

1                   Reproduction of *Tracing the emergence of the memorability benefit*

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6 Preparation, Writing - Introduction & Result & Editing; Lin Ye: Writing - Original Draft  
7 Preparation, Writing - Introduction & Result; Liu Yikang: Writing - Result & Discussion;  
8 Cai Yajing: Writing - Introduction & Discussion; Li Xianzhi: Writing - Method &  
9 Discussion.

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## Abstract

We reproduced a study and explored how a memorability benefit emerges as visual information is encoded into Very Long-Term Memory through Visual Working Memory.

The researchers proposed three hypotheses: efficiency (memorable stimuli require fewer cognitive resources to encode into long-term memory), competitiveness (memorable stimuli are more successful in obtaining cognitive resources), and stickiness (memorable stimuli are less likely to be forgotten after passing through the encoding bottleneck). They conducted two experiments, manipulating stimulus memorability, set size, and competition among stimuli during working memory tasks.

Basically identical to the original results, our results supported the efficiency and competitiveness hypotheses in working memory tasks, but only the efficiency advantage translated into improved performance in long-term memory. Furthermore, memorable stimuli were found to be less likely to be forgotten, supporting the stickiness hypothesis. Overall, the study shows that the memorability benefit emerges across multiple cognitive processes.

*Keywords:* Reproducibility, R, Memorability benefi, VLTM, VWM

Word count: X

## Reproduction of *Tracing the emergence of the memorability benefit*

In this paper we will try to reproduce the results of *Tracing the emergence of the memorability benefit*(<https://doi.org/10.1016/j.cognition.2023.105489>). Thus, we adopted the code from: <https://osf.io/jgqh7/>.

## Introduction

Humans have a remarkable ability to store large numbers of images in visual long-term memory(VLTM), but not all visual information can be remembered equally well.

The variability in VLTM encoding success has been traditionally studied from a subject-centric perspective, focusing on individual differences in memory encoding processes.

However, this approach overlooks stimulus-intrinsic factors that consistently influence memory encoding success across individuals. Recent research has shown that certain stimuli are more likely to be remembered by different individuals, regardless of their individual differences in memory encoding processes(Isola, Xiao, Parikh, Torralba, & Oliva, 2014).This indicates the presence of stimulus-intrinsic properties that make an image more memorable or forgettable.

While memorability has been studied across various stimuli, no previous research has examined when the distinction between memorable and forgettable stimuli occurs during the encoding stage of VLTM.

The process of visual information being encoded into VLTM is influenced by the capacity-limited visual working memory (VWM) system. Specifically, high VWM capacity predicts better subsequent VLTM performance for stimuli encoded during the VWM task.

The relationship between VWM and VLTM suggests two possible mechanisms for the emergence of the memorability benefit: efficiency and competitiveness. Memorable stimuli

may be more efficiently represented in VWM, requiring fewer cognitive resources(the former), or they may have a competitive advantage in obtaining the necessary cognitive resources(the latter).

Additionally, the memorability benefit may continue to develop even after visual information passes through the VWM bottleneck, with memorable stimuli being less prone to forgetting and better retained in VLTM.

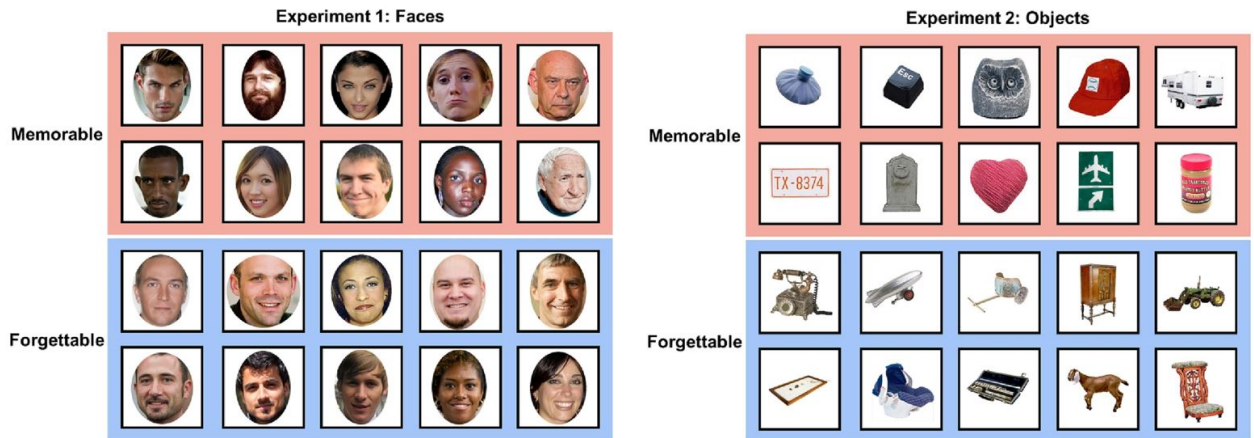
Thus, the researchers aim to investigate how the memorability benefit emerges by examining how much visual information passes through visual working memory (VWM) and “sticks” in visual long-term memory (VLTM).

## Methods

### Participants

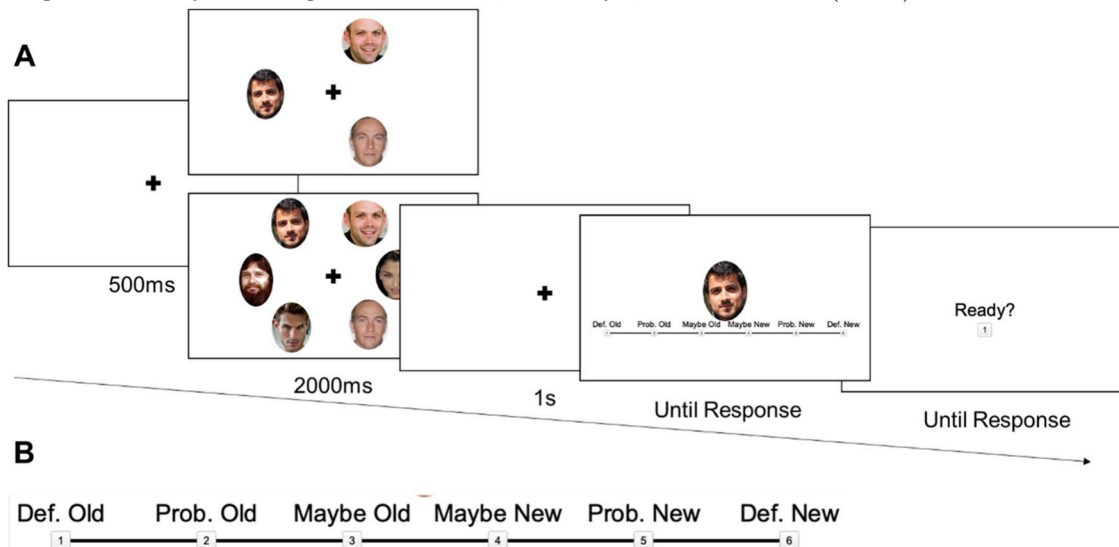
In Experiment 1(faces), 156 psychology students from the University of Toronto Mississauga (mean age = 19.61 years, SD = 3.645, 105 females) were recruited. In Experiment 2(objects), the authors used Prolific to recruit 156 young adults (mean age = 24.35 years; SD = 3.521; 92 females) who resided in the U.S. or Canada at the time of the experiment.

## 69 Stimuli and Procedure

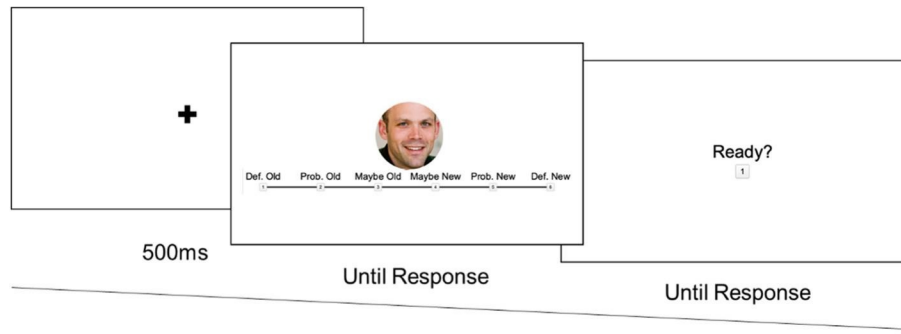


70

71 The researchers conducted two experiments to examine how memorability benefits emerge  
 72 by manipulating the stimulus memorability, set size, and degree of competition among  
 73 stimuli as participants encoded them in the context of a working memory task.  
 74 Subsequently, their memory for the encoded stimuli was tested in a VLTM task.  
 75 Specifically, in Experiment 1, they first selected the top 468 memorable face images and  
 76 the top 468 forgettable face images from Bainbridge, Isola, and Oliva (2013). In  
 77 Experiment 2, they first selected the top 234 memorable object images and the top 234  
 78 forgettable object images from Saito, Kolisnyk, and Fukuda (2023).



79



## Apparatus

The experiments were programmed and run using Inquisit 6 (Inquisit 6, 2020). Since the experiments were conducted online, the computers and monitors participants used were variable. Thus, the size of the stimuli was adjusted according to the monitor size of the participants' computers. More precisely, each stimulus was presented within an imaginary square whose side was 12% the size of the shorter side of their computer monitors.

## Data analysis

To confirm that VWM performance predicted VLTm performance, researchers conducted a series of correlational analyses between VWM and VLTm performance. To quantify memory performance using the same metric for both VWM and VLTm recognition tasks, they used the area under the receiver operating characteristic curves (AUC). The receiver operating characteristic curve is drawn by plotting the cumulative hit rate (the proportion of "old" responses when the stimulus is old) on the y-axis against the cumulative false alarm rate (the proportion of "old" responses when the stimulus is new) on the x-axis from the highest confidence old response (Definitely Old) to the lowest confidence old response (or the highest confidence new response (Definitely New)). The AUC will equal 1 when participants recognized all the encoded information with highest confidence (Definitely Old) and rejected all the new information with highest confidence (Definitely New). On the other hand, when participants cannot discriminate old from new

information at all, the AUC will be equal to 0.5.

To investigate the efficiency and competitiveness hypotheses, they conducted a series of repeated measures ANOVAs examining the differential impacts of Array Type and Memorability on AUC for both VWM and VLTM.

To compute the proportion with which the amount of information in VWM is retained in VLTM, they defined the memory “stickiness” as  $(\text{AUC for VLTM task} - 0.5) / (\text{AUC for VWM recognition task} - 0.5)$ .

To investigate the stickiness hypothesis in the context of storage efficiency, they conducted a series of repeated measures ANOVAs examining the differential impacts of Array Type and Memorability on memory stickiness.

## Results

In the VWM task, performance was better for memorable stimuli compared to forgettable stimuli, supporting the efficiency hypothesis. In addition, the researchers found that when in direct competition, memorable stimuli were also better at attracting limited VWM resources than forgettable stimuli, supporting the competitiveness hypothesis. However, only the efficiency advantage translated to a performance benefit in VLTM. Lastly, they found that memorable stimuli were less likely to be forgotten after they passed through the encoding bottleneck imposed by VWM, supporting the “stickiness” hypothesis. Thus, their results demonstrate that the memorability benefit develops across multiple cognitive processes.

##	Length	Class	Mode
##	6681	character	character

## Reproduction Procedure

122

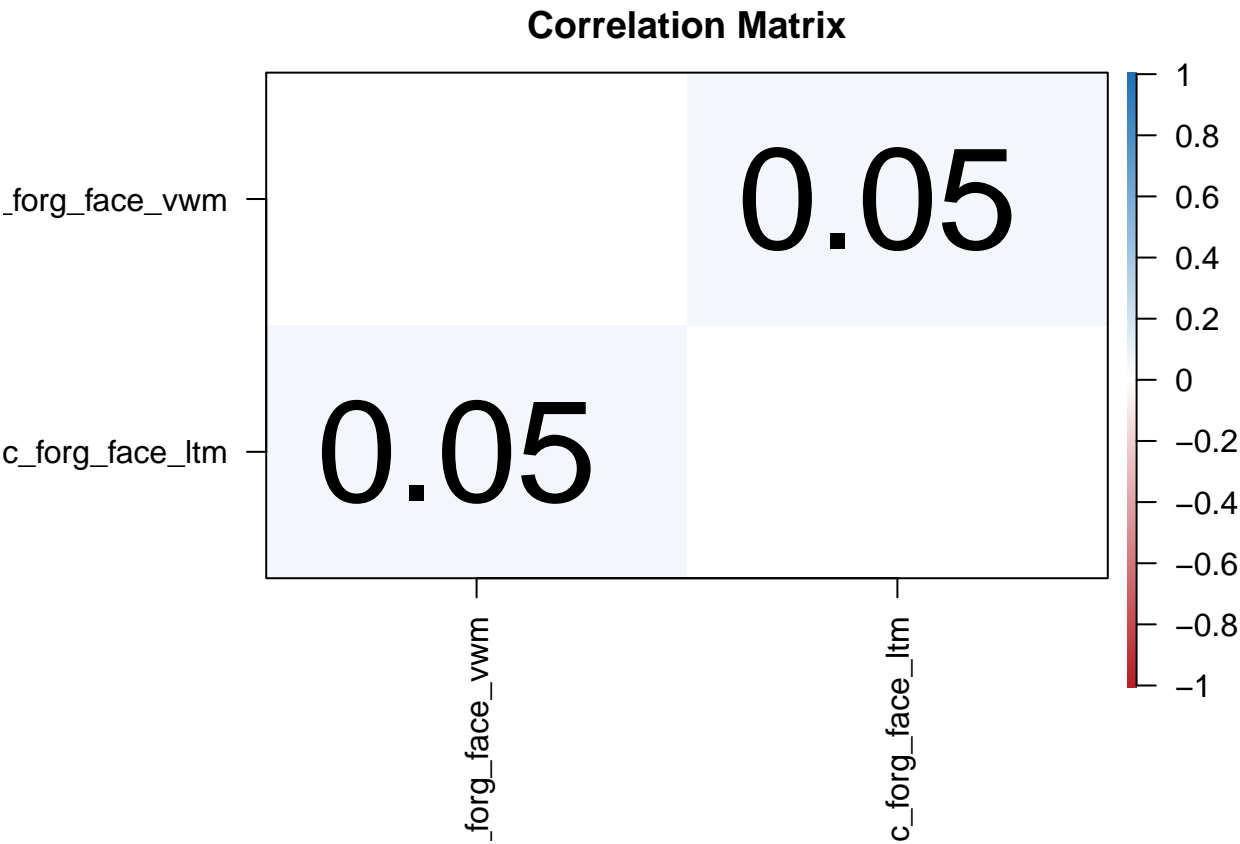
123 Firstly, we trim the raw data and save them separately for further analysis. Secondly,  
 124 we conduct correlation and regression analysis to verify the prediction relationship between  
 125 VWM performance and VLTm performance. Thirdly, we conduct 2 (ArrayType: Pure 3  
 126 and Pure 6)  $\times$  2(Memorability: Memorable and Forgettable) repeated measures ANOVA  
 127 on AUC to test the efficiency hypothesis. Similarly, we conduct 2 (ArrayType: Pure 6 and  
 128 Mixed 6)  $\times$  2(Memorability: Memorable and Forgettable) repeated measures ANOVA on  
 129 AUC to test the competitive hypothesis. Fourthly, 2 (ArrayType: Pure 3 and Pure 6)  $\times$   
 130 2(Memorability: Memorable and Forgettable) rm ANOVA on stickiness and 2 (ArrayType:  
 131 Mixed 6 and Pure 6)  $\times$  2(Memorability: Memorable and Forgettable) rm ANOVA on  
 132 stickiness are conducted to test the stickiness hypothesis. Importantly, given that the  
 133 demographic information is not included in the raw data, the descriptive statistics results  
 134 are not presented. We used R (Version 4.2.3; R Core Team, 2023) and the R-packages  
 135 *bayestestR* (Version 0.13.1; Makowski, Ben-Shachar, & Lüdtke, 2019), *bruceR* (Version  
 136 0.8.10; Bao, 2023), *dplyr* (Version 1.1.2; Wickham, François, Henry, Müller, & Vaughan,  
 137 2023), *ggplot2* (Version 3.4.2; Wickham, 2016), *papaja* (Version 0.1.1.9001; Aust & Barth,  
 138 2022), *patchwork* (Version 1.1.2; Pedersen, 2022), and *tidyr* (Version 1.3.0; Wickham,  
 139 Vaughan, & Girlich, 2023) for all our analyses. The results will be reported below.



