B  
2714 for parameter- and model-level inference at the level of individual observers).

2715 Mice:

2716 • In line with humans, mice were biased toward perceptual history in  $54.03\% \pm 0.17\%$   
2717 of trials ( $T(163) = -7.52$ ,  $p = 3.44 \times 10^{-12}$ ; Figure 4A and Supplemental Figure S1D).  
2718 Perceptual history effects remained significant ( $\beta = 0.51 \pm 4.49 \times 10^{-3}$ ,  $z = 112.84$ ,  $p <$   
2719  $2.2 \times 10^{-308}$ ) when controlling for external sensory information ( $\beta = 2.96 \pm 4.58 \times 10^{-3}$ ,  
2720  $z = 646.1$ ,  $p < 2.2 \times 10^{-308}$ ) and general response biases toward one of the two potential  
2721 outcomes ( $\beta = -1.78 \pm 0.02$ ,  $z = -80.64$ ,  $p < 2.2 \times 10^{-308}$ ). When eliminating perceptual  
2722 history as a predictor of individual choices, AIC increased by  $\delta_{AIC} = 1.48 \times 10^4$ , arguing  
2723 against the notion that choice randomness and general response bias are the only  
2724 determinants of perceptual performance (see Supplemental Figure S4C-D for parameter-  
2725 and model-level inference within individual mice).

2726 Second, we analyzed dynamic changes in history- and stimulus-congruence (i.e., smoothed  
2727 probabilities for stimulus-congruence, history-congruence and general response bias in sliding  
2728 10 trial time-windows). Under H1, one would expect a significant negative correlation between  
2729 the dynamic probability of stimulus- and history-congruence. At the model level, one would

2730 expect higher AIC in a model without history-congruence as a predictor of stimulus-congruence,  
2731 indicating that changes in the probability of history-congruence influence stimulus-congruence  
2732 beyond noise ( $H0_1$ ) and general response bias ( $H0_2$ ).

2733 In both humans and mice, we found a significant negative correlation between history-  
2734 congruence and stimulus-congruence while controlling for general response bias. When elimi-  
2735 nating the dynamic probability of history-congruence as a predictor of stimulus-congruence,  
2736 we found higher AIC (providing model-level evidence against  $H0_1$  and  $H0_2$ ). The section  
2737 5.4 or our original manuscript (*Fluctuations between internal and external mode modulate*  
2738 *perceptual performance beyond the effect of general response biases*) complements these control  
2739 analyses and has been moved to the Supplement to stream-line the manuscript (following the  
2740 Comment 12 by Reviewer 1 and Comment 9 by Reviewer 3). We have modified the main  
2741 manuscript in the following way:

2742 Humans:

2743 • Finally, we ensured that fluctuations in stimulus- and history-congruence are linked to  
2744 each other, while controlling for fluctuations in the strength of general response biases.

2745 When perceptual choices were less biased toward external information, participants  
2746 relied more strongly on internal information acquired from perceptual history (and vice  
2747 versa,  $\beta = -0.05 \pm 5.63 \times 10^{-4}$ ,  $T(2.1 \times 10^6) = -84.21$ ,  $p < 2.2 \times 10^{-308}$ ), controlling  
2748 for fluctuations in the strength of general response biases ( $\beta = -0.06 \pm 5.82 \times 10^{-4}$ ,  
2749  $T(2.1 \times 10^6) = -103.51$ ,  $p < 2.2 \times 10^{-308}$ ).

2750 • (...) Likewise, eliminating the dynamic fluctuations in history-congruence as a predictor  
2751 of fluctuations in stimulus-congruence yielded an increase in AIC by  $\delta_{AIC} = 7.06 \times 10^3$ .  
2752 These results provided model-level evidence against the null hypotheses that fluctuations  
2753 in stimulus-congruence are driven exclusively by choice randomness or general response  
2754 bias (see Supplemental Section 9.2 for an in-depth assessment of general response bias).

2755 Mice:

- 2756 • As in humans, fluctuations in the strength of history-congruent biases had a significant  
2757 effect on stimulus-congruence ( $\beta_1 = -0.12 \pm 7.17 \times 10^{-4}$ ,  $T(1.34 \times 10^6) = -168.39$ ,  $p <$   
2758  $2.2 \times 10^{-308}$ ) beyond the effect of ongoing changes in general response biases ( $\beta_2 = -0.03$   
2759  $\pm 6.94 \times 10^{-4}$ ,  $T(1.34 \times 10^6) = -48.14$ ,  $p < 2.2 \times 10^{-308}$ ). Eliminating the dynamic  
2760 fluctuations in history-congruence as a predictor of fluctuations in stimulus-congruence  
2761 resulted in an increase in AIC by  $\delta_{AIC} = 2.8 \times 10^4$ . This confirmed that, in both humans  
2762 and mice, perceptual performance is modulated by systematic fluctuations between  
2763 externally- and internally-oriented modes of sensory processing that exist beyond general  
2764 response bias (see Supplemental Section 9.2 for an in-depth assessment of general  
2765 response bias).

