How sleeping minds decide: state-specific reconfigurations of lexical decision-making

3 4	Tao X	Xia ^{1*} , Chuan-Peng Hu ² , Basak Türker ³⁵ , Esteban Munoz Musat ³⁵ , Lionel Naccache ³⁴ , Isabelle Arnulf ³⁵ , Delphine Oudiette ^{35*} , Xiaoqing Hu ^{16*}			
5	1.	Department of Psychology, The State Key Laboratory of Brain and Cognitive Sciences, The University			
6		of Hong Kong, Hong Kong SAR, China.			
/	2.	School of Psychology, Nanjing Normal University, Nanjing 210024, China			
8 9	3.	Sorbonne Université, Institut du Cerveau—Paris Brain Institute—ICM, INSERM, CNRS, Paris, France.			
10	4.	AP-HP, Hôpital Pitié-Salpêtrière, Service de Neurophysiologie Clinique, Paris, France.			
11 12	5.	AP-HP, Hôpital Pitié-Salpêtrière, Service des Pathologies du Sommeil, National Reference Centre for Narcolepsy, Paris, France.			
13	6.	HKU-Shenzhen Institute of Research and Innovation, Shenzhen, China.			
14	*Corres	ponding authors:			
15	Xiaoqing Hu: E-mail: xiaoqinghu@hku.hk, Delphine Oudiette: E-mail: delphine.oudiette@gmail.com,				
16	Tao Xia: E-mail: psytao18@connect.hku.hk				
17					
18	Abstract:				
19	Decisi	on-making is a core cognitive function that enables adaptive behavior across diverse			
20	contexts. While extensively studied in wakefulness, its persistence and reconfiguration across				
21	sleep states remain poorly understood. Here, we use computational modeling to examine				
22	lexical decision-making across wakefulness N1 sleep and lucid RFM sleep in both healthy				
23	participants (HP) and participants with parcolency (NP). Using facial electromyography				

(EMG) to capture real-time behavioral responses to spoken words and pseudowords during

sleep, we quantify how decision-making strategies adapt under different sleep and

26 consciousness states. Our findings reveal two key insights. First, decision-making

27 mechanisms are dynamically reconfigured across sleep states. In N1 sleep, the advantage for

- word (vs. pseudoword) judgments is supported by faster sensory encoding and motor
- 29 preparation, combined with efficient evidence accumulation. In contrast, in lucid REM sleep, 30 the word advantage is driven exclusively by enhanced evidence accumulation, while sensory
- encoding and motor preparation remain unchanged. Second, cross-state comparisons reveal
- distinct patterns of preservation and impairment. In N1 sleep, word judgment remains largely
- intact, whereas pseudoword judgment is significantly impaired, characterized by prolonged
- 34 stimulus encoding, delayed motor preparation, and reduced evidence accumulation. In
- 35 contrast, lucid REM sleep is marked by a global reduction in processing efficiency, reflected
- in slower evidence accumulation and elevated decision thresholds for both words and
- 37 pseudowords. These results demonstrate that rather than being uniformly degraded, decision-
- 38 making is dynamically reconfigured across sleep stages, reflecting adaptive neurocognitive
- 39 strategies that sustain cognition in altered states of consciousness. By identifying state-
- 40 specific computational mechanisms, this study provides new insights into the brain's
- 41 resilience and flexibility under changing cognitive and physiological conditions.
- 42 Key words: lucid dreaming, lexical decision, sleep, consciousness, drift diffusion model
- 43

44

45 Introduction

46 Decision-making is core for human cognition, supporting individuals to adaptively navigate

- 47 complex environments. While decision-making during wakefulness has been extensively
- 48 studied, how the brain supports this process during sleep remains poorly understood. Sleep is
- 49 increasingly recognized as an active cognitive state, during which the brain continues to
- 50 process sensory information, acquire and consolidate memories, and even engage in goal-
- 51 directed behaviour (Andrillon et al., 2016; Arzi et al., 2012; Konkoly et al., 2021; Türker et
- al., 2023; Xia et al., 2024). Despite these intriguing findings (Konkoly et al., 2021; Türker et
 al., 2023), the computational mechanisms that enable decision-making to persist and adapt
- 54 under the distinct sleep states remain unclear. Here, leveraging unique data involving lexical
- 55 decision makings during sleep and lucid dreaming (Türker et al., 2023), we investigated how
- sleeping minds reconfigure its computational strategies across wakefulness and different
- sleep states. By uncovering the computational mechanisms underlying decision-making
- 58 during sleep, our findings provide novel insights into how cognitive processes are
- 59 dynamically restructured across altered states of consciousness.

60 Sleep is not a uniform state but a progression through distinct neural stages, each imposing

- 61 unique constraints on cognitive processing. In N1 sleep, the transition from wakefulness is
- 62 gradual; sensory processing remains partially intact, allowing recognition of familiar stimuli,
- but higher-order cognitive functions are reduced (Andrillon et al., 2016; Blume et al., 2017;
- Lacaux et al., 2024; Wislowska et al., 2022). As sleep deepens into N2 and N3, slow-wave
- activity increases, thalamocortical connectivity diminishes, and responsiveness to external
- 66 stimuli further declines, with the brain prioritizing endogenous memory consolidation
- 67 (Diekelmann & Born, 2010; Massimini, 2005; Strauss et al., 2015). In contrast, REM sleep—
- often referred to as "paradoxical sleep"—is characterized by wake-like cortical activity and
 vivid dreaming experiences (Brown et al., 2012; Hobson & Friston, 2012). A particularly
- 70 intriguing phenomenon is lucid REM sleep, in which individuals become aware that they are
- 71 dreaming and can even exert voluntary control over dream content (Filevich et al., 2015;
- 72 Voss et al., 2014; Zerr et al., 2024). This state represents a unique hybrid of internally
- 73 generated cognition and externally responsive awareness, bridging the gap between sleep and
- 74 wakefulness and offering a powerful model for experimentally probing cognitive processes
- 75 during sleep.

76 A recent study demonstrated that individuals in lucid REM sleep can perceive and respond to

77 questions presented by an experimenter in real time, using predefined eye movements (EOG)

- or facial muscle contractions (EMG) (Konkoly et al., 2021). Moreover, EMG-based lexical
 decision tasks—where individuals distinguish words from pseudowords by contracting facial
- decision tasks—where individuals distinguish words from pseudowords by contracting facial
 muscles—have revealed that lexical decision-making remains possible throughout different
- muscles—have revealed that lexical decision-making remains possible throughout different
 sleep states, including lucid REM sleep (Türker et al., 2023). These findings provide key
- evidence that the sleeping minds remain a remarkable ability not only to process external
- stimuli but also to engage in higher-level cognitive functions, such as lexical judgments.
- However, the computational mechanisms underlying decision-making across different sleep
- states remain poorly understood, requiring further investigation.
- 86 To address this question, we employed drift diffusion modelling (DDM), a computational
- 87 framework widely used to quantify the cognitive processes underlying decision-making

(Ratcliff et al., 2004, 2016). The DDM conceptualizes decision-making as the gradual

- 89 accumulation of noisy sensory evidence until a decision threshold is reached (Myers et al.,
- 90 2022). Key parameters include the drift rate: how efficiently evidence is accumulated; the
- non-decision time: the time needed for sensory encoding, motor preparation, and other non decisional processes; and the decision threshold: the amount of evidence required to make a
- decision processes, and the decision threshold, the amount of evidence required to make adecision, reflecting the trade-off between speed and accuracy. Prior studies have shown that
- decision, renecting the trade-off between speed and accuracy. Frior studies have shown that
 differences in lexical decision-making—such as distinguishing words from pseudowords—
- 95 are primarily driven by drift rate and non-decision times (Donkin et al., 2009; Ratcliff et al.,
- 2004). However, to account for potential variations in decision-making strategies across
- 97 wakefulness and sleep, we also included the decision threshold (a) in our model. Adjustments
- to the decision threshold are particularly important in contexts like sleep, where individuals
- must navigate the trade-off between speed and accuracy (Ratcliff et al., 2004; Ratcliff &
- 100 McKoon, 2008). By applying DDM to EMG-measured muscle responses during a lexical
- decision task, we quantified how these parameters shift across wakefulness, light NREM
- sleep, and lucid REM sleep, revealing the computational trade-offs that sustain decision-making under altered sleep states.