140

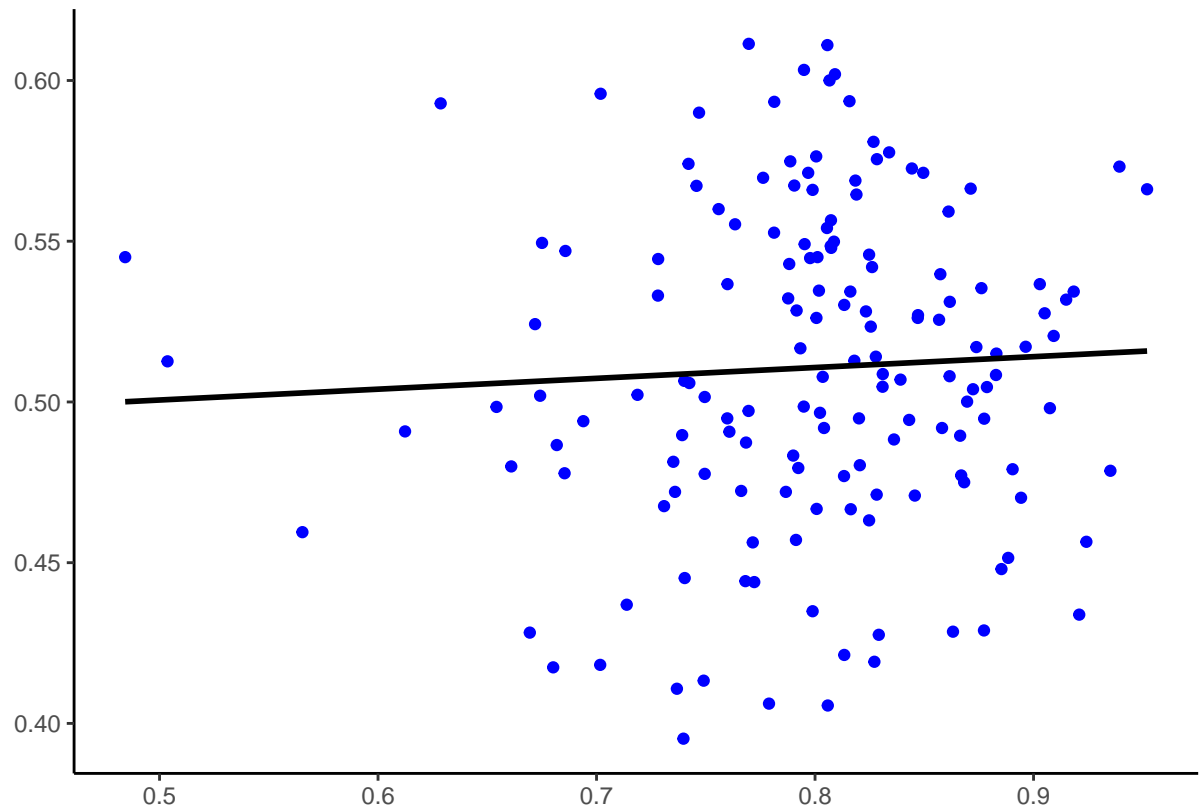
Reproduction Results

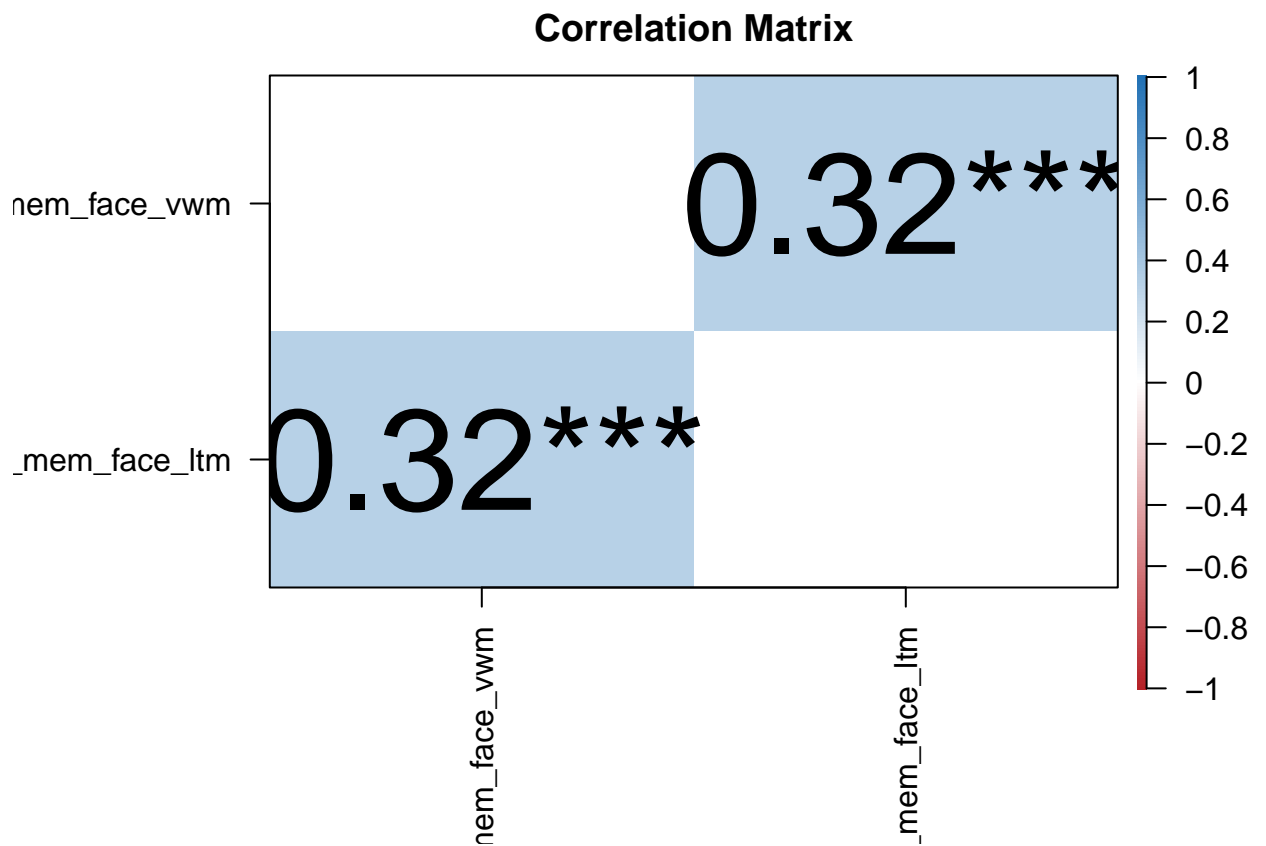
141 VWM performance predicts VLTm performance



142

```
143 ## Correlation matrix is displayed in the RStudio `Plots` Pane.
144 ##
145 ## Pearson's r and 95% confidence intervals:
146 ##
147 ##           r      [95% CI]      p      N
148 ##
149 ## auc_forg_face_vwm-auc_forg_face_ltm  0.05 [-0.11, 0.21]  .517    156
150 ##
```