2766 Third, we analyzed full and history-conditioned psychometric curves in external and internal  
2767 mode as well as across modes. Under our main hypothesis that periodic reductions in  
2768 sensitivity to external information are driven by increases in the impact of perceptual history,  
2769 one would expect (i) a history-dependent increase in biases and lapses (effects of perceptual  
2770 history), and (ii), a history-independent increase in threshold (reduced sensitivity to external  
2771 information). Conversely, if what we identified as internal mode processing was in fact driven  
2772 by random choices, one would expect (i), a history-independent increase in lapses (choice  
2773 randomness), (ii), no change in bias (no effect of perceptual history), and (iii), reduced  
2774 thresholds (reduced sensitivity to external information). In both humans and mice, we  
2775 observed the pattern predicted by H1. In response to the comments by Reviewer 1 and 3,  
2776 we have significantly streamlined the manuscript and moved our assessment of psychometric  
2777 functions to the Supplement. We now provide a summary of our results in the main manuscript  
2778 to make our reasoning with respect to  $H0_1$  and  $H1$  more explicit:

2779 Humans:

2780 • To confirm that changes in the sensitivity to external information are indicative of  
2781 internal mode processing, we estimated full and history-dependent psychometric curves  
2782 during internal, external, and across modes. If, as we hypothesized, internal mode  
2783 processing reflects an enhanced impact of perceptual history, one would expect a history-  
2784 dependent increase in biases and lapses as well as a history-independent increase in  
2785 threshold. Conversely, if internal mode processing were driven by random choices, one  
2786 would expect a history-independent increase in lapses and threshold, and no change in  
2787 bias. In line with our prediction, we found that internal mode processing was associated  
2788 with a history-dependent increase in bias and lapse as well as a history-independent  
2789 increase in threshold (Supplemental Section 9.3.1 and Supplemental Figure S6). This  
2790 confirms that internal mode processing is indeed driven by an enhanced impact of  
2791 perceptual history.

2792 Mice:

2793 • When fitting full and history-conditioned psychometric curves to the data from the IBL  
2794 database, we observed that internal mode processing was associated with a history-  
2795 dependent increase in bias and lapse as well as a history-independent increase in threshold  
2796 (Supplemental Section 9.3.2 and Supplemental Figure S7). This provided further evidence  
2797 for the hypothesis that internal mode processing is driven by an enhanced impact of  
2798 perceptual history, as opposed to increased choice randomness.

### 2799 10.3.3 Comment 3

2800 **From a mechanistic (sequential sampling) perspective, several previous papers**  
2801 **have examined whether choice history biases influence the starting point or the**  
2802 **drift rate of the evidence accumulation process. Under the former formulation,**  
2803 **reliance on the evidence vs. reliance on the previous choice will be naturally**  
2804 **anti-correlated (the less weight you place on the evidence the more impactful the**

choice history will be, assuming that the last choice is represented as a starting point bias). This seems to be mapping onto the computational model the authors describe, in which there is a weight on the prior, a weight on the likelihood and the assumption that these weights fluctuate in anti-phase. It is not obvious that this anti-phase relationship needs to be imposed ad-hoc. Or whether it would emerge naturally (using a mechanistic or Bayesian framework). More generally, the authors assert that without an external mechanism prior biases would be impossible to overcome, and this would misfit the data. However, it would be important to a) actually show that the results cannot be explained by a single mechanism in which the anti-phase relationship is emergent rather than ad-hoc, b) relate the current framework with previous mechanistic considerations of serial choice biases.

We would like to thank the reviewer for pointing this out. We agree that both normative Bayesian and mechanistic drift diffusion are bound to lead to anti-correlated effects of sensory information and perceptual history *at the level of individual trials*. This, however, does not necessarily entail slow fluctuations in the impact of sensory information and perceptual history that evolve *over many consecutive trials*. We now provide a systematic model comparison and discuss our model in relation to drift diffusion models and descriptive models that assume slow changes in the latent parameters underlying perceptual decision-making (such as Roy et al., Neuron 2021 or Ashwood et al. Nature Neuroscience et al. 2022). We also discuss the ad-hoc nature of the bimodal inference model in the subsection *Limitations and open questions*.

- We used a maximum likelihood procedure to fit the bimodal inference model (M1, Figure 1F) to the behavioral data from the Confidence database<sup>20</sup> and the IBL database<sup>21</sup>, optimizing the parameters  $\alpha$ ,  $H$ ,  $amp_{LLR}$ ,  $amp_\psi$ ,  $f$ ,  $p$ , and  $\zeta$  (see Methods for details and Supplemental Table T2 for a summary of the parameters of the bimodal inference model).

2831 We validated our model in three steps: First, to show that bimodal inference does not  
2832 emerge spontaneously in normative Bayesian models of evidence accumulation, but  
2833 requires the ad-hoc addition of anti-phase oscillations in prior and likelihood precision,  
2834 we compared the bimodal inference model to four control models (M2-5, Figure 1G).  
2835 In these models, we successively removed the anti-phase oscillations (M2-M4) and the  
2836 integration of information across trials (M5) from the bimodal inference model and  
2837 performed a model comparison based on AIC.

- 2838 • Model M2 ( $AIC_2 = 5.7 \times 10^4$  in humans and  $4.94 \times 10^4$  in mice) and Model M3 ( $AIC_3$   
2839  $= 6.9 \times 10^4$  in humans and  $5.99 \times 10^4$  in mice) incorporated only oscillations of either  
2840 likelihood or prior precision. Model M4 ( $AIC_4 = 9.8 \times 10^4$  in humans and  $9.19 \times 10^4$  in  
2841 mice) lacked any oscillations of likelihood and prior precision and corresponded to the  
2842 normative model proposed by Glaze et al.<sup>51</sup>. In model M5 ( $AIC_4 = 1.16 \times 10^5$  in humans  
2843 and  $1.14 \times 10^5$  in mice), we furthermore removed the integration of information across  
2844 trials, such that perception depended only in incoming sensory information (Figure 1G).
- 2845 • The bimodal inference model achieved the lowest AIC across the full model space ( $AIC_1$   
2846  $= 4.73 \times 10^4$  in humans and  $4.28 \times 10^4$  in mice) and was clearly superior to the normative  
2847 Bayesian model of evidence accumulation ( $\delta_{AIC} = -5.08 \times 10^4$  in humans and  $-4.91 \times 10^4$   
2848 in mice; Supplemental Figure S9).
- 2849 • In sum, computational modeling suggested that between-mode fluctuations are best  
2850 explained by two interlinked processes (Figure 1E): (i), the dynamic accumulation of  
2851 information across successive trials mandated by normative Bayesian models of evidence  
2852 accumulation and, (ii), ongoing anti-phase oscillations in the impact of external and  
2853 internal information.
- 2854 • Could bimodal inference emerge spontaneously in normative models of perceptual  
2855 decision-making? In predictive processing, the relative precision of prior and likelihood  
2856 determines their integration into the posterior that determines the content of perception.

