

1 **MOLECULAR CORRELATE OF MOUSE EXECUTIVE FUNCTION. TOP-DOWN**
2 **and BOTTOM-UP INFORMATION FLOWS COMPLEMENTATION by *Ntng* GENE**
3 **PARALOGS**

4

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20 ABSTRACT

21 Executive function (EF) is a regulatory construct of learning and a main characteristic of
22 general cognitive abilities. Genetic variations underlying the architecture of cognitive
23 phenotypes are likely to affect EF. Mice lacking one of *Ntng* gene paralogs, encoding the
24 vertebrate brain-specific presynaptic Netrin-G proteins, exhibit prominent deficits in the EF
25 control. Brain areas responsible for gating the bottom-up and top-down information flows
26 differentially express *Ntng1* and *Ntng2*, distinguishing neuronal circuits involved in
27 perception and cognition. As a result, high and low cognitive demand tasks (HCD and LCD,
28 respectively) modulate *Ntng1* and *Ntng2* associations either with attention and impulsivity
29 (AI) or working memory (WM), in a complementary manner. During the LCD *Ntng2*-
30 supported neuronal gating of AI and WM dominates over the *Ntng1*-associated circuits. This
31 is reversed during the HCD, when the EF requires a larger contribution of cognitive control,
32 supported by *Ntng1*, over the *Ntng2* pathways. Since human *NTNG* orthologs have been
33 reported to affect human IQ (1), and an array of neurological disorders (2), we believe that
34 mouse *Ntng* gene paralogs serve an analogous role but influencing brain executive function.

35

35 INTRODUCTION

36

37 Executive function (EF) is a heterogeneous construct that can be viewed as a set of
38 processes executively supervising cognitive behaviors (3). EF is an umbrella term for
39 working memory (WM), attention and impulsivity (AI), and response inhibition, and is
40 thought to account for the variance in cognitive performance (4). WM, due to its storage and
41 processing components, is viewed as a bimodal flexible system of a limited capacity. Since
42 WM maintains current information and simultaneously supports its execution, as a latent
43 factor underlying intelligence (5), it has been termed as “the central executive” (6) attention-
44 controlling system dependent on consciousness (7). However an awareness-independent
45 model has been also proposed (8,9). General learning (Ln) ability depends on attention and
46 WM interaction (10) as well as perception, the causal and informational ground for the
47 higher cognitive functions (11). Perception guides our thinking about and acting upon the
48 world and serves as an input to cognition, via a short-term memory mediated interactions
49 (12). A possible mechanism linking perception and cognition would be attention (13).

50 Perception (bottom-up) and cognition (top-down) have been historically viewed as
51 independently operating encapsulating domains. Such embodiment has paved a ground for
52 the view that perceptual experiences can be influenced by cognitive state (for references see
53 14), consequently elaborated into the brain predictive coding approach currently dominating
54 cognitive neuroscience (15), and positing that attention is a property of brain computation
55 network (16). However this has been challenged by the opposite opinion that “Cognition
56 does not affect perception” (17). Regardless whether or not such a cognitive-sensory
57 dichotomy exists, herein we view perception and cognition as two main information streams
58 the EF exerts its actions upon, possibly through active association.

59 We have previously described the function of two vertebrate-specific brain-expressed
60 presynaptic gene paralogs, *NTNG1* and *NTNG2*, complementary affecting verbal
61 comprehension and WM in human subjects, which underwent an accelerated evolution in
62 primates and extinct hominins (1). This pair of genes is also implicated in the phenomena of
63 antagonistic pleiotropy, a trade-off between the evolution-driven cognitive function
64 elaboration and an array of concomitant neuropathologies, rendering the human brain
65 phenotypically fragile (2). *Ntngs* also complementary diversify the mouse behavior (18).

66 Despite the fact that EF abrogation is a major determinant of problem behavior and
67 disability in neuropsychiatric disorders (19), the genetics underlying EF remains elusive with
68 no causative vector agents (e.g. genes) have yet been reported. Herein we show that *NTNG*
69 paralogs affecting human IQ also affect mouse learning and brain executive functioning.

70 RESULTS

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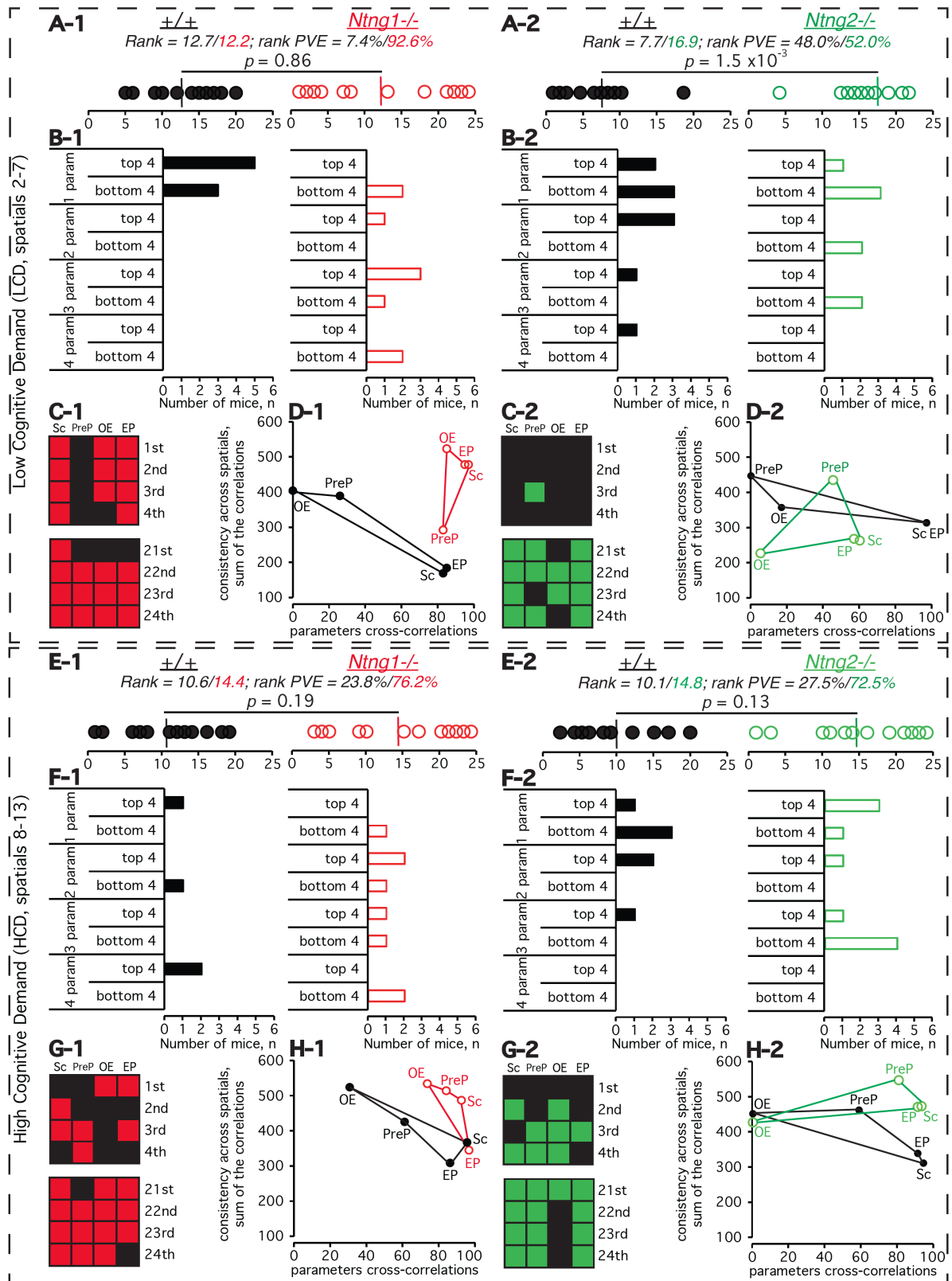
72 **Randomizing mouse genotypes to search for causal behavioral interactions.** We used a
73 novel non-parametric data analysis approach for two distinct behavioral paradigms: 5-choice
74 serial reaction time task (5-CSRTT, 20), and radial arm maze (RAM), measuring selective
75 attention and impulsivity (AI), and spatial working memory (WM), respectively, in *Ntng1*^{-/-}
76 and *Ntng2*^{-/-} mice. We calculated mouse genotype-independent ranking (as for a mixed
77 population), and the rank variance (as a proportion of variance explained, PVE) for each
78 behavioral parameter and for both paradigms. This approach allowed us to avoid common in
79 literature a genotype-attributed single parameter reporting bias (Supplementary Figures 1
80 (SF1) and 2 (SF2)), and permitted us to compare observed phenotypes between the both
81 paradigms for the genetically independent groups of mice, simultaneously searching for
82 potential interactions among them. We were able to follow the dynamics of behavioral
83 heterogeneity and to deduce a causal inference between the mouse phenotypic and genotypic
84 traits interaction affecting executive function (EF).