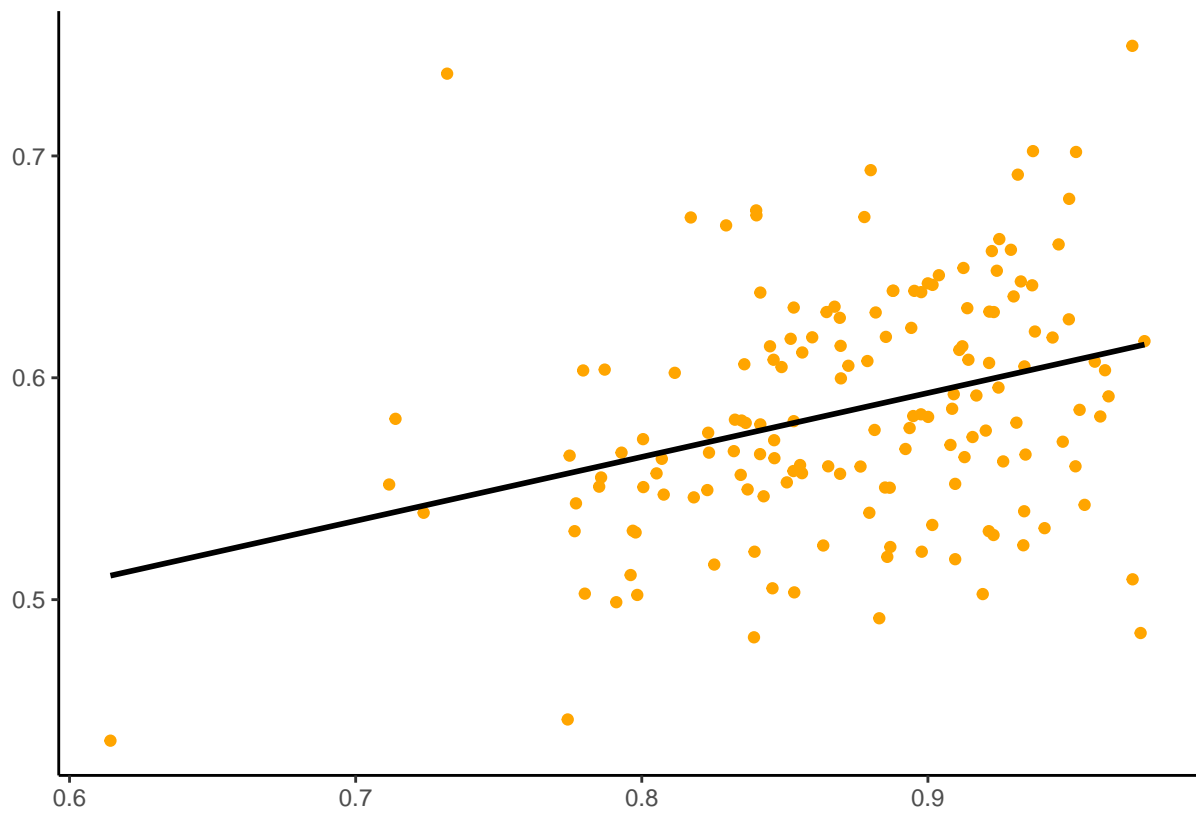


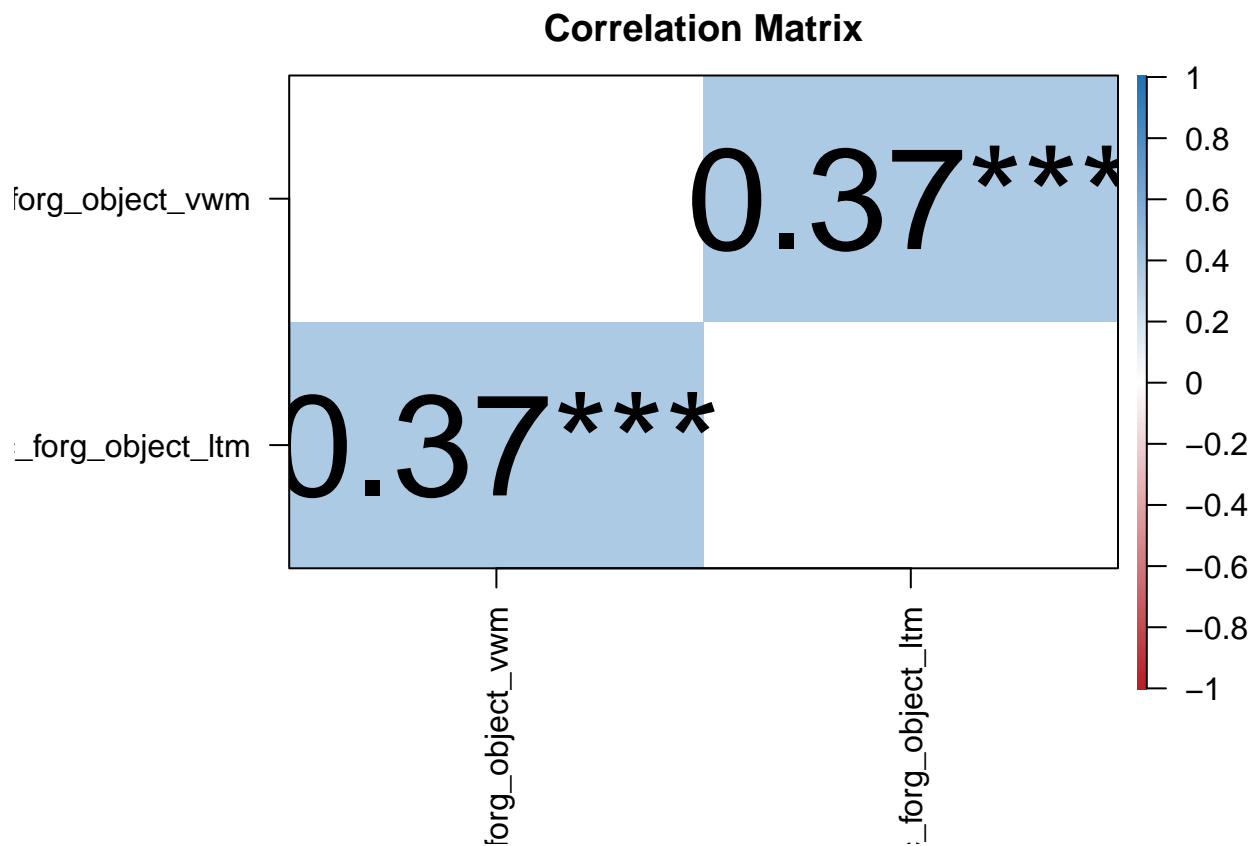
152

```

153 ## Correlation matrix is displayed in the RStudio `Plots` Pane.
154 ##
155 ## Pearson's r and 95% confidence intervals:
156 ##
157 ##           r      [95% CI]      p      N
158 ##
159 ## auc_mem_face_vwm-auc_mem_face_ltm  0.32 [0.17, 0.46] <.001 *** 156
160 ##

```



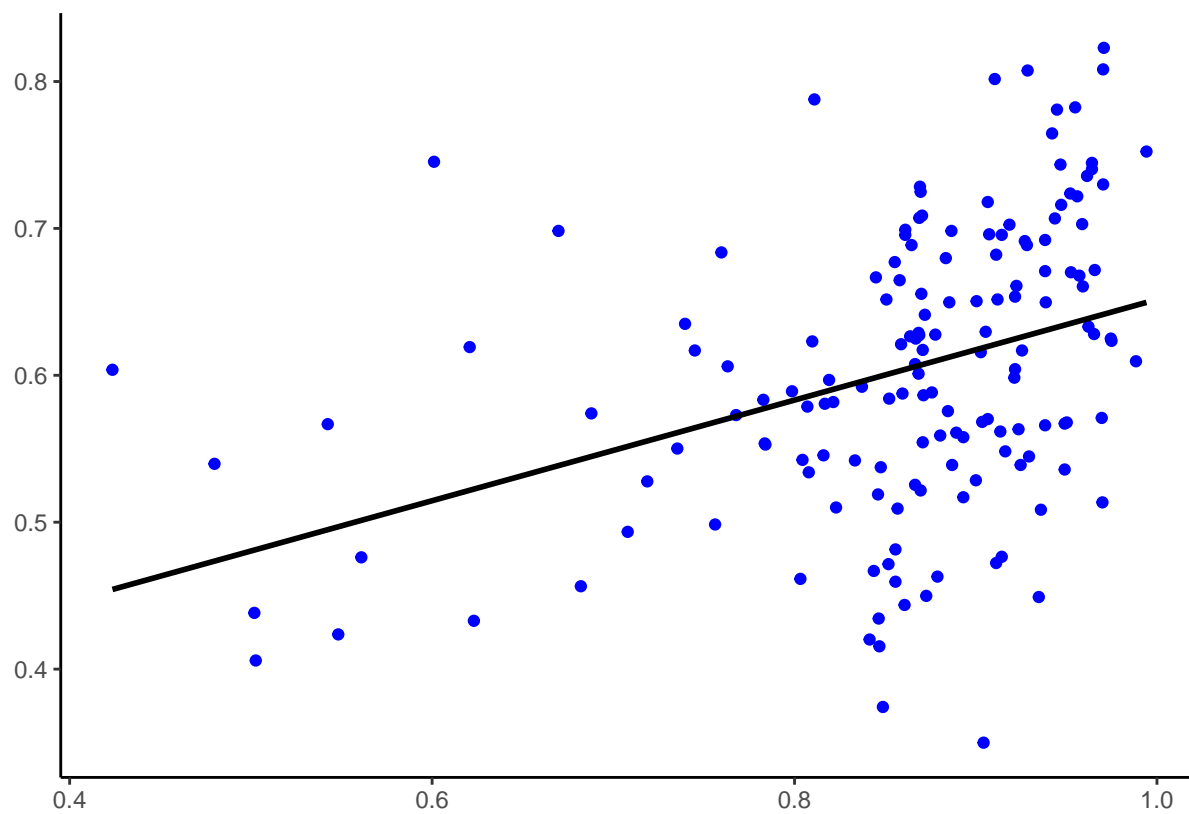


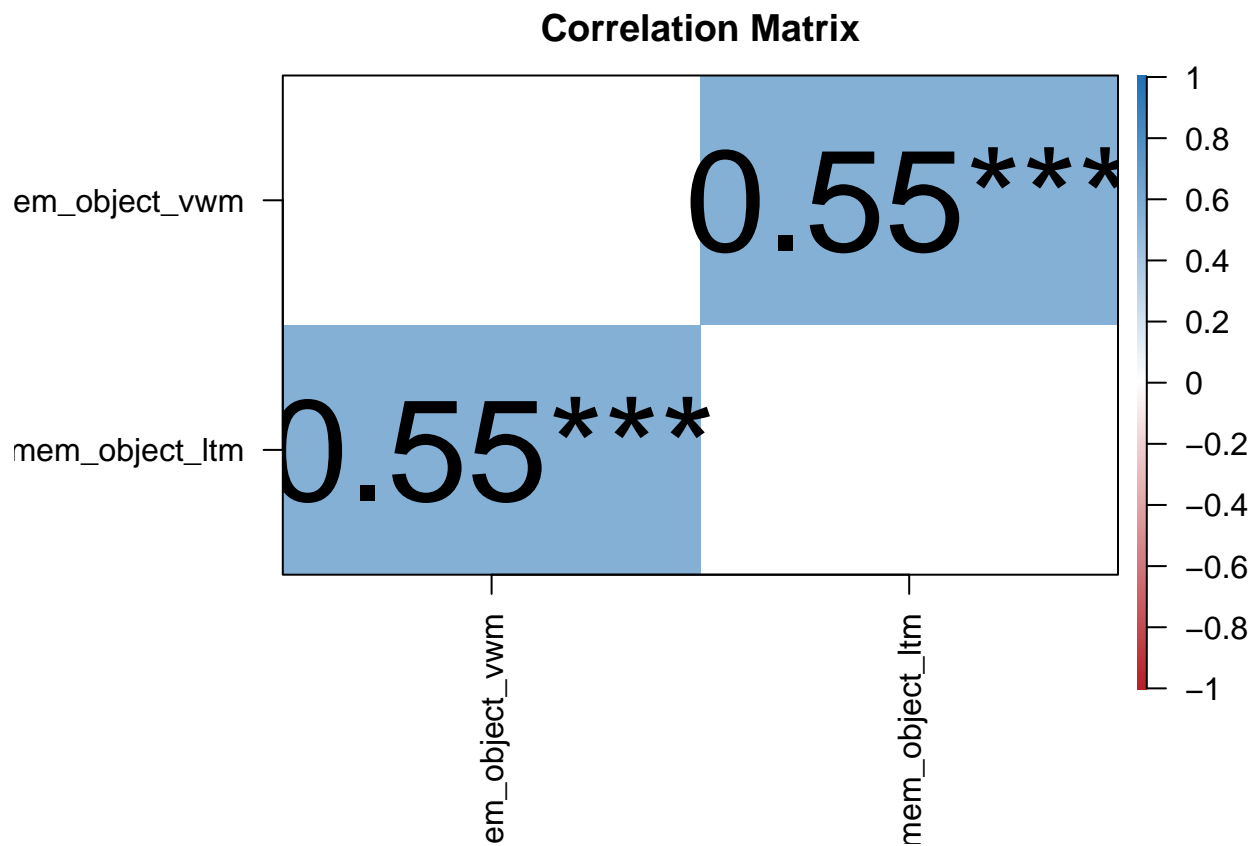
162

```

163 ## Correlation matrix is displayed in the RStudio `Plots` Pane.
164 ##
165 ## Pearson's r and 95% confidence intervals:
166 ##
167 ##               r      [95% CI]      p      N
168 ##
169 ## auc_forg_object_vwm-auc_forg_object_ltm  0.37 [0.23, 0.50] <.001 *** 156
170 ##