2857 At the level of individual trials, the perceptual impact of internal predictions generated  
2858 from perceptual history (prior precision) and external sensory information (likelihood  
2859 precision) are thus necessarily anti-correlated. The same holds for mechanistic models of  
2860 drift diffusion, which understand choice history biases as driven by changes in the starting  
2861 point<sup>51</sup> or the drift rate of evidence accumulation<sup>32</sup>. Under the former formulation,  
2862 perceptual history is bound to have a stronger influence on perception when less weight  
2863 is given to incoming sensory evidence, assuming that the last choice is represented as a  
2864 starting point bias. The effects of choice history in normative Bayesian and mechanistic  
2865 drift diffusion models can be mapped onto one another via the Bayesian formulation  
2866 of drift diffusion<sup>60</sup>, where the inverse of likelihood precision determines the amount of  
2867 noise in the accumulation of new evidence, and prior precision determines the absolute  
2868 shift in its starting point<sup>60</sup>.

- 2869 • While it is thus clear that the impact of perceptual history and sensory evidence are anti-  
2870 correlated *at each individual trial*, we here introduce anti-phase oscillations as an ad-hoc  
2871 modification to model slow fluctuations in prior and likelihood precision that evolve *over*  
2872 *many consecutive trials* and are not mandated by normative Bayesian or mechanistic  
2873 drift diffusion models. The bimodal inference model provides a reasonable explanation  
2874 of the linked autocorrelations in stimulus- and history-congruence, as evidenced by  
2875 formal model comparison, successful prediction of RTs and confidence as out-of-training  
2876 variables, and a qualitative reproduction of our empirical data from posterior model  
2877 parameter as evidence against over- or under-fitting.
- 2878 • Of note, similar non-stationarities have been observed in descriptive models that assume  
2879 continuous<sup>61</sup> or discrete<sup>12</sup> changes in the latent states that modulate perceptual decision-  
2880 making at slow timescales. A recent computational study<sup>62</sup> has used a Hidden Markov  
2881 model to investigate perceptual decision-making in the IBL database<sup>21</sup>. In analogy  
2882 to our findings, the authors observed that mice switch between temporally extended

2883 *strategies* that last for more than 100 trials: During *engaged* states, perception was highly  
2884 sensitive to external sensory information. During *disengaged* states, in turn, choice  
2885 behavior was prone to errors due to enhanced biases toward one of the two perceptual  
2886 outcomes<sup>62</sup>. Despite the conceptual differences to our approach (discrete states in a  
2887 Hidden Markov model that correspond to switches between distinct decision-making  
2888 strategies<sup>62</sup> vs. gradual changes in mode that emerge from sequential Bayesian inference  
2889 and ongoing fluctuations in the impact of external relative to internal information), it is  
2890 tempting to speculate that engaged/disengaged states and between-mode fluctuations  
2891 might tap into the same underlying phenomenon.

- 2892 • A third open question concerns the computational underpinnings of bimodal inference.  
2893 The addition of slow anti-phase oscillations to the integration of prior and likelihood rep-  
2894 resents an ad-hoc modification of a normative Bayesian model of evidence accumulation<sup>51</sup>.  
2895 While the bimodal inference model is supported by formal model comparison, the suc-  
2896 cessful prediction of out-of-training variables and the qualitative reproduction of our  
2897 empirical data in simulations from posterior model parameters, it is an important task for  
2898 future research to test whether between-mode fluctuations can emerge spontaneously in  
2899 hierarchical models of Bayesian inference, whether modes are continuous<sup>19</sup> or discrete<sup>62</sup>,  
2900 and whether bimodal inference can be causally manipulated by experimental variables.  
2901 We speculate that between-mode fluctuations may separate the perceptual contribu-  
2902 tion of internal predictions and external sensory data in time, creating unambiguous  
2903 learning signals that benefit inference about the precision of prior and likelihood, re-  
2904 spectively. This proposition should be tested empirically by relating the phenomenon of  
2905 bimodal inference to performance in, e.g., reversal learning, probabilistic reasoning, or  
2906 metacognition.

2907 **10.3.4 Comment 4**

2908 The authors need to unpack their definition of history biases since in previous  
2909 work biases due to the response or the identity of the stimulus at the previous  
2910 trial are treated differently. Here, the authors focus on response biases but it  
2911 is not clear whether they could examine also stimulus-driven history biases (in  
2912 paradigms where stimulus-response is remapped on each trial).

2913 We would like to thank the reviewer for raising this important point. We defined the  
2914 history-biases reported in our main manuscript by comparing the *response about the perceived*  
2915 stimulus category (A vs. B) at the current and at the preceding trial (choice history). An  
2916 alternative would have been to define history biases by comparing the choice at the current  
2917 trial to the stimulus category *presented* at the preceding trial (stimulus history). As we show  
2918 below, perceptual responses tended to be biased not only toward choice history, but also (but  
2919 to a lesser degree) to stimulus history. This is expected, as perception was *stimulus-congruent*  
2920 on approximately 75% of trials, causing the effects of the preceding response and the preceding  
2921 stimulus to be highly correlated. We therefore compared the effects on choice history and  
2922 stimulus history induced by trials at which perception was *stimulus-incongruent*, since those  
2923 trials lead to opposite predictions regarding the perceptual choice at the subsequent trial.