85

86 **Affected AI for both *Ntng* paralogs, and WM for the *Ntng2* gene, modulated by the**
87 **cognitive demand.** Analysis of the 5-CSRTT data (ST1-1) has revealed that *Ntng1*^{-/-}
88 population of mice is characterised by an extreme span of its rank distribution (PVE>90%)
89 occupying not only bottom 4 but also top 4 rank positions and outcompeting their wild type
90 littermates (Fig.1(A-D)-1). *Ntng1* ablation generates mice with both strong proficit and
91 deficit of AI, extending far beyond a single affected parameter estimate (Fig.1C,G), but with
92 the averaged rank per a genotype undistinguishable of that of their wild type littermates, and
93 more than 90% of variance attributable to the *Ntng1*^{-/-} genotype (Fig.1A-1). A higher
94 cognitive demand task phase (HCD) reduces the rank variance down to 76% but at the
95 expense of a lower rank (Fig.1E-1), similarly to *Ntng2*^{-/-} mice (Fig.1E-2). During the low
96 cognitive demand task phase (LCD), contrary to *Ntng1*^{-/-} mice, *Ntng2*^{-/-} subjects' rank is
97 twice lower comparing to their genetically unmodified siblings but the rank variances are the
98 same (Fig.1(A-D)-2), and this is the main difference in the AI phenotype between the *Ntng*
99 paralog knockouts, attributable to the magnitude of the demand.

100 Robustness of the WM deficit upon *Ntng2* deletion in mice is the most prominently
101 evidenced by the bottom 4 mouse ranks, 13/12 out of 16 are occupied by the knockout mice
102 (Fig.2(A-G)-2) and by low behavioral consistency across the sessions and parameters cross-
103 correlations (Fig.2H-2) during the HCD. At the same time, the absence of *Ntng1* in mice
104 affected only the LCD sessions performance (Fig.2(A-D)-1) but did not render them

105 behaviorally distinguishable from the wild type littermates during the HCD (Fig.2(E-H)-1).



106 Figure 1. 5-choice serial reaction time task (5-CSRTT) for *Ntn1*^{-/-} and *Ntn2*^{-/-} mice. See figure legend overleaf.

107

108 **Proficit and deficit in learning associated with the *Ntn*^{-/-} genotypes.** The intricate
109 segregation of the *Ntn*^{-/-} gene paralogs-associated behavioral phenotypes within the distinct
110 modules of EF (Fig.3) has prompted us to analyse the operant conditioning learning (Ln) by

111 **Figures 1,2. Attention and Impulsivity (AI) and working memory (WM) estimate and**
112 **the effect of cognitive demand produced by the analysis of rank and its variance for**
113 ***Ntng1*^{-/-} and *Ntng2*^{-/-} mice. A,E.** Mice ranks and rank PVE (proportion of variance
114 explained) based on four parameter rank measures (SF1,2) as detailed in ST1-1,2-1 (for
115 *Ntng1*^{-/-}) and ST1-2,2-2 (for *Ntng2*^{-/-}). The rank sorting was done in a genotype-independent
116 manner. Ranking for each out of four parameters was done independently of other
117 parameters with a final re-ranking of the ranks sum to generate the final rank (shown). In
118 case of an equal sum of the ranks, the mice were given identical ranks. PVE was calculated
119 as a square of within genotype rank variance divided on the sum of each genotype variances
120 squares multiplied on 100%. **B,F.** Mice rank distribution across one-to-four parameters as
121 top 4 and bottom 4 performers. **C,G.** Genotype-specific rank placing among the mice. **D,H.**
122 Behavioral consistency of mice across the sessions (*y* axis, sum of r^2 correlations of a single
123 session ranks *vs.* final ranks for each mouse across the sessions) and behavioral parameter
124 cross-correlations (*x* axis, the r^2 correlation of a parameter final ranking *vs.* final ranking for
125 all 4 parameters). The gene ablation-specific phenotype severity can be assessed visually by
126 matching each parameter-corresponding vertexes of the obtained quadruples. *p* value
127 represents a Wilcoxon rank sum test. See SM for further details.