```



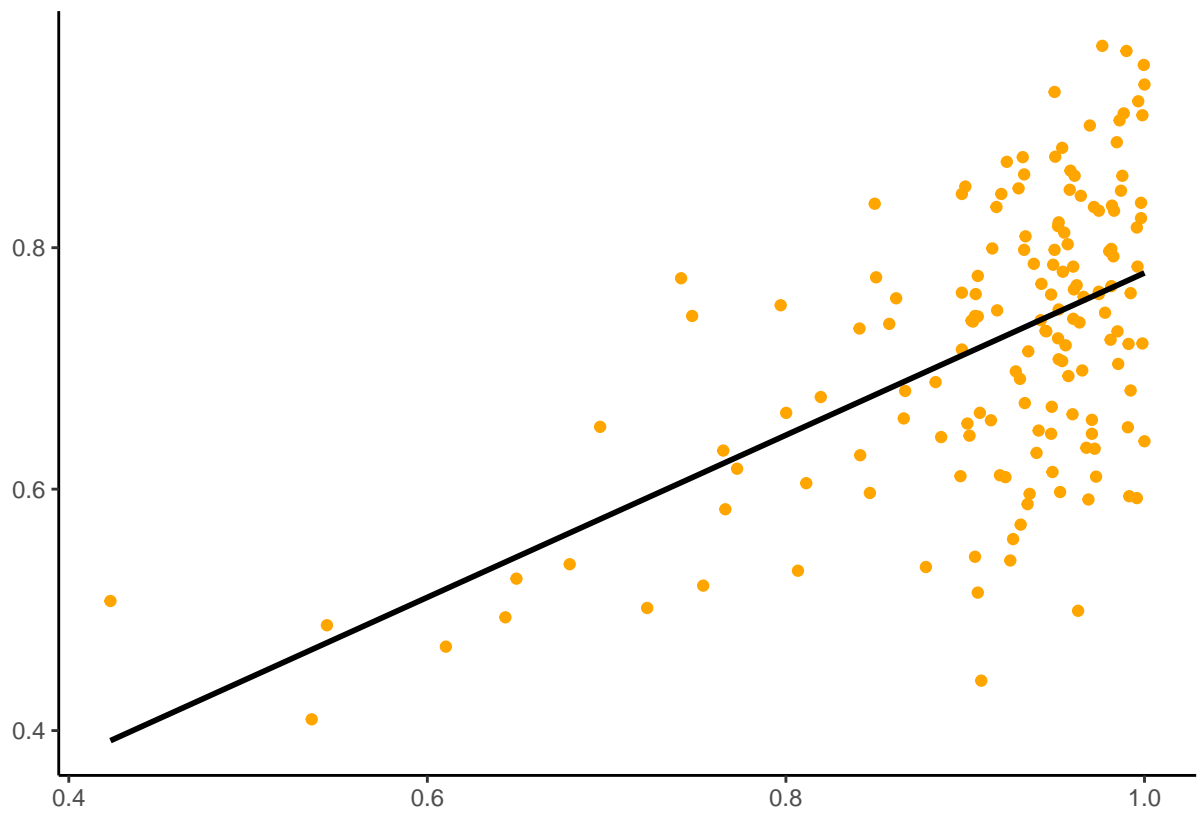


172

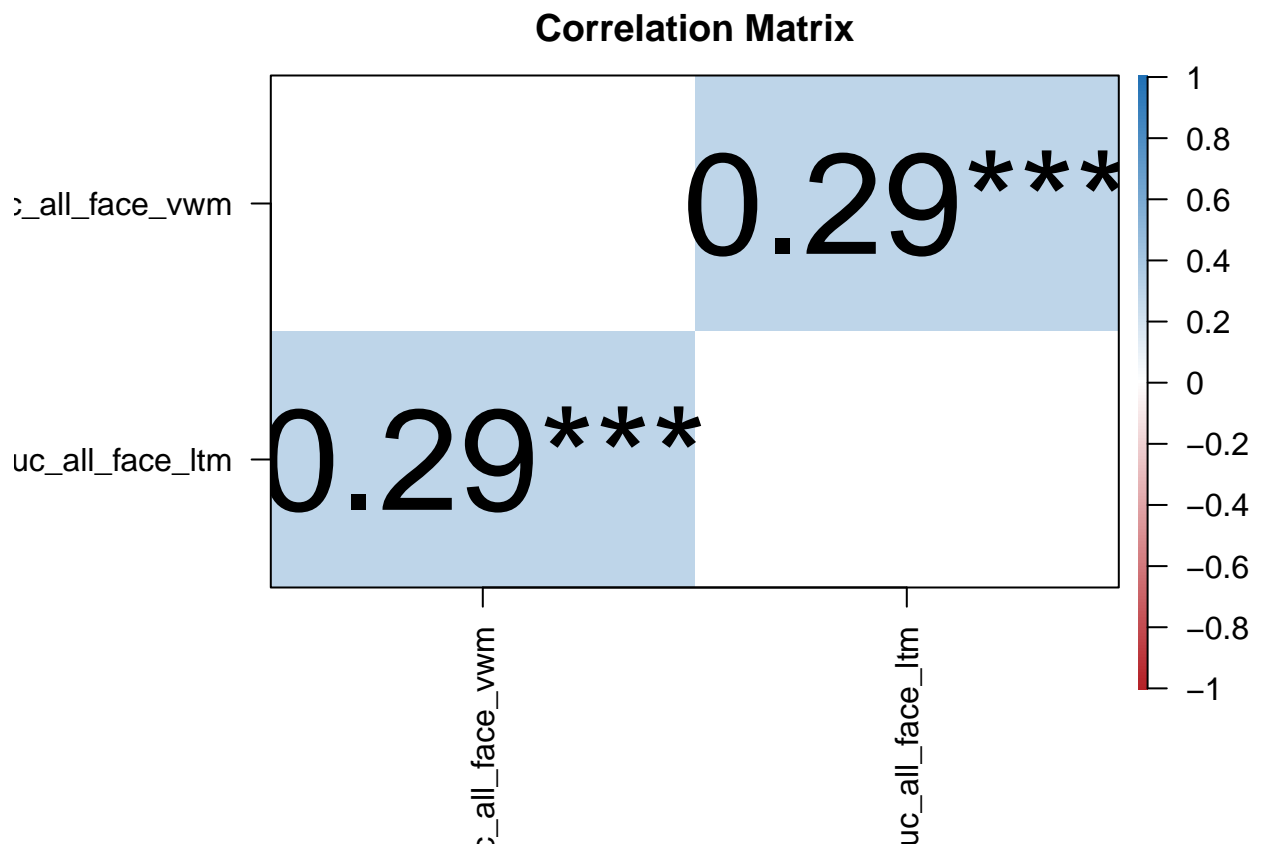
```

173 ## Correlation matrix is displayed in the RStudio `Plots` Pane.
174 ##
175 ## Pearson's r and 95% confidence intervals:
176 ##
177 ##               r      [95% CI]      p      N
178 ##
179 ## auc_mem_object_vwm-auc_mem_object_ltm  0.55 [0.43, 0.65] <.001 *** 156
180 ##

```





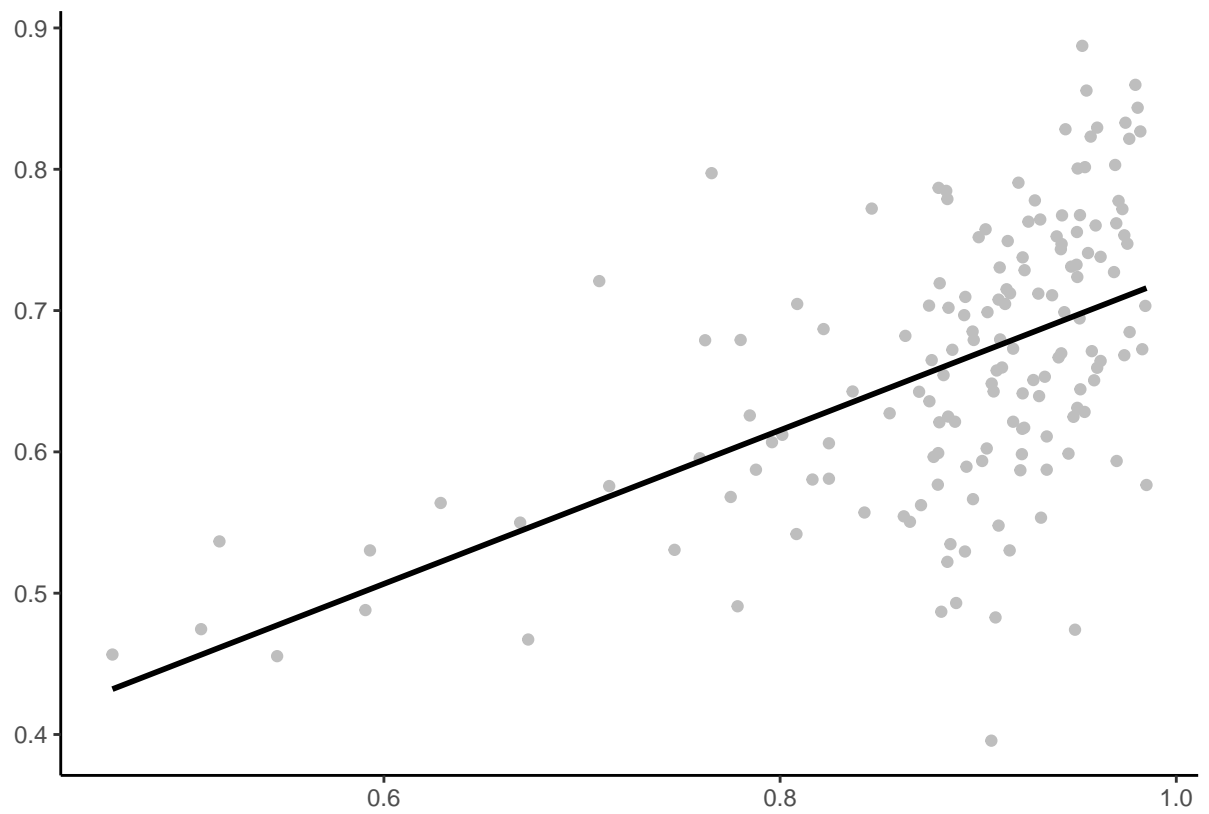


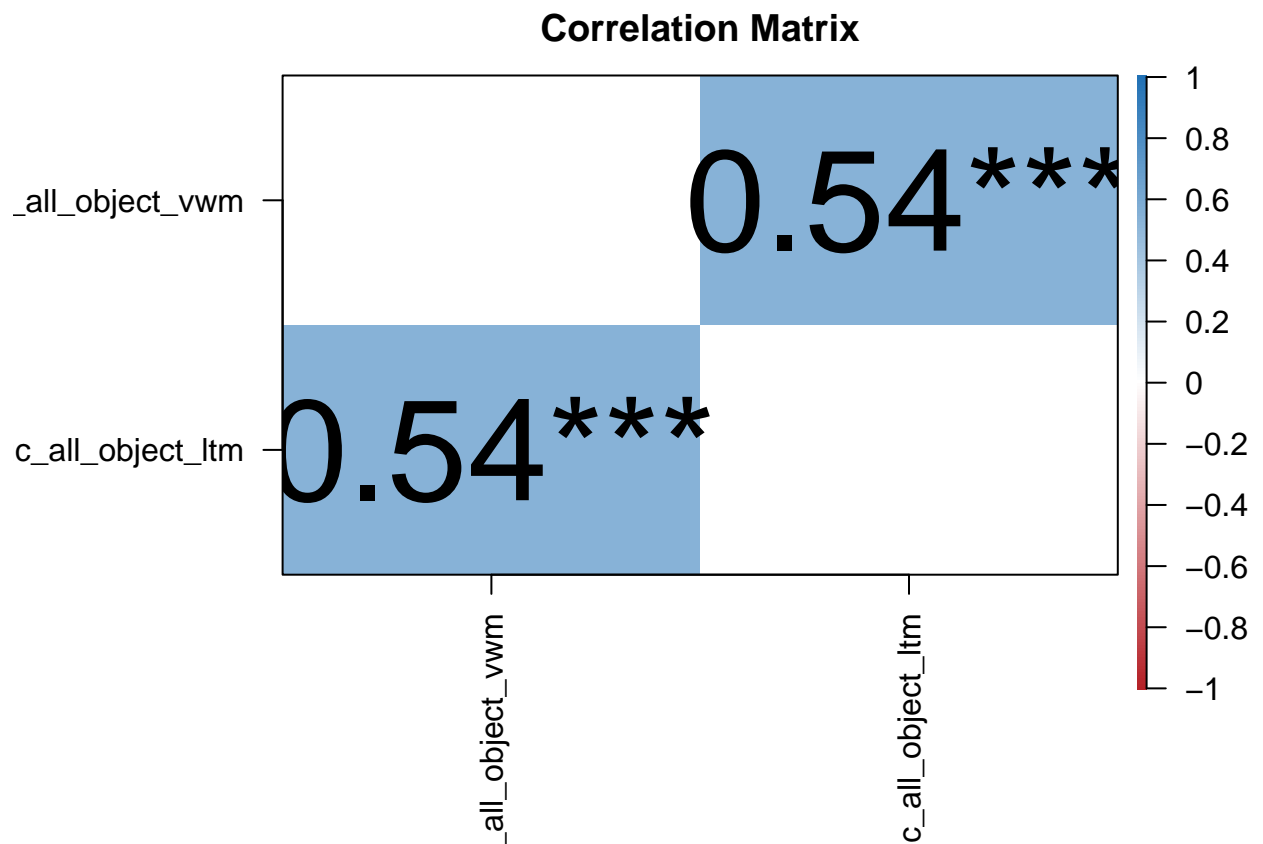
182

```

183 ## Correlation matrix is displayed in the RStudio `Plots` Pane.
184 ##
185 ## Pearson's r and 95% confidence intervals:
186 ##
187 ##           r      [95% CI]      p      N
188 ##
189 ## auc_all_face_vwm-auc_all_face_ltm  0.29 [0.14, 0.43] <.001 *** 156
190 ##

```



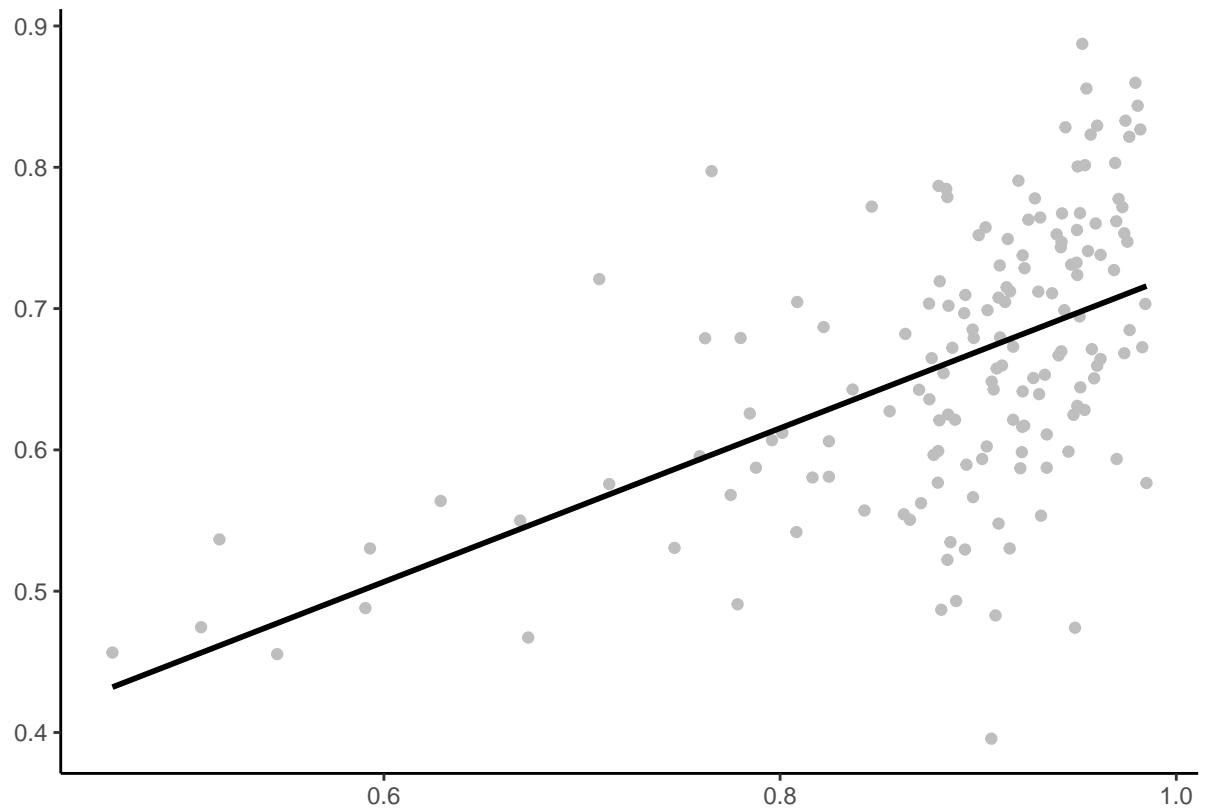


192

```

193 ## Correlation matrix is displayed in the RStudio `Plots` Pane.
194 ##
195 ## Pearson's r and 95% confidence intervals:
196 ##
197 ##               r      [95% CI]      p      N
198 ##
199 ## auc_all_object_vwm-auc_all_object_ltm  0.54 [0.41, 0.64] <.001 *** 156
200 ##

```



201

202 **Testing the efficiency hypothesis: memorable stimuli are more efficiently**  
 203 **represented in VWM than forgettable stimuli**

```

204 ## [1] "----- EMMEANS (effect = \"A_\") -----"
205 ## [2] ""
206 ## [3] "Joint Tests of \"A_\": "
207 ## [4] " "
208 ## [5] " Effect \"B_\\" df1 df2      F      p      ^p [90% CI of ^p]"
209 ## [6] " "
210 ## [7] "      A_ Forg    1 155 552.669 <.001 ***    .781 [.735, .816]"
211 ## [8] "      A_ Mem     1 155 433.024 <.001 ***    .736 [.682, .778]"
212 ## [9] " "
213 ## [10] "Note. Simple effects of repeated measures with 3 or more levels"