2924 As expected, perceptual choices were attracted toward perceptual choices at preceding  
2925 stimulus-incongruent trials (i.e., a positive effect of choice history). By contrast, perceptual  
2926 choices tended to be repelled away from the stimulus presented the preceding trial. This  
2927 repulsion of choices away from stimuli presented at stimulus-incongruent trials confirms  
2928 that the choices at stimulus-incongruent trials were the primary driver of serial effects in  
2929 perception in both humans and mice.

2930 We now refer to our analysis on stimulus history as an additional confound, which we present  
2931 in detail in the Supplement 9.1 of our manuscript:

- 2932 • (...) These serial biases were effects of choice history, i.e., driven by the experiences  
2933 reported at the preceding trial, and could not be attributed to stimulus history, i.e., to  
2934 effects of the stimuli presented at the preceding trial (Supplemental Section 9.1).

2935 Supplement:

- 2936 • The main manuscript reports the effects of perceptual history, which we defined as the  
2937 impact of the choice at the preceding trial on the choice at the current trial (henceforth  
2938 *choice history*). *Stimulus history*, which is defined as the impact of the stimulus presented  
2939 at the preceding trial on the choice at the present trial, represents an alternative approach  
2940 to this. Here, we compare the effects of choice history to the effects of stimulus history.
- 2941 • We observed a significant bias toward stimulus history (humans:  $49.76\% \pm 0.1\%$  of trials,  
2942  $\beta = 1.26 \pm 0.94$ ,  $T(373.62) = 1.34$ ,  $p = 0.18$ ; mice:  $51.11\% \pm 0.08\%$  of trials,  $T(164)$   
2943  $= 13.4$ ,  $p = 3.86 \times 10^{-28}$ ). The bias toward stimulus history was smaller than the bias  
2944 toward choice history (humans:  $\beta = -3.53 \pm 0.5$ ,  $T(66.53) = -7.01$ ,  $p = 1.48 \times 10^{-9}$ ;  
2945 mice:  $T(164) = -17.21$ ,  $p = 1.43 \times 10^{-38}$ ).
- 2946 • The attraction of choices toward both preceding choices and stimuli is expected, as  
2947 perception was *stimulus-congruent* on approximately 75% of trials, causing choices and  
2948 stimuli to be highly correlated. We therefore compared the effects of choice history and  
2949 stimulus history after *stimulus-incongruent* (i.e., *error*) trials, since those trials lead to  
2950 opposite predictions regarding the perceptual choice at the subsequent trial.
- 2951 • As expected from the findings presented in the main manuscript, perceptual choices were  
2952 attracted toward perceptual choices when the inducing trial was stimulus-incongruent  
2953 (i.e., a positive effect of choice history; humans:  $\beta = 0.19 \pm 1.4 \times 10^{-4}$ ,  $z = 1.36 \times 10^3$ ,  $p <$   
2954  $2.2 \times 10^{-308}$ ; mice:  $\beta = 0.92 \pm 0.01$ ,  $z = 88.82$ ,  $p < 2.2 \times 10^{-308}$ ). By contrast, perceptual  
2955 choices tended to be repelled away from the stimulus presented at preceding stimulus-  
2956 incongruent trial (i.e., a negative effect of stimulus history; humans:  $\beta = -0.19 \pm 0.01$ ,

2957  $z = -16.47$ ,  $p = 5.99 \times 10^{-61}$ : mice:  $\beta = -0.92 \pm 0.01$ ,  $z = -88.76$ ,  $p < 2.2 \times 10^{-308}$ ).

2958 This repulsion of choices away from stimuli presented at stimulus-incongruent trials  
2959 confirmed that choices (which are anti-correlated to stimuli at stimulus-incongruent  
2960 trials) were the primary driver of attracting serial effects in perception.

- 2961 • In sum, the above results suggest that, in both humans and mice, serial dependencies  
2962 were better explained by the effects of choice history as opposed to the effects of stimulus  
2963 history. This aligns with a result recently published for the IBL database, where mice  
2964 were shown to follow an *action-kernel* as opposed to a *stimulus-kernel* model when  
2965 integrating information across trials<sup>81</sup>.

2966 **10.3.5 Comment 5**

2967 Previous work, which the authors acknowledges in their Discussion (6.5), distin-  
2968 guishes repetitive history biases from alternating biases. For instance, in Braun,  
2969 Urai & Donner (2018, JoN) participants are split into repetitive or alternating.  
2970 Shouldn't the authors define the history bias in a similar fashion? The authors  
2971 point out that attracting and repelling biases operate simultaneously across  
2972 different timescales. However, this is not warranted given Braun et. al and other  
2973 similar papers. It is not clear how this more nuanced definition of history bias  
2974 would alter the conclusions.

2975 Our empirical results show that, on average, history biases tend to be repetitive (Figure 2A,  
2976 Figure 3A, and the biases in the psychometric functions in the Supplemental Figure S6-7).  
2977 In fact, only 2 of the 66 experiments we included from the Confidence database<sup>20</sup> showed  
2978 significant alternating biases (Supplemental Figure S1, please note that history-congruence  
2979 was not used in the inclusion algorithm). However, this does not rule out the possibility that  
2980 there are periods of alternating biases in the other experiments with net repeating effects.