To gain deeper insight into how decision-making adapts across sleep states, we studied 104 participants with narcolepsy, a condition characterized by unstable sleep-wake transitions and 105 frequent lucid dreams (Baird et al., 2019; Dodet et al., 2015; Mota-Rolim & Araujo, 2013). 106 Because individuals with narcolepsy often experience heightened dream awareness and 107 control, this condition provides a unique natural model for investigating decision-making in 108 lucid REM sleep. Participants completed a lexical decision task during both wakefulness and 109 sleep, allowing us to examine how cognitive processes adapt across altered states of 110 consciousness. Our findings reveal that core cognitive components-such as non-decition 111 times, evidence accumulation, and decision thresholds—are not simply degraded during 112 sleep. Instead, they are dynamically reconfigured, highlighting the brain's remarkable ability 113 to sustain cognition despite shifting cognitive states. 114

115

116 **Results**

- 117 We first investigated the computational mechanisms underlying lexical decision-making
- across wakefulness, N1, N2, non-lucid REM, and lucid REM sleep. Using DDM, we
- examined how these mechanisms adapt across sleep states to determine how sleep alters
- 120 decision-making processes. Specifically, we assessed behavioural performance—measuring
- 121 reaction times (RTs) and accuracy—as well as computational parameters derived from DDM:
- non-decision time (reflecting sensory encoding and motor preparation), drift rate (reflecting
- the efficiency of evidence accumulation), and decision threshold (reflecting decision caution).
- By comparing these parameters across states, we aimed to determine the extent to which
- 125 lexical decision-making is preserved, impaired, or reconfigured during different sleep states.

126 Lexical decision-making during wakefulness

- 127 To establish a baseline for decision-making processes, we first examined lexical decision-
- 128 making during wakefulness. As expected, participants responded faster to words than
- 129 pseudowords, reflecting more efficient linguistic processing.

- 130 Among healthy participants (HP), RTs were significantly faster for words compared to
- 131 pseudowords (median_{diff} = -0.171, 95% HDI [-0.221, -0.126], Figure 2A right), while
- accuracy differences were not significant (median_{diff} = -0.116, 95% HDI [-0.485, 0.243],
- 133Figure 2A left). DDM revealed that the RT advantage for words was driven by shorter non-
- decision times (median_{diff} = -0.106, 95% HDI [-0.149, -0.061], Figure 2C), reflecting efficient
- stimulus encoding and motor preparation. Drift rates (evidence accumulation) and decision
- thresholds (decision caution) were similar for words and pseudowords (all 95% HDIs
- 137 overlapped with 0, Figure 2C, 2E).
- 138 In contrast, individual with narcolepsy (NP) exhibited abnormal lexical decision-making
- patterns. While RTs were faster for words than pseudowords (median_{diff} = -0.149, 95% HDI
- 140 [-0.210, -0.088], Figure 2B right), accuracy was lower for words (median_{diff} = -0.512, 95%)
- 141 HDI [-0.889, -0.135], Figure 2B left). These deficits were reflected in faster non-decision
- times (median_{diff} = -0.101, 95% HDI [-0.156, -0.048], Figure 2D) but significantly slower
- drift rates (median_{diff} = -0.184, 95% HDI [-0.388, -0.001], Figure 2F) for words, suggesting
- 144 impaired evidence accumulation. Decision thresholds were comparable across words and
- 145 pseudowords (all 95% HDIs overlapped with 0, Figure 2G, 2H).
- 146 Thus, while HPs demonstrated efficient lexical decision-making during wakefulness,
- 147 characterized by robust sensory encoding and motor preparation for words. NPs exhibited
- 148 disrupted evidence accumulation, potentially reflecting cognitive impairments associated
- 149 with narcolepsy (Naumann et al., 2006). Having established these baseline differences, we
- 150 next examined how lexical decision-making is reconfigured across sleep states.

151 State-specific mechanisms of lexical decision-making N1 and lucid REM sleep

- 152 Despite transitioning into sleep, participants retained the ability to make lexical decisions
- during both N1 sleep and lucid REM sleep, as indicated by faster and more accurate
- 154 responses to words than pseudowords (see below). However, the mechanisms underlying this
- 155 word advantage differed between these states.
- 156 In N1 sleep, RTs were significantly faster for words compared to pseudowords in both HPs
- 157 (median_{diff} = -0.390, 95% HDI [-0.575, -0.208], Figure S2A right) and NPs (median_{diff} = -
- 158 0.160, 95% HDI [-0.265, -0.058], Figure 3A right). Accuracy was also higher for words than
- 159 pseudowords in both groups (HP: median_{diff} = 1.571, 95% HDI [0.479, 2.783], Figure S2A
- 160 left; NP: median_{diff} = 0.604, 95% HDI [0.107, 1.113], Figure 3A left). In lucid REM sleep,
- 161 participants with narcolepsy similarly showed faster RTs (median_{diff} = -0.169, 95% HDI [-
- 162 0.281, -0.051], Figure 3B right) and higher accuracy (median_{diff} = 0.674, 95% HDI [0.186,
- 163 1.161], Figure 3B left) for words compared to pseudowords. These findings indicate that
- 164 lexical decision-making remains functional in both states.
- 165 To uncover the mechanisms underlying lexical decisions during N1 and lucid REM sleep, we
- applied drift diffusion modelling. The results revealed distinct mechanisms supporting the
- 167 word advantage in each state. In N1 sleep, the word advantage was driven by shorter non-
- 168 decision times for words than pseudowords, reflecting more efficient sensory encoding and
- 169 motor preparation in HPs (median_{diff} = -0.213, 95% HDI [-0.367, -0.062], Figure S2B) and
- 170 NPs (median_{diff} = -0.098, 95% HDI [-0.188, -0.001], Figure 3C). Additionally, higher drift
- rate for words than pseudowords in HPs (median_{diff} = 0.732, 95% HDI [0.105, 1.433], Figure
- 172 S2C) and NPs (median_{diff} = 0.308, 95% HDI [0.018, 0.589], Figure 3E), suggest enhanced

- 173 evidence accumulation, facilitating more efficient lexical decision-making in both groups.
- 174 Importantly, decision thresholds did not differ between words and pseudowords in both
- groups (all 95% HDIs overlapped with 0, Figure 3G, Figure S2E), indicating stable decision
- threshold across stimuli. These findings suggest that lexical decisions in N1 sleep were
- supported by preserved sensory encoding and motor preparation, along with efficient
- 178 evidence accumulation.
- 179 In lucid REM sleep, the word advantage was primarily supported by higher drift rates for
- words than pseudowords (median_{diff} = 0.274, 95% HDI [0.015, 0.543], Figure 3F), indicating
- selective improvements in evidence accumulation for words. Unlike N1 sleep, non-decision
- times and decision thresholds did not differ between words and pseudowords (all 95% HDIs
- overlapped with 0, Figure 3 DH), suggesting that sensory encoding and motor preparation,along with decision threshold were stable across stimulus types during lucid REM sleep.
- 185 These findings suggest that lexical decisions in lucid REM sleep relied predominantly on
- selective improvements in evidence accumulation for words, rather than changes in non-
- 187 decision times or decision caution.
- 188 Together, lexical decision-making in N1 and lucid REM sleep relied on distinct
- 189 computational strategies. In N1 sleep, faster responses and higher accuracy were supported
- by both faster sensory encoding, motor preparation, and more efficient evidence
- 191 accumulation. In lucid REM sleep, the word advantage was primarily driven by enhanced
- 192 evidence accumulation, while sensory encoding, motor preparation, and decision caution
- 193 remained unchanged.

194 Absence of lexical decision-making in N2 and non-lucid REM sleep

- 195 In contrast to N1 and lucid REM sleep, participants were unable to distinguish between
- 196 words and pseudowords in N2 and non-lucid REM sleep. There were no significant
- 197 differences in RTs, accuracy, or any decision-making parameters (drift rates, non-decision
- 198 times, or decision thresholds) between words and pseudowords (all 95% HDIs overlapped
- 199 with 0, Figure S3). These findings indicate that lexical decision-making mechanisms are
- 200 functionally absent in these deeper sleep states, likely reflecting reduced sensory processing
- 201 and diminished cognitive engagement.

202 Dynamic reconfiguration of lexical decision-making across wakefulness, N1 sleep, and 203 lucid REM sleep

- Having established that word judgments in N1 and lucid REM sleep rely on distinct
- 205 computational mechanisms, we next examine how lexical decision-making adapts across
- wakefulness, N1 sleep, and lucid REM sleep. By integrating both behavioural performance
- and computational modelling, we identified gradual yet distinct changes in sensory encoding,
- 208 motor preparation, evidence accumulation, and decision caution across these states, using
- 209 wakefulness as a baseline for optimal performance.

Wakefulness vs. N1 Sleep: robust word processing and impaired pseudoword processing

- To examine how N1 sleep reconfigures decision-making processes for lexical decisions, we
- 213 compared behavioural and computational results between wakefulness and N1 sleep in both

214 HP and NP groups. The findings revealed a selective preservation of word processing, while215 pseudoword judgments were significantly impaired.