```

```

214 ## [11] "are different from the results obtained with SPSS MANOVA syntax."
215 ## [12] ""
216 ## [13] "Estimated Marginal Means of \"A_\": \"
217 ## [14] "                \"
218 ## [15] " \"A_\" \"B_\" Mean [95% CI of Mean]      S.E."
219 ## [16] "                \"
220 ## [17] " SS3. Forg  0.892 [0.879, 0.905] (0.006)"
221 ## [18] " SS6. Forg  0.737 [0.721, 0.752] (0.008)"
222 ## [19] " SS3. Mem   0.941 [0.933, 0.950] (0.004)"
223 ## [20] " SS6. Mem   0.812 [0.799, 0.826] (0.007)"
224 ## [21] "                \"
225 ## [22] ""
226 ## [23] "Pairwise Comparisons of \"A_\": \"
227 ## [24] "                \"
228 ## [25] "      Contrast \"B_\" Estimate      S.E.  df        t      p      Cohen's d [95% CI of
229 ## [26] "                \"
230 ## [27] " SS6. - SS3. Forg   -0.155 (0.007) 155 -23.509 <.001 *** -1.844 [-1.999, -1.689]
231 ## [28] " SS6. - SS3. Mem    -0.129 (0.006) 155 -20.809 <.001 *** -1.531 [-1.676, -1.385]
232 ## [29] "                \"
233 ## [30] "Pooled SD for computing Cohen's d: 0.084"
234 ## [31] "No need to adjust p values."
235 ## [32] ""
236 ## [33] "Disclaimer:"
237 ## [34] "By default, pooled SD is Root Mean Square Error (RMSE).\"
238 ## [35] "There is much disagreement on how to compute Cohen's d.\"
239 ## [36] "You are completely responsible for setting `sd.pooled`.\"
240 ## [37] "You might also use `effectsize::t_to_d()` to compute d.\"

```

```

241 ## [38] ""

242 ## [1] ""

243 ## [2] "==== ANOVA (Within-Subjects Design) ====="

244 ## [3] ""

245 ## [4] "Descriptives:"

246 ## [5] "          "

247 ## [6] " \"A_\" \"B_\" Mean S.D. n"

248 ## [7] "          "

249 ## [8] " SS3. Forg 0.527 (0.067) 156"

250 ## [9] " SS3. Mem 0.640 (0.076) 156"

251 ## [10] " SS6. Forg 0.502 (0.070) 156"

252 ## [11] " SS6. Mem 0.554 (0.077) 156"

253 ## [12] "          "

254 ## [13] "Total sample size: N = 156"

255 ## [14] ""

256 ## [15] "ANOVA Table:"

257 ## [16] "Dependent variable(s): A_SS3&B_Forg, A_SS3&B_Mem, A_SS6&B_Forg, A_SS6&B_Mem"

258 ## [17] "Between-subjects factor(s): -"

259 ## [18] "Within-subjects factor(s): A_, B_"

260 ## [19] "Covariate(s): -"

261 ## [20] "          "

262 ## [21] "          MS MSE df1 df2          F          p          ^p [90% CI of ^p]          ^G"

263 ## [22] "          "

264 ## [23] "A_          0.474 0.004    1 155 124.695 <.001 ***    .446 [.353, .525] .127"

265 ## [24] "B_          1.068 0.005    1 155 203.842 <.001 ***    .568 [.488, .634] .246"

266 ## [25] "A_ * B_    0.147 0.004    1 155 38.096 <.001 ***    .197 [.112, .287] .043"

267 ## [26] "          "

```

```

268 ## [27] "MSE = mean square error (the residual variance of the linear model)"
269 ## [28] " 2p = partial eta-squared = SS / (SS + SSE) = F * df1 / (F * df1 + df2)"
270 ## [29] " 2p = partial omega-squared = (F - 1) * df1 / (F * df1 + df2 + 1)"
271 ## [30] " 2G = generalized eta-squared (see Olejnik & Algina, 2003)"
272 ## [31] "Cohen's f2 = 2p / (1 - 2p)"
273 ## [32] ""
274 ## [33] "Levene's Test for Homogeneity of Variance:"
275 ## [34] "No between-subjects factors. No need to do the Levene's test."
276 ## [35] ""
277 ## [36] "Mauchly's Test of Sphericity:"
278 ## [37] "The repeated measures have only two levels. The assumption of sphericity is alw
279 ## [38] ""

280 ## [1] "----- EMMEANS (effect = \"A_\") -----"
281 ## [2] ""
282 ## [3] "Joint Tests of \"A_\": "
283 ## [4] " "
284 ## [5] " Effect \"B_\\" df1 df2 F p 2p [90% CI of 2p]"
285 ## [6] " "
286 ## [7] " A_ Forg 1 155 12.837 <.001 *** .076 [.023, .151]"
287 ## [8] " A_ Mem 1 155 141.691 <.001 *** .478 [.388, .554]"
288 ## [9] " "
289 ## [10] "Note. Simple effects of repeated measures with 3 or more levels"
290 ## [11] "are different from the results obtained with SPSS MANOVA syntax."
291 ## [12] ""
292 ## [13] "Estimated Marginal Means of \"A_\": "
293 ## [14] " "
294 ## [15] " \"A_\\" \"B_\\" Mean [95% CI of Mean] S.E."

```

```

295 ## [16] "
296 ## [17] " SS3. Forg 0.527 [0.516, 0.537] (0.005)"
297 ## [18] " SS6. Forg 0.502 [0.491, 0.513] (0.006)"
298 ## [19] " SS3. Mem 0.640 [0.628, 0.652] (0.006)"
299 ## [20] " SS6. Mem 0.554 [0.542, 0.566] (0.006)"
300 ## [21] "
301 ## [22] ""
302 ## [23] "Pairwise Comparisons of \"A_\": \"
303 ## [24] "
304 ## [25] " Contrast \"B_\" Estimate S.E. df t p Cohen's d [95% CI of
305 ## [26] "
306 ## [27] " SS6. - SS3. Forg -0.024 (0.007) 155 -3.583 <.001 *** -0.263 [-0.408, -0.118]
307 ## [28] " SS6. - SS3. Mem -0.086 (0.007) 155 -11.903 <.001 *** -0.926 [-1.079, -0.772]
308 ## [29] "
309 ## [30] "Pooled SD for computing Cohen's d: 0.093"
310 ## [31] "No need to adjust p values."
311 ## [32] ""
312 ## [33] "Disclaimer:"
313 ## [34] "By default, pooled SD is Root Mean Square Error (RMSE).\"
314 ## [35] "There is much disagreement on how to compute Cohen's d.\"
315 ## [36] "You are completely responsible for setting `sd.pooled`.\"
316 ## [37] "You might also use `effectsize::t_to_d()` to compute d.\"
317 ## [38] ""

318 ## [1] ""
319 ## [2] "===== ANOVA (Within-Subjects Design) =====\"
320 ## [3] ""
321 ## [4] "Descriptives:"

```



```

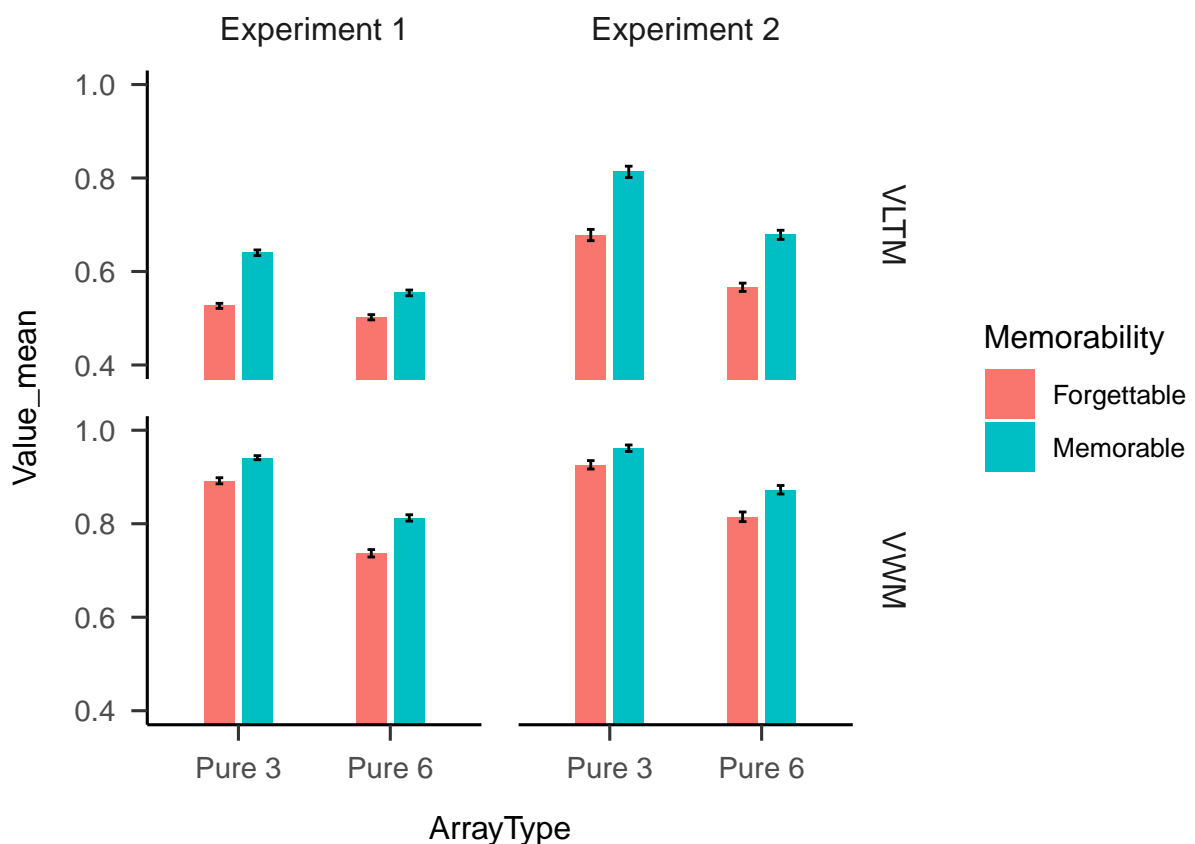
322 ## [5] "          "
323 ## [6] " \"A_\" \"B_\" Mean    S.D.    n"
324 ## [7] "          "
325 ## [8] " SS3. Forg 0.678 (0.151) 156"
326 ## [9] " SS3. Mem  0.813 (0.151) 156"
327 ## [10] " SS6. Forg 0.566 (0.110) 156"
328 ## [11] " SS6. Mem  0.678 (0.122) 156"
329 ## [12] "          "
330 ## [13] "Total sample size: N = 156"
331 ## [14] ""
332 ## [15] "ANOVA Table:"
333 ## [16] "Dependent variable(s):      A_SS3&B_Forg, A_SS3&B_Mem, A_SS6&B_Forg, A_SS6&B_Me
334 ## [17] "Between-subjects factor(s): -"
335 ## [18] "Within-subjects factor(s):  A_, B_"
336 ## [19] "Covariate(s):              -"
337 ## [20] "          "
338 ## [21] "          MS    MSE df1 df2          F      p      ^2p [90% CI of ^2p]    ^2G"
339 ## [22] "          "
340 ## [23] "A_          2.369 0.010    1 155 246.658 <.001 ***    .614 [.540, .674] .174"
341 ## [24] "B_          2.386 0.011    1 155 219.761 <.001 ***    .586 [.508, .650] .175"
342 ## [25] "A_ * B_    0.021 0.007    1 155    2.882 .092 .    .018 [.000, .067] .002"
343 ## [26] "          "
344 ## [27] "MSE = mean square error (the residual variance of the linear model)"
345 ## [28] " ^2p = partial eta-squared = SS / (SS + SSE) = F * df1 / (F * df1 + df2)"
346 ## [29] " ^2p = partial omega-squared = (F - 1) * df1 / (F * df1 + df2 + 1)"
347 ## [30] " ^2G = generalized eta-squared (see Olejnik & Algina, 2003)"
348 ## [31] "Cohen's f^2 = ^2p / (1 - ^2p)"

```

```

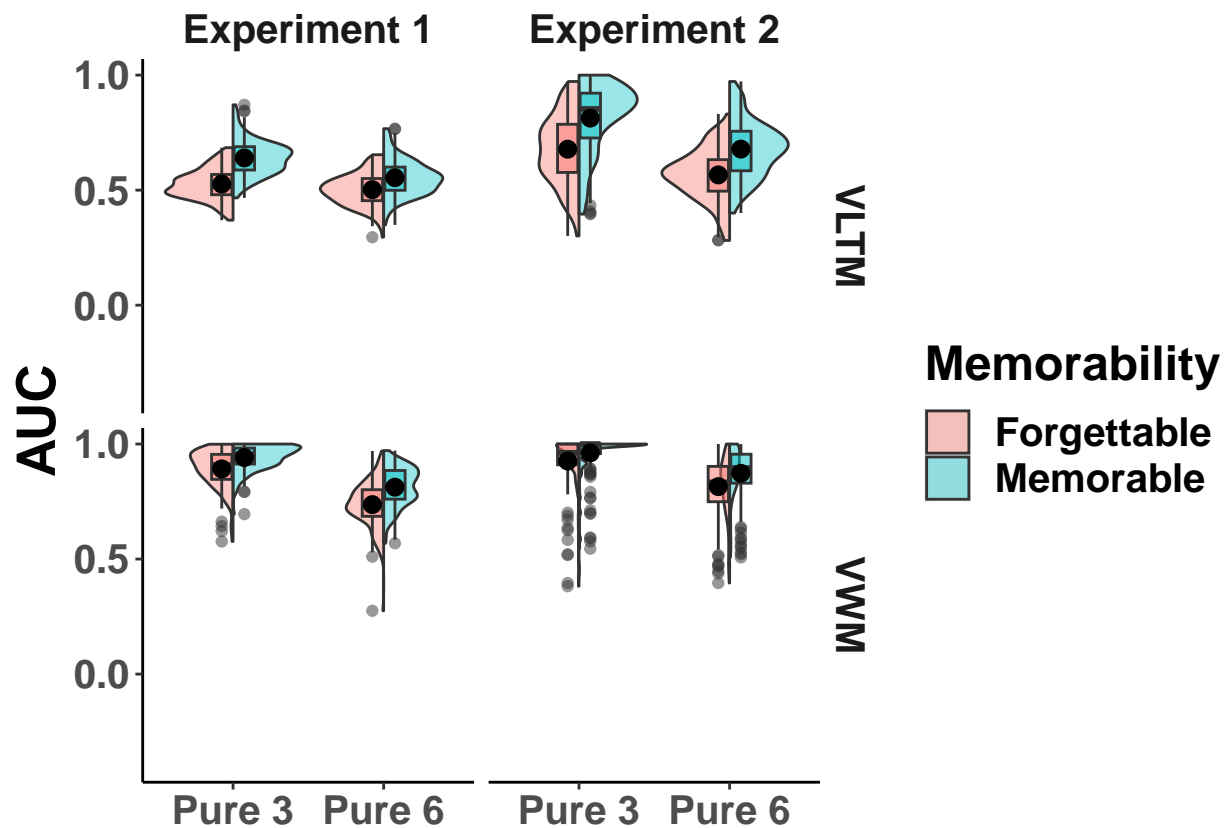
349 ## [32] ""
350 ## [33] "Levene's Test for Homogeneity of Variance:"
351 ## [34] "No between-subjects factors. No need to do the Levene's test."
352 ## [35] ""
353 ## [36] "Mauchly's Test of Sphericity:"
354 ## [37] "The repeated measures have only two levels. The assumption of sphericity is alw
355 ## [38] ""

```



356

357 We use simple barplot for comparing with the paper result, but it is too simple to be  
 358 informative, so we create another split violin plot.



