

Barkan et al (2012) data analysis using randomly generated data - V4

Yvonne JIN

7/14/2022

```
df <- read_sav("NOCHECK - [RRR] Barkan et al. (2012) Ethical dissonance  
[Yvonne Yaqi Jin] - V2_June 22, 2022_09.35.sav")
```

Study response processing

General measurements score calculation: Manipulation check and MASC uses averaged score of individual items.

Manipulation Check - Self Esteem Scale

```
df$ManiCheck <- df %>% dplyr::select(starts_with("ManiCheck")) %>% rowMeans()  
# Add package name before function "select"  
# to prevent confusion with same name functions in other packages
```

Study 3 MASC - Multi Aspect Scale of Cheating

```
df$MASC_set1 <- df %>% dplyr::select(starts_with("MASC_set1")) %>% rowMeans()  
df$MASC_set2 <- df %>% dplyr::select(starts_with("MASC_set2")) %>% rowMeans()  
df$MASC_set3 <- df %>% dplyr::select(starts_with("MASC_set3")) %>% rowMeans()
```

Study 3 BIDR - The Balanced Inventory of Desirable Responding

Scoring: Respondents are asked to rate the 40-items on a 7 point scale according to their level of agreement with the item (stated as propositions). The scoring key is balanced. All even number statements of self-deceptive positivity (former 20 statements) are negatively keyed. All odd number statements of impression management (latter 20 statements) are negatively keyed. After reversing the negatively keyed items, one point is added for each extreme response (6 or 7). Total scores on the both constructs can range from 0 to 20. Thus, high scores are only attained by respondents who give exaggeratedly desirable responses. All 40 items may be summed to give an overall measure of social desirable responding.

```
#-----#  
### self deceptive positivity  
  
# positively keyed statements  
BIDR_self_deceptive_odd <- df %>%  
dplyr::select("BIDR_Self_deceptive_2", "BIDR_Self_deceptive_4", "BIDR_Self_dece  
ptive_6", "BIDR_Self_deceptive_8", "BIDR_Self_deceptive_10", "BIDR_Self_deceptiv  
e_12", "BIDR_Self_deceptive_14", "BIDR_Self_deceptive_16", "BIDR_Self_deceptive_  
18", "BIDR_Self_deceptive_20")
```

```

# iterate the item to avoid counting variables like
"BIDR_Self_deceptive_DO_20"

BIDR_self_deceptive_odd_recode <-
as.data.frame(ifelse(BIDR_self_deceptive_odd > 5, 1,0))

# negatively keyed statements
BIDR_self_deceptive_even <- df %>%
dplyr::select("BIDR_Self_deceptive_1","BIDR_Self_deceptive_3","BIDR_Self_dece
ptive_5","BIDR_Self_deceptive_7","BIDR_Self_deceptive_9","BIDR_Self_deceptive
_11","BIDR_Self_deceptive_13","BIDR_Self_deceptive_15","BIDR_Self_deceptive_1
7","BIDR_Self_deceptive_19")

BIDR_self_deceptive_even_recode <-
as.data.frame(ifelse(BIDR_self_deceptive_even < 3, 1,0))

#-----#
### impression management

# positively keyed statements
BIDR_impre_manage_even <- df %>%

dplyr::select("BIDR_Impre_manage_2","BIDR_Impre_manage_4","BIDR_Impre_manage_
6","BIDR_Impre_manage_8","BIDR_Impre_manage_10","BIDR_Impre_manage_12","BIDR_
Impre_manage_14","BIDR_Impre_manage_16","BIDR_Impre_manage_18","BIDR_Impre_ma
nage_20")

BIDR_impre_manage_even_recode <- as.data.frame(ifelse(BIDR_impre_manage_even
> 5, 1,0))

# negatively keyed statements
BIDR_impre_manage_odd <- df %>%
dplyr::select("BIDR_Impre_manage_1","BIDR_Impre_manage_3","BIDR_Impre_manage_
5","BIDR_Impre_manage_7","BIDR_Impre_manage_9","BIDR_Impre_manage_11","BIDR_I
mpre_manage_13","BIDR_Impre_manage_15","BIDR_Impre_manage_17","BIDR_Impre_man
age_19")
# iterate the item to avoid counting variables like "BIDR_Impre_manage_DO_11"

BIDR_impre_manage_odd_recode <- as.data.frame(ifelse(BIDR_impre_manage_odd <
3, 1,0))

#-----#
# merge all recoded score into one dataframe

recode_BIDR_self_deceptive <- BIDR_self_deceptive_odd_recode %>%
  cbind(BIDR_self_deceptive_even_recode)

recode_BIDR_impre_manage <- BIDR_impre_manage_odd_recode %>%
  cbind(BIDR_impre_manage_even_recode)

```

```
# add up recoded score to form an overall score, add to main dataframe
df$BIDR_self_deceptive <- recode_BIDR_self_deceptive %>% rowSums()
df$BIDR_impre_manage <- recode_BIDR_impre_manage %>% rowSums()
```

Condition marking

Conditions allocated for each participants and the order of experiments presented are marked in Qualtrics by variables starting with "FL".

```
# find block order of conditions
block_order <- df %>% dplyr::select(starts_with("FL"))
colnames(block_order)

## [1] "FL_9_DO_RecallManipulation_EthicalDissonancebyWriting_UnethicalB"
## [2] "FL_9_DO_RecallManipulation_EthicalDissonanceWithoutWriting"
## [3] "FL_9_DO_RecallManipulation_WorthyConduct"
## [4] "FL_9_DO_RecallManipulation_Neutral"
## [5] "FL_9_DO_RecallManipulation_NegativeValence"
## [6] "FL_11_DO_Experiment1_HiringDecisionasHR"
## [7] "FL_11_DO_FL_25"
## [8] "FL_25_DO_Experiment2scenario1_JobInterviewAdvice"
## [9] "FL_25_DO_FL_27"
## [10] "FL_27_DO_Experiment2scenario2_ExchangingProductAdvice_Female"
## [11] "FL_27_DO_Experiment2scenario2_ExchangingProductAdvice_Male"
## [12] "FL_38_DO_MultiAspectScaleofCheatingMASC_Set1"
## [13] "FL_38_DO_MultiAspectScaleofCheatingMASC_Set2"
## [14] "FL_38_DO_MultiAspectScaleofCheatingMASC_Set3"
## [15] "FL_38_DO_BalancedInventoryofDesirableRespondingBIDR_SelfDeceptiv"
## [16] "FL_38_DO_BalancedInventoryofDesirableRespondingBIDR_ImpressionMa"

# Mark study presentation order
df$study_order = ifelse(df$FL_11_DO_Experiment1_HiringDecisionasHR ==
1, "Exp1First", "Exp2First")
```

Slicing dataframe into five recall conditions.

```
## ethical dissonance & writing response
ethi_dis_write <- df %>%
filter(FL_9_DO_RecallManipulation_EthicalDissonancebyWriting_UnethicalB == 1)
%>%
  dplyr::select("study_order",
    "ManiCheck", # precalculated average
    starts_with("Exp1"),
    starts_with("Exp2"),
    "MASC_set1", "MASC_set2", "MASC_set3", # precalculated average
    "BIDR_self_deceptive", "BIDR_impre_manage", # precalculated
    age:CountryName) %>% #demographic data and condition marker
mutate(condition = "Dissonance_write")

## ethical dissonance & writing response
```

```

ethi_dis_nowrite <- df %>%
filter(FL_9_DO_RecallManipulation_EthicalDissonanceWithoutWriting == 1) %>%
  dplyr::select("study_order",
    "ManiCheck",
    starts_with("Exp1"),
    starts_with("Exp2"),
    "MASC_set1", "MASC_set2", "MASC_set3",
    "BIDR_self_deceptive", "BIDR_impre_manage",
    age:CountryName) %>%
mutate(condition = "Dissonance_no_write")

## control: worthy conduct
con_worthy <- df %>% filter(FL_9_DO_RecallManipulation_WorthyConduct == 1)
%>%
  dplyr::select("study_order",
    "ManiCheck",
    starts_with("Exp1"),
    starts_with("Exp2"),
    "MASC_set1", "MASC_set2", "MASC_set3",
    "BIDR_self_deceptive", "BIDR_impre_manage",
    age:CountryName) %>%
mutate(condition = "Worthy") # control condition: worthy conduct

## control: neutral event
con_neutral <- df %>% filter(FL_9_DO_RecallManipulation_Neutral == 1) %>%
  dplyr::select("study_order",
    "ManiCheck",
    starts_with("Exp1"),
    starts_with("Exp2"),
    "MASC_set1", "MASC_set2", "MASC_set3",
    "BIDR_self_deceptive", "BIDR_impre_manage",
    age:CountryName) %>%
mutate(condition = "Neutral") # control condition: Neutral behavior

## control: neutral event
con_neg <- df %>% filter(FL_9_DO_RecallManipulation_NegativeValence ==1) %>%
  dplyr::select("study_order",
    "ManiCheck",
    starts_with("Exp1"),
    starts_with("Exp2"),
    "MASC_set1", "MASC_set2", "MASC_set3",
    "BIDR_self_deceptive", "BIDR_impre_manage",
    age:CountryName) %>%
mutate(condition = "Negative") # control condition: negative valence

```

Combine data segments with condition marking.

```

cleaned_df <- ethi_dis_write %>%
  rbind(ethi_dis_nowrite) %>%
  rbind(con_worthy) %>%

```

```

rbind(con_neutral) %>%
rbind(con_neg)

colnames(cleaned_df)

## [1] "study_order"      "ManiCheck"      "Exp1_prob_hiring"
## [4] "Exp1_loyalty"     "Exp1_honesty"   "Exp2_S1_seen_wrong"
## [7] "Exp2_S1_self_action" "Exp2_S1_guide_other" "Exp2_S2F_seen_wrong"
## [10] "Exp2_S2F_self_action" "Exp2_S2F_guide_other" "Exp2_S2M_seen_wrong"
## [13] "Exp2_S2M_self_action" "Exp2_S2M_guide_other" "MASC_set1"
## [16] "MASC_set2"        "MASC_set3"      "BIDR_self_deceptive"
## [19] "BIDR_impre_manage" "age"            "gender"
## [22] "origcount"        "residence"      "soc_class"
## [25] "engunder"         "funnel_pay"     "assignmentId"
## [28] "hitId"            "CountryCode"    "CountryName"
## [31] "condition"