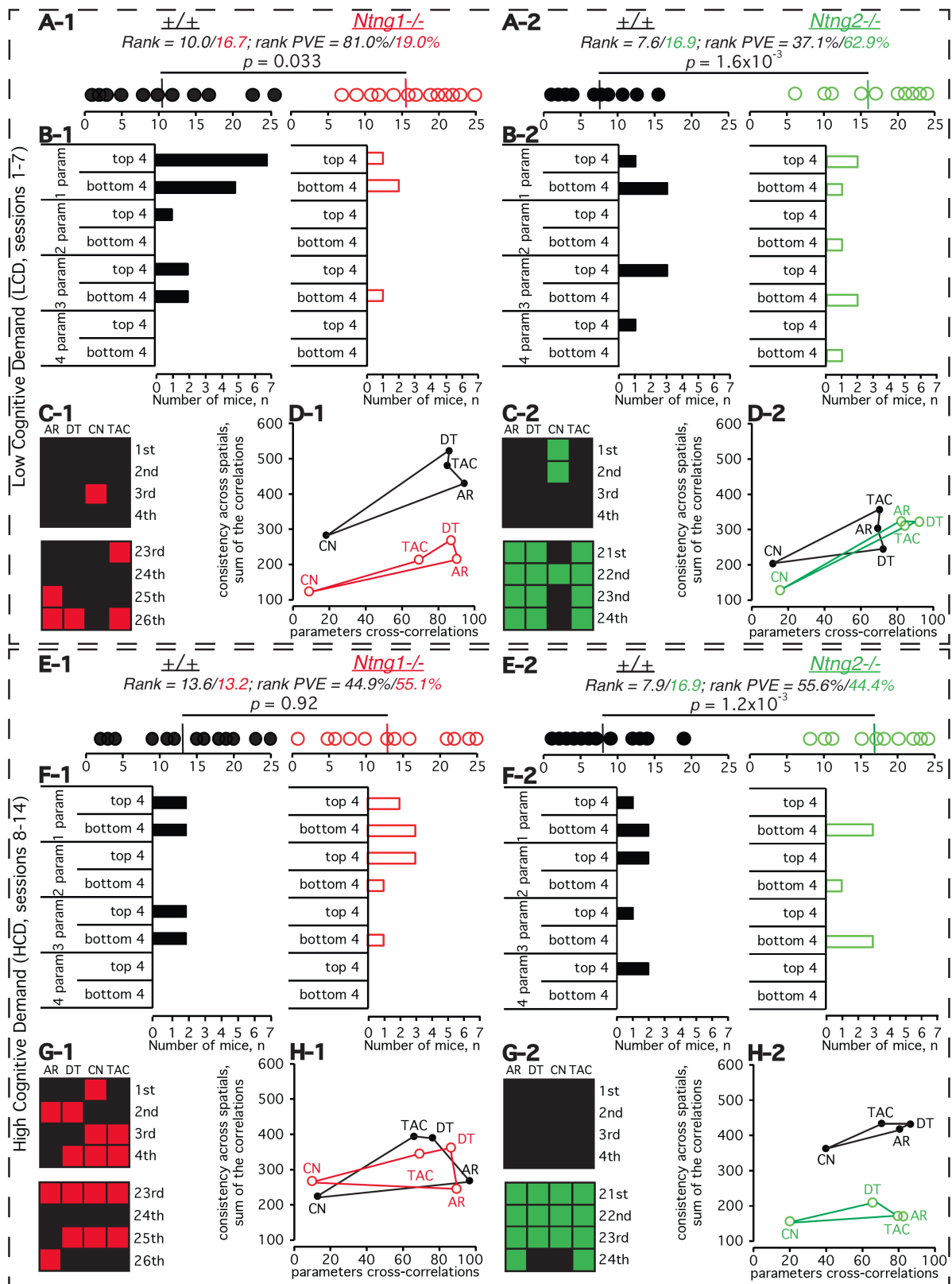
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129 mice, assuming that AI and WM may there interact. And indeed, *Ntng1*^{-/-} mice outperform
130 their control group learning faster during the LCD (Fig.4(A,B)-1, LCD) but are unable to
131 sustainably cope with the growing cognitive demand (Fig.4(A,B)-1, HCD). At the same
132 time, *Ntng2*^{-/-} mice display a prominent deficit of Ln (Fig.4(A,B)-2, LCD), which is
133 becoming stronger with the growing demand to succeed (Fig.4(A,B)-2, HCD). In overall, the
134 pattern of Ln behavior caused by the genetic ablation of both *Ntngs* completely matches that
135 of WM testing on the RAM (Fig.2), summarised in Fig.3. The contribution of AI to the Ln
136 deficit is further demonstrated by the rank correlations of Ln *vs.* AI (from Fig.1) which is
137 stronger during the HCD for both genetically distinct mouse populations (Fig.4C-1,2).

138

139 **Complementary expression of *Ntng* paralogs in the brain and their interaction.** The
140 robust phenotype of the abrogated EF for both *Ntng* gene paralogs affecting either AI or
141 WM, or both, is supported by the predominant expression of both genes within the heavily
142 loaded with the information processing brain areas, complementary sequestering them within
143 bottom-up (for *Ntng1*) and top-down (for *Ntng2*) neuronal pathways (Fig.5A-C). The
144 presented hierarchy for the *Ntng* paralogs brain distribution is supported by two times lower
145 level of the *Ntng2* expression in *Ntng1*^{-/-} background after the life-long cognitive training in

146 senile mice (Fig.5D-2), with no effect on *Ntng1* expression when *Ntng2* is absent (Fig.5D-1).



147 Figure 2. Radial arm maze (RAM) for *Ntng1*^{-/-} and *Ntng2*^{-/-} mice. See figure legend overleaf.

148

149 **Robust genotype prediction based on the phenotype input, the rank.** To assess the causal
 150 inference of the genes perturbations on behavioral output we have calculated the probability
 151 clustering for each genotype based only on the ranking data input, in genotype-blind manner

152 (Fig.6A). The obtained pattern corroborates the causal relationship between the genotypes
153 and associated with them phenotypes of the affected EF (Fig.3) closely resembling the
154 experimental data (Fig.1.2).

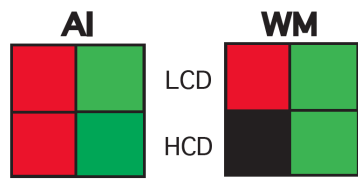


Figure 3. Summary of the EF behavioral phenotypes associated with either *Ntn1*^{-/-} or *Ntn2*^{-/-} gene paralogs ablation.

155

156 **Mouse behavioral phenotypic proximity assessment.** To calculate a phenotypic distance
157 between the genotypes comprising a single mixed population we used the obtained ranks and
158 plotted them against the related PVE for each behavioral parameter, generating two linear
159 plots (Fig.6B), each representing a single contributing genotype. This let us further to
160 calculate the phenotypic distance (using the classical Euclidean geometry) between the
161 genotypes as the shortest distance between two parallel lines. The obtained geometrical plots
162 are in a full agreement with the experimentally observed behaviors (Figs.1-3) but
163 additionally pinpoint the contribution of each individual parameter sometimes located outside
164 of the main cluster with others, e.g. PreP for the *Ntn1*^{-/-} (Fig.6B-1, AI-LCD), OE for the
165 *Ntn1*^{-/-} (Fig.6B-2, AI-HCD), and CN for the *Ntn2*^{-/-} (Fig.6B-2, WM-LCD). Using the Ln
166 rank and its PVE from Fig.4 as (x,y) coordinates we have assessed the phenotypic proximity
167 of the *Ntn1*^{-/-} and *Ntn2*^{-/-} mouse AI and WM phenotypes to the Ln deficit.