Testing the competitiveness hypothesis: memorable stimuli attract more VWM resources than forgettable stimuli

```
## [1] ""
## [2] "===== ANOVA (Within-Subjects Design) ====="
## [3] ""
## [4] "Descriptives:"
## [5] "                "
## [6] "  \"A_\" \"B_\"  Mean    S.D.    n"
## [7] "                "
## [8] " Mixed. Forg 0.725 (0.092) 156"
## [9] " Mixed. Mem  0.836 (0.085) 156"
## [10] " SS6.   Forg 0.737 (0.099) 156"
```

```

372 ## [11] " SS6.    Mem  0.812 (0.084) 156"
373 ## [12] "                "
374 ## [13] "Total sample size: N = 156"
375 ## [14] ""
376 ## [15] "ANOVA Table:"
377 ## [16] "Dependent variable(s):      A_Mixed&B_Forg, A_Mixed&B_Mem, A_SS6&B_Forg, A_SS6&
378 ## [17] "Between-subjects factor(s): -"
379 ## [18] "Within-subjects factor(s):  A_, B_"
380 ## [19] "Covariate(s):              -"
381 ## [20] "                                "
382 ## [21] "                MS    MSE df1 df2          F      p      2p [90% CI of 2p]    2G"
383 ## [22] "                                "
384 ## [23] "A_          0.005 0.005   1 155   1.058 .305          .007 [.000, .044] .001"
385 ## [24] "B_          1.366 0.004   1 155 313.183 <.001 ***    .669 [.603, .721] .213"
386 ## [25] "A_ * B_    0.050 0.004   1 155  11.775 <.001 ***    .071 [.019, .144] .010"
387 ## [26] "                                "
388 ## [27] "MSE = mean square error (the residual variance of the linear model)"
389 ## [28] " 2p = partial eta-squared = SS / (SS + SSE) = F * df1 / (F * df1 + df2)"
390 ## [29] " 2p = partial omega-squared = (F - 1) * df1 / (F * df1 + df2 + 1)"
391 ## [30] " 2G = generalized eta-squared (see Olejnik & Algina, 2003)"
392 ## [31] "Cohen's f2 = 2p / (1 - 2p)"
393 ## [32] ""
394 ## [33] "Levene's Test for Homogeneity of Variance:"
395 ## [34] "No between-subjects factors. No need to do the Levene's test."
396 ## [35] ""
397 ## [36] "Mauchly's Test of Sphericity:"
398 ## [37] "The repeated measures have only two levels. The assumption of sphericity is alw

```

```

399 ## [38] ""

400 ## [1] "----- EMMEANS (effect = \"A_\") -----"

401 ## [2] ""

402 ## [3] "Joint Tests of \"A_\": "

403 ## [4] "

404 ## [5] " Effect \"B_\ " df1 df2 F p ^p [90% CI of ^p]"

405 ## [6] "

406 ## [7] " A_ Forg 1 155 2.228 .138 .014 [.000, .060]"

407 ## [8] " A_ Mem 1 155 11.292 <.001 *** .068 [.018, .140]"

408 ## [9] "

409 ## [10] "Note. Simple effects of repeated measures with 3 or more levels"

410 ## [11] "are different from the results obtained with SPSS MANOVA syntax."

411 ## [12] ""

412 ## [13] "Estimated Marginal Means of \"A_\": "

413 ## [14] "

414 ## [15] " \"A_\ " \"B_\ " Mean [95% CI of Mean] S.E."

415 ## [16] "

416 ## [17] " Mixed. Forg 0.725 [0.710, 0.739] (0.007)"

417 ## [18] " SS6. Forg 0.737 [0.721, 0.752] (0.008)"

418 ## [19] " Mixed. Mem 0.836 [0.823, 0.849] (0.007)"

419 ## [20] " SS6. Mem 0.812 [0.799, 0.826] (0.007)"

420 ## [21] "

421 ## [22] ""

422 ## [23] "Pairwise Comparisons of \"A_\": "

423 ## [24] "

424 ## [25] " Contrast \"B_\ " Estimate S.E. df t p Cohen's d [95% CI c

425 ## [26] "

```

```

426 ## [27] " SS6. - Mixed. Forg      0.012 (0.008) 155  1.493  .138      0.129 [-0.042,  0.29
427 ## [28] " SS6. - Mixed. Mem      -0.024 (0.007) 155 -3.360 <.001 *** -0.249 [-0.396, -0.10
428 ## [29] "                                "
429 ## [30] "Pooled SD for computing Cohen's d: 0.094"
430 ## [31] "No need to adjust p values."
431 ## [32] ""
432 ## [33] "Disclaimer:"
433 ## [34] "By default, pooled SD is Root Mean Square Error (RMSE).\"
434 ## [35] "There is much disagreement on how to compute Cohen's d.\"
435 ## [36] "You are completely responsible for setting `sd.pooled`.\"
436 ## [37] "You might also use `effectsize::t_to_d()` to compute d.\"
437 ## [38] ""

438 ##  [1] ""
439 ##  [2] "==== ANOVA (Within-Subjects Design) =====\"
440 ##  [3] ""
441 ##  [4] "Descriptives:\"
442 ##  [5] "                \"
443 ##  [6] "  \"A_\" \"B_\"  Mean    S.D.    n\"
444 ##  [7] "                \"
445 ##  [8] " Mixed. Forg 0.802 (0.130) 156\"
446 ##  [9] " Mixed. Mem  0.891 (0.132) 156\"
447 ## [10] " SS6.   Forg 0.815 (0.129) 156\"
448 ## [11] " SS6.   Mem  0.873 (0.114) 156\"
449 ## [12] "                \"
450 ## [13] "Total sample size: N = 156\"
451 ## [14] ""
452 ## [15] "ANOVA Table:\"

```

```

453 ## [16] "Dependent variable(s):      A_Mixed&B_Forg, A_Mixed&B_Mem, A_SS6&B_Forg, A_SS6&
454 ## [17] "Between-subjects factor(s): -"
455 ## [18] "Within-subjects factor(s):  A_, B_"
456 ## [19] "Covariate(s):                -"
457 ## [20] "                                "
458 ## [21] "              MS      MSE df1 df2          F      p      2p [90% CI of 2p]    2G"
459 ## [22] "                                "
460 ## [23] "A_          0.001 0.005   1 155   0.207 .650          .001 [.000, .026] .000"
461 ## [24] "B_          0.839 0.008   1 155 102.498 <.001 ***    .398 [.303, .482] .078"
462 ## [25] "A_ * B_    0.037 0.007   1 155   5.440 .021 *      .034 [.003, .093] .004"
463 ## [26] "                                "
464 ## [27] "MSE = mean square error (the residual variance of the linear model)"
465 ## [28] " 2p = partial eta-squared = SS / (SS + SSE) = F * df1 / (F * df1 + df2)"
466 ## [29] " 2p = partial omega-squared = (F - 1) * df1 / (F * df1 + df2 + 1)"
467 ## [30] " 2G = generalized eta-squared (see Olejnik & Algina, 2003)"
468 ## [31] "Cohen's f2 = 2p / (1 - 2p)"
469 ## [32] ""
470 ## [33] "Levene's Test for Homogeneity of Variance:"
471 ## [34] "No between-subjects factors. No need to do the Levene's test."
472 ## [35] ""
473 ## [36] "Mauchly's Test of Sphericity:"
474 ## [37] "The repeated measures have only two levels. The assumption of sphericity is alw
475 ## [38] ""

476 ##  [1] "----- EMMEANS (effect = \"A_\") -----"
477 ##  [2] ""
478 ##  [3] "Joint Tests of \"A_\": "
479 ##  [4] "

```

```

480 ## [5] " Effect \"B_\" df1 df2      F      p      ^p [90% CI of ^p]"
481 ## [6] "
482 ## [7] "      A_ Forg    1 155 1.829  .178      .012 [.000, .055]"
483 ## [8] "      A_ Mem     1 155 5.058  .026 *    .032 [.002, .090]"
484 ## [9] "
485 ## [10] "Note. Simple effects of repeated measures with 3 or more levels"
486 ## [11] "are different from the results obtained with SPSS MANOVA syntax."
487 ## [12] ""
488 ## [13] "Estimated Marginal Means of \"A_\": "
489 ## [14] "
490 ## [15] "  \"A_\" \"B_\" Mean [95% CI of Mean]    S.E."
491 ## [16] "
492 ## [17] " Mixed. Forg  0.802 [0.781, 0.823] (0.010)"
493 ## [18] " SS6.   Forg  0.815 [0.794, 0.835] (0.010)"
494 ## [19] " Mixed. Mem   0.891 [0.870, 0.912] (0.011)"
495 ## [20] " SS6.   Mem   0.873 [0.855, 0.891] (0.009)"
496 ## [21] "
497 ## [22] ""
498 ## [23] "Pairwise Comparisons of \"A_\": "
499 ## [24] "
500 ## [25] "      Contrast \"B_\" Estimate    S.E.  df      t      p      Cohen's d [95% CI c
501 ## [26] "
502 ## [27] " SS6. - Mixed. Forg    0.013 (0.010) 155  1.352  .178      0.111 [-0.051,  0.27
503 ## [28] " SS6. - Mixed. Mem    -0.018 (0.008) 155 -2.249  .026 *   -0.156 [-0.293, -0.01
504 ## [29] "
505 ## [30] "Pooled SD for computing Cohen's d: 0.116"
506 ## [31] "No need to adjust p values."

```



```

507 ## [32] ""
508 ## [33] "Disclaimer:"
509 ## [34] "By default, pooled SD is Root Mean Square Error (RMSE).\"
510 ## [35] "There is much disagreement on how to compute Cohen's d.\"
511 ## [36] "You are completely responsible for setting `sd.pooled`.\"
512 ## [37] "You might also use `effectsize::t_to_d()` to compute d.\"
513 ## [38] ""

514 ## [1] ""
515 ## [2] "==== ANOVA (Within-Subjects Design) =====\"
516 ## [3] ""
517 ## [4] "Descriptives:\"
518 ## [5] "                \"
519 ## [6] "  \"A_\" \"B_\" Mean    S.D.    n\"
520 ## [7] "                \"
521 ## [8] " Mixed. Forg 0.503 (0.062) 156\"
522 ## [9] " Mixed. Mem  0.562 (0.069) 156\"
523 ## [10] " SS6.   Forg 0.502 (0.070) 156\"
524 ## [11] " SS6.   Mem  0.554 (0.077) 156\"
525 ## [12] "                \"
526 ## [13] "Total sample size: N = 156\"
527 ## [14] ""
528 ## [15] "ANOVA Table:\"
529 ## [16] "Dependent variable(s):      A_Mixed&B_Forg, A_SS6&B_Forg, A_Mixed&B_Mem, A_SS6&
530 ## [17] "Between-subjects factor(s): -\"
531 ## [18] "Within-subjects factor(s):  A_, B_\"
532 ## [19] "Covariate(s):              -\"
533 ## [20] "                \"