```

Response formatting for study 1 and study 2 DVs

Change the data type of DVs to numeric, so the ANOVA test and ggstatsplot works properly.

```

DVs <- c("Exp1_prob_hiring", "Exp1_loyalty", "Exp1_honesty",
"Exp2_S1_seen_wrong", "Exp2_S1_self_action", "Exp2_S1_guide_other",
"Exp2_S2F_seen_wrong", "Exp2_S2F_self_action", "Exp2_S2F_guide_other",
"Exp2_S2M_seen_wrong", "Exp2_S2M_self_action", "Exp2_S2M_guide_other")
cleaned_df[DVs] <- apply(cleaned_df[DVs], as.numeric)

```

Merge study 2 scenario 2, female and male case together.

```

cleaned_df$Exp2_S2_seen_wrong_T2 =
coalesce(cleaned_df$Exp2_S2F_seen_wrong, cleaned_df$Exp2_S2M_seen_wrong)
cleaned_df$Exp2_S2_self_action_T2 =
coalesce(cleaned_df$Exp2_S2F_self_action, cleaned_df$Exp2_S2M_self_action)
cleaned_df$Exp2_S2_guide_other_T2 =
coalesce(cleaned_df$Exp2_S2F_guide_other, cleaned_df$Exp2_S2M_guide_other)

# output cleaned data
write.csv(cleaned_df, "stimulated_cleaned_data.csv", fileEncoding = "UTF-8")

```

Descriptive data

Manipulation Check

overall

```
jmv::descriptives(data = cleaned_df, vars = vars(ManiCheck))
```

Descriptives

		ManiCheck
N		1000
Missing		0
Mean		2.9947
Median		3.0000
Standard deviation		0.55788
Minimum		1.5000
Maximum		4.5000

by condition

```
jmv::descriptives(  
  formula = ManiCheck ~ condition,  
  data = cleaned_df,  
  missing = FALSE,  
  median = FALSE,  
  variance = TRUE,  
  min = FALSE,  
  max = FALSE,  
  ci = TRUE)
```

Descriptives			
		condition	ManiCheck
N		Dissonance_no_write	199
		Dissonance_write	200
		Negative	200
		Neutral	201
		Worthy	200
Mean		Dissonance_no_write	3.0235
		Dissonance_write	2.9975
		Negative	2.9250
		Neutral	2.9751
		Worthy	3.0525
95% CI mean lower bound		Dissonance_no_write	2.9396
		Dissonance_write	2.9205
		Negative	2.8454
		Neutral	2.8993
		Worthy	2.9833
95% CI mean upper bound		Dissonance_no_write	3.1073
		Dissonance_write	3.0745
		Negative	3.0046
		Neutral	3.0509
		Worthy	3.1217
Standard deviation		Dissonance_no_write	0.60373
		Dissonance_write	0.55554
		Negative	0.57462
		Neutral	0.54817
		Worthy	0.49946
Variance		Dissonance_no_write	0.36449
		Dissonance_write	0.30862
		Negative	0.33019
		Neutral	0.30049
		Worthy	0.24946

```
# Study 1
## total
jmv::descriptives(data = cleaned_df, vars = vars(Exp1_prob_hiring, Exp1_loyalty, Exp1_honesty))
```

```
## Descriptives
```

	Exp1_prob_hiring	Exp1_loyalty	Exp1_honesty
N	1000	1000	1000
Missing	0	0	0
Mean	4.9990	4.9600	4.9280
Median	5.0000	5.0000	5.0000
Standard deviation	2.6122	2.5991	2.5560
Minimum	1.0000	1.0000	1.0000
Maximum	9.0000	9.0000	9.0000

```
## by condition
jmv::descriptives(
  formula = Exp1_prob_hiring + Exp1_loyalty + Exp1_honesty ~ condition,
  data = cleaned_df,
  missing = FALSE, median = FALSE)
```


Descriptives

##		condition	Exp1_prob_hiring	Exp1_loyalty	Exp1_honesty
##	N	Dissonance_no_write	199	199	199
##		Dissonance_write	200	200	200
##		Negative	200	200	200
##		Neutral	201	201	201
##		Worthy	200	200	200
##	Mean	Dissonance_no_write	4.9849	4.9146	5.0402
##		Dissonance_write	5.1450	4.8450	4.9800
##		Negative	4.9450	5.2400	4.7150
##		Neutral	5.0398	4.8607	4.8308
##		Worthy	4.8800	4.9400	5.0750
##	Standard deviation	Dissonance_no_write	2.5256	2.6738	2.6871
##		Dissonance_write	2.5996	2.6450	2.5381
##		Negative	2.6414	2.5564	2.5389
##		Neutral	2.6605	2.5594	2.5261
##		Worthy	2.6497	2.5650	2.4941
##	Minimum	Dissonance_no_write	1.0000	1.0000	1.0000
##		Dissonance_write	1.0000	1.0000	1.0000
##		Negative	1.0000	1.0000	1.0000
##		Neutral	1.0000	1.0000	1.0000
##		Worthy	1.0000	1.0000	1.0000
##	Maximum	Dissonance_no_write	9.0000	9.0000	9.0000
##		Dissonance_write	9.0000	9.0000	9.0000
##		Negative	9.0000	9.0000	9.0000
##		Neutral	9.0000	9.0000	9.0000
##		Worthy	9.0000	9.0000	9.0000

```
# Study 2 scenario 1
## total
jmv::descriptives(
  data = cleaned_df,
  vars = vars(Exp2_S1_seen_wrong, Exp2_S1_self_action, Exp2_S1_guide_other),
  missing = FALSE, median = FALSE)

## Descriptives
##
##      Exp2_S1_seen_wrong      Exp2_S1_self_action      Exp2_S1_guide_other
##
##      N              1000              1000              1000
##      Mean            5.1420            5.0940            5.1420
##      Standard deviation 2.6040            2.6363            2.5870
##      Minimum          1.0000            1.0000            1.0000
##      Maximum          9.0000            9.0000            9.0000
##
## by condition
jmv::descriptives(
  formula = Exp2_S1_seen_wrong + Exp2_S1_self_action + Exp2_S1_guide_other ~ condition,
  data = cleaned_df,
  missing = FALSE, median = FALSE)
```

## Descriptives					
		condition	Exp2_S1_seen_wrong	Exp2_S1_self_action	Exp2_S1_guide_other
## N		Dissonance_no_write	199	199	199
		Dissonance_write	200	200	200
		Negative	200	200	200
		Neutral	201	201	201
		Worthy	200	200	200
## Mean		Dissonance_no_write	5.0352	5.0553	5.1005
		Dissonance_write	4.8900	4.9850	5.2550
		Negative	5.1700	5.0150	5.2300
		Neutral	5.1294	5.3632	5.0100
		Worthy	5.4850	5.0500	5.1150
## Standard deviation		Dissonance_no_write	2.6080	2.5863	2.5366
		Dissonance_write	2.5926	2.6627	2.5598
		Negative	2.6621	2.6362	2.6233
		Neutral	2.5046	2.6538	2.6476
		Worthy	2.6391	2.6500	2.5836
## Minimum		Dissonance_no_write	1.0000	1.0000	1.0000
		Dissonance_write	1.0000	1.0000	1.0000
		Negative	1.0000	1.0000	1.0000
		Neutral	1.0000	1.0000	1.0000
		Worthy	1.0000	1.0000	1.0000
## Maximum		Dissonance_no_write	9.0000	9.0000	9.0000
		Dissonance_write	9.0000	9.0000	9.0000
		Negative	9.0000	9.0000	9.0000
		Neutral	9.0000	9.0000	9.0000
		Worthy	9.0000	9.0000	9.0000

```
# Study scenario 2
```

```
## total
```

```
jmv::descriptives(  
  data = cleaned_df,  
  vars = vars(Exp2_S2_seen_wrong_T2, Exp2_S2_self_action_T2, Exp2_S2_guide_other_T2),  
  missing = FALSE, median = FALSE)
```

```
## Descriptives
```

```
##
```

	Exp2_S2_seen_wrong_T2	Exp2_S2_self_action_T2	Exp2_S2_guide_other_T2
##			
## N	1000	1000	1000
## Mean	5.0620	5.0780	4.9700
## Standard deviation	2.4804	2.5827	2.6130
## Minimum	1.0000	1.0000	1.0000
## Maximum	9.0000	9.0000	9.0000

```
##
```

```
## by condition
```

```
jmv::descriptives(  
  formula = Exp2_S2_seen_wrong_T2 + Exp2_S2_self_action_T2 + Exp2_S2_guide_other_T2 ~ condition,  
  data = cleaned_df,  
  missing = FALSE, median = FALSE)
```

```
## Descriptives
```

```
##
```

	condition	Exp2_S2_seen_wrong_T2	Exp2_S2_self_action_T2	Exp2_S2_guide_other_T2
##				
## N	Dissonance_no_write	199	199	199
##	Dissonance_write	200	200	200
##	Negative	200	200	200
##	Neutral	201	201	201
##	Worthy	200	200	200
## Mean	Dissonance_no_write	5.2663	4.8442	5.1508
##	Dissonance_write	5.4100	5.0050	4.7400
##	Negative	4.8350	5.2050	5.3500
##	Neutral	5.0299	5.0547	4.4876
##	Worthy	4.7700	5.2800	5.1250
## Standard deviation	Dissonance_no_write	2.4109	2.6055	2.5893
##	Dissonance_write	2.3386	2.5053	2.6357
##	Negative	2.5258	2.7295	2.5770