- 216 For words, RTs (median_{diff} = 0.020, 95% HDI [-0.106, 0.148]), and accuracy (median_{diff} = -
- 217 0.163, 95% HDI [-1.216, 0.765]) were comparable between wakefulness and N1 sleep,
- suggesting word judgment during N1 sleep remained stable. DDM confirmed that non-
- 219 decision times, drift rate, and decision threshold for words did not significantly differ
- between wakefulness and N1 sleep (all 95% HDIs overlapped with 0, Figure 4A, 4B, 4C),
- suggesting that semantic networks supporting word judgment remained intact during N1
- sleep.
- In contrast, pseudoword judgment was significantly impaired during N1 sleep. RTs were
- slower (median_{diff} = -0.199, 95% HDI [-0.345, -0.057]), and accuracy was lower (median_{diff} = -0.199, 95% HDI [-0.345, -0.057]), and accuracy was lower (median_{diff} = -0.199, 95% HDI [-0.345, -0.057]), and accuracy was lower (median_{diff} = -0.199, 95% HDI [-0.345, -0.057]), and accuracy was lower (median_{diff} = -0.199, 95% HDI [-0.345, -0.057]), and accuracy was lower (median_{diff} = -0.199, 95% HDI [-0.345, -0.057]), and accuracy was lower (median_{diff} = -0.199, 95% HDI [-0.345, -0.057]), and accuracy was lower (median_{diff} = -0.199, 95% HDI [-0.345, -0.057]), and accuracy was lower (median_{diff} = -0.199, 95% HDI [-0.345, -0.057]), and accuracy was lower (median_{diff} = -0.199, 95% HDI [-0.345, -0.057]), and accuracy was lower (median_{diff} = -0.199, 95% HDI [-0.345, -0.057]), and accuracy was lower (median_{diff} = -0.199, 95% HDI [-0.345, -0.057]), and accuracy was lower (median_{diff} = -0.199, 95% HDI [-0.345, -0.057]), and accuracy was lower (median_{diff} = -0.199, 95% HDI [-0.345, -0.057]), and accuracy was lower (median_{diff} = -0.199, 95% HDI [-0.345, -0.057]), and accuracy was lower (median_{diff} = -0.199, 95% HDI [-0.345, -0.057]), and accuracy was lower (median_{diff} = -0.199, 95% HDI [-0.345, -0.057]), and accuracy was lower (median_{diff} = -0.199, 95% HDI [-0.345, -0.057]), and accuracy was lower (median_{diff} = -0.199, 95% HDI [-0.345, -0.057]), and accuracy was lower (median_{diff} = -0.199, 95% HDI [-0.345, -0.057]), and accuracy was lower (median_{diff} = -0.199, 95% HDI [-0.345, -0.057]), 95% HDI [-0.345, -0.057]), 95%
- 1.519, 95% HDI [0.823, 2.236]), reflecting greater difficulty in processing novel or
- ambiguous stimuli during N1 sleep. DDM revealed that this impairment was driven by slower
- non-decision times (median_{diff} = -0.120, 95% HDI [-0.215, -0.009], Figure 4D) and lower
- drift rate (median_{diff} = 0.630, 95% HDI [0.074, 1.115], Figure 4E), while the decision
- threshold remained unchanged between wakefulness and N1 sleep (95%HDI overlapped with
- 230 0, Figure 4F).
- A similar pattern was observed in the NP group, where pseudoword processing exhibited a
- significantly slower drift rate compared to wakefulness (median_{diff} = -0.468, 95% HDI [-
- 233 0.688, -0.252]), while non-decision times and decision thresholds remained unchanged (all
- 234 95% HDIs overlapped with 0). However, as with HPs, word processing remained stable
- 235 across wakefulness and N1 sleep, with no significant differences in non-decision times, drift
- rates, or decision thresholds (all 95% HDIs overlapped with 0).
- 237 These findings suggest that while lexical representations remain accessible during N1 sleep,
- 238 decisions requiring phonological decoding and inhibitory control (e.g., pseudowords) are
- disproportionately affected, likely due to sleep-related reductions in cognitive resources. The
- similarity of this pattern across both groups supports the idea that familiar word judgment is
- 241 preserved during N1 sleep, whereas processing novel or ambiguous stimuli becomes less
- efficient due to state-dependent cognitive constraints.
- 243

Lucid REM sleep vs. wakefulness and N1 sleep: slower and less efficient lexical decisions

- Building on these observations, we next examined how lucid REM sleep reconfigured
- 247 decisional processing to perform lexical decision relative to wakefulness and N1 sleep.
- 248 Unlike N1 sleep, where word processing remained largely intact, lucid REM sleep was
- associated with global reductions in processing efficiency.
- 250 Participants exhibited slower RTs across both stimulus types during lucid REM sleep. For
- words, RTs were significantly slower compared to wakefulness (median_{diff} = 0.242, 95% HDI
- 252 [0.141, 0.344]) and N1 sleep (median_{diff} = 0.185, 95% HDI [0.075, 0.308]). A similar pattern
- 253 was observed for pseudowords, with RTs significantly slower compared to wakefulness
- 254 (median_{diff} = 0.261, 95% HDI [0.161, 0.366]) and N1 sleep (median_{diff} = 0.195, 95% HDI
- 255 [0.080, 0.312]).

- 256 Despite the generalized slowing, accuracy patterns differed between stimulus types. Word
- 257 accuracy remained stable, showing no significant differences compared to wakefulness
- 258 (median_{diff} = -0.418, 95% HDI [-0.916, 0.045]) or N1 sleep (median_{diff} = -0.474, 95% HDI [-
- 1.011, 0.088]). In contrast, pseudoword accuracy was significantly impaired during lucid REM sleep, with lower accuracy compared to wakefulness (median_{diff} = -1.607, 95% HDI [-
- 260 REM sleep, with lower accuracy compared to wakerumess (median $d_{iff} = -1.007, 95\%$ HDI [-261 2.087, -1.129]) and N1 sleep (median $d_{iff} = -0.549, 95\%$ HDI [-1.030, -0.059]). These findings
- suggest that while participants retained access to words, their ability to process pseudowords
- 263 was selective impaired in lucid REM sleep.
- 264 DDM revealed that lexical decision-making in lucid REM sleep was characterized by reduced
- evidence accumulation and increased decision caution. Drift rates were significantly lower
- 266 for both words and pseudowords, indicating diminished processing efficiency (words:
- 267 median_{diff} = -0.349, 95% HDI [-0.660, -0.023]; pseudowords: median_{diff} = -0.806, 95% HDI [-
- 268 1.072, -0.544], Figure 5B, 5D) compared to wakefulness. A similar reduction in drift rate was
- 269 observed when comparing lucid REM sleep to N1 sleep, with lower values for both words
- 270 (median_{diff} = -0.372, 95% HDI [-0.754, -0.014]) and pseudowords (median_{diff} = -0.341, 95% HDI [-0.635, -0.056] Figure 5B, 5D)
- 271 HDI [-0.635, -0.056], Figure 5B, 5D).
- 272 In addition to slower evidence accumulation, participants exhibited elevated decision
- thresholds for both words and pseudowords, suggesting that participants adopted a more
- 274 cautious decision-making strategy, likely as compensation for reduced processing efficiency.
- 275 Thresholds were significantly higher in lucid REM sleep compared to wakefulness (words:
- 276 median_{diff} = 0.684, 95% HDI [0.259, 1.149]; pseudowords: median_{diff} = 0.453, 95% HDI
- 277 [0.102, 0.775], Figure 5C, 5F) and N1 sleep (words: median_{diff} = 0.578, 95% HDI [0.067,
- 278 1.075]; pseudowords: median_{diff} = 0.599, 95% HDI [0.261, 0.949], Figure 5C, 5F). Despite
- these changes, non-decision times remained stable across wakefulness, N1 sleep, and lucid
- 280 REM sleep (all 95% HDIs overlapped with 0, Figure 5A, 5D), indicating that stimulus
- encoding and response preparation were preserved across states.
- 282 Together, these findings reveal a progressive shift in lexical decision-making across
- wakefulness, N1 sleep, and lucid REM sleep. While N1 sleep preserved word judgment but
- impaired pseudoword processing, lucid REM sleep was associated with a generalized
- reduction in processing efficiency. Participants compensated for this inefficiency by adopting
- a more cautious decision-making strategy, reflected in elevated decision thresholds.
- 287 Importantly, non-decision times remained stable across all states, suggesting that stimulus
- encoding and motor preparation were preserved despite changes in decision-making
- efficiency.
- 290

291 **Discussion**

292 This study investigated how lexical decision-making processes adapt across distinct states of

- consciousness—wakefulness, N1 sleep, and lucid REM sleep—by integrating behavioural
- data and computational modelling with the drift diffusion model. Analyzing key decision
- 295 parameters—non-decision times, drift rates, and decision thresholds—revealed state-specific
- adaptations in decision-making and how they dynamically reconfigure across states of
- 297 consciousness. Our findings indicate that N1 sleep preserves both non-decision processes
- 298 (sensory encoding and motor preparation) and evidence accumulation (drift rate) to support

lexical decisions, whereas lucid REM sleep relies primarily on evidence accumulation.