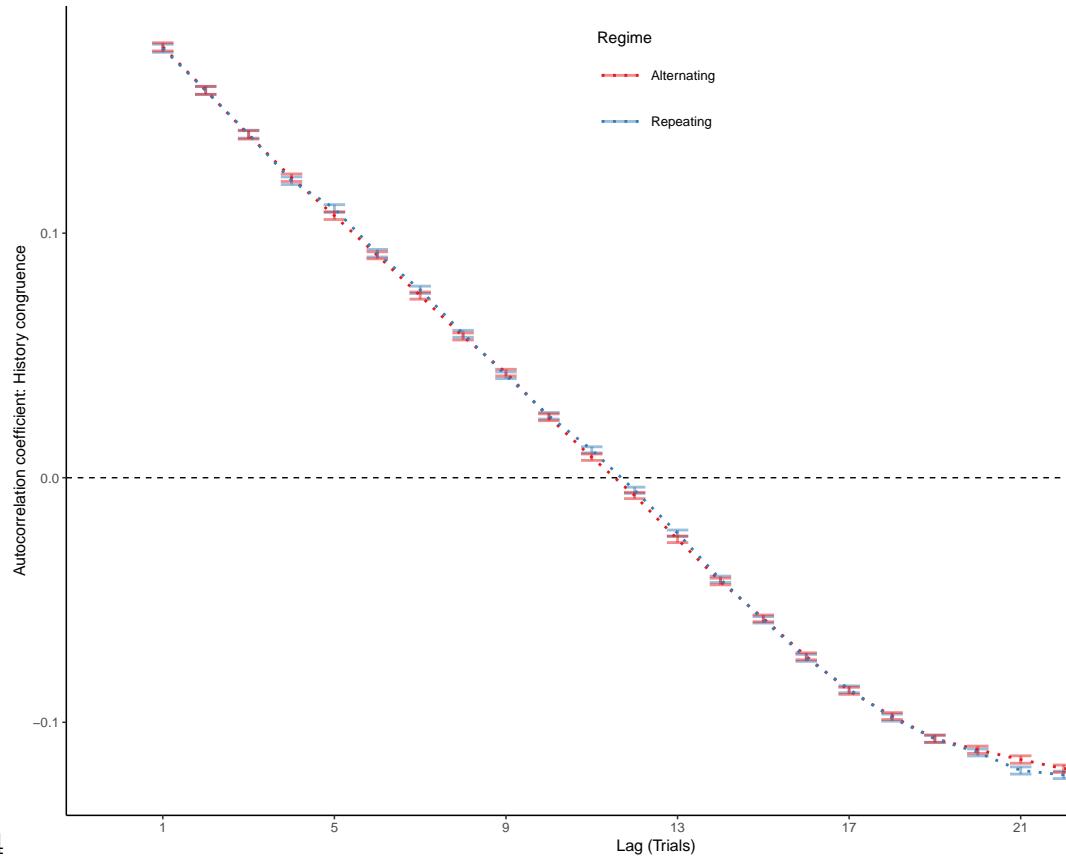
2981 Importantly, our central finding of autocorrelation in history-congruence does not distinguish

2982 between alternating and repetitive history biases. In the plot below, we show autocorrelation  
2983 curves for fluctuations in history-congruence for both alternation (hazard = 0.8) and repetition  
2984 (hazard = 0.2). Both were simulated for 10 blocks of a random duration between 15  
2985 and 30 trials, interleaved with 10 blocks with no history biases (hazard = 0.5). This  
2986 simulation illustrates that the autocorrelation of alternating and repeating biases is identical  
2987 for symmetric pairs of hazard rates. The autocorrelation of history-congruence and the  
2988 associated internal mode processing is therefore not tied to repeating biases, but accommodates  
2989 alternating biases as well (which seem to be, on average and in our data, less frequent). We  
2990 therefore did not separate alternating from repeating biases in our analysis of mode.

2991 We apologize for not having recognized this aspect in the previous version of the discussion.  
2992 We have rewritten the paragraph on alternating and repeating biases in the discussion,  
2993 referring to the plot below, which we have added to the Supplemental Materials.

2994 • Second, our results point to an attraction of perception toward preceding choices.  
2995 Previous work has shown that perceptual decision-making is concurrently affected by  
2996 both attractive and repulsive serial biases that operate on distinct time-scales and  
2997 serve complementary functions for sensory processing<sup>27,75,76</sup>: Short-term attraction may  
2998 serve the decoding of noisy sensory inputs and increase the stability of perception,  
2999 whereas long-term repulsion may enable efficient encoding and sensitivity to change<sup>27</sup>.  
3000 In the data analyzed here, history biases tended to be repetitive (Figure 2A, Figure  
3001 3A, Supplemental Figure S6 and S7), as only 2 of the 66 experiments of the Confidence  
3002 database<sup>20</sup> showed significant alternating biases (Supplemental Figure S1). However,  
3003 as we show in Supplemental Figure S14, fluctuations in both alternating and repeating  
3004 history biases generate overlapping autocorrelation curves. Our analysis of between-mode  
3005 fluctuations is therefore not tied exclusively to repeating biases, but accommodates  
3006 alternating biases as well, such that both may lead to internally-biased processing  
3007 and reduced sensitivity to external sensory information. Future work could apply our

3008 approach to paradigms that boost alternating as opposed to repeating biases, as this  
3009 would help to better understand how repetition and alternation are linked in terms of  
3010 their computational function and neural implementation<sup>27</sup>.



3011 **Supplemental Figure S14**

- 3012 • **Supplemental Figure S14.** Autocorrelation of history-congruence of alternating and  
3013 repeating biases. Here, we simulate the autocorrelation of history-congruence in  $10^3$   
3014 synthetic participants. In the repeating regime (blue), history-congruence fluctuated  
3015 between 50% and 80% (blue) in interleaved blocks (10 blocks per condition with a  
3016 random duration between 15 and 30 trials). In the alternation regime (red), history-  
3017 congruence fluctuated between 50% and 20%. The resulting autocorrelation curves for  
3018 history-congruence overlap, indicating that our analysis is able to accommodate both  
3019 repeating and alternating biases.