168

169 **Task learning (Ln) as an outcome of AI and MW interactions.** With the assumption that
170 shorter distance from the Ln coordinates to the genotype-specific linear plot generates higher
171 likelihood that the given genotype contributes to the Ln associated behavior, we were able to
172 build a relationship graph among the Ln, AI and WM interactions modulated by the
173 cognitive demand (Fig.7A). The dynamics of the *Ntn* gene paralogs hierarchy interaction is
174 presented on Fig.7B, calculated by the reciprocal plug-in of the rank and its PVE for one
175 gene paralog into the linear plot for the other one (ST7).

176

177 DISCUSSION

178

179 **Inferring causal relationship for the *Ntn* paralogs ablation caused perturbations with
180 the EF abrogation phenotypes.** The hierarchy of WM and selective attention interplay has
181 been always a point of fierce debate (21). In the present study we look at this interaction
182 through the prism of mouse operant conditioning learning ability, perturbed by either of

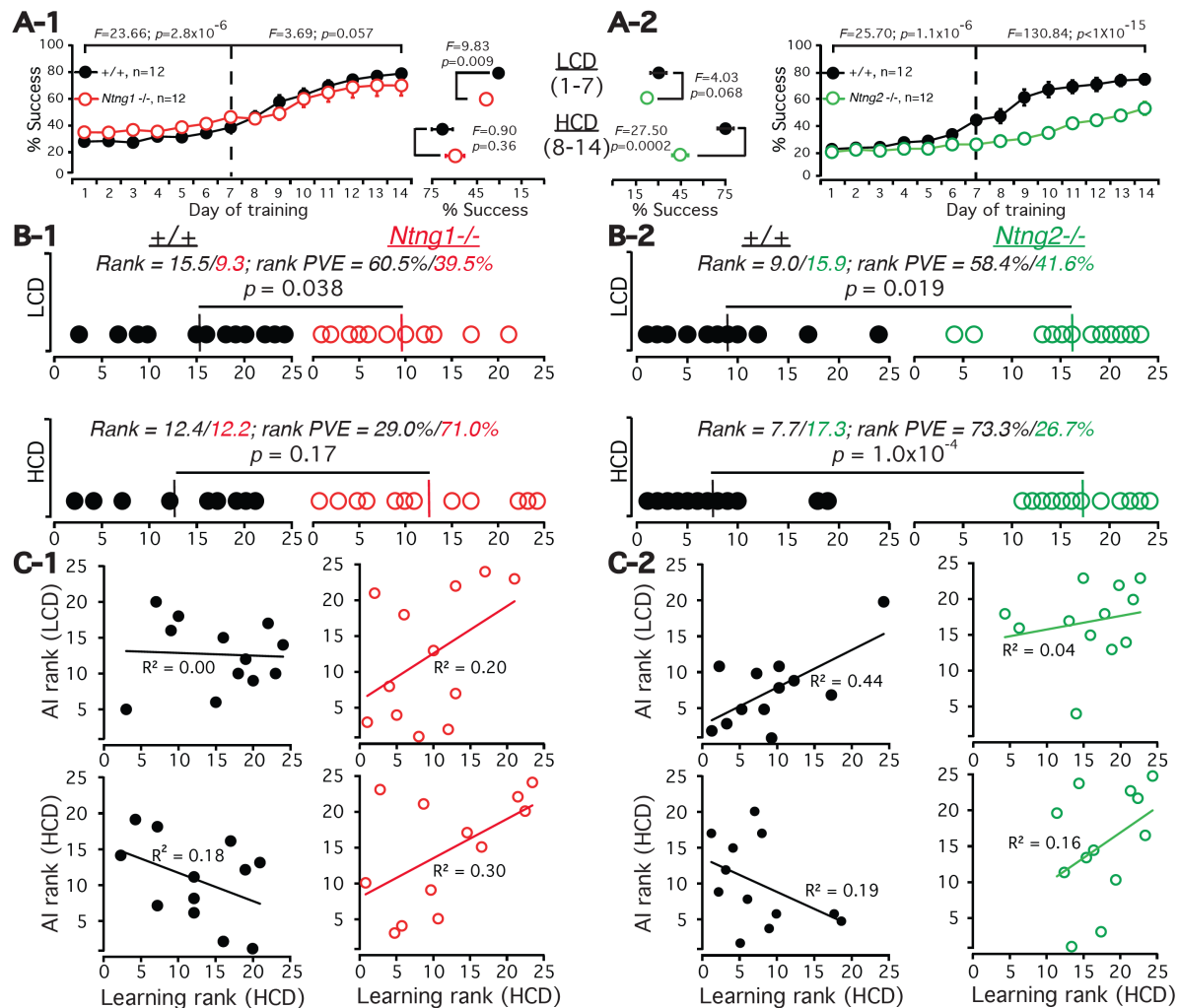


Figure 4. Operant conditioning (5-CSRTT) Learning (Ln) by *Ntn1*^{-/-} and *Ntn2*^{-/-} mice. A. Learning curves for the operant conditioning learning (reward collection) over the training period (spatial 1 of 5-CSRTT) with averaged performance behavior for the days (1-7) and (8-14), middle panel, defined as low cognitive demand (LCD) and high cognitive demand (HCD) sessions, respectively. One and two-way ANOVA was used for the statistics. B. Ranks and PVE comparisons over the LCD and HCD. The rank sorting was done in a genotype-independent manner, similar to Fig.1 and Fig.2, but using only one parameter, success (Sc), see ST4-1 and ST4-2. Rank statistics was by Wilcoxon rank sum test. C. Learning (Ln) vs. attention and impulsivity (AI) rank correlations (from Fig.1A-1,2).

183

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185 *Ntn* gene paralogs ablation (Fig.4). Since it is known that averaging animal behavior across
 186 individual subjects (SF1-1,1-2) may smear out control variables (22), we used rank instead
 187 of classical data mean (Figs.1-3) approach and the rank variance (proportion of variance
 188 explained, PVE) per genotype, as a measure of difference (23:p.16), to assess the behavioral
 189 variability caused by the genetic variations interacting with the experimental demand. To
 190 proof causal inferences between the behavior of *Ntn*^{-/-} mice and the gene ablation, we used
 191 mouse rank as a randomized dependent variable of the mixed population noting that any
 192 other non-randomized variables would be only correlational (24). That is, we have presented
 193 the mouse behavioral rank distribution as a function of genotype, when one of the *Ntn*