- Notably, decision-making exhibited a progressive shift across states: while N1 sleep
- 301 maintained efficient word judgments, it showed selective impairments in pseudoword
- 302 judgments, reflected in prolonged non-decision times and slower drift rate. In contrast, lucid
- 303 REM sleep exhibited a generalized decline in decision-making efficiency, characterized by
- reduced drift rates and elevated decision thresholds for both words and pseudowords. These
- results suggest that the brain dynamically reallocates cognitive resources to sustain task
- 306 performance under the distinct state of consciousness.
- Although wakefulness served as our baseline, its lexical decision-making profile revealed
 notable deviations from prior findings, particularly regarding the mechanisms underlying the
 word advantage. While past research suggests that both drift rate and non-decision time
- 310 contribute to faster word responses (Donkin et al., 2009; Ratcliff et al., 2004; Wagenmakers
- et al., 2008), our results indicate that this advantage in wakefulness was driven solely by non-
- decision time, with no drift rate differences between words and pseudowords. This
- discrepancy may stem from the spoken auditory lexical decision task, as auditory word
- recognition relies more on incremental phonological encoding and feedforward activation
- rather than rapid evidence accumulation (Hickok & Poeppel, 2007; Marslen-Wilson, 1987).
- 316 Unlike visual word recognition, which engages orthographic feedback and lexical
- competition (Coltheart et al., 2001; Wagenmakers et al., 2008), spoken word processing
- unfolds over time, potentially diminishing the role of drift rate. Additionally, NPs exhibited
- 319 slower response times, reduced accuracy, and lower drift rates, consistent with prior evidence
- 320 that orexinergic dysfunction disrupts wake-state stability and cognitive vigilance (Dauvilliers
- et al., 2007; Scammell, 2015). These wakefulness-specific differences underscore the
- 322 importance of considering baseline cognitive variability when interpreting sleep-related
- 323 effects.

324 The ability to perform lexical decisions during N1 sleep indicates that the transition from

- 325 wakefulness to light sleep does not lead to a complete shutdown of higher-order cognition.
- 326 Instead, the brain retains functional connectivity and sufficient computational capacity to
- 327 process external stimuli, particularly those with strong semantic or lexical associations
- 328 (Andrillon et al., 2016; Kouider et al., 2014; Siclari & Tononi, 2017). Both HPs and NPs
- 329 preserved the word advantage, characterized by shorter non-decision times and higher drift
- rates for words. This suggests that familiar, meaningful stimuli continue to benefit from
 efficient sensory encoding and robust evidence accumulation even in early sleep states
- efficient sensory encoding and robust evidence accumulation even in early sleep states
 (Andrillon & Kouider, 2020; Perrin et al., 1999; Portas et al., 2000). These findings align
- 333 with theories proposing that N1 sleep retains partial access to the global workspace, allowing
- meaningful stimuli to penetrate higher-order cognitive systems (Dehaene & Changeux,
- 335 2011).
- Lucid REM sleep exhibited a distinct lexical decision-making profile, fundamentally 336 diverging from both wakefulness and N1 sleep. Unlike N1 sleep, where both early-stage 337 processing (non-decision time) and evidence accumulation (drift rate) contributed to lexical 338 decision, decision-making in lucid REM sleep relied solely on evidence accumulation. The 339 absence of non-decision time modulation suggests that sensory encoding and motor 340 preparation are no longer limiting factors, likely reflecting the altered neural dynamics of 341 lucidity (Dresler et al., 2015; Voss et al., 2014). Lucid dreaming is associated with increased 342 prefrontal activity and enhanced metacognition, which may enable participants to engage in 343

goal-directed tasks despite the atypical sensory environment (Filevich et al., 2015). In this
state, external stimuli may be processed less efficiently, forcing lexical decisions to depend
entirely on post-sensory evidence accumulation. These findings suggest that lucidity induces
a computational reconfiguration of decision-making, demonstrating how cognitive processes
can adapt to hybrid states of consciousness characterized by partial reinstatement of executive
control within a modified sensory landscape.

Having established state-specific effects, we also compared lexical decision-making between 350 351 wakefulness and N1 sleep to examine how the sleeping brain adapts decision strategies. 352 Despite overall slowing in N1 sleep, lexical decisions for words remained relatively preserved, likely due to the robustness of semantic memory networks, which enable rapid 353 access to familiar word representations with minimal cognitive effort (Andrillon et al., 2016; 354 Hickok & Poeppel, 2007). Automatic retrieval of well-established meanings requires minimal 355 cognitive control, making it more resistant to sleep-related impairments. In contrast, lexical 356 decisions for pseudowords were selectively impaired, as reflected in slower response times, 357 lower accuracy, prolonged non-decision times, and reduced evidence accumulation. Unlike 358 words, pseudowords lack semantic associations and require greater bottom-up sensory 359 encoding and cognitive flexibility, which are particularly vulnerable to the 360 neurophysiological constraints of sleep (Andrillon & Kouider, 2020). The prolonged non-361 decision times observed for pseudowords further suggest inefficiencies in early-stage 362 processing. This pattern reveals a hierarchical prioritization of cognitive resources, where the 363 brain maintains efficient processing for familiar, meaningful stimuli while deprioritizing 364

365 resource-intensive operations.

366 Lexical decision-making in lucid REM sleep among narcolepsy participants was marked by

367 slower evidence accumulation (drift rate) and elevated decision thresholds compared to

368 wakefulness, reflecting the cognitive demands of this altered state. Narcolepsy is

369 characterized by intrusive REM features, including heightened internal imagery, dream-like

mentation, and dysregulated arousal states (Dauvilliers et al., 2007; Voss et al., 2014), which

371 likely compete with external stimuli for cognitive resources, thereby introducing cognitive

noise and reducing the efficiency of evidence accumulation. To compensate for this increased

uncertainty, participants adopted a more cautious decision strategy, setting higher decision
thresholds to mitigate errors (Forstmann et al., 2016; Ratcliff et al., 2016). Despite these

adjustments, non-decision times remained stable, indicating that sensory encoding and motor

preparation were preserved, even as evidence accumulation became less efficient.

377 Unlike N1 and lucid REM sleep, participants exhibited no evidence of lexical decision-

making during N2 or non-lucid REM sleep in either group. Behavioural and computational
analyses revealed no significant differences between words and pseudowords, suggesting that

higher-order cognitive functions and evidence accumulation were absent in these states. This

aligns with research indicating that deeper sleep states, such as N2 and REM, involve reduced

thalamocortical connectivity and sensory disconnection, restricting processing to lower-level

sensory areas with limited capacity for decision-related computations (Andrillon & Kouider,

2020; Nir et al., 2011). However, this finding contrasts with Türker et al. (2023), who

reported above-chance responses to verbal stimuli across all sleep states, including N2 and

REM. One explanation for this discrepancy is that while participants in Türker et al. (2023)

387 may have exhibited stimulus-driven motor responses, our drift diffusion modelling suggests

that these responses were not indicative of true lexical decision-making. Instead, they likely

reflect automatic sensory-motor processing, such as priming effects or residual auditory-

- motor coupling, which can persist in deep sleep despite the absence of volitional decision
- 391 processes (Andrillon et al., 2016; Kouider et al., 2014). This interpretation reinforces the idea
- that higher-order linguistic operations require a minimal level of wake-like cortical
 integration, which may be present in N1 and lucid REM but absent in N2 and non-lucid REM
- 394 sleep.

By integrating behavioural and computational approaches, this study provides a new

framework for studying high-order cognition beyond wakefulness, offering insights into how

the brain maintains residual cognitive functions in altered states of consciousness. While ourBayesian and DDM analyses accounted for unbalanced trial conditions, future studies with

- 399 larger sample sizes and overnight paradigms could further enhance statistical power (Ratcliff
- 400 et al., 2016). Additionally, our investigation of lucid REM sleep was limited to participants

401 with narcolepsy, raising questions about the generalizability of these effects to healthy

402 individuals (Baird et al., 2019). Future studies using high-density EEG or neuroimaging

403 could further elucidate the neural mechanisms underlying sleep-based decision-making.

These findings have broad implications for sleep's role in cognition, the nature of conscious

405 processing across vigilance states, and the neural mechanisms that shape decision-making

- 406 under varying levels of arousal and awareness.
- 407

408 Methods

409 This study presents a novel analysis of data originally collected in 2020 at the Sleep Clinic of

410 Pitié-Salpêtrière Hospital, France, as part of an experiment previously published (Türker et

al., 2023). The study adhered to the Declaration of Helsinki, and ethical approval was granted

by the local ethics committee (CPP Ile-de-France 8). All participants provided written

413 informed consent before participation.