```

```

534 ## [21] "          MS    MSE df1 df2          F          p          ^p [90% CI of ^p]    ^G"
535 ## [22] "          "
536 ## [23] "A_          0.003 0.003    1 155    1.021    .314          .007 [.000, .044] .001"
537 ## [24] "B_          0.476 0.006    1 155   78.909 <.001 ***    .337 [.242, .425] .136"
538 ## [25] "A_ * B_    0.002 0.003    1 155    0.506    .478          .003 [.000, .034] .001"
539 ## [26] "          "
540 ## [27] "MSE = mean square error (the residual variance of the linear model)"
541 ## [28] " ^p = partial eta-squared = SS / (SS + SSE) = F * df1 / (F * df1 + df2)"
542 ## [29] " ^p = partial omega-squared = (F - 1) * df1 / (F * df1 + df2 + 1)"
543 ## [30] " ^G = generalized eta-squared (see Olejnik & Algina, 2003)"
544 ## [31] "Cohen's f^2 = ^p / (1 - ^p)"
545 ## [32] ""
546 ## [33] "Levene's Test for Homogeneity of Variance:"
547 ## [34] "No between-subjects factors. No need to do the Levene's test."
548 ## [35] ""
549 ## [36] "Mauchly's Test of Sphericity:"
550 ## [37] "The repeated measures have only two levels. The assumption of sphericity is alw
551 ## [38] ""

552 ## [1] ""
553 ## [2] "===== ANOVA (Within-Subjects Design) ====="
554 ## [3] ""
555 ## [4] "Descriptives:"
556 ## [5] "          "
557 ## [6] "    \"A_\" \"B_\"  Mean    S.D.    n"
558 ## [7] "          "
559 ## [8] " Mixed. Forg 0.565 (0.105) 156"
560 ## [9] " Mixed. Mem  0.672 (0.137) 156"

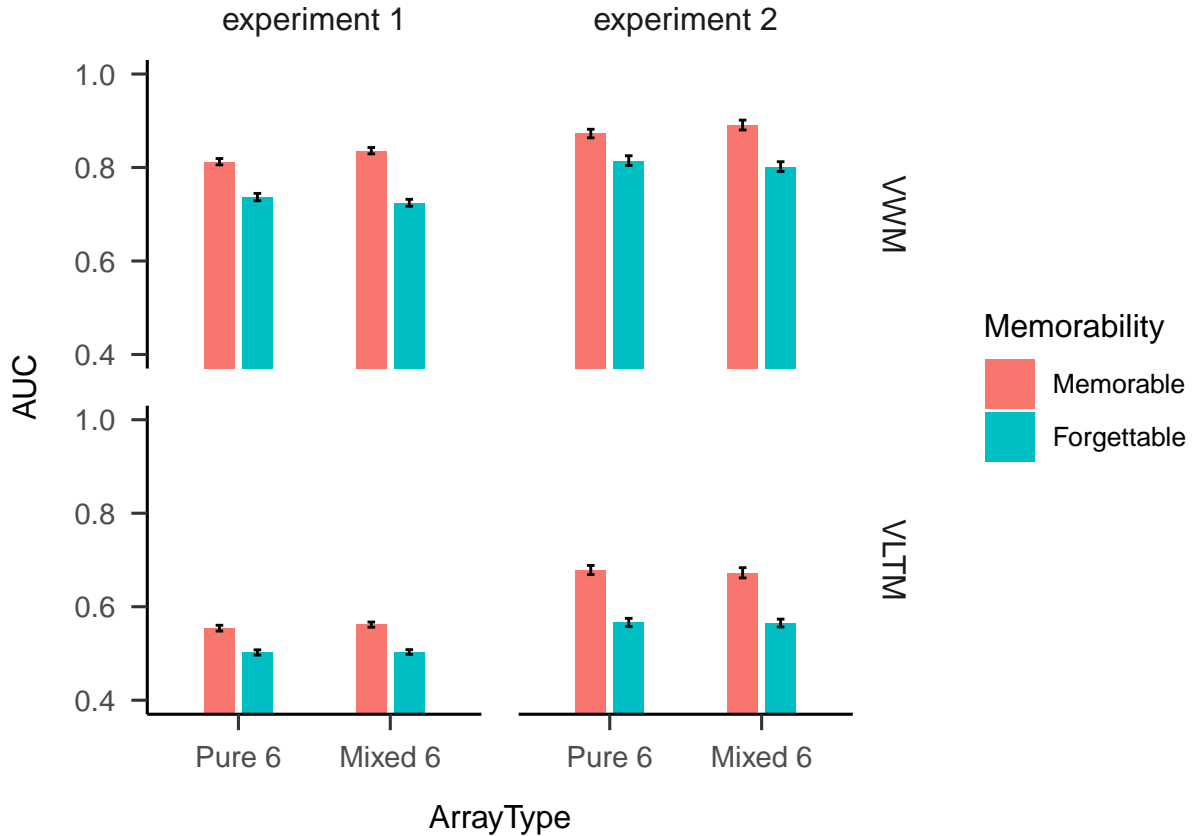
```

```

561 ## [10] " SS6.   Forg 0.566 (0.110) 156"
562 ## [11] " SS6.   Mem  0.678 (0.122) 156"
563 ## [12] "           "
564 ## [13] "Total sample size: N = 156"
565 ## [14] ""
566 ## [15] "ANOVA Table:"
567 ## [16] "Dependent variable(s):      A_Mixed&B_Forg, A_SS6&B_Forg, A_Mixed&B_Mem, A_SS6&B_Mem"
568 ## [17] "Between-subjects factor(s): -"
569 ## [18] "Within-subjects factor(s):  A_, B_"
570 ## [19] "Covariate(s):              -"
571 ## [20] "                               "
572 ## [21] "           MS    MSE df1 df2        F      p      2p [90% CI of 2p]    2G"
573 ## [22] "                               "
574 ## [23] "A_           0.002 0.006    1 155    0.319  .573           .002 [.000, .030] .000"
575 ## [24] "B_           1.881 0.011    1 155  174.476 <.001 ***    .530 [.444, .600] .176"
576 ## [25] "A_ * B_     0.001 0.006    1 155    0.138  .711           .001 [.000, .023] .000"
577 ## [26] "                               "
578 ## [27] "MSE = mean square error (the residual variance of the linear model)"
579 ## [28] " 2p = partial eta-squared = SS / (SS + SSE) = F * df1 / (F * df1 + df2)"
580 ## [29] " 2p = partial omega-squared = (F - 1) * df1 / (F * df1 + df2 + 1)"
581 ## [30] " 2G = generalized eta-squared (see Olejnik & Algina, 2003)"
582 ## [31] "Cohen's f2 = 2p / (1 - 2p)"
583 ## [32] ""
584 ## [33] "Levene's Test for Homogeneity of Variance:"
585 ## [34] "No between-subjects factors. No need to do the Levene's test."
586 ## [35] ""
587 ## [36] "Mauchly's Test of Sphericity:"

```

588 ## [37] "The repeated measures have only two levels. The assumption of sphericity is alw  
 589 ## [38] ""



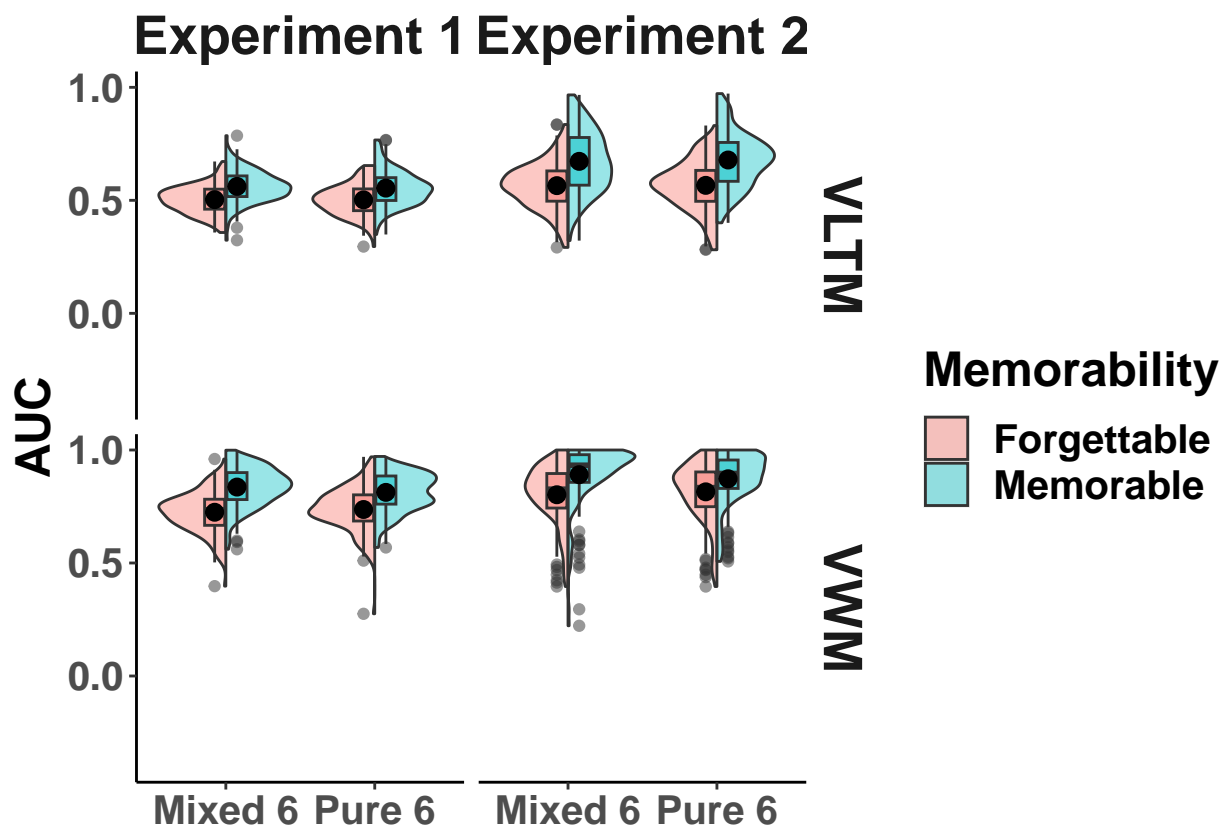
590

591 Our results are identical to the original results.

592 In both Experiment 1 and Experiment 2, memorable stimuli had higher Area Under  
 593 the Curve (AUC) values compared to forgettable stimuli in both the Visual Working  
 594 Memory (VWM) and Very Long-Term Memory (VLTM) tasks.

595 Notably, there was a significant interaction between memorability and array type in  
 596 VWM. When memorable stimuli were encoded with forgettable stimuli, the VWM  
 597 performance for memorable stimuli was higher compared to when all stimuli were  
 598 memorable. This finding supports the competitiveness hypothesis.

599 However, this competitive advantage did not transfer to VLTM, as there was no main  
 600 effect of array type or interaction between array type and memorability in VLTM.



Testing the stickiness hypothesis: memorable stimuli are stickier than forgettable stimuli

since the author didn't explicitly mention the recoding job in paper, to ensure the recoding definitely exists, here we show the anova result of experiment1 – 2 (ArrayType: Pure 3 and Pure 6)  $\times$  2 (Memorability: Memorable and Forgettable) repeated measures ANOVA on stickiness, for convenience, this is the only replication result. next we will use the original data(without recoding) to do data analysis.

##

## ===== ANOVA (Within-Subjects Design) =====

##

## Descriptives:

```

613 ##
614 ##  "A_" "B_"  Mean    S.D.    n
615 ##
616 ##  SS3. Forg 0.113 (0.155) 156
617 ##  SS3. Mem  0.317 (0.167) 156
618 ##  SS6. Forg 0.141 (0.228) 156
619 ##  SS6. Mem  0.211 (0.223) 156
620 ##
621 ## Total sample size: N = 156
622 ##
623 ## ANOVA Table:
624 ## Dependent variable(s):      A_SS3&B_Forg, A_SS3&B_Mem, A_SS6&B_Forg, A_SS6&B_Mem
625 ## Between-subjects factor(s): -
626 ## Within-subjects factor(s):  A_, B_
627 ## Covariate(s):              -
628 ##
629 ##           MS    MSE df1 df2      F      p      2p [90% CI of 2p]      2G
630 ##
631 ## A_           0.237 0.035    1 155   6.708   .011 *      .041 [.005, .104] .010
632 ## B_           2.932 0.042    1 155  69.938 <.001 ***   .311 [.216, .400] .110
633 ## A_ * B_     0.696 0.031    1 155  22.782 <.001 ***   .128 [.057, .213] .028
634 ##
635 ## MSE = mean square error (the residual variance of the linear model)
636 ## 2p = partial eta-squared = SS / (SS + SSE) = F * df1 / (F * df1 + df2)
637 ## 2p = partial omega-squared = (F - 1) * df1 / (F * df1 + df2 + 1)
638 ## 2G = generalized eta-squared (see Olejnik & Algina, 2003)
639 ## Cohen's f2 = 2p / (1 - 2p)

```

```

640 ##
641 ## Levene's Test for Homogeneity of Variance:
642 ## No between-subjects factors. No need to do the Levene's test.
643 ##
644 ## Mauchly's Test of Sphericity:
645 ## The repeated measures have only two levels. The assumption of sphericity is always me

646 ##
647 ## ===== ANOVA (Within-Subjects Design) =====
648 ##
649 ## Descriptives:
650 ##
651 ##   "A_" "B_"  Mean    S.D.    n
652 ##
653 ##  SS3. Forg 0.071 (0.198) 156
654 ##  SS3. Mem  0.315 (0.171) 156
655 ##  SS6. Forg 0.021 (0.684) 156
656 ##  SS6. Mem  0.168 (0.329) 156
657 ##
658 ## Total sample size: N = 156
659 ##
660 ## ANOVA Table:
661 ## Dependent variable(s):      A_SS3&B_Forg, A_SS3&B_Mem, A_SS6&B_Forg, A_SS6&B_Mem
662 ## Between-subjects factor(s): -
663 ## Within-subjects factor(s):  A_, B_
664 ## Covariate(s):              -
665 ##
666 ##           MS    MSE df1 df2      F      p      ^2p [90% CI of ^2p]      ^2G

```

```

667 ##
668 ## A_          1.515 0.149    1 155 10.188  .002 **    .062 [.015, .132] .015
669 ## B_          5.952 0.147    1 155 40.571 <.001 ***   .207 [.121, .298] .056
670 ## A_ * B_    0.365 0.123    1 155  2.975  .087 .     .019 [.000, .068] .004
671 ##
672 ## MSE = mean square error (the residual variance of the linear model)
673 ## 2p = partial eta-squared = SS / (SS + SSE) = F * df1 / (F * df1 + df2)
674 ## 2p = partial omega-squared = (F - 1) * df1 / (F * df1 + df2 + 1)
675 ## 2G = generalized eta-squared (see Olejnik & Algina, 2003)
676 ## Cohen's f2 = 2p / (1 - 2p)
677 ##
678 ## Levene's Test for Homogeneity of Variance:
679 ## No between-subjects factors. No need to do the Levene's test.
680 ##
681 ## Mauchly's Test of Sphericity:
682 ## The repeated measures have only two levels. The assumption of sphericity is always me
683 ##
684 ## ===== ANOVA (Within-Subjects Design) =====
685 ##
686 ## Descriptives:
687 ##
688 ## "A_" "B_" Mean    S.D.    n
689 ##
690 ## SS3. Forg 0.361 (0.706) 156
691 ## SS3. Mem  0.660 (0.341) 156
692 ## SS6. Forg 0.232 (1.573) 156
693 ## SS6. Mem  0.483 (0.602) 156