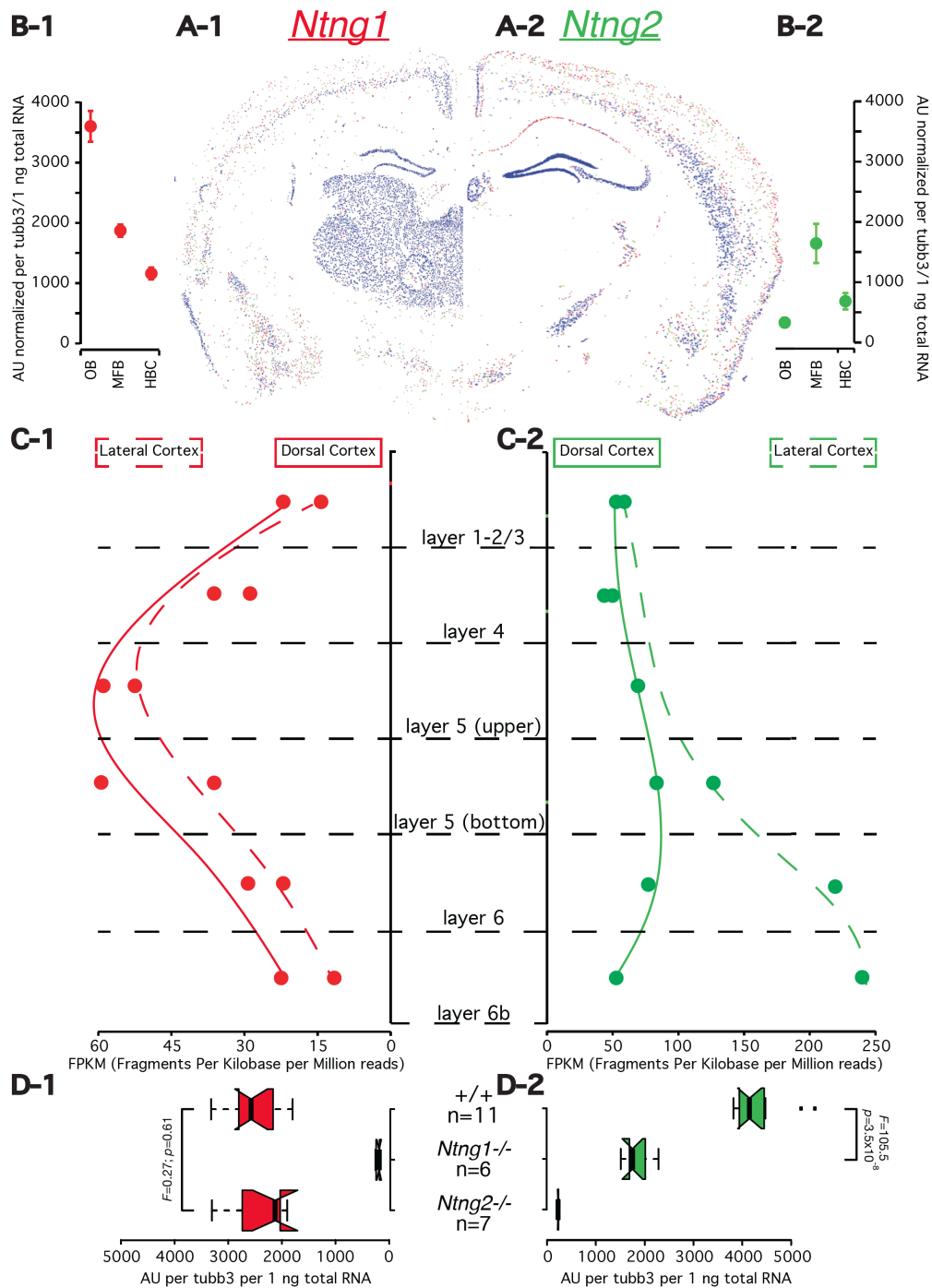


Figure 5. Complementary expression and transcription of *Ntn1* and *Ntn2* paralogs in the mouse brain. (A) *In situ* hybridization of *Ntn1* (left) and *Ntn2* (right) in the mouse brain. From Allen Brain Atlas, accession numbers are RP_050607_01_H05 and RP_050810_04_D08, respectively. The expression colors are inverted. (B) qRT-PCR of total mRNA for *Ntn1* and *Ntn2* paralogs in rough brain fractions of adult naïve male mice (7-8 months old): OB = olfactory bulb; MFB = mid- and front brain; HBC = hindbrain and cerebellum, n=6 mice (ST5-1). (C) Total level of *Ntn1* and *Ntn2* mRNA expression calculated based on RNA-seq of the mouse brain cortical layers reconstructed for *Ntn1* and *Ntn2* paralogs expression from GSE27243 generated by Belgard et al. (51). See Supplementary Methods (SM) for the details of data processing, ST5-2, ST5-2_Cuff and ST5-2_iReck (zipped) for the transcriptome assembly. (D) Effect of genetic background on *Ntn1* and *Ntn2* paralogs expression level in MFB as detected by qRT-PCR (ST5-3). Senile (20-21 months old) life-long cognitively trained mice have been used (from Fig.1). One-way ANOVA was used for the statistics.

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paralogs has been genetically ablated. At the same time, we have tried to elaborate on the statement that the structure of genotype-phenotype map is the matter and not the variance components of the population itself (25). The open question in such genotype-phenotype