##		Neutral	2.5766	2.6042	2.6117
##		Worthy	2.5057	2.4641	2.5832
##	Minimum	Dissonance_no_write	1.0000	1.0000	1.0000
##		Dissonance_write	1.0000	1.0000	1.0000
##		Negative	1.0000	1.0000	1.0000
##		Neutral	1.0000	1.0000	1.0000
##		Worthy	1.0000	1.0000	1.0000
##	Maximum	Dissonance_no_write	9.0000	9.0000	9.0000
##		Dissonance_write	9.0000	9.0000	9.0000
##		Negative	9.0000	9.0000	9.0000
##		Neutral	9.0000	9.0000	9.0000
##		Worthy	9.0000	9.0000	9.0000
##					

Study 3

total

```
jmv::descriptives(
  data = cleaned_df,
  vars = vars(MASC_set1, MASC_set2, MASC_set3, BIDR_self_deceptive, BIDR_impre_manage))
```

Descriptives

	MASC_set1	MASC_set2	MASC_set3	BIDR_self_deceptive	BIDR_impre_manage
N	1000	1000	1000	1000	1000
Missing	0	0	0	0	0
Mean	4.2504	3.7433	4.0185	5.7450	5.6970
Median	4.2500	3.7500	4.0000	6.0000	6.0000
Standard deviation	0.36106	0.40792	1.4358	2.0323	1.9988
Minimum	3.1250	2.5833	1.0000	1.0000	1.0000
Maximum	5.3125	4.9167	7.0000	13.000	13.000

condition

```
jmv::descriptives(
  formula = MASC_set1 + MASC_set2 + MASC_set3 + BIDR_self_deceptive + BIDR_impre_manage ~ condition,
  data = cleaned_df,
  missing = FALSE, median = FALSE)
```

Descriptives

##

##		condition	MASC_set1	MASC_set2	MASC_set3	BIDR_self_deceptive	BIDR_impre_manage
##							
##	N	Dissonance_no_write	199	199	199	199	199
##		Dissonance_write	200	200	200	200	200
##		Negative	200	200	200	200	200
##		Neutral	201	201	201	201	201
##		Worthy	200	200	200	200	200
##	Mean	Dissonance_no_write	4.2349	3.7638	4.0653	5.8141	5.7337
##		Dissonance_write	4.2606	3.7846	4.0050	5.8150	5.7200
##		Negative	4.2606	3.7033	4.0500	5.6550	5.6550
##		Neutral	4.2525	3.7430	4.0373	5.7612	5.6915
##		Worthy	4.2431	3.7221	3.9350	5.6800	5.6850
##	Standard deviation	Dissonance_no_write	0.36058	0.36706	1.4867	1.9438	2.1259
##		Dissonance_write	0.35328	0.41757	1.4562	2.1480	1.8866
##		Negative	0.35978	0.43863	1.3800	2.0899	1.9965
##		Neutral	0.38679	0.42743	1.4688	1.9138	2.1271
##		Worthy	0.34636	0.38305	1.3948	2.0710	1.8609
##	Minimum	Dissonance_no_write	3.3750	2.8333	1.0000	1.0000	1.0000
##		Dissonance_write	3.2500	2.5833	1.0000	2.0000	1.0000
##		Negative	3.1250	2.7500	1.0000	1.0000	1.0000
##		Neutral	3.1875	2.5833	1.0000	1.0000	1.0000
##		Worthy	3.1875	2.5833	1.0000	2.0000	2.0000
##	Maximum	Dissonance_no_write	5.0000	4.6667	7.0000	12.000	13.000
##		Dissonance_write	5.1250	4.9167	7.0000	13.000	10.000
##		Negative	5.2500	4.9167	7.0000	12.000	11.000
##		Neutral	5.3125	4.9167	7.0000	13.000	12.000
##		Worthy	5.1250	4.7500	7.0000	12.000	11.000

```
# Age and Gender distribution
```

```
jmv::descriptives(  
  data = cleaned_df,  
  vars = vars(age, gender))
```

```
##
```

```
## DESCRIPTIVES
```

```
##
```

```
## Descriptives
```

```
##
```

```
##
```

	age	gender
--	-----	--------

```
##
```

```
## N 1000 1000
```

```
## Missing 0 0
```

```
## Mean 50.430 2.5110
```

```
## Median 51.000 3.0000
```

```
## Standard deviation 28.796 1.1077
```

```
## Minimum 0.0000 1.0000
```

```
## Maximum 100.00 4.0000
```

```
##
```

```
# plot descriptive table
```

```
#tableby.control()
```

```
#table_one <- tableby(age ~ ., data = cleaned_df)
```

```
#table_one
```

```
#summary(table_one, title = "Descriptive Data")
```

Planned Analysis - Main Analysis

Manipulation check - ANOVA

```
jmv::ANOVA(  
  formula = ManiCheck ~ condition,  
  data = cleaned_df,  
  effectSize = "eta",  
  modelTest = TRUE,  
  homo = TRUE,  
  postHocES = "d",  
  postHocEsCi = TRUE,  
  #emMeans = ~ condition,  
  emmTables = TRUE)
```

```
## ANOVA - ManiCheck
```

```
##
```

	Sum of Squares	df	Mean Square	F	p	η^2
Overall model	1.8829	4	0.47072	1.5156	0.19545	
condition	1.8829	4	0.47072	1.5156	0.19545	0.00606
Residuals	309.0331	995	0.31059			

```
##
```

```
## ASSUMPTION CHECKS
```

```
##
```

```
## Homogeneity of Variances Test (Levene's)
```

```
##
```

```
##
```

F	df1	df2	p
2.6690	4	995	0.03105

```
##
```

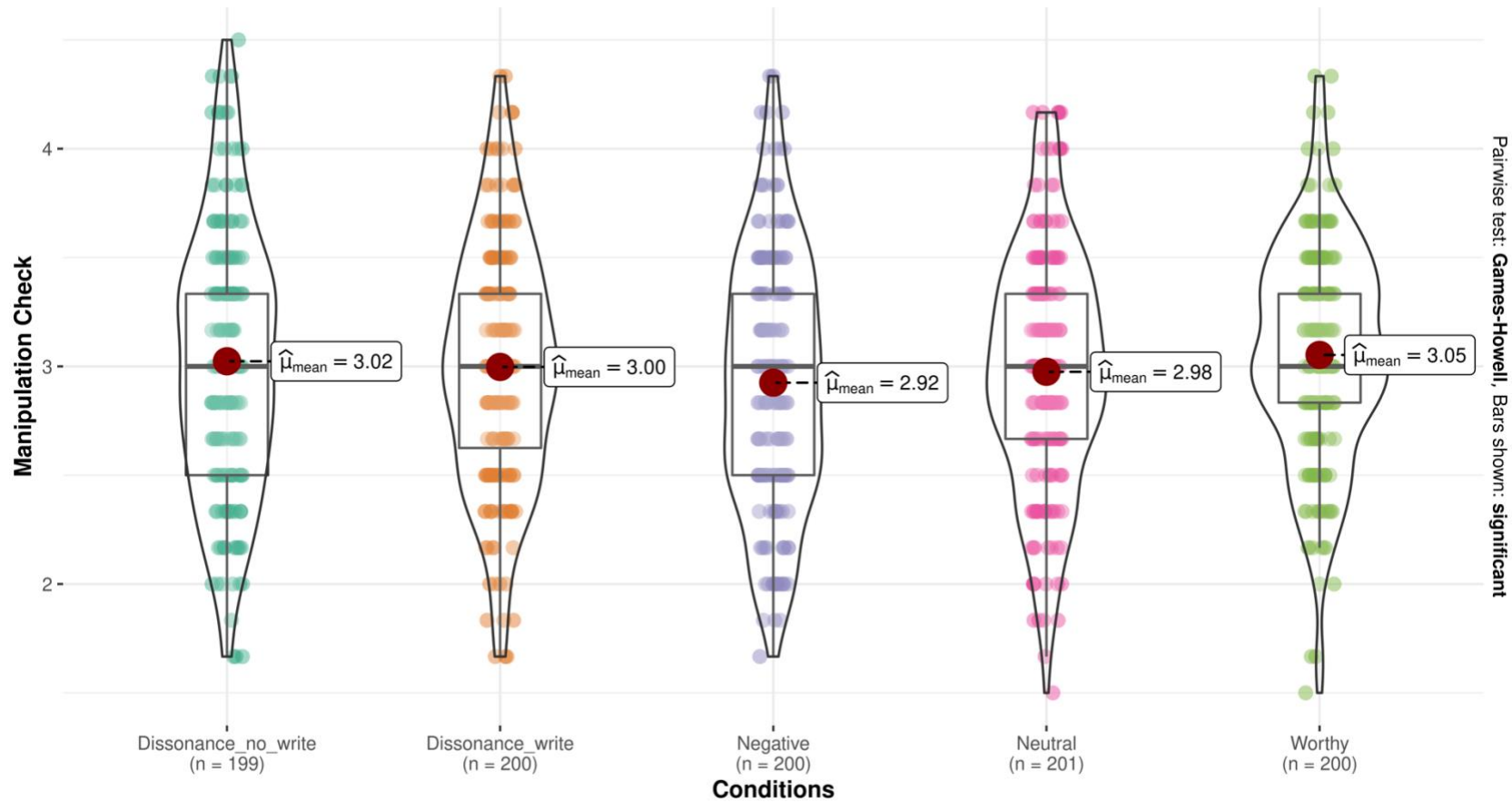
```
# plot the APA style table
```

```
ANOVA_man_i_check <- lm(ManiCheck ~ condition, data = cleaned_df)
```



```
# plot ggstatsplot and save
ggstatsplot::ggbetweenstats(
  data = cleaned_df, y = ManiCheck, x = condition,
  originaltheme = TRUE,
  ylab = "Manipulation Check", xlab = "Conditions")
```