414 Thirty individuals diagnosed with narcolepsy (NP; 14 women; mean age: 35 ± 11 years) and

415 22 healthy participants (HP; 10 women; mean age: 24 ± 4 years) were recruited. Participants

with narcolepsy were diagnosed according to international diagnostic criteria and recruited

417 from the National Reference Center for Narcolepsy at the Pitié-Salpêtrière Hospital. Among

418 NPs, 80% reported frequent lucid dreaming (\geq 3 lucid dreams per week), whereas none of

the HPs reported a history of lucid dreaming. Three participants (two NPs and one HP) were

420 excluded due to technical issues during data acquisition, leaving 27 NPs (21 frequent lucid

dreamers) and 21 HPs in the final analyses. Participants were compensated financially for
 their involvement. For detailed demographic and clinical information, see the previously

422 their involvement. For detailed demographi423 published study (Türker et al., 2023).

424 Experimental design

425 Task Overview

426 Participants performed a lexical decision task in which they determined whether auditory

427 stimuli were real words or pseudowords. Responses were indicated via brief contractions of

- 428 facial muscles: the corrugator (frowning) and zygomatic (smiling) muscles. The muscle-
- 429 response mappings were counterbalanced across participants. Stimuli were presented in
- 430 pseudorandomized order, ensuring each stimulus was presented only once to prevent

- 431 repetition effects. Participants completed a 10-minute familiarization session before data
- 432 collection to practice the task and ensure comfort with the auditory stimuli, which were
- 433 played at an average volume of 48 dB and adjusted for individual audibility.

434 Nap Protocol

- 435 Participants with narcolepsy completed five 20-minute nap sessions, interspersed with 80-
- 436 minute breaks, while HPs completed a single uninterrupted 100-minute daytime nap. Each
- ap session consisted of 10 active ("ON") periods, during which six stimuli (three words,
- three pseudowords) were presented every 9–11 seconds against a background of continuous
- 439 white noise. These "ON" periods alternated with 1-minute "OFF" intervals, during which
- only white noise was delivered. Across sessions, 60 stimuli (30 words, 30 pseudowords) were
- 441 presented per participant, with presentation lists randomized to mitigate order effects.

442 Stimuli

- 443 Auditory stimuli were selected from the MEGALEX database (Ferrand et al., 2018) and
- 444 included French words and pseudowords spoken by a female voice. Stimuli were
- standardized to a duration of 690 ms and controlled for frequency and emotional valence. To
- ensure consistency, each participant received five unique stimulus lists, randomized across
- 447 nap sessions. Stimuli were delivered via speakers using Psychtoolbox in MATLAB
- 448 (MathWorks), with a randomized inter-stimulus interval of 9–11 seconds.

449 Electrophysiological recording

- 450 Electrophysiological data were collected using a 10-channel EEG setup (Fp1, Fp2, Cz, C3,
- 451 C4, Pz, P3, P4, O1, O2), following the international 10–20 system. Signals were referenced
- to the right mastoid (A2 electrode). Additional recordings included electrooculography
- 453 (EOG) from two electrodes positioned to capture eye movements, electromyography (EMG)
- 454 from three channels (chin muscles for sleep staging and the zygomatic and corrugator
- 455 muscles to record behavioral responses), and electrocardiography (ECG) from one channel to
- record heart activity. All signals were recorded continuously at a sampling rate of 2,048 Hz
- 457 using a Grael 4K PSG/EEG amplifier (Medical Data Technology, Compumedics).

458 Sleep scoring and identification of lucid dream

- 459 Sleep stages were scored offline by a certified sleep expert according to American Academy
- of Sleep Medicine guidelines (Berry et al., 2017) using Profusion (Compumedics). EEG and
- 461 EOG signals were filtered between 0.3–15 Hz, EMG between 10–100 Hz, and ECG between
- 462 0.3–70 Hz. Sleep stages were scored in 30-second epochs as wakefulness, N1, N2, N3, or
- 463 REM sleep. Micro-arousals were defined as alpha activity lasting 3–15 seconds, with arousals
- 464 exceeding 15 seconds classified as wakefulness. For REM sleep, micro-arousals were further
- characterized by transient increases in EMG tone. Trials containing micro-arousals were
- 466 excluded from subsequent analyses.
- 467 Lucid REM sleep was identified based on participants' self-reports following each nap
- session. If a participant reported a lucid dream, all REM epochs from that session were
- 469 classified as lucid REM sleep. No HPs reported lucid dreams.

470 Muscle Response Analysis

- 471 EMG signals were segmented into 10-second mini-epochs corresponding to sleep stages.
- 472 Mini-epochs with micro-arousals were excluded. Muscle contractions were classified as valid
- 473 responses if at least two consecutive contractions were detected; single contractions
- 474 (twitches) were excluded as non-responses. Scoring reliability was validated by reanalyzing
- 475 10% of the data with a second blinded scorer, yielding 84% agreement.

476 **Drift diffusion model analysis.**

To investigate the mechanisms underlying lexical decision-making across wakefulness and
sleep stages, we employed the Drift Diffusion Model (DDM), a well-established framework
for modeling two-choice decision-making tasks (Ratcliff et al., 2016). The DDM assumes

- that decisions arise from a continuous process of evidence accumulation, where sensoryinformation about the two options (e.g., words and pseudowords) is integrated over time until
- 482 a decision threshold is reached. The model decomposes behavioral data (accuracy and
- 483 response times) into distinct cognitive parameters, providing insights into the underlying
- 484 decision-making processes. The DDM decomposes this process into four main components:
- the starting point (z), which indicates a predecision bias; the nondecision time (t), which
- 486 covers factors unrelated to the actual decision and is often linked to the encoding, motor
- 487 execution, and lexical access in lexical tasks; the drift rate (v), which represents the speed of
- 488 information accumulation; and the decision threshold (*a*), which indicate when enough
- 489 evidence has been collected to make a decision.
- 490 Previous findings suggest that differences in lexical decision behavior are primarily driven by
- drift rate and non-decision time (Donkin et al., 2009; Ratcliff et al., 2004). However, to
- 492 account for potential variations in decision-making strategies across wakefulness and sleep,
- 493 we also included decision threshold (a) in our model. This approach allowed us to examine
- 494 how drift rate (v), non-decision time (t), and decision threshold (a) were modulated by word
- 495 type and state of consciousness (wakefulness and sleep states). Predecision bias (starting
- point) was estimated at the participant level and assumed to remain constant across word type
- and sleep states, as our primary interest lay in the interaction between evidence accumulation,
 decision thresholds, and state-dependent cognitive dynamics (Donkin et al., 2009; Herz et al.,
 2022; Ratcliff et al., 2004). Separate HDDM analyses were conducted for HP and NP to
- 500 assess group-specific effects (Figure 1C).

501 We used a Bayesian hierarchical approach with the HDDM 0.8 tool in Docker to estimate 502 these parameters (Pan et al., 2022), assuming that participants' parameters are drawn from a

shared distribution. We applied Markov Chain Monte Carlo (MCMC) sampling to generate
10,000 samples, discarding the first 1,000 as burn-in. Model convergence was checked by
inspecting trace plots, autocorrelation, and the Gelman–Rubin R-hat statistic (ensuring R-hat

< 1.1). We applied HDDM regression analysis separately for HP and NP using the following
 model:

508
$$a, v, t = \beta_{0j} + \beta_{1j} * Word_{type} + \beta_{2j} * Sleep_{stages} + \beta_{3j} * Word_{type} * Sleep_{stages}$$

509 $z = \beta_{0j}$

510 Statistics.

511 We only included response trials where stimuli were presented in the current study.

Additionally, trials with microarousal (HP: 15%; NP: 13.6%) were excluded from the

analysis. N3 (0.07%) and REM (1%) sleep trials in HP were excluded due to insufficient trial
numbers. To eliminate the possibility of random muscle contractions, we excluded trials in

- numbers. To eliminate the possibility of random muscle contractions, we excluded trials in
 which participants exhibited only a single muscle contraction (HP: 0.6%; NP: 1.5%). Lastly,
- responses with times less than 0.69 seconds or greater than 9.9 seconds were excluded from
- the analysis. Moreover, outliers were excluded according to the conservative criterion of
- 518 mean \pm 2.5 median absolute deviation (MAD) based on RT.
- 519 Our study aimed to uncover the computational processes underlying lexical decision-making 520 across wakefulness and sleep in healthy participants (HP) and individuals with narcolepsy
- 521 (NP) using the drift diffusion framework. Participants (III) and individuals with harcotepsy 521 (NP) using the drift diffusion framework. Participants performed a lexical decision task
- 522 (LDT) during wakefulness and continued the task throughout sleep, using facial muscle
- 523 contractions (zygomatic and corrugator muscles) to indicate whether spoken stimuli were
- words or pseudowords in the French lexicon (Figure 1A). Polysomnography, along with
- additional EMG sensors, was used to confirm sleep stages and capture behavioral responses.
- 526 This setup allowed us to collect both accuracy and RT data for lexical judgments during
- 527 wakefulness and sleep. To analyze behavioral performance, we applied a Bayesian linear
- 528 mixed model (BLMM) to trial-level accuracy and RT data. Fixed factors included word type
- 529 (words vs. pseudowords) and sleep stages, while participants were modeled as a random
- factor (Figure 2). BLMM is particularly suited for analyzing hierarchical data structures,
- addressing individual variability and imbalances in trial numbers (Franke & Roettger, 2019;
- 532 Gelman et al., 2014; Sorensen et al., 2016).
- 533 The model is specified as follows:

534
$$\mu_j = \beta_{0j} + \beta_{1j} * Word_{type} + \beta_{2j} * Sleep_{stages} + \beta_{3j} * Word_{type} * Sleep_{stages}$$
(1)

535 Where μ_j represents either response accuracy or reaction time, and *j* represents the subject. 536 For response accuracy, we used the Bernoulli family to model the binary data. For reaction 537 time, we employed the shifted lognormal family to appropriately model the RT data.