```



```

694 ##
695 ## Total sample size: N = 156
696 ##
697 ## ANOVA Table:
698 ## Dependent variable(s):      A_SS3&B_Forg, A_SS3&B_Mem, A_SS6&B_Forg, A_SS6&B_Mem
699 ## Between-subjects factor(s): -
700 ## Within-subjects factor(s):  A_, B_
701 ## Covariate(s):              -
702 ##
703 ##           MS      MSE df1 df2      F      p      2p [90% CI of 2p]      2G
704 ##
705 ## A_           3.682 0.885   1 155   4.160   .043 *      .026 [.000, .081] .007
706 ## B_          11.803 0.882   1 155  13.376 <.001 ***   .079 [.024, .155] .022
707 ## A_ * B_     0.089 0.848   1 155   0.105   .746      .001 [.000, .021] .000
708 ##
709 ## MSE = mean square error (the residual variance of the linear model)
710 ## 2p = partial eta-squared = SS / (SS + SSE) = F * df1 / (F * df1 + df2)
711 ## 2p = partial omega-squared = (F - 1) * df1 / (F * df1 + df2 + 1)
712 ## 2G = generalized eta-squared (see Olejnik & Algina, 2003)
713 ## Cohen's f2 = 2p / (1 - 2p)
714 ##
715 ## Levene's Test for Homogeneity of Variance:
716 ## No between-subjects factors. No need to do the Levene's test.
717 ##
718 ## Mauchly's Test of Sphericity:
719 ## The repeated measures have only two levels. The assumption of sphericity is always me
720 ##

```

```

721 ## ===== ANOVA (Within-Subjects Design) =====
722 ##
723 ## Descriptives:
724 ##
725 ##      "A_" "B_"  Mean    S.D.    n
726 ##
727 ##  Mixed. Forg 0.399 (1.990) 156
728 ##  Mixed. Mem  0.413 (0.868) 156
729 ##  SS6.   Forg 0.232 (1.573) 156
730 ##  SS6.   Mem  0.483 (0.602) 156
731 ##
732 ## Total sample size: N = 156
733 ##
734 ## ANOVA Table:
735 ## Dependent variable(s):      A_Mixed&B_Forg, A_Mixed&B_Mem, A_SS6&B_Forg, A_SS6&B_Mem
736 ## Between-subjects factor(s): -
737 ## Within-subjects factor(s):  A_, B_
738 ## Covariate(s):              -
739 ##
740 ##           MS    MSE df1 df2      F      p      2p [90% CI of 2p]      2G
741 ##
742 ## A_          0.369 1.719    1 155 0.215  .644      .001 [.000, .026] .000
743 ## B_          2.759 1.977    1 155 1.396  .239      .009 [.000, .049] .002
744 ## A_ * B_     2.177 1.928    1 155 1.129  .290      .007 [.000, .045] .002
745 ##
746 ## MSE = mean square error (the residual variance of the linear model)
747 ## 2p = partial eta-squared = SS / (SS + SSE) = F * df1 / (F * df1 + df2)

```

```

748 ##  $\eta^2_p$  = partial omega-squared = (F - 1) * df1 / (F * df1 + df2 + 1)
749 ##  $\eta^2_G$  = generalized eta-squared (see Olejnik & Algina, 2003)
750 ## Cohen's  $f^2$  =  $\eta^2_p$  / (1 -  $\eta^2_p$ )
751 ##
752 ## Levene's Test for Homogeneity of Variance:
753 ## No between-subjects factors. No need to do the Levene's test.
754 ##
755 ## Mauchly's Test of Sphericity:
756 ## The repeated measures have only two levels. The assumption of sphericity is always me

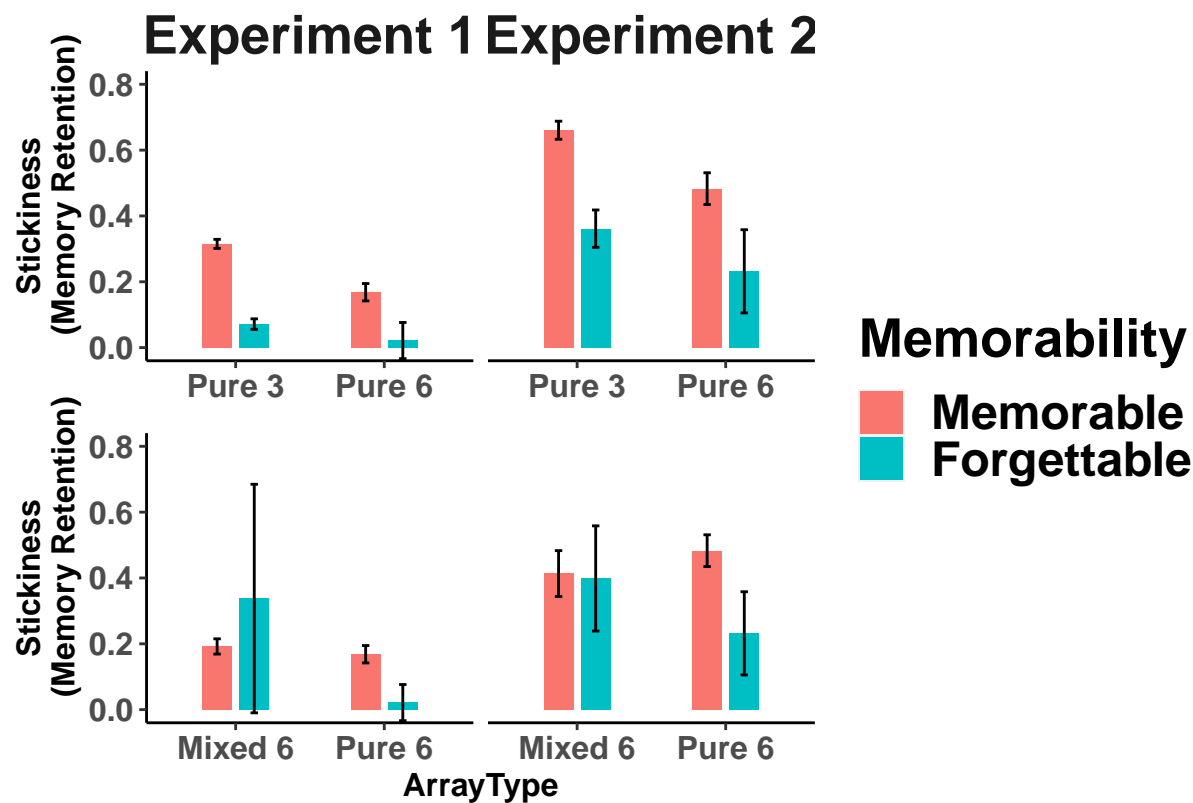
757 ##
758 ## ===== ANOVA (Within-Subjects Design) =====
759 ##
760 ## Descriptives:
761 ##
762 ##      "A_" "B_"  Mean    S.D.    n
763 ##
764 ## Mixed. Forg 0.337 (4.323) 156
765 ## Mixed. Mem  0.192 (0.289) 156
766 ## SS6.   Forg 0.021 (0.684) 156
767 ## SS6.   Mem  0.168 (0.329) 156
768 ##
769 ## Total sample size: N = 156
770 ##
771 ## ANOVA Table:
772 ## Dependent variable(s):      A_Mixed&B_Forg, A_Mixed&B_Mem, A_SS6&B_Forg, A_SS6&B_Mem
773 ## Between-subjects factor(s): -
774 ## Within-subjects factor(s):  A_, B_

```

```

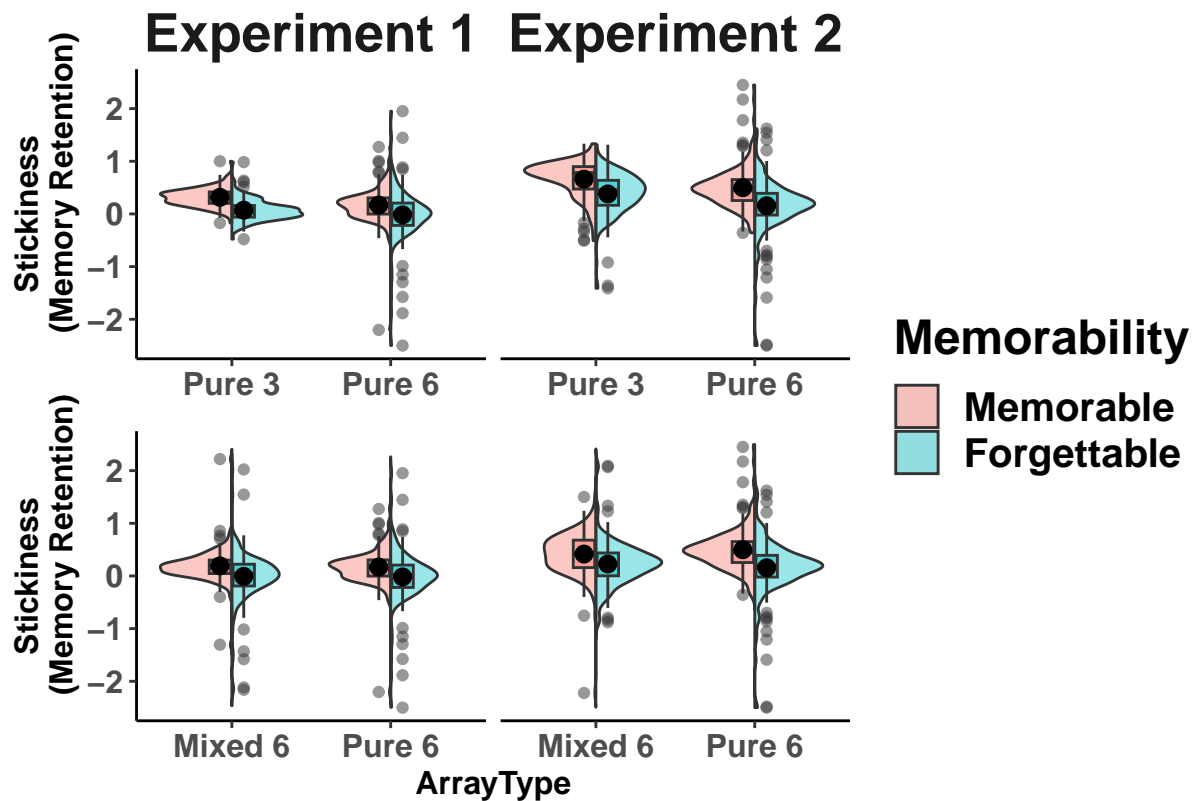
775 ## Covariate(s):          -
776 ##
777 ##           MS      MSE df1 df2      F      p      2p [90% CI of 2p]      2G
778 ##
779 ## A_          4.504 5.076    1 155 0.887  .348          .006 [.000, .041] .001
780 ## B_          0.000 4.383    1 155 0.000  .996          .000 [.000, .000] .000
781 ## A_ * B_    3.335 4.540    1 155 0.735  .393          .005 [.000, .039] .001
782 ##
783 ## MSE = mean square error (the residual variance of the linear model)
784 ## 2p = partial eta-squared = SS / (SS + SSE) = F * df1 / (F * df1 + df2)
785 ## 2p = partial omega-squared = (F - 1) * df1 / (F * df1 + df2 + 1)
786 ## 2G = generalized eta-squared (see Olejnik & Algina, 2003)
787 ## Cohen's f2 = 2p / (1 - 2p)
788 ##
789 ## Levene's Test for Homogeneity of Variance:
790 ## No between-subjects factors. No need to do the Levene's test.
791 ##
792 ## Mauchly's Test of Sphericity:
793 ## The repeated measures have only two levels. The assumption of sphericity is always me

```



794

```
795 ## Warning: Removed 9 rows containing non-finite values (`stat_ydensity()`).  
  
796 ## Warning: Removed 9 rows containing non-finite values (`stat_boxplot()`).  
  
797 ## Warning: Removed 9 rows containing non-finite values (`stat_summary()`).  
  
798 ## Warning: Removed 15 rows containing non-finite values (`stat_ydensity()`).  
  
799 ## Warning: Removed 15 rows containing non-finite values (`stat_boxplot()`).  
  
800 ## Warning: Removed 15 rows containing non-finite values (`stat_summary()`).  
  
801 ## Warning: Removed 115 rows containing missing values (`geom_split_violin()`).
```



## Discussion

### Efficiency benefit

For the efficiency benefit of memorable stimuli, memorable stimuli benefit from existing long-term memory representations. Existing long-term memory representations can assist working memory performance by reducing the need for active maintenance of stimuli in visual working memory.

Also, the hypothesis does not fully explain the findings because both memorable and forgettable stimuli were presented equally in the experiments. Memorable and forgettable. Future studies should explore cognitive mechanisms that allow efficient representations of novel but memorable stimuli.

## Competitive benefit

we speculate that differences in attentional allocation during encoding might play a role in this competitive advantage. memorable stimuli are more likely to attract attention, leading to the observed competitive advantage in VWM.

However, it remains unclear what specifically attracts attention to memorable stimuli. A recent study by (Bainbridge, 2020) suggests that perceptual saliency is unlikely to be the sole factor, as memorable stimuli do not capture attention in a stimulus-driven manner. Therefore, attentional allocation differences between memorable and forgettable stimuli are likely to occur post-perceptually.

Importantly, while the competitive benefit was observed in VWM, it did not translate into VLTM. Therefore, although memorable stimuli may attract more attention, attentional allocation alone does not fully explain their memorability.

## Stickiness

The study's findings indicate that memorable stimuli are more "stickier" or better retained in visual working memory (VWM) compared to forgettable stimuli. However, the underlying mechanisms that produce the memorability benefit within VWM and the stickiness benefit might be dissociable. Recent research suggests that despite differences in VWM capacity, the rate at which information remains in very long-term memory (VLTM) is comparable between young adults and school-aged children, indicating dissociable mechanisms (Forsberg, Guitard, Adams, Pattanakul, & Cowan, 2022). Moreover, the rate of encoding into VWM can be independent of the rate of forgetting.

Future research should investigate whether the mechanisms leading to memorability and stickiness benefits are distinct and how memorable stimuli resist interference or better consolidate in VWM, potentially through robust decay resistance or a combination of both

837 factors. Additional studies are needed to shed light on the developmental aspects of the  
838 stickiness of memorable and forgettable stimuli.



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