$F_{\text{Welch}}(4, 496.92) = 1.57, p = 0.18, \hat{\omega}_p^2 = 4.53\text{e-}03, \text{CI}_{95\%} [0.00, 1.00], n_{\text{obs}} = 1,000$



$\log_e(\text{BF}_{01}) = 5.31, \hat{R}_{\text{Bayesian}}^2 = 0.00, \text{CI}_{95\%}^{\text{HDI}} [0.00, 0.00], r_{\text{Cauchy}}^{\text{JZS}} = 0.71$

```
# save the table and plot to local folder. Might interrupt with knitting, hence disabled after export.
apa.aov.table(ANOVA_manipulation_check, filename = "Manipulation check ANOVA.doc", table.number = 1)
ggsave("ManipulationCheck_plot.png", plot = ManipulationCheck_plot,
  width = 9, height = 5.5, dpi = 600)
```

Study 1 - ANOVA

Study 1 DV1 - Likelihood of Hiring the candidate with ethically questionable behavior.

```
jmv::ANOVA(  
  formula = Exp1_prob_hiring ~ condition,  
  data = cleaned_df,  
  effectSize = "eta",  
  modelTest = TRUE,  
  homo = TRUE,  
  postHocES = "d",  
  postHocEsCi = TRUE,  
  emmTables = TRUE)
```

```
## ANOVA - Exp1_prob_hiring
```

```
##
```

	Sum of Squares	df	Mean Square	F	p	η^2
Overall model	8.0526	4	2.0132	0.29419	0.88183	
condition	8.0526	4	2.0132	0.29419	0.88183	0.00118
Residuals	6808.9464	995	6.8432			

```
##
```

```
##  
## ASSUMPTION CHECKS
```

```
## Homogeneity of Variances Test (Levene's)
```

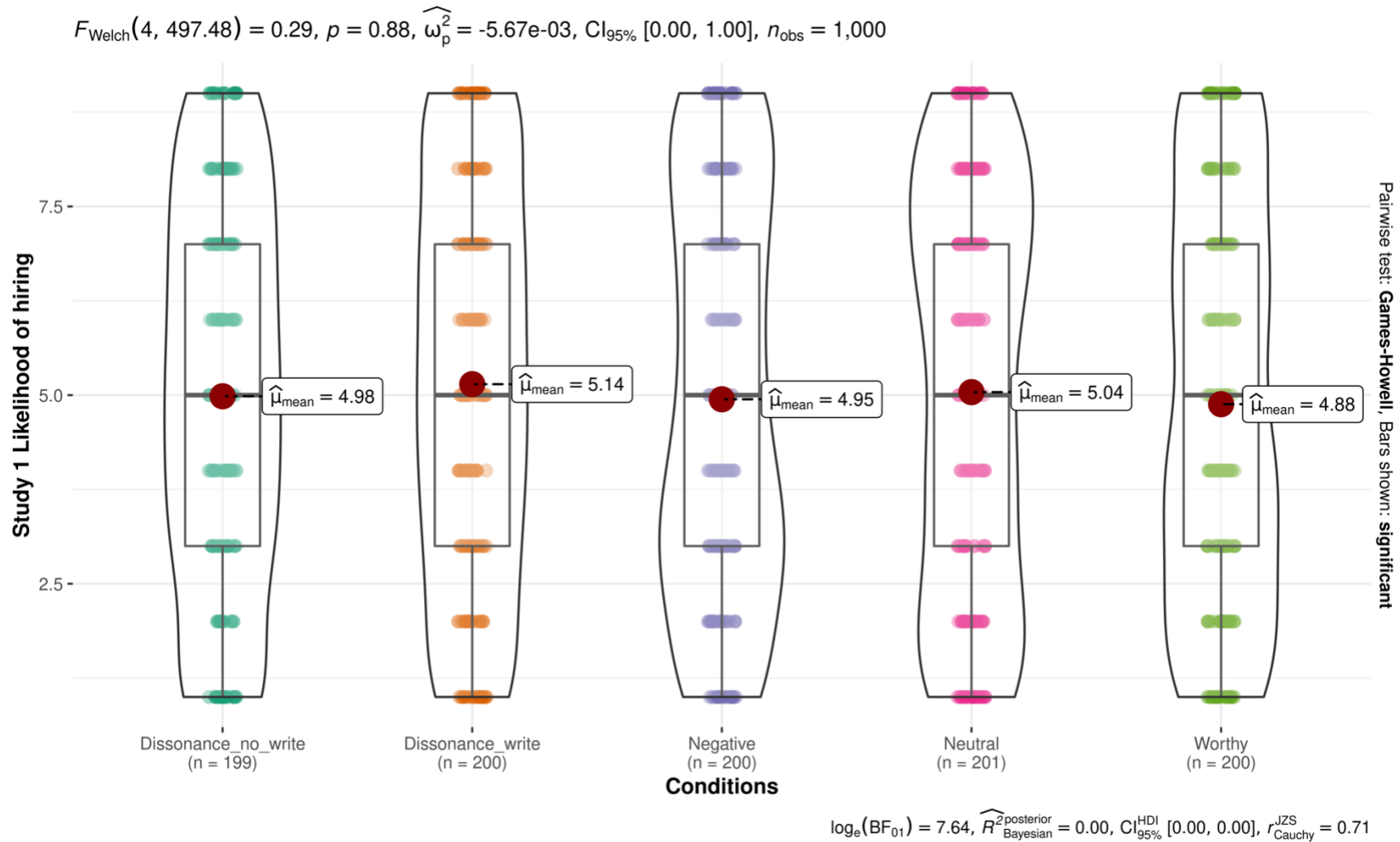
```
##
```

F	df1	df2	p
0.80689	4	995	0.52081

```
##
```

```
ANOVA_Study1_DV1 <- lm(Exp1_prob_hiring ~ condition, data = cleaned_df)
```

```
# plot ggstatsplot and save
ggstatsplot::ggbetweenstats(
  data = cleaned_df, y = Exp1_prob_hiring, x = condition,
  originaltheme = TRUE,
  ylab = "Study 1 Likelihood of hiring", xlab = "Conditions")
```



```
apa.aov.table(ANOVA_Study1_DV1, filename = "Exp1 DV1 ANOVA.doc", table.number = 2)
ggsave(
  "Study1DV1Hiring.png", plot = last_plot(),
  width = 9, height = 5.5, dpi = 600)
```

Study 1 DV2 - Perceived Loyalty to company if the candidate is hired.

```
jmv::ANOVA(  
  formula = Exp1_loyalty ~ condition,  
  data = cleaned_df,  
  effectSize = "eta",  
  modelTest = TRUE,  
  homo = TRUE,  
  postHocES = "d",  
  postHocEsCi = TRUE,  
  emmTables = TRUE)
```

```
## ANOVA - Exp1_loyalty
```

```
##
```

	Sum of Squares	df	Mean Square	F	p	η^2
Overall model	20.798	4	5.1994	0.76899	0.54547	
condition	20.798	4	5.1994	0.76899	0.54547	0.00308
Residuals	6727.602	995	6.7614			

```
##
```

```
##
```

```
##
```

```
## ASSUMPTION CHECKS
```

```
##
```

```
## Homogeneity of Variances Test (Levene's)
```

```
##
```