538 During the analysis of reaction time, we conducted a control analysis by adding response 539 accuracy as a fixed factor to examine whether correct or incorrect responses would show 540 different reaction times:

541
$$\mu_{j} = \beta_{0j} + \beta_{1j} * Word_{types} + \beta_{2j} * Accuracy + \beta_{3j} * Sleep_{stages} + \beta_{4j} * Word_{type} *$$

542 $Accuracy * Sleep_{stages}$ (2)

For each model, we ran four MCMC chains with 5,000 samples each, discarding the first 500
samples as a warm-up. We assessed model convergence using the Gelman–Rubin R-hat
statistic, ensuring (R-hat < 1.1). Statistical inferences were based on the 95% Highest
Density Interval (HDI) of the posterior distribution. Effects were considered significant if the
95% HDI did not include 0.

548

549 Data availability

All data will be available on the Open Science Framework (OSF) upon publication:

- 551 https://osf.io/r8szg/
- 552 Code availability

- All analysis codes will be accessible on the Open Science Framework (OSF) upon
- 554 publication: https://osf.io/r8szg/
- 555
- 556
- 557

- 559 Andrillon, T., & Kouider, S. (2020). The vigilant sleeper: Neural mechanisms of sensory
- 560 (de)coupling during sleep. *Current Opinion in Physiology*, 15, 47–59.
- 561 https://doi.org/10.1016/j.cophys.2019.12.002
- Andrillon, T., Poulsen, A. T., Hansen, L. K., Léger, D., & Kouider, S. (2016). Neural
- 563 Markers of Responsiveness to the Environment in Human Sleep. *The Journal of*

564 *Neuroscience*, *36*(24), 6583–6596. https://doi.org/10.1523/JNEUROSCI.0902-

- 565 16.2016
- 566 Arzi, A., Shedlesky, L., Ben-Shaul, M., Nasser, K., Oksenberg, A., Hairston, I. S., & Sobel,

567 N. (2012). Humans can learn new information during sleep. *Nature Neuroscience*,

- 568 15(10), 1460–1465. https://doi.org/10.1038/nn.3193
- 569 Baird, B., Mota-Rolim, S. A., & Dresler, M. (2019). The cognitive neuroscience of lucid
- 570 dreaming. *Neuroscience & Biobehavioral Reviews*, *100*, 305–323.
- 571 https://doi.org/10.1016/j.neubiorev.2019.03.008
- 572 Berry, R. B., Brooks, R., Gamaldo, C., Harding, S. M., Lloyd, R. M., Quan, S. F., Troester,
- 573 M. T., & Vaughn, B. V. (2017). AASM Scoring Manual Updates for 2017 (Version
 574 2.4). *Journal of Clinical Sleep Medicine*, *13*(05), 665–666.
- 575 https://doi.org/10.5664/jcsm.6576
- 576 Blume, C., Del Giudice, R., Lechinger, J., Wislowska, M., Heib, D. P. J., Hoedlmoser, K., &
- 577 Schabus, M. (2017). Preferential processing of emotionally and self-relevant stimuli
- 578 persists in unconscious N2 sleep. *Brain and Language*, *167*, 72–82.
- 579 https://doi.org/10.1016/j.bandl.2016.02.004

- 580 Brown, R. E., Basheer, R., McKenna, J. T., Strecker, R. E., & McCarley, R. W. (2012).
- 581 Control of Sleep and Wakefulness. *Physiological Reviews*, 92(3), 1087–1187.
- 582 https://doi.org/10.1152/physrev.00032.2011
- 583 Coltheart, M., Rastle, K., Perry, C., Langdon, R., & Ziegler, J. (2001). DRC: A Dual Route
- 584 Cascaded Model of Visual Word Recognition and Reading Aloud. *Psychological*
- 585 *Review*, 108(1), 204–256. https://doi.org/10.1037/0033-295X.108.1.204
- 586 Dauvilliers, Y., Arnulf, I., & Mignot, E. (2007). Narcolepsy with cataplexy. 369.
- 587 Dehaene, S., & Changeux, J.-P. (2011). Experimental and Theoretical Approaches to
- 588 Conscious Processing. *Neuron*, *70*(2), 200–227.
- 589 https://doi.org/10.1016/j.neuron.2011.03.018
- 590 Diekelmann, S., & Born, J. (2010). The memory function of sleep. *Nature Reviews*

591 *Neuroscience*, *11*(2), 114–126. https://doi.org/10.1038/nrn2762

- 592 Dodet, P., Chavez, M., Leu-Semenescu, S., Golmard, J.-L., & Arnulf, I. (2015). Lucid
- 593 Dreaming in Narcolepsy. *Sleep*, *38*(3), 487–497. https://doi.org/10.5665/sleep.4516
- 594 Donkin, C., Donkin, C., Heathcote, A., Heathcote, A., Brown, S., Brown, S., & Andrews, S.
- 595 (2009). Non-Decision Time Effects in the Lexical Decision Task. *Proceedings of the*
- 596 *31st Annual Conference of the Cognitive Science Society. Austin: Cognitive Science*597 *Society.*
- 598 Dresler, M., Wehrle, R., Spoormaker, V. I., Steiger, A., Holsboer, F., Czisch, M., & Hobson,
- J. A. (2015). Neural correlates of insight in dreaming and psychosis. *Sleep Medicine Reviews*, 20, 92–99. https://doi.org/10.1016/j.smrv.2014.06.004
- 601 Filevich, E., Dresler, M., Brick, T. R., & Kühn, S. (2015). Metacognitive Mechanisms
- 602 Underlying Lucid Dreaming. *The Journal of Neuroscience*, *35*(3), 1082–1088.
- 603 https://doi.org/10.1523/JNEUROSCI.3342-14.2015

604	Forstmann, B. U., Ratcliff, R., & Wagenmakers, EJ. (2016). Sequential Sampling Models in
605	Cognitive Neuroscience: Advantages, Applications, and Extensions. Annual Review
606	of Psychology, 67(1), 641-666. https://doi.org/10.1146/annurev-psych-122414-
607	033645
608	Herz, D. M., Bange, M., Gonzalez-Escamilla, G., Auer, M., Ashkan, K., Fischer, P., Tan, H.,
609	Bogacz, R., Muthuraman, M., Groppa, S., & Brown, P. (2022). Dynamic control of
610	decision and movement speed in the human basal ganglia. Nature Communications,
611	13(1), 7530. https://doi.org/10.1038/s41467-022-35121-8
612	Hickok, G., & Poeppel, D. (2007). The cortical organization of speech processing. Nature
613	Reviews Neuroscience, 8(5), 393-402. https://doi.org/10.1038/nrn2113
614	Hobson, J. A., & Friston, K. J. (2012). Waking and dreaming consciousness: Neurobiological
615	and functional considerations. Progress in Neurobiology, 98(1), 82–98.
616	https://doi.org/10.1016/j.pneurobio.2012.05.003
617	Konkoly, K. R., Appel, K., Chabani, E., Mangiaruga, A., Gott, J., Mallett, R., Caughran, B.,
618	Witkowski, S., Whitmore, N. W., Mazurek, C. Y., Berent, J. B., Weber, F. D., Türker,
619	B., Leu-Semenescu, S., Maranci, JB., Pipa, G., Arnulf, I., Oudiette, D., Dresler, M.,
620	& Paller, K. A. (2021). Real-time dialogue between experimenters and dreamers
621	during REM sleep. Current Biology, 31(7), 1417-1427.e6.
622	https://doi.org/10.1016/j.cub.2021.01.026
623	Kouider, S., Andrillon, T., Barbosa, L. S., Goupil, L., & Bekinschtein, T. A. (2014). Inducing
624	Task-Relevant Responses to Speech in the Sleeping Brain. Current Biology, 24(18),
625	2208-2214. https://doi.org/10.1016/j.cub.2014.08.016
626	Lacaux, C., Strauss, M., Bekinschtein, T. A., & Oudiette, D. (2024). Embracing sleep-onset
627	complexity. Trends in Neurosciences, 47(4), 273–288.
628	https://doi.org/10.1016/j.tins.2024.02.002