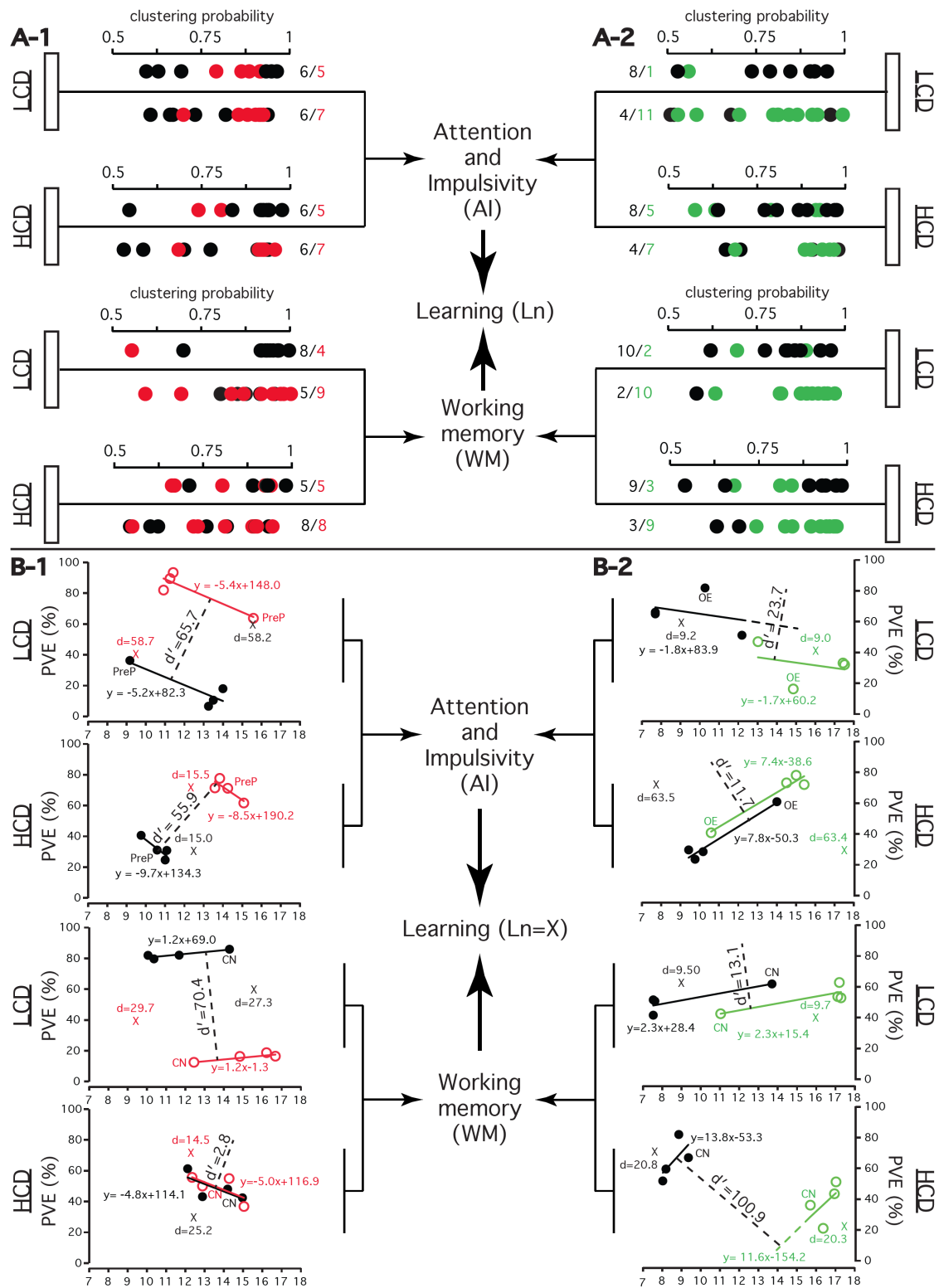


Figure 6. Behavioral phenotypic proximity assessment for the *Ntn1*^{-/-} and *Ntn2*^{-/-} genotypes and their wild type littermates by two approaches: genotype predictions by C-means fuzzy clustering (A), and by linear regression plot of genotype-specific rank PVE vs. rank (B). **A.** Casual genotype-phenotype relationship evidence. C-means fuzzy clustering (Euclidean C-means) was done in a genotype-blind manner as described in SM. See ST6-1 and ST6-2 for the exact values of clustering probabilities. **B.** Descriptive proximity of the operant conditioning learning explained by the AI and WM phenotypes for *Ntn1*^{-/-} paralog mice. Distance between the genotypes (d' , dashed line), presented geometrically by the linear equation, was calculated as $d' = |c_2 - c_1|$, where $ax + by + c = 0$ (Euclidean geometry). Distance from the learning coordinates (L_n) to the genotype-describing line was calculated as $d = |c - (y_{L_n} - ax_{L_n})|$. Rank (x coordinates) and PVE values (y coordinates) are from Fig. 1A,E (AI); Fig. 2A,E (WM); and Fig. 4B (L_n), ST7. Data for the *Ntn1*^{-/-}/wt population (RAM) are likely to incorporate 7.69% error since they were not normalised to the total number of animals as for the other populations ($n = 26$ vs. $n = 24$ mice).

199 interaction paradigm is to what degree a genetic variability is capacitive enough to explain
200 the phenotypic variance and the strength of such causal interaction. More specifically, how
201 far the behavioral (whole organism) variability (under the pressure of the growing cognitive
202 demand) represents the neuronal (cellular) variability caused by a gene knockout exerted
203 perturbations.

204

205 **Cognitive phenotypes of the *Ntn1*^{-/-} mice.** None of the vertebrate brain specific
206 presynaptically expressed *Ntn1*^{-/-} nor *Ntn2*^{-/-} mice exhibit gross anatomical or
207 developmental abnormalities (26) rendering them unique models to study the brain cognitive
208 functions in the absence of any “house-keeping” functional distortions and avoiding gene-
209 manipulations-exerted non-causal confounders. Noteworthy the resemblance of *Ntn1*^{-/-} and
210 *Ntn2*^{-/-} mice behavioral phenotypes with the human schizophrenia subjects behavioral
211 etiology (characterised by the EF control pathologies), both genes have been reportedly
212 associated with (1,2). Two different populations of mice were used for two different
213 behavioral paradigms to avoid the phenomena of learning transfer between the behavioral
214 tests, and, at the same time, to check for the genotype induced phenotypic stability across the
215 different paradigms but sharing the principal underlying component of WM testing. And
216 indeed, slow operant conditioning learning (5-CSRTT) for *Ntn2*^{-/-} mice has been recorded
217 (Fig.4A,B-2) and is explainable by the dysfunction of procedural (working) memory robustly
218 affecting the RAM performance (Fig.2A-H-2).

219

220 **Behavior consistency assessment using rank.** We have also characterised the behavior of
221 mice as a heterogeneously randomized population through the assessment of rank
222 consistency across the sessions and relative to other parameters (Figs.1-2D,H). Parameters
223 cross-correlation coefficients (r^2 , x axis) indicate a probability value of how much the rank
224 of a mouse for a certain parameter contributes to the global (total) ranking comprised of all
225 four parameters. If a mouse fails to keep its performance consistent either over the multiple
226 sessions or a parameter, its rank is instantly occupied either by the same or by a different
227 genotype littermate, and such event would be dynamically reflected in the r^2 . But ranks
228 changes and their permutations may not necessary have any dramatic consequences in the
229 total rank calculations as soon the rank fluctuations are taking place within the same
230 genotype-specific variance boundaries. But they are more reflective of a behavior
231 inconsistency of an individual mouse reflected in the sum of the correlation variances per
232 spatial or session (y axis).

233

234 **WM deficit driven optimal strategy deprivation for the *Ntng2*^{-/-} mice.** The global spatial
 235 WM deficit for the *Ntng2*^{-/-} mice has been found robustly expressed across the three RAM
 236 parameters (Fig.2A-H-2) except for CN (arm choice number during the first 8 arm entries).
 237 This parameter represents a strategy development (during LCD) and its optimisation (during
 238 HCD) for the maximum reward collection efficiency, akin predictive type behavior of the
 239 likelihood of potential success. The fact that the *Ntng2*^{-/-} mice outperform their wt littermates
 240 in CN (but during the LCD only, Fig.2C-2) reflects the chosen strategy (or a complete lack
 241 of any) of a pure random choice of a baited arm to visit, corroborating the global WM deficit
 242 (inability for strategic thinking) for the knockouts (evident from the other parameters) but
 243 with an opposite valence.