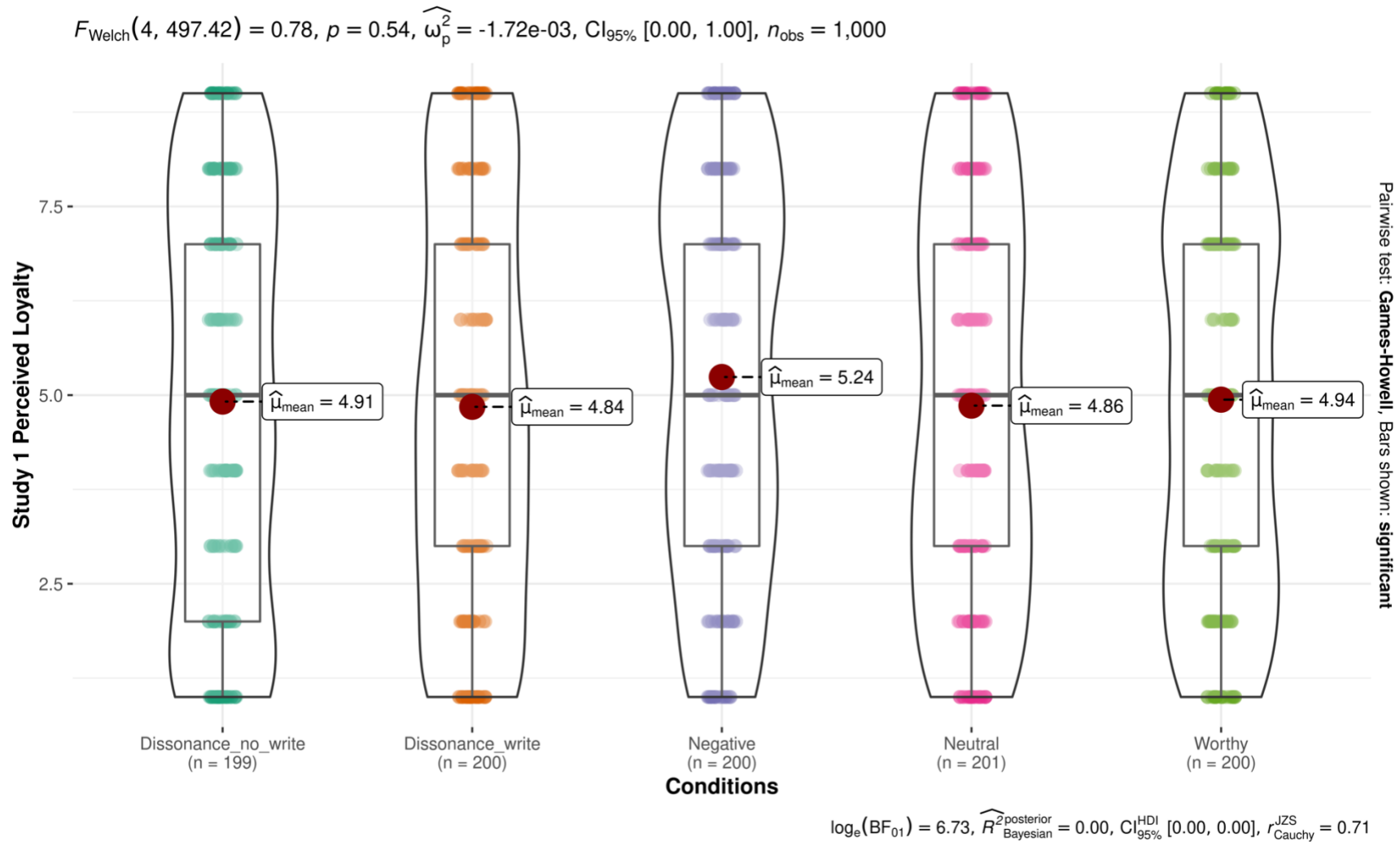
```
##
```

F	df1	df2	p
0.19355	4	995	0.94181

```
##
```

```
ANOVA_exp1_DV2 <- lm(Exp1_loyalty ~ condition, data = cleaned_df)
```

```
# plot ggstatsplot and save
ggstatsplot::ggbetweenstats(
  data = cleaned_df, y = Exp1_loyalty, x = condition,
  originaltheme = TRUE,
  ylab = "Study 1 Perceived Loyalty", xlab = "Conditions")
```



```
apa.aov.table(ANOVA_exp1_DV2, filename = "Exp1 DV2 ANOVA.doc", table.number = 3)
ggsave(
  "Study1DV2Loyalty.png", plot = last_plot(),
  width = 9, height = 5.5, dpi = 600)
```

Study 1 DV3 - Perceived honesty of the candidate.

```
jmv::ANOVA(  
  formula = Exp1_honesty ~ condition,  
  data = cleaned_df,  
  effectSize = "eta",  
  modelTest = TRUE,  
  homo = TRUE,  
  postHocES = "d",  
  postHocEsCi = TRUE,  
  emmTables = TRUE)
```

```
## ANOVA - Exp1_honesty
```

```
##
```

	Sum of Squares	df	Mean Square	F	p	η^2
Overall model	18.339	4	4.5847	0.70090	0.59141	
condition	18.339	4	4.5847	0.70090	0.59141	0.00281
Residuals	6508.477	995	6.5412			

```
##
```

```
##
```

```
##
```

```
## ASSUMPTION CHECKS
```

```
##
```

```
## Homogeneity of Variances Test (Levene's)
```

```
##
```

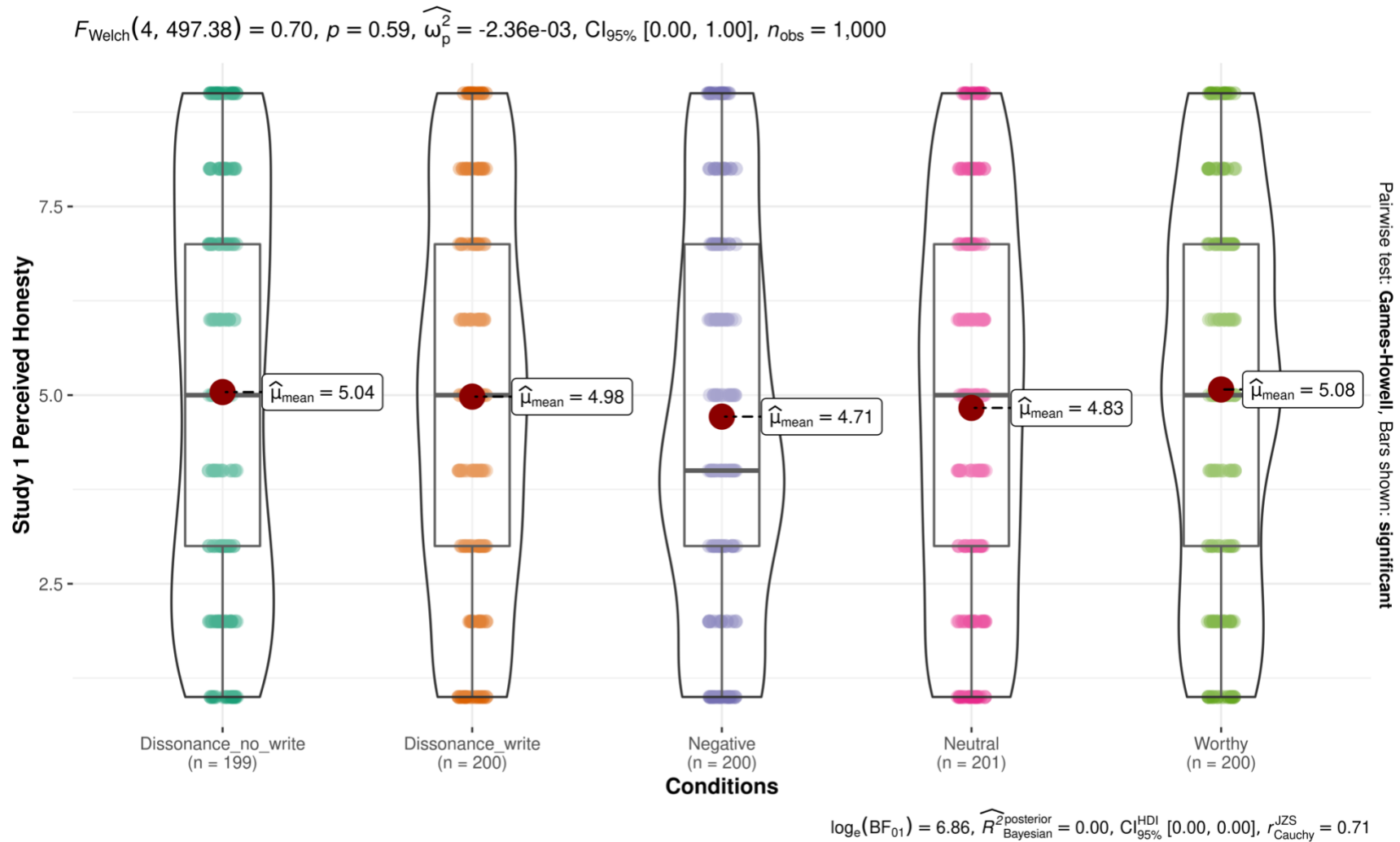
```
##
```

F	df1	df2	p
1.2563	4	995	0.28548

```
##
```

```
ANOVA_exp1_DV3 <- lm(Exp1_honesty ~ condition, data = cleaned_df)
```

```
# plot ggstatsplot and save
ggstatsplot::ggbetweenstats(
  data = cleaned_df, y = Exp1_honesty, x = condition,
  originaltheme = TRUE,
  ylab = "Study 1 Perceived Honesty", xlab = "Conditions")
```



```
apa.aov.table(ANOVA_exp1_DV3, filename = "Exp1 DV3 ANOVA.doc", table.number = 4)
ggsave(
  "Study1DV3Honesty.png", plot = last_plot(),
  width = 9, height = 5.5, dpi = 600)
```

Study 2 - Repeated ANOVA

Pivot to long format for ggstatsplot.

```
# add a column of unique participant ID
cleaned_df <- dplyr::mutate(cleaned_df, ID = row_number())

#pivot longer
df_s2DV1 <- pivot_longer(cleaned_df, cols = c(Exp2_S1_seen_wrong, Exp2_S2_seen_wrong_T2), names_to =
"scenario", values_to = "Exp2_seen_wrong")
df_s2DV2 <- pivot_longer(cleaned_df, cols = c(Exp2_S1_self_action, Exp2_S2_self_action_T2), names_to =
"scenario", values_to = "Exp2_self_action")
df_s2DV3 <- pivot_longer(cleaned_df, cols = c(Exp2_S1_guide_other, Exp2_S2_guide_other_T2), names_to =
"scenario", values_to = "Exp2_guide_other")

# combine three DVs
df_s2long <- df_s2DV1 %>% dplyr::select("ID", "condition", "scenario", "Exp2_seen_wrong") %>%
dplyr::mutate(Exp2_seen_wrong = as.numeric(Exp2_seen_wrong)) %>%
  cbind(Exp2_self_action = as.numeric(df_s2DV2$Exp2_self_action)) %>%
  cbind(Exp2_guide_other = as.numeric(df_s2DV3$Exp2_guide_other))

# rename the scenario variable for plotting
df_s2long <- df_s2long %>%
  mutate(scenario = case_when(
    scenario == "Exp2_S1_seen_wrong" ~ "Scenario 1 Leaking interview questions",
    scenario == "Exp2_S2_seen_wrong_T2" ~ "Scenario 2 Changing used product"))
```


Study 2 DV2 - Perception of suggested actions as wrong.

```
jmv::anovaRM(  
  data = cleaned_df,  
  rm = list(  
    list(  
      label="scenario",  
      levels=c("S1", "S2"))),  
  rmCells = list(  
    list(  
      measure="Exp2_S1_seen_wrong",  
      cell="S1"),  
    list(  
      measure="Exp2_S2_seen_wrong_T2",  
      cell="S2")),  
  bs = condition,  
  effectSize = "eta",  
  rmTerms = ~ scenario,  
  bsTerms = ~ condition,  
  leveneTest = TRUE,  
  #emMeans = ~ scenario:condition,  
  emmTables = TRUE,  
  groupSumm = TRUE)
```

```
##  
## REPEATED MEASURES ANOVA  
##  
## Within Subjects Effects
```

	Sum of Squares	df	Mean Square	F	p	η^2
scenario	3.1736	1	3.1736	0.50144	0.47904	0.00025
scenario:condition	92.4966	4	23.1242	3.65371	0.00580	0.00716
Residual	6297.3034	995	6.3289			

```
## Note. Type 3 Sums of Squares  
##  
##
```