3020 10.3.6 Comment 6

3021 The arousal hypothesis seems to be ruled out too easily, merely in the presence  
3022 of a non-monotonic “state” vs. RT pattern. Arousal can have an inverted U-  
3023 shaped effect on behavioral performance and recent paper has demonstrated  
3024 a non-monotonic effect of tonic arousal (baseline pupil) on RTs and accuracy  
3025 (<https://www.biorxiv.org/content/10.1101/2023.07.28.550956.abstract>). More  
3026 generally, the RT and confidence analyses need to be complemented, perhaps by  
3027 computational modeling using sequential sampling models, as these behavioral  
3028 metrics have multiple mechanistic mappings (e.g., a fast RT might correspond to  
3029 high SNR or an impulsive decisions driven by a starting point bias).

3030 We would like to thank the reviewer for this important point. Considering this Comment  
3031 and the Comment 3 by Reviewer 1, we realize that the quadratic relationships between  
3032 mode and RTs/confidence do not represent a convincing defensive analysis against the  
3033 potential contributions of arousal to the phenomenon that we have identified as between-  
3034 mode fluctuations. Rather, we now interpret the fluctuations of RTs/confidence with mode  
3035 as indicative of a scenario in which between-mode fluctuations modulate a decision-variable  
3036 that determines not only the perceptual choices, but also the speed and confidence at which  
3037 they are made.

3038 Therefore, as a first response to this comment, we have re-phrased our assessment of RT and  
3039 confidence in the following way:

3040 Humans:

- 3041 • The above results point to systematic fluctuations in the *decision variable*<sup>44</sup> that deter-  
3042 mines perceptual choices, causing enhanced sensitivity to external stimulus information  
3043 during external mode and increased biases toward preceding choices during internal  
3044 mode. As such, fluctuations in mode should influence downstream aspects of behavior

3045 and cognition that operate on the perceptual decision variable<sup>44</sup>. To test this hypothesis  
3046 with respect to motor behavior and metacognition, we asked how bimodal inference  
3047 relates to response times (RTs) and confidence reports. (...).

- 3048 • (...) In sum, the above results indicate that reporting behavior and metacognition do  
3049 not map linearly onto the mode of sensory processing. Rather, they suggest that slow  
3050 fluctuations in the respective impact of external and internal information are most likely  
3051 to affect perception at an early level of sensory analysis<sup>46,47</sup>. Such low-level processing  
3052 may thus integrate perceptual history with external inputs into a decision variable<sup>44</sup>  
3053 that influences not only perceptual choices, but also the speed and confidence at which  
3054 they are made.
- 3055 • In what follows, we probe alternative explanations for between-mode fluctuations, test  
3056 for the existence of modes in mice, and propose a predictive processing model that  
3057 explains fluctuations in mode ongoing shifts in the precision afforded to external sensory  
3058 information relative to internal predictions driven by perceptual history.

3059 Mice:

- 3060 • The above results confirm that fluctuations between internally- and externally-biased  
3061 modes generalize to perceptual decision-making in mice. As in humans, we hypothesized  
3062 that bimodal inference modulates the decision variable<sup>44</sup> that determines not only  
3063 perceptual choices, but also downstream aspects of mouse behavior<sup>44</sup>. (...). When  
3064 fitting full and history-conditioned psychometric curves to the data from the IBL  
3065 database, we observed that internal mode processing was associated with a history-  
3066 dependent increase in bias and lapse as well as a history-independent increase in threshold  
3067 (Supplemental Section 9.3.2 and Supplemental Figure S7). Over time, the frequency of  
3068 history-congruent choices increased alongside stimulus-congruence and speed of response  
3069 as mice were exposed to the experiment, arguing against the proposition that biases

3070 toward perceptual history reflected an unspecific response strategy in mice who were  
3071 not sufficiently trained on the IBL task.

3072 Second, we have re-structured the section of defensive analyses, where we contrast the  
3073 phenomenon that we identify as fluctuating modes in perception with stereotypical or random  
3074 responses as evidence of low task engagement, and not specifically with attention or arousal,  
3075 which we discuss below. To streamline the manuscript, we report those analyses in detail in  
3076 the Supplement (see Comments 12 by Reviewer 1 and Comment 9 by Reviewer 3).

3077 • The core assumption of bimodal inference - that ongoing changes in the sensitivity to  
3078 external information are driven by internal predictions induced via perceptual history  
3079 - needs to be contrasted against two alternative hypotheses: When making errors,  
3080 observers may not engage with the task and respond stereotypically, i.e., exhibit stronger  
3081 general biases toward one of the two potential outcomes, or simply choose randomly.  
3082 Logistic regression confirmed that perceptual history made a significant contribution to  
3083 perception ( $\beta = 0.11 \pm 5.79 \times 10^{-3}$ ,  $z = 18.53$ ,  $p = 1.1 \times 10^{-76}$ ) over and above the  
3084 ongoing stream of external sensory information ( $\beta = 2.2 \pm 5.87 \times 10^{-3}$ ,  $z = 375.11$ ,  $p <$   
3085  $2.2 \times 10^{-308}$ ) and general response biases toward ( $\beta = 15.19 \pm 0.08$ ,  $z = 184.98$ ,  $p <$   
3086  $2.2 \times 10^{-308}$ ).

3087 • When eliminating perceptual history as a predictor of individual choices at individual  
3088 trials, AIC increased by  $\delta_{AIC} = 1.64 \times 10^3$  (see Supplemental Figure S4A-B for parameter-  
3089 and model-level inference at the level of individual observers). Likewise, when eliminating  
3090 slow fluctuations in history-congruence as a predictor of slow fluctuations in stimulus-  
3091 congruence across trials, we observed an increase in AIC by  $\delta_{AIC} = 7.06 \times 10^3$ . These  
3092 results provided model-level evidence against the null hypotheses that fluctuations in  
3093 stimulus-congruence are driven exclusively by choice randomness or general response  
3094 bias (see Supplemental Section 9.2 for an in-depth assessment of general response bias).