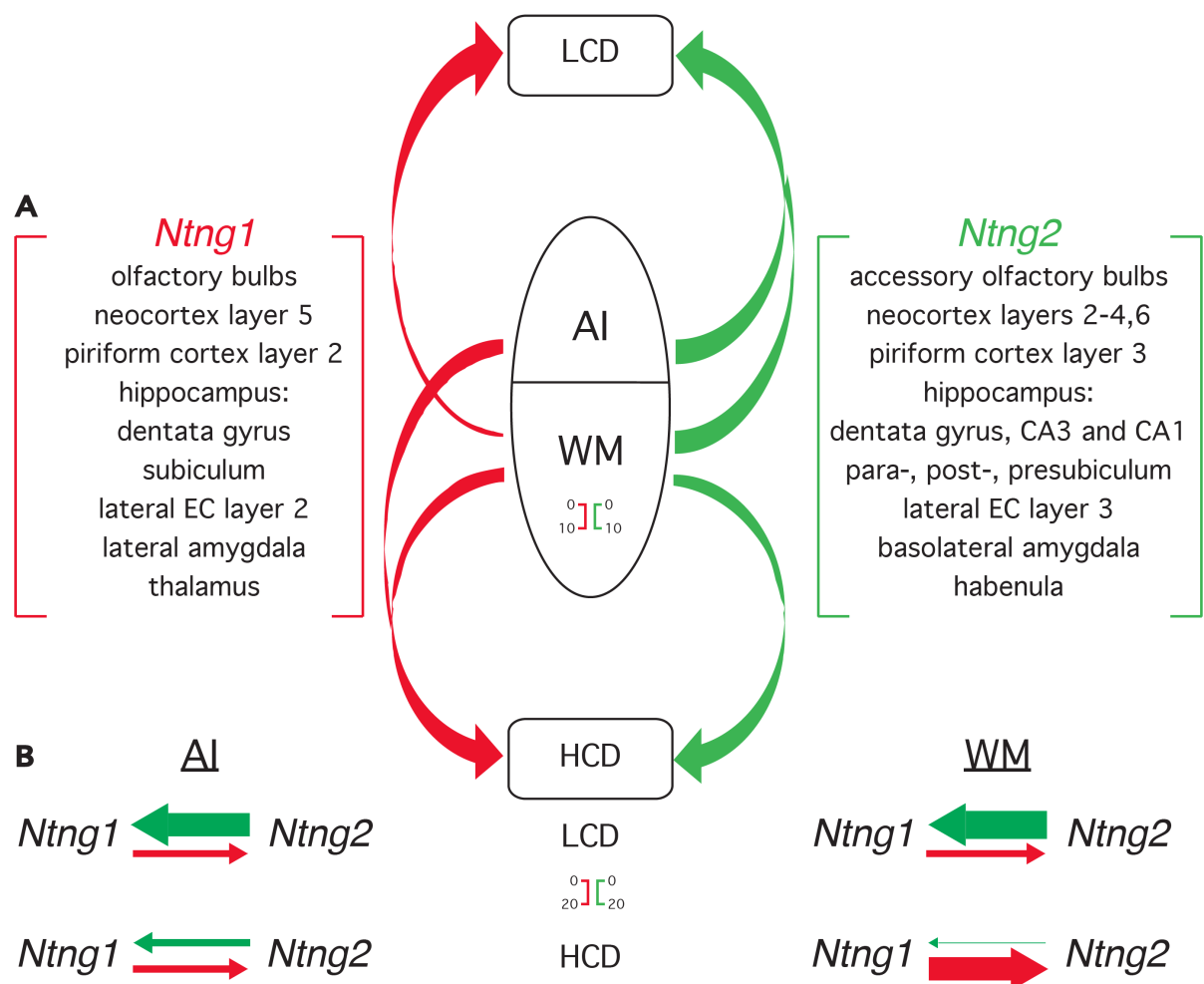


Figure 7. *Ntng* paralogs interaction as a molecular correlate of AI and WM modalities during learning. A. AI and WM interactions modulated by the cognitive demand during the operant conditioning earning (Ln), complementary contributed by the differentially expressed *Ntng* paralogs (see Fig.5 and (52)). B. Dynamicity of *Ntng* paralogs hierarchy interactions under LCD and HCD contributing to AI and WM. Each arrow base width (the scale bar is shown) is expressed in AU and corresponds to $(1/d*100)$ value from Fig.6B (for Ln=X), see ST7. Out of scale arrows (AI-*Ntng1*-LCD and AI-*Ntng2*-HCD) are not shown.

244

245

246 **Paralogs brain expression supporting the behavioral phenotypes.** The phenotypic

247 complementarities among the *Ntng1*^{-/-} and *Ntng2*^{-/-} mice, associated either with the abrogated
248 AI or WM, or both (Fig.3), are supported by the complementary brain expression pattern of
249 these gene paralogs (Fig.5A). If *Ntng1* is expressed mostly in the primary somatosensory
250 gating areas (e.g. OB, thalamus and hypothalamus nuclei, midbrain and medulla, Fig.5A,B-
251 1), *Ntng2* dominates within the cortex (with the skewed expression saturation towards the
252 lateral cortex), hippocampus (HPC), amygdala and claustrum, endopiriform and reticular
253 nuclei, Fig5A-2), pointing the gene role of parsing top-down signals. If the sensory
254 perception, as an entry point into the attentional state, is determined by the strength of the
255 subcortical thalamus-PFC (pre-frontal cortex) pathways (27), the reciprocal interactions
256 between mPFC and HPC are pivotal for the WM functioning (28,29), with the HPC known
257 to encode perceptual representations into memories through the correct attentional states
258 (30). Complementing this, thalamocortical projections are vital for mediating sensation,
259 perception, and consciousness (31-33). It is assumed that WM, despite its distributed nature
260 (34), consists of an executive component spread over the frontal lobes and sensory cortices
261 and interacted by the attention (7,35).

262

263 **Brain lamina-specific enrichment and EF control contribution by the *Ntng* paralogs.**

264 The emergence of a six-layered neocortex is a known hallmark of the mammalian brain
265 specialization devoted to the EF control (36,37). Both *Ntng* gene paralogs are extensively
266 expressed and mutually sequestered among the separate layers of the cortex (Fig.5C). *Ntng1*
267 is predominantly located in layers 4/5 (Fig.5C-1), probably supporting the arrival of the
268 bottom-up signals (38), while *Ntng2* is located in the superficial layers 2/3 and deeper layers
269 5/6 (Fig.5C-2), reported as a source of top-down inputs in attention and WM demanding
270 tasks (39). Besides that, *Ntng2* has been also marked as a gene classifier for the granule
271 neurons enriched in the cortex layer 6 (40). In overall, the complementary patterning of the
272 *Ntng* gene paralogs expression supports the laminar-specific distribution of the attention-
273 directed modalities.