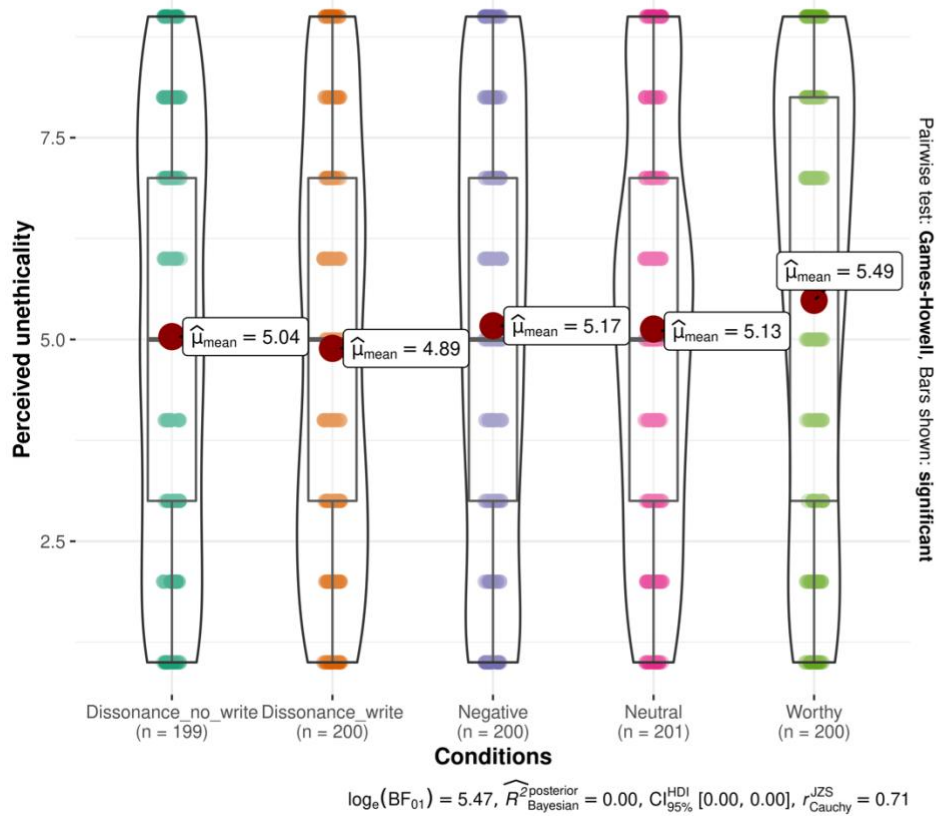
```
## Between Subjects Effects
##
##      Sum of Squares    df    Mean Square    F        p        η²
## -----
## condition            6.2895         4        1.5724    0.23981    0.91584    0.00049
## Residual            6523.9025       995        6.5567
## -----
## Note. Type 3 Sums of Squares
##
##
## ASSUMPTIONS
##
## Homogeneity of Variances Test (Levene's)
##
##      F        df1    df2    p
## -----
## Exp2_S1_seen_wrong    0.66907     4    995    0.61353
## Exp2_S2_seen_wrong_T2  1.58287     4    995    0.17664
## -----
##
##
## Group Summary
##
##      condition    N    Excluded
## -----
## Dissonance_no_write    199         0
## Dissonance_write       200         0
## Negative               200         0
## Neutral                201         0
## Worthy                 200         0
## -----
```

*# ggstatsplot for condition comparisons in between-subjects designs repeated across all levels of a grouping variable.
link to tutorial: https://indrajeetpatil.github.io/ggstatsplot/reference/grouped_ggbetweenstats.html*

```
ggstatsplot::grouped_ggbetweenstats(
  data = df_s2long, y = Exp2_seen_wrong, x = condition,
  grouping.var = scenario,
  ylab = "Perceived unethicality", xlab = "Conditions")
```

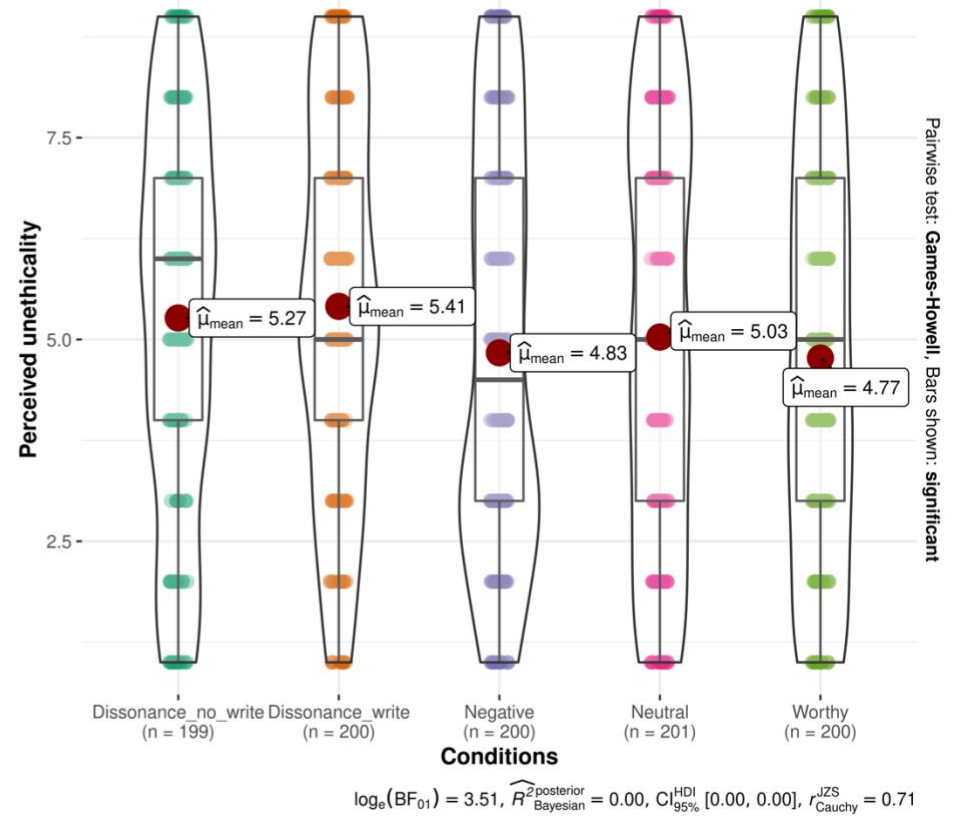
Scenario 1 Leaking interview questions

$F_{\text{Welch}}(4, 497.41) = 1.40, p = 0.23, \hat{\omega}_p^2 = 3.19\text{e-}03, \text{CI}_{95\%} [0.00, 1.00], n_{\text{obs}} = 1,000$



Scenario 2 Changing used product

$F_{\text{Welch}}(4, 497.38) = 2.54, p = 0.04, \hat{\omega}_p^2 = 0.01, \text{CI}_{95\%} [0.00, 1.00], n_{\text{obs}} = 1,000$



```
ggsave(
  "Study2DV1SeenWrong.png", plot = last_plot(),
  width = 11.8, height = 6, dpi = 600)
```

Study 2 DV2 - Likelihood of the self conducting similar behavior.

```
jmv::anovaRM(  
  data = cleaned_df,  
  rm = list(  
    list(  
      label="scenario",  
      levels=c("S1", "S2"))),  
  rmCells = list(  
    list(  
      measure="Exp2_S1_self_action",  
      cell="S1"),  
    list(  
      measure="Exp2_S2_self_action_T2",  
      cell="S2")),  
  bs = condition,  
  effectSize = "eta",  
  rmTerms = ~ scenario,  
  bsTerms = ~ condition,  
  leveneTest = TRUE,  
  #emMeans = ~ scenario:condition,  
  emmTables = TRUE,  
  groupSumm = TRUE)
```

```
##  
## REPEATED MEASURES ANOVA  
##  
## Within Subjects Effects
```

	Sum of Squares	df	Mean Square	F	p	η^2
scenario	0.12645	1	0.12645	0.017775	0.89396	0.00001
scenario:condition	22.80635	4	5.70159	0.801501	0.52427	0.00168
Residual	7078.06565	995	7.11363			

```
## Note. Type 3 Sums of Squares  
##  
##
```

Between Subjects Effects

	Sum of Squares	df	Mean Square	F	p	η^2
condition	19.505	4	4.8763	0.74798	0.55943	0.00143
Residual	6486.703	995	6.5193			

Note. Type 3 Sums of Squares

ASSUMPTIONS

Homogeneity of Variances Test (Levene's)

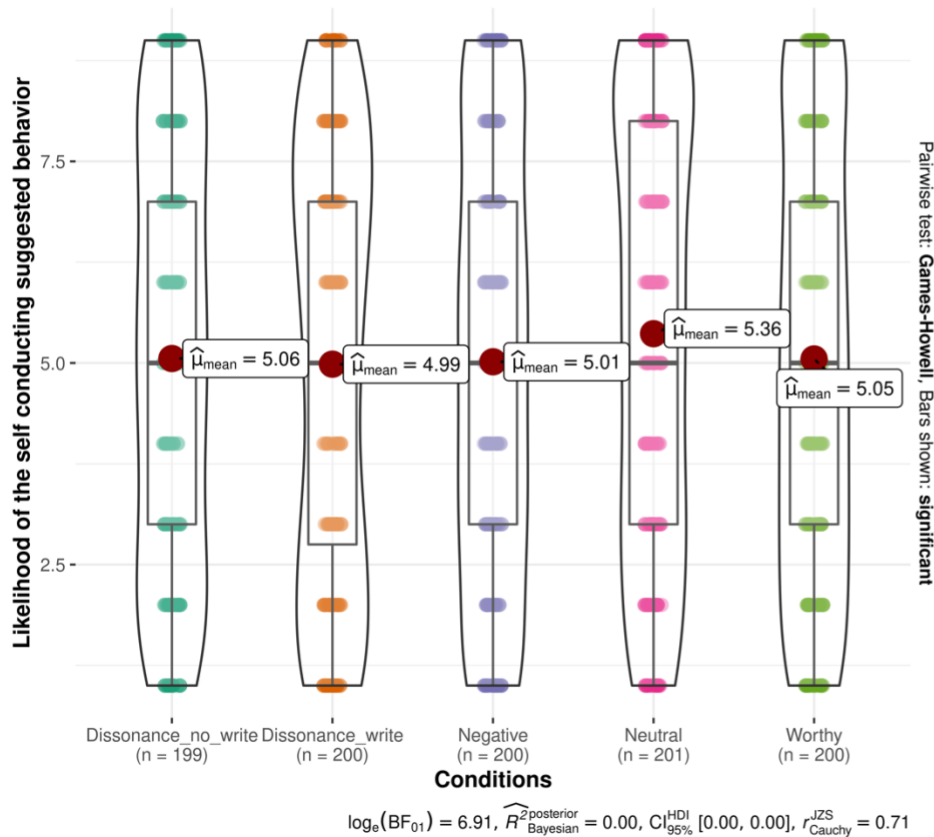
	F	df1	df2	p
Exp2_S1_self_action	0.26660	4	995	0.89949
Exp2_S2_self_action_T2	1.47802	4	995	0.20670