- 629 Marslen-Wilson, W. D. (1987). Functional parallelism in spoken word-recognition.
- 630 *Cognition*, 25(1–2), 71–102. https://doi.org/10.1016/0010-0277(87)90005-9
- 631 Massimini, M. (2005). Breakdown of Cortical Effective Connectivity During Sleep. Science,

632 *309*(5744), 2228–2232. https://doi.org/10.1126/science.1117256

- 633 Mota-Rolim, S. A., & Araujo, J. F. (2013). Neurobiology and clinical implications of lucid
- dreaming. *Medical Hypotheses*, 81(5), 751–756.
- 635 https://doi.org/10.1016/j.mehy.2013.04.049
- 636 Myers, C. E., Interian, A., & Moustafa, A. A. (2022). A practical introduction to using the
- 637 drift diffusion model of decision-making in cognitive psychology, neuroscience, and
- health sciences. *Frontiers in Psychology*, *13*, 1039172.
- 639 https://doi.org/10.3389/fpsyg.2022.1039172
- Naumann, A., Bellebaum, C., & Daum, I. (2006). Cognitive deficits in narcolepsy. *Journal of Sleep Research*, *15*(3), 329–338. https://doi.org/10.1111/j.1365-2869.2006.00533.x
- 642 Nir, Y., Staba, R. J., Andrillon, T., Vyazovskiy, V. V., Cirelli, C., Fried, I., & Tononi, G.
- 643 (2011). Regional Slow Waves and Spindles in Human Sleep. *Neuron*, 70(1), 153–169.
 644 https://doi.org/10.1016/j.neuron.2011.02.043
- 645 Pan, W., Geng, H., Zhang, L., Fengler, A., Frank, M. J., Zhang, R., & Hu, C.-P. (2022). A
- 646 Hitchhiker's Guide to Bayesian Hierarchical Drift-Diffusion Modeling with

647 dockerHDDM. *PsyArXiv*. https://doi.org/10.31234/osf.io/6uzga

- 648 Perrin, F., GarcÂõa-Larrea, L., MauguieÁre, F., & Bastuji, H. (1999). A differential brain
- 649 response to the subject's own name persists during sleepq. *Clinical Neurophysiology*.
- 650 Portas, C. M., Krakow, K., Josephs, O., Armony, J. L., & Frith, C. D. (2000). Auditory
- 651 Processing across the Sleep-Wake Cycle: Simultaneous EEG and fMRI Monitoring in
- 652 Humans. Neuron, 28(3), 991–999. https://doi.org/doi.org/10.1016/S0896-
- 653 6273(00)00169-0

- 654 Ratcliff, R., Gomez, P., & McKoon, G. (2004). A Diffusion Model Account of the Lexical
- 655 Decision Task. *Psychological Review*, *111*(1), 159–182. https://doi.org/10.1037/0033-
- 656 295X.111.1.159
- 657 Ratcliff, R., & McKoon, G. (2008). The Diffusion Decision Model: Theory and Data for
- Two-Choice Decision Tasks. *Neural Computation*, 20(4), 873–922.
- 659 https://doi.org/10.1162/neco.2008.12-06-420
- 660 Ratcliff, R., Smith, P. L., Brown, S. D., & McKoon, G. (2016). Diffusion Decision Model:
- 661 Current Issues and History. *Trends in Cognitive Sciences*, 20(4), 260–281.
- 662 https://doi.org/10.1016/j.tics.2016.01.007
- 663 Scammell, T. E. (2015). Narcolepsy. New England Journal of Medicine, 373(27), 2654–
- 664 2662. https://doi.org/10.1056/NEJMra1500587
- Siclari, F., & Tononi, G. (2017). Local aspects of sleep and wakefulness. *Current Opinion in Neurobiology*, 44, 222–227. https://doi.org/10.1016/j.conb.2017.05.008
- 667 Strauss, M., Sitt, J. D., King, J.-R., Elbaz, M., Azizi, L., Buiatti, M., Naccache, L., Van
- 668 Wassenhove, V., & Dehaene, S. (2015). Disruption of hierarchical predictive coding
- 669 during sleep. *Proceedings of the National Academy of Sciences*, *112*(11).
- 670 https://doi.org/10.1073/pnas.1501026112
- Türker, B., Musat, E. M., Chabani, E., Fonteix-Galet, A., Maranci, J.-B., Wattiez, N., Pouget,
- 672 P., Sitt, J., Naccache, L., Arnulf, I., & Oudiette, D. (2023). Behavioral and brain
- responses to verbal stimuli reveal transient periods of cognitive integration of the
- external world during sleep. *Nature Neuroscience*, *26*(11), 1981–1993.
- 675 https://doi.org/10.1038/s41593-023-01449-7
- 676 Voss, U., Holzmann, R., Hobson, A., Paulus, W., Koppehele-Gossel, J., Klimke, A., &
- 677 Nitsche, M. A. (2014). Induction of self awareness in dreams through frontal low

678	current stimulation of	gamma activity.	. Nature N	Veuroscience,	17(6),	810-812.
		A			- · (- / ,	

- 679 https://doi.org/10.1038/nn.3719
- 680 Wagenmakers, E.-J., Ratcliff, R., Gomez, P., & McKoon, G. (2008). A diffusion model
- 681 account of criterion shifts in the lexical decision task. *Journal of Memory and*
- 682 *Language*, 58(1), 140–159. https://doi.org/10.1016/j.jml.2007.04.006
- 683 Wislowska, M., Klimesch, W., Jensen, O., Blume, C., & Schabus, M. (2022). Sleep-Specific
- 684 Processing of Auditory Stimuli Is Reflected by Alpha and Sigma Oscillations. *The*
- 685 *Journal of Neuroscience*, 42(23), 4711–4724.
- 686 https://doi.org/10.1523/JNEUROSCI.1889-21.2022
- Kia, T., Chen, D., Zeng, S., Yao, Z., Liu, J., Qin, S., Paller, K. A., Torres Platas, S. G.,
- 688 Antony, J. W., & Hu, X. (2024). Aversive memories can be weakened during human
- sleep via the reactivation of positive interfering memories. *Proceedings of the*
- 690 *National Academy of Sciences*, *121*(31), e2400678121.
- 691 https://doi.org/10.1073/pnas.2400678121
- 692 Zerr, P., Adelhöfer, N., & Dresler, M. (2024). The neuroscience of lucid dreaming: Past,
- 693 present, future. *Neuron*, *112*(7), 1040–1044.
- 694 https://doi.org/10.1016/j.neuron.2024.03.008
- 695
- 696

697 Acknowledgements

698 We would like to express our gratitude to Dr. Menglu Chen for offering valuable feedback 699 and suggestions on this article and its visualizations. The research was supported by the

700 Ministry of Science and Technology of China STI2030-Major Projects (No.

2022ZD0214100), National Natural Science Foundation of China (No. 32171056), General

Research Fund (No. 17614922) of Hong Kong Research Grants Council to X. H. The funders

- had no involvement in the study design, data collection and analysis, publication decisions, or
- 704 manuscript preparation.
- 705
- 706

Contributions

T.X. conceived and designed the project. T.X. performed the formal data analysis. T.X. and

X.H wrote the original draft. C.H., B.T., E.M., L.N., I.A., D.O., and X.H reviewed and edited

710 the article, providing valuable suggestions.

711 Competing interests

- 712 The authors declare no competing interests

- , 1,

- , 20

- ___.