274

275 **Evidence for the cognitive control taking over the perceptual load.** Analysing AI and
276 WM interaction during the task learning (Fig.7A), we have revealed that HCD recruits more
277 *Ntng1* (bottom-up) expressing circuitry comparing to LCD, both by WM and AI, reciprocally
278 replacing the preceding *Ntng2* (top-down) contribution. This potentially points to an
279 augmented peripheral sensory control by upregulating the bottom-up information stream.
280 How to explain such intricacy? Attention exploits a conserved circuitry motif predating the
281 neocortex emergence (41) and WM probably exapts the motor control of forward action

282 modeling also elaborated since ancient times (42). The archaic origin of both modalities
283 limits the fundamental brain resource and constrains information processing, forcing trade-
284 offs among the objects of targeted attention through the top-down control and, possibly,
285 causing a competition between the sensory inputs (43,44) by driving attention at
286 representations in sensory areas where the latter gains entry into WM (7). A model has been
287 proposed that selective attention control is directly linked to the executive control part of the
288 WM system (45) corroborating the statement that attention and WM should no longer be
289 regarded as two separate concepts, see (46) for references. The top-down control of primary
290 sensory processing by higher cortical areas (through the recurrent inputs) has an essential
291 role in sensory perception, as we have just demonstrated. The pervasive penetration of the
292 cognitive control, supported by *Ntng2*, affects the sensory inputs, provided by the *Ntng1*
293 expression.

294

295 **An IQ for mice.** The EF control variance attributes to the cognitive performance variance
296 and does not exist independently of general intelligence (47) as a critical determinant of
297 human cognition (48). It is no wonder then that, in our hands, the genes affecting WM and
298 attention in mice are the same ones affecting IQ in humans (1) and also associated with a
299 variety of devastating neurological disorders (2) representing a strong case of antagonistic
300 functional pleiotropy. The open challenge is to find out to what degree, using *Ntng* gene
301 paralogs as benchmarks, we would be able to conclusively draw on either domain specific or
302 domain general cognitive abilities of mice, or any other non-human animal subjects
303 behavioral intelligence.

304

305 Conclusively, *Ntng1* participates in bottom-up, and *Ntng2* in top-down brain
306 information flows support, representing an integrative complementary agreement between
307 perception and cognition as two interacting functions of the brain.

308

309 CONCLUSION

310

311 The view of Brain (and Mind) as a modular (domain) system is appealing to evolutionary
312 thinking (49) but is strongly biased towards “the prominence of neural reductionism” (22)
313 dominating the modern neuroscience. There is no strict definition of what a cognitive domain
314 is but it can be viewed as a product of interaction between the top-down and bottom-up
315 underlying neuronal circuits forming bidirectional feedback loops for the executively
316 decisive and sensory information flows controlling its own self. Genes selectively expressed

317 within such circuits via a non-overlapping pattern represent a tantalizing target to study the
318 cognitive domain make-up and its evolution. An ancient *Ntng* gene duplication (>500 million
319 years ago, preceding the Cambrian explosion) and subsequent co-evolution within the
320 vertebrate genomes made *Ntng* gene paralogs to segregate within the top-down and bottom-
321 up evolving information paths, presumably via subfunctionalisation, under the growing
322 ecological demand (first land/water fish met) but different epistatic environment, both gene
323 paralogs are embedded into. Perception and cognition interplay had eventually culminated
324 in a reflectively subjective representation of the external world, also called consciousness,
325 and explicitly controlled by the EF. Unrevealing molecular correlates of the domain-specific
326 cognitive abilities would help us better understand behavior, e.g. to clearly dissect it on
327 actions (as self-generated thoughts) and responses (cue-induced actions), as a decomposable
328 conjunction supporting the robust functioning of the Brain holistic state.

329

330 MATERIALS AND METHODS

331

332 **Animals and behavioral set-ups.** The original behavioral datasets have been partially
333 published by us in (18). All raw data are provided in [ST1-ST4](#) and [SF1,2](#). Knockout animals
334 and the behavioral set-ups are described in (18).

335

336 **Data analysis.** All raw data including their ranks and PVE calculations with all formulas and
337 graphs are presented in [ST1-ST4](#). The dynamics of the rank change for a specific parameter
338 over the course of study and its congruence with other parameters is depicted on [Figs.1-](#)
339 [2D,H](#). No robustness calculations of the rank distribution pattern resistance to a sequential
340 removal of a single behavioral subject were done; neither estimate for the minimal number of
341 the top/bottom ranks representing the obtained pattern, it was empirically decided to be equal
342 to top and bottom four ([Figs.1-2](#)).

343

344 **Definition of LCD and HCD.** During the 5-CSRTT the cognitive demand was incremented
345 by a shorter cue duration and longer inter-trial intervals, as specified in (18). As for the
346 RAM, the second week of testing (sessions 8-14) was done with half-closed/half-opened
347 doors under the gradually building cognitive demand, internally driven by the behavior
348 optimisation strategy for the maximum likelihood of reward collection, top-down executive-
349 attentional pressure to optimise the behavioral performance outcome, contextually similar to
350 the operant conditioning learning (Ln) of spatial 1 of the 5-CSRTT ([Fig.4](#)).

351

352 **Real-time qPCR (qRT-PCR).** Primers specifically targeting beginning of each *Ntng* gene
353 paralogs full-length transcripts were designed using Primer3Plus:
354 <http://www.bioinformatics.nl/cgi-bin/primer3plus/primer3plus.cgi>. Frozen brains RNA was
355 isolated from the MFB using RNeasy Plus Minikit (Qiagen) and the cDNA was synthesised
356 by the QuantiTect[®] Reverse Transcription kit (Qiagen) using a mix of the random hexamers
357 and oligodT primers. cDNA synthesised from 1 ng of total RNA was used per a single qRT-
358 PCR reaction. The lack of genomic DNA and the absence of external contamination were
359 confirmed by the RT-minus reactions. Neuronal-specific *tubb3* transcript (β -tubulinIII) was
360 used as an internal normaliser during the qRT-PCR co-amplifications. The C_t values were
361 collected at the threshold value of 0.4 and the arbitrary units (AU) were calculated as:

$$362 \quad 2^{-(C_t(\text{amplicon}) - C_t(\text{normalizer}))} * 10,000$$

363

364 **RNA-seq cortical layers *Ntng* transcriptome reconstruction.** See [SM](#) for the details.

365

366 **Fuzzy C-Means Clustering.** Represents a type of a sequential competitive learning
367 algorithm exhibiting the stochastic approximation problem (50). Was used for the genotype
368 predictions based on the behavioral ranks input under the genotype-blind input conditions.
369 The details are described in the [SM](#).

370

371 **Statistics.** Correlation coefficients (r^2) were obtained with Excel. One and two-way
372 ANOVA was calculated using StatPlus (AnalystSoft Inc.). Wilcoxon rank sum test was done
373 by Matlab (v.7.9.0 2009b) by the function *ranksum*.

374

375 SUPPLEMENTARY MATERIALS ([SM](#))

376 Contain Supplementary Figures ([SF1-2](#)), Tables ([ST1-7](#)), Methods and References. [ST1-ST5](#)
377 are provided as Excel files.

378

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384

385 COMPETING INTERESTS

386 Authors would like to express a lack of any competing interests associated with the work.

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