Group Summary

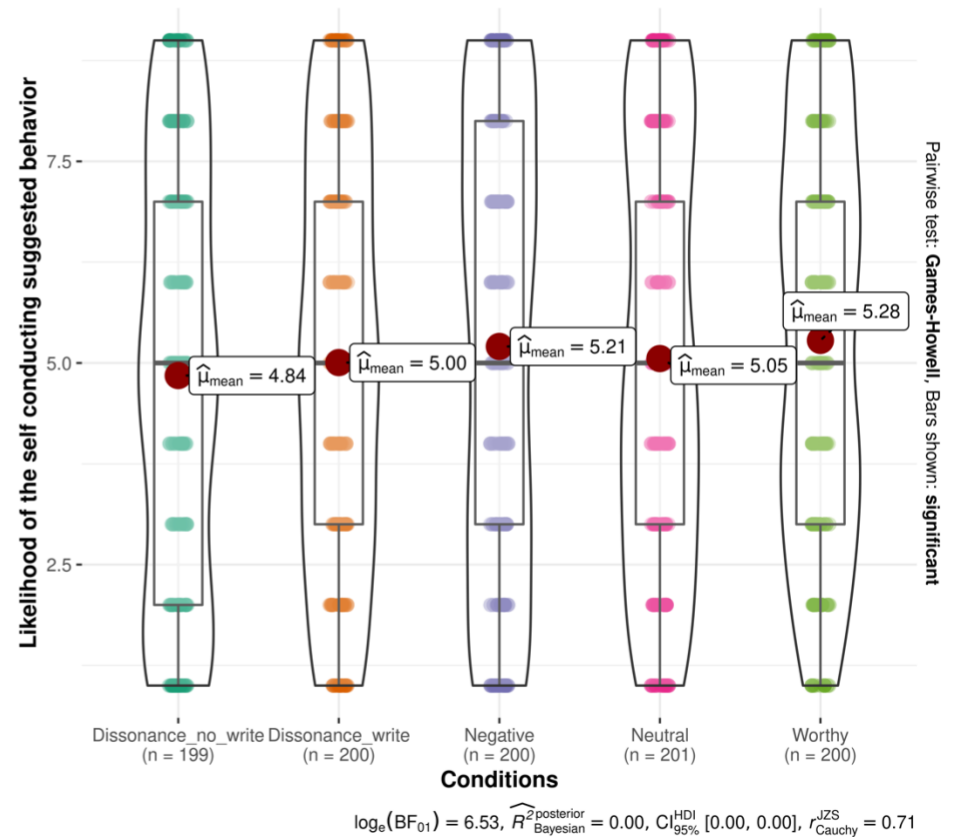
condition	N	Excluded
Dissonance_no_write	199	0
Dissonance_write	200	0
Negative	200	0
Neutral	201	0
Worthy	200	0

```
ggstatsplot::grouped_ggbetweenstats(  
  data = df_s2long, y = Exp2_self_action, x = condition,  
  grouping.var = scenario,  
  ylab = "Likelihood of the self conducting suggested behavior", xlab = "Conditions")
```

Scenario 1 Leaking interview questions

$$F_{\text{Welch}}(4, 497.49) = 0.67, p = 0.61, \hat{\omega}_p^2 = -2.65\text{e-}03, \text{CI}_{95\%} [0.00, 1.00], n_{\text{obs}} = 1,000$$


Scenario 2 Changing used product

$$F_{\text{Welch}}(4, 497.34) = 0.89, p = 0.47, \hat{\omega}_p^2 = -8.96\text{e-}04, \text{CI}_{95\%} [0.00, 1.00], n_{\text{obs}} = 1,000$$


```
ggsave(
  "Study2DV2SelfAction.png", plot = last_plot(),
  width = 11.8, height = 6, dpi = 600)
```

Study 2 DV3 - Likelihood of advising others to perform unethical but self-benefiting behavior.

```
jmv::anovaRM(  
  data = cleaned_df,  
  rm = list(  
    list(  
      label="scenario",  
      levels=c("S1", "S2"))),  
  rmCells = list(  
    list(  
      measure="Exp2_S1_guide_other",  
      cell="S1"),  
    list(  
      measure="Exp2_S2_guide_other_T2",  
      cell="S2")),  
  bs = condition,  
  effectSize = "eta",  
  rmTerms = ~ scenario,  
  bsTerms = ~ condition,  
  leveneTest = TRUE,  
  #emMeans = ~ scenario:condition,  
  emmTables = TRUE,  
  groupSumm = TRUE)
```

```
##  
## REPEATED MEASURES ANOVA  
##  
## Within Subjects Effects
```

	Sum of Squares	df	Mean Square	F	p	η^2
scenario	14.694	1	14.6935	2.1604	0.14193	0.00109
scenario:condition	40.857	4	10.2143	1.5018	0.19951	0.00302
Residual	6767.351	995	6.8014			

```
## Note. Type 3 Sums of Squares  
##  
##
```

Between Subjects Effects

	Sum of Squares	df	Mean Square	F	p	η^2
condition	64.788	4	16.1969	2.4293	0.04618	0.00479
Residual	6633.940	995	6.6673			

Note. Type 3 Sums of Squares

ASSUMPTIONS

Homogeneity of Variances Test (Levene's)

	F	df1	df2	p
Exp2_S1_guide_other	0.339167	4	995	0.85162
Exp2_S2_guide_other_T2	0.087681	4	995	0.98629

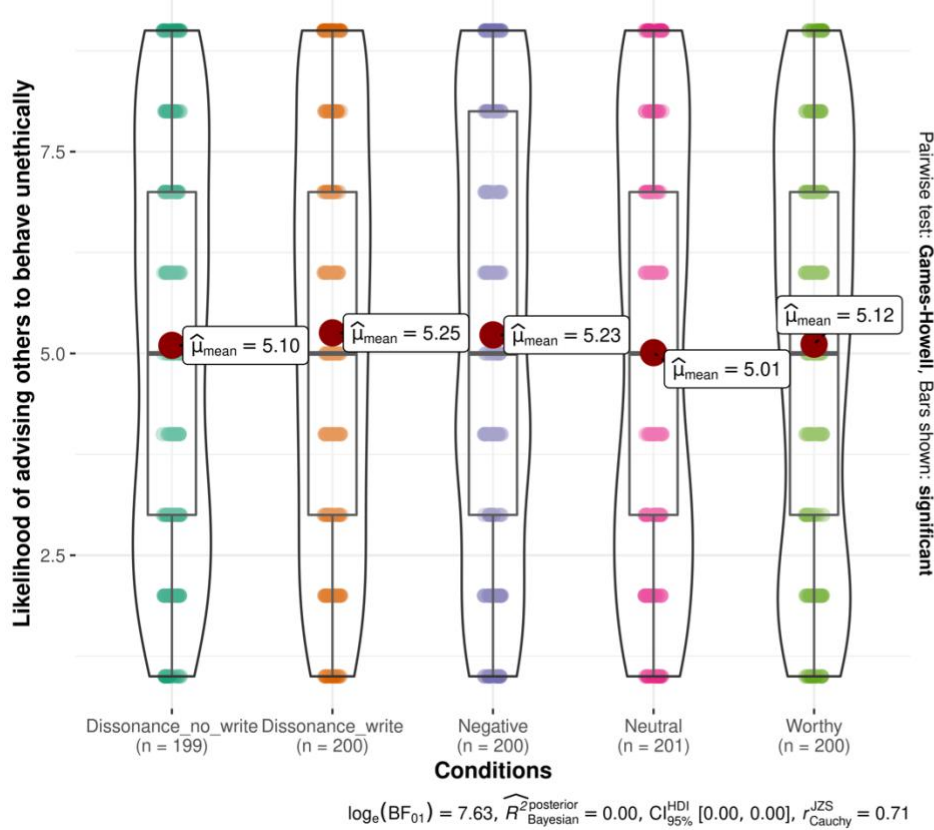
Group Summary

condition	N	Excluded
Dissonance_no_write	199	0
Dissonance_write	200	0
Negative	200	0
Neutral	201	0
Worthy	200	0


```
ggstatsplot::grouped_ggbetweenstats(
  data = df_s2long, y = Exp2_guide_other, x = condition,
  grouping.var = scenario,
  ylab = "Likelihood of advising others to behave unethically", xlab = "Conditions"
)
```