3095 • To confirm that changes in the sensitivity to external information are indicative of  
3096 internal mode processing, we estimated full and history-dependent psychometric curves  
3097 during internal, external, and across modes. If, as we hypothesized, internal mode  
3098 processing reflects an enhanced impact of perceptual history, one would expect a history-  
3099 dependent increase in biases and lapses as well as a history-independent increase in  
3100 threshold. Conversely, if internal mode processing were driven by random choices, one  
3101 would expect a history-independent increase in lapses and threshold, and no change in  
3102 bias. In line with our prediction, we found that internal mode processing was associated  
3103 with a history-dependent increase in bias and lapse as well as a history-independent  
3104 increase in threshold (Supplemental Section 9.3 and Supplemental Figure S6-7). This  
3105 confirmed that internal mode processing is indeed driven by an enhanced impact of  
3106 perceptual history.

- 3107 • In line with this, the quadratic relationship between mode and confidence (Figure  
3108 2J) suggested that biases toward internal information do not reflect a post-perceptual  
3109 strategy or repeating preceding choices when the subjective confidence in the perceptual  
3110 decision is low. Moreover, while responses became faster with increased exposure  
3111 to the experiments of the Confidence database, the frequency of history-congruent  
3112 choices increased over time, speaking against the proposition that participants may  
3113 stereotypically repeat preceding choices when not yet familiar with the experimental  
3114 task (see Supplemental Section).
- 3115 • Taken together, our results thus argue against recurring intervals of low task engagement,  
3116 which may be signaled by stereotypical or random responses, as an alternative explanation  
3117 for the phenomenon that we identify as bimodal inference.

3118 Third, in response the Comment 3 by Reviewer 1, we now interpret the quadratic relationship  
3119 of mode to RTs/confidence in the context of predictive processing views on attention<sup>53</sup>. Based  
3120 on the Bayesian formulation of drift diffusion<sup>60</sup>, we propose that the effects of likelihood on

3121 prior precision on the decision variable and, consequently, on confidence and RTs can be  
3122 translated into the mechanistic framework of drift diffusion. Specifically, Bitzer et al. relate  
3123 likelihood precision to noise in the accumulation process, and prior precision to the amount  
3124 of shift in the starting point<sup>60</sup>. As a third response to this comment, we have re-written  
3125 our discussion of the quadratic relationship of mode to RTs and Confidence, focusing on  
3126 predictive processing models attention, which we relate to mechanistic drift diffusion models:

- 3127 • How does attention relate to between-mode fluctuations? According to predictive  
3128 processing, attention corresponds to the precision afforded to the probability distributions  
3129 that underlie perceptual inference<sup>53</sup>. As outlined above, between-mode fluctuations  
3130 can be understood as ongoing shifts in the precision afforded to likelihood (*external*  
3131 *mode*) and prior (*internal mode*), respectively. When the precision afforded to prior or  
3132 likelihood increases, posterior precision increases, which leads to faster RTs and higher  
3133 confidence. When defined from the perspective of predictive processing as the precision  
3134 afforded to likelihood and prior<sup>53</sup>, fluctuations in attention may thus provide a plausible  
3135 explanation for the quadratic relationship of mode to RTs and confidence (Figure 2H  
3136 and J; Figure 3I; Figure 4I). Such effects of attention in the predictive processing sense  
3137 can be directly related to mechanistic drift diffusion models<sup>60</sup>, where both larger shifts  
3138 in starting point (related to increased prior precision in internal mode) and lower noise  
3139 in the accumulation of evidence (related to increased likelihood precision in external  
3140 mode) may explain faster and more confident responses.

3141 Given the correspondence between normative Bayesian and mechanistic drift diffusion  
3142 models<sup>60</sup>, we believe that we would not gain additional insights into the role of arousal  
3143 and additional potential confounds or causes of between-mode fluctuations by fitting drift  
3144 diffusion models as an alternative class of behavioral models to our data. To understand the  
3145 relation of arousal to the bimodal inference, we think that it is necessary to look at data  
3146 beyond behavior, such as pupillometry, video tracking of response behavior, or neural data.

3147 While this is beyond the scope of the current manuscript, we plan to do these analyses in  
3148 a follow-up paper, using data published by the IBL after this paper was submitted. The  
3149 IBL data now contains eye tracking, video tracking of response behavior, and neuropixel  
3150 recordings across the whole mouse brain<sup>71</sup>. As a fourth response to this comment, we have  
3151 re-written our discussion of attention and arousal:

- 3152 • Outside of the predictive processing field, attention is often understood in the context of  
3153 task engagement<sup>63</sup>, which varies according to the availability of cognitive resources that  
3154 are modulated by factors such as tonic arousal, familiarity with the task, or fatigue<sup>63</sup>. Our  
3155 results suggest that internal mode processing cannot be completely reduced to intervals  
3156 of low task engagement: In addition to shorter RTs and elevated confidence, choices  
3157 during internal mode were not random or globally biased, but driven by perceptual  
3158 history (Supplemental Figures S6-7). Moreover, our computational model identified  
3159 the dominant timescale of between-mode fluctuations at  $0.11\sqrt{1/N_{trials}}$ , which may be  
3160 compatible with fluctuations in arousal<sup>64</sup>, but is faster than to be expected for the  
3161 development of task familiarity or fatigue.
- 3162 • However, in interpreting the impact of between-mode fluctuations on perceptual accuracy,  
3163 speed of response and confidence, it is important to consider that global modulators  
3164 such as tonic arousal are known to have non-linear effects on task performance<sup>65</sup>: In  
3165 perceptual tasks, performance seems to be highest during mid-level arousal, whereas low-  
3166 and high-level arousal lead to reduced accuracy and slower responses<sup>65</sup>. This contrasts  
3167 with the effects of bimodal inference, where accuracy increases linearly as one moves  
3168 from internal to external mode, and responses become faster at both ends of the mode  
3169 spectrum.
- 3170 • Of note, high phasic arousal has been shown to suppress multi-domain biases in decision-  
3171 making in humans and mice<sup>66-68</sup>, including the biases toward perceptual history<sup>28</sup> that  
3172 we implicate in internal mode processing. The increase in response speed and history

3173 congruence over time (Supplemental Section 9.4) may argue against insufficient training  
3174 as an alternative explanation for internal mode processing, but may also taken as a  
3175 sign of waning arousal. The multiple mechanistic mappings to RTs and confidence  
3176 therefore warrant more direct measures of arousal (such as pupil size<sup>28,65,66,68–70</sup>, motor  
3177 behavior<sup>69,70</sup>, or neural data<sup>71</sup>) to better delineate bimodal inference from fluctuations  
3178 in global modulators of task performance.