- 743 Table S1

744 Mean and SEM of trial numbers across sleep states and word types in HPs group

		Healthy Group	
	Wake (Mean \pm SE)	$N1(Mean \pm SE)$	$N2(Mean \pm SE)$
Words	48.2 ± 7.92	5 ± 0.89	3 ± 0.59
Pseudowords	46.7 ± 7.67	3.33 ± 0.44	2.77 ± 0.71

Table S2

747 Mean and SEM of trial numbers across sleep states and word types in NPs group

	Individual with narcolepsy				
	Wake	N1	N2	REM	Lucid REM
	(Mean \pm SE)	(Mean \pm SE)	(Mean \pm SE)	(Mean \pm SE)	(Mean \pm SE)
Words	26.4 ± 5.79	9.04 ± 1.68	8.92 ± 9.17	12.2 ± 3.97	14.4 ± 2.15
Pseudowords	27.1 ± 5.94	8.69 ± 1.53	9.17 ± 1.78	11.6 ± 3.64	15.5 ± 2.24





751 Figure 1. Experiment Design A. Experimental Procedure. Participants performed a lexical 752 decision task during daytime nap sessions, responding to spoken stimuli (words or 753 pseudowords) with facial muscle contractions. Responses involved either frowning (corrugator muscle contractions) or smiling (zygomatic muscle contractions), with the 754 muscle-response mapping counterbalanced across participants. Participants with narcolepsy 755 (NP) completed five 20-minute naps, interspersed with 80-minute breaks, while healthy 756 participants (HP) underwent a single 100-minute nap. Example EMG traces illustrate 757 corrugator and zygomatic responses during wakefulness and REM sleep in NPs. Each 758 participant was exposed to pseudorandomized auditory stimuli, ensuring no stimulus 759 repetition across trials. B. Drift Diffusion Model (DDM) Schematic. The DDM decomposes 760 decision-making into distinct cognitive components: the starting point (z), representing pre-761 decision bias; the drift rate (v), indicating the speed and quality of evidence accumulation; the 762 decision threshold (a), reflecting the amount of evidence required to make a decision; and the 763 non-decision time (t), encompassing processes unrelated to evidence accumulation (e.g., 764 stimulus encoding, motor execution, and lexical access). The figure illustrates evidence 765 accumulation over time, with green and purple traces representing correct and incorrect 766 decisions, respectively. The model captures both trial-level response times and accuracy data. 767 C. Hierarchical Bayesian HDDM Framework. A hierarchical Bayesian implementation of the 768 DDM (HDDM) was used to estimate group- and participant-level parameters. Group-level 769 parameters (mean, m, and variance, s) were estimated simultaneously with individual-level 770 parameters (z, a, v, and t), accounting for trial-by-trial variations due to experimental factors 771 (WT: word type; ST: sleep stages). At the trial level (T), parameters a, v, and t were 772 modulated by word type (words vs. pseudowords) and sleep stages (wakefulness, N1, N2, 773 REM, and lucid REM). Observed data (accuracy and reaction time) are represented as shaded 774

circles, while group and individual parameters are shown as unshaded circles within the

- nested plate structure. This hierarchical approach improves parameter estimation by
- 777 leveraging shared information across participants.





778

A, D. Behavioral Results: Response Accuracy and Reaction Time. Bayesian Linear Mixed

781 Model (BLMM) results for lexical decisions in HP (left panels) and NP (right panels) during

782 wakefulness. The x-axis represents the estimated mean for response accuracy (top) and

reaction time (bottom). Light blue lines indicate the 95% Highest Density Interval (HDI) for

- pseudowords, and green lines indicate words. The purple line represents the posterior
- distribution of the contrast between words and pseudowords. If the purple line overlaps with

0 (gray vertical line), no significant difference is observed between words and pseudowords.

- 787 Conversely, if the purple line does not overlap with 0, this indicates a significant difference
- between the two stimulus types. B, E. Drift Rate (v). Posterior distributions of drift rates for
- words (green) and pseudowords (light blue) during wakefulness in HP (left panels) and NP
 (right panels). The left panels show the posterior distributions for each word type, while the
- right panels display the posterior distribution of the contrast between words and
- 792 pseudowords. The horizontal black lines represent the 95% HDI, and the vertical gray line (0)
- ⁷⁹³ indicates the null hypothesis. Drift rate measures the speed and quality of evidence
- accumulation; a contrast excluding 0 indicates a significant difference in drift rates between
- words and pseudowords. C, F. Non-Decision Times (t). Posterior distributions of non-
- decision times for words (green) and pseudowords (light blue) in HP (left panels) and NP
- 797 (right panels). Non-decision time reflects processes outside the evidence accumulation phase,
- such as sensory encoding and motor preparation. The left panels show the posterior
- distributions for each word type, while the right panels display the posterior distribution of
- the contrast between words and pseudowords. Horizontal black lines represent the 95% HDI,
- and vertical gray lines denote 0. If 0 is excluded from the 95% HDI, this indicates a
- significant difference in non-decision times between words and pseudowords.



805 Figure 3. Mechanism of lexical decision during N1 and lucid REM sleep.

804

(A, C) BLMM results for response accuracy and reaction time in lexical decisions during N1 806 sleep and lucid REM sleep in participants with narcolepsy. The N1 sleep results for healthy 807 participants exhibited the same behavioral pattern and computational mechanisms as in 808 participants with narcolepsy and are presented in Figure S2. The X-axis represents the 809 estimated mean response accuracy or reaction time. The light blue line indicates the 95% 810 Highest Density Interval (HDI) of the posterior probability for pseudowords, while the green 811 line represents words. The purple line denotes the contrast between words and pseudowords. 812 If the purple line overlaps with 0 (gray vertical line), there is no significant difference 813 814 between words and pseudowords. If the purple line does not overlap with 0, it indicates a significant difference between words and pseudowords. (B, D) Posterior distributions of non-815 decision times, drift rate, and decision threshold for words and pseudowords during N1 and 816



826



Posterior distributions of decision parameters for words and pseudowords in the HP group, 828

comparing wakefulness and N1 sleep. The NP group exhibited a similar pattern, with 829

selective impairment in pseudoword processing during sleep (see Results). Panels depict (A) 830

non-decision time, (B) drift rate, and (C) decision threshold. Asterisks (*) indicate significant 831 differences, where the posterior distribution contrast between wakefulness and N1 sleep does 832

not overlap with 0. "n.s." denotes non-significant differences, where the posterior distribution 833

contrast overlaps with 0. 834



837 Figure 5. Slower and less efficient lexical decisions during lucid REM sleep

Posterior distributions of decision parameters for words and pseudowords in the NP group,
comparing lucid REM sleep, wakefulness, and N1 sleep. Parameters include (A) non-decision
time, (B) drift rate, and (C) decision threshold. Here, we specifically compare lucid REM
sleep with wakefulness and N1 sleep, while results for N1 vs. wakefulness are reported in the
Results section. Asterisks (*) denote significant differences, where the posterior distribution
contrast does not overlap with 0. "n.s." indicates non-significant differences, where the



Figure S1. Differences in Reaction Time between Words and Pseudowords across 850 wake/sleep stages in Healthy Participants (HP) and Participants with Narcolepsy (NP). This 851 figure depicts the reaction time differences for words and pseudowords, considering both 852 correct and incorrect responses. The X-axis denotes the estimated mean of reaction time. The 853 light blue line represents the 95% Highest Density Interval (HDI) of the posterior probability 854 for pseudowords, while the green line represents words. The purple line indicates the contrast 855 between words and pseudowords. If the purple line overlaps with the 0 (gray line), it suggests 856 no significant difference between words and pseudowords. Conversely, if the purple line does 857 not overlap with 0, it indicates a significant difference between words and pseudowords. 858





862 Figure S2 Mechanism of lexical decision during N1 in healthy participants.

(A)BLMM results for response accuracy and reaction time in lexical decisions during N1 863 sleep in healthy participants. The X-axis represents the estimated mean response accuracy or 864 reaction time. The light blue line indicates the 95% Highest Density Interval (HDI) of the 865 866 posterior probability for pseudowords, while the green line represents words. The purple line denotes the contrast between words and pseudowords. If the purple line overlaps with 0 (gray 867 vertical line), there is no significant difference between words and pseudowords. If the purple 868 line does not overlap with 0, it indicates a significant difference between words and 869 870 pseudowords. (B, C, D) Posterior distributions of non-decision times, drift rate, and decision threshold for words and pseudowords during N1 and lucid REM sleep, along with their 871 contrasts. The left panels show the fitted posterior distributions for words and pseudowords. 872 The right-side histogram plots display the contrasts between words and pseudowords, with 873 horizontal black lines representing the 95% HDI and vertical gray lines denoting 0. If 0 is not 874 within the 95% HDI, the difference is considered statistically significant. 875





Figure S3 Absence of lexical decision-making during N2 sleep (HP & NP) and non-lucid REM sleep (NP)

(A, B, I) Response accuracy and reaction time during N2 and non-lucid REM sleep. The X axis shows mean accuracy and reaction time. The light blue and green lines represent

- pseudowords and words, respectively. The purple line indicates the difference between them.
 If the purple line overlaps with 0 (gray vertical line), there is no significant difference.
- (B, C, D, E, F, G, H, J) Distributions of non-decision time, drift rate, and decision threshold.
- Left panels show results for words and pseudowords. Right panels display their differences,
- with black lines marking the 95% HDI and the gray vertical line indicating 0. If 0 is within
- the 95% HDI, there is no significant difference, confirming that lexical decision-making is
- absent in these states.
- 889
- 890
- 891
- 892
- 893
- 894