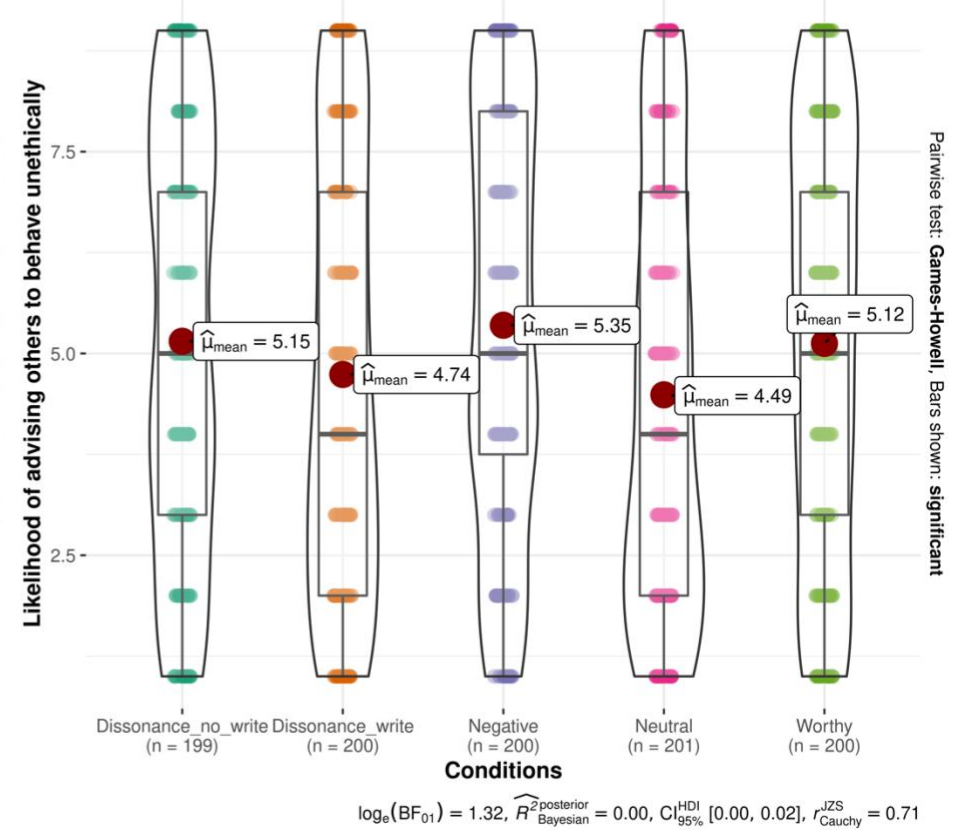
Scenario 1 Leaking interview questions

$F_{\text{Welch}}(4, 497.49) = 0.30, p = 0.88, \hat{\omega}_p^2 = -5.63\text{e-}03, \text{CI}_{95\%} [0.00, 1.00], n_{\text{obs}} = 1,000$



Scenario 2 Changing used product

$F_{\text{Welch}}(4, 497.49) = 3.59, p = 6.73\text{e-}03, \hat{\omega}_p^2 = 0.02, \text{CI}_{95\%} [5.99\text{e-}04, 1.00], n_{\text{obs}} = 1,000$



```
ggsave(
  "Study2DV3AdviseOthers.png", plot = last_plot(),
  width = 11.8, height = 6, dpi = 600)
```

Study 3 - MASC

Calculate ANOVA, generate APA style ANOVA table, and plot ggstatsplot.

```
# Overall measurements for all participants.
```

```
## MASC set 1
```

```
jmv::ANOVA(  
  formula = MASC_set1 ~ condition,  
  data = cleaned_df,  
  effectSize = "eta",  
  modelTest = TRUE,  
  homo = TRUE,  
  postHocES = "d",  
  postHocEsCi = TRUE,  
  #emMeans = ~ condition,  
  emmTables = TRUE)
```

```
## ANOVA - MASC_set1
```

```
##
```

	Sum of Squares	df	Mean Square	F	p	η^2
Overall model	0.10094	4	0.025235	0.19294	0.94213	
condition	0.10094	4	0.025235	0.19294	0.94213	0.00078
Residuals	130.13330	995	0.130787			

```
##
```

```
## ASSUMPTION CHECKS
```

```
## Homogeneity of Variances Test (Levene's)
```

```
##
```

F	df1	df2	p
0.60309	4	995	0.66049

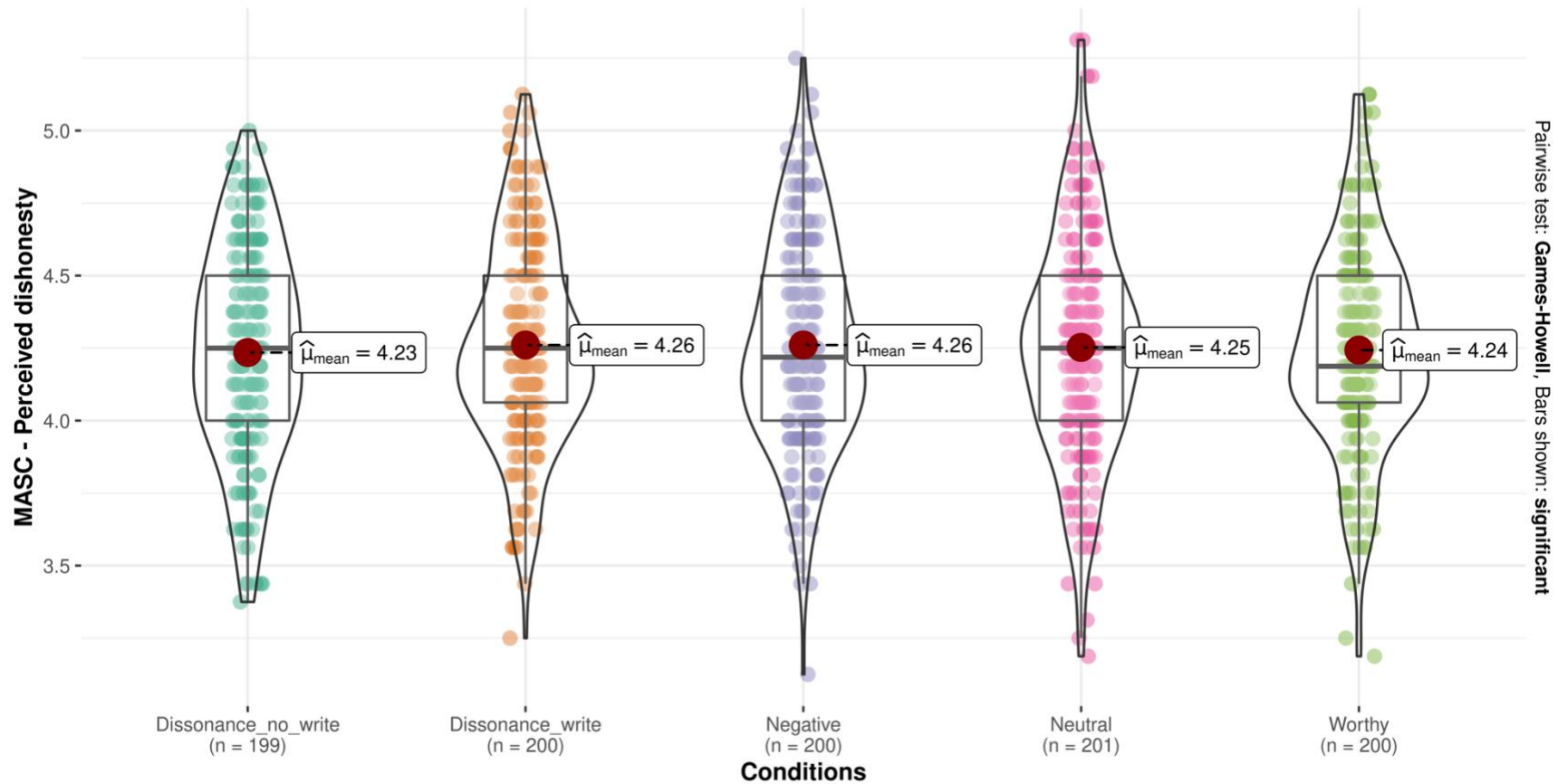
```
##
```

```
ANOVA_study3_MASC1 <- lm(MASC_set1 ~ condition, data = cleaned_df)
```

```
ggstatsplot::ggbetweenstats(
  data = cleaned_df, y = MASC_set1, x = condition,
  originaltheme = TRUE,
  ylab = "MASC - Perceived dishonesty", xlab = "Conditions",
  title = "Multi Aspect Scale of Cheating (MASC) - Likelihood of others to behave dishonestly")
```

Multi Aspect Scale of Cheating (MASC) - Likelihood of others to behave dishonestly

$F_{\text{Welch}}(4, 497.37) = 0.20, p = 0.94, \hat{\omega}_p^2 = -6.44\text{e-}03, \text{CI}_{95\%} [0.00, 1.00], n_{\text{obs}} = 1,000$



$\log_e(\text{BF}_{01}) = 7.84, \hat{R}_{\text{Bayesian}}^2 = 0.00, \text{CI}_{95\%}^{\text{HDI}} [0.00, 0.00], r_{\text{Cauchy}}^{\text{JZS}} = 0.71$

```
apa.aov.table(ANOVA_study3_MASC1, filename = "Exp3 MASC set1 ANOVA.doc", table.number = 5)
ggsave(
  "MASC1_Dishonesty_plot.png", plot = last_plot(),
  width = 9, height = 5.5, dpi = 600)
```

MASC set 2

```
jmv::ANOVA(  
  formula = MASC_set2 ~ condition,  
  data = cleaned_df,  
  effectSize = "eta",  
  modelTest = TRUE,  
  homo = TRUE,  
  postHocES = "d",  
  postHocEsCi = TRUE,  
  #emMeans = ~ condition,  
  emmTables = TRUE)
```

ANOVA - MASC_set2

	Sum of Squares	df	Mean Square	F	p	η^2
Overall model	0.83417	4	0.20854	1.2545	0.28622	
condition	0.83417	4	0.20854	1.2545	0.28622	0.00502
Residuals	165.39917	995	0.16623			

ASSUMPTION CHECKS

Homogeneity of Variances Test (Levene's)