3179 **10.3.7 Comment 7**

3180 **In several analysis the authors present an effect and then show that this effects**  
3181 **persists when key variables/ design aspects are also taken into account (see an**  
3182 **example at around line 70). It makes more sense to present only one single**  
3183 **analysis in which these key variables are controlled for. Results cannot be**  
3184 **interpreted if they are spurious factors driving them so it is not clear why some**  
3185 **of the results are presented in two versions (“uncontrolled” and “controlled”**  
3186 **analyses).**

3187 We apologize for this. We have updated our manuscript accordingly and have omitted,  
3188 whenever possible, reports of uncontrolled analyses (highlighted in the main text). The most  
3189 significant changes are summarized here:

- 3190 • Group-level autocorrelation curves in humans: In line with previous work<sup>8</sup>, we found that  
3191 the probability of stimulus-congruence was not independent across successive trials: At  
3192 the group level, stimulus-congruent perceptual choices were significantly autocorrelated  
3193 for up to 15 trials (Figure 2B), controlling for task difficulty and the sequence of presented  
3194 stimuli (Supplemental Figure 2A-B). (...) In close analogy to stimulus-congruence, we  
3195 found history-congruence to be significantly autocorrelated for up to 21 trials (Figure 2B),  
3196 while controlling for task difficulty and the sequence of presented stimuli (Supplemental  
3197 Figure 2A-B).

- 3198 • Group-level autocorrelation curves in mice: At the group level, we found significant auto-  
3199 correlations in both stimulus-congruence (42 consecutive trials) and history-congruence  
3200 (8 consecutive trials (Figure 3B), while controlling for the respective autocorrelation of  
3201 task difficulty and external stimulation (Supplemental Figure 2C-D).
- 3202 • Correlation between stimulus- and history-congruence in humans: When perceptual  
3203 choices were less biased toward external information, participants relied more strongly  
3204 on internal information acquired from perceptual history (and vice versa,  $\beta = -0.05 \pm$   
3205  $5.63 \times 10^{-4}$ ,  $T(2.1 \times 10^6) = -84.21$ ,  $p < 2.2 \times 10^{-308}$ , **controlling for fluctuations in**  
3206 **general response biases**; Supplemental Section 9.2).
- 3207 • Correlation between stimulus- and history-congruence in mice: Fluctuations in the  
3208 strength of history-congruent biases had a significant effect on stimulus-congruence ( $\beta_1$   
3209  $= -0.12 \pm 7.17 \times 10^{-4}$ ,  $T(1.34 \times 10^6) = -168.39$ ,  $p < 2.2 \times 10^{-308}$ ) beyond the effect  
3210 of ongoing changes in general response biases ( $\beta_2 = -0.03 \pm 6.94 \times 10^{-4}$ ,  $T(1.34 \times 10^6)$   
3211  $= -48.14$ ,  $p < 2.2 \times 10^{-308}$ ).

### 3212 10.3.8 Comment 8

3213 The central empirical finding is potentially important but is currently shadowed  
3214 by more speculative sections/ discussions. For instance, the section on the  
3215 adaptive merits of the computational model is relatively weaker compared to the  
3216 empirical results. In particular, the model is simulated without feedback (whereas  
3217 most experiments employ trial by trial feedback) and does not outperform the  
3218 baseline model in accuracy but in other secondary metrics.

3219 We agree with the Reviewer (see also a similar suggestion by Reviewer 1 in Comment 9).  
3220 We have removed the section 5.8 and the associated subsection of the discussion from our  
3221 manuscript. We will develop a model on the potential function of between-mode fluctuations  
3222 in a separate publication.

3223 **Minor comments:**

3224 **10.3.9 Comment 9**

3225 **The amount of statistical analysis and results is often overwhelming. The authors  
3226 could streamline the presentation better such that the main result is brought to  
3227 the foreground. Currently the manuscript resembles a technical report.**

3228 We apologize for this. From the Results, we have moved a number of sections to the  
3229 Supplemental Materials to stream-line the manuscript (i.e., our analysis of general response  
3230 biases [former section 5.4], the analysis of psychometric functions [former section 5.5], and  
3231 the respective paragraphs on the IBL database). From the Discussion, we have removed the  
3232 section on self-organized criticality (also following the suggestion of Reviewer 1). We have  
3233 also moved more peripheral statistical results to the figure legends and the method section:

3234 • We have moved the statistics on exponential decay in the autocorrelation to the figure  
3235 legends of Figure 2B and 3B.

3236 • We have shortened the description of logistic regression models that predict the stimulus-  
3237 and history-congruence at the index trial from the stimulus- and history-congruence at  
3238 the preceding trials.

3239 • The section on mouse behavior now matches the logic and presentation of results in the  
3240 human section.

3241 We hope that these changes will increase the readability of our manuscript.

3242 **10.3.10 Comment 10**

3243 **Some typos or omissions may alter the meaning in various places. Indicatively,  
3244 in lines 273, 439, 649.**

3245 Thanks a lot, we have corrected these typos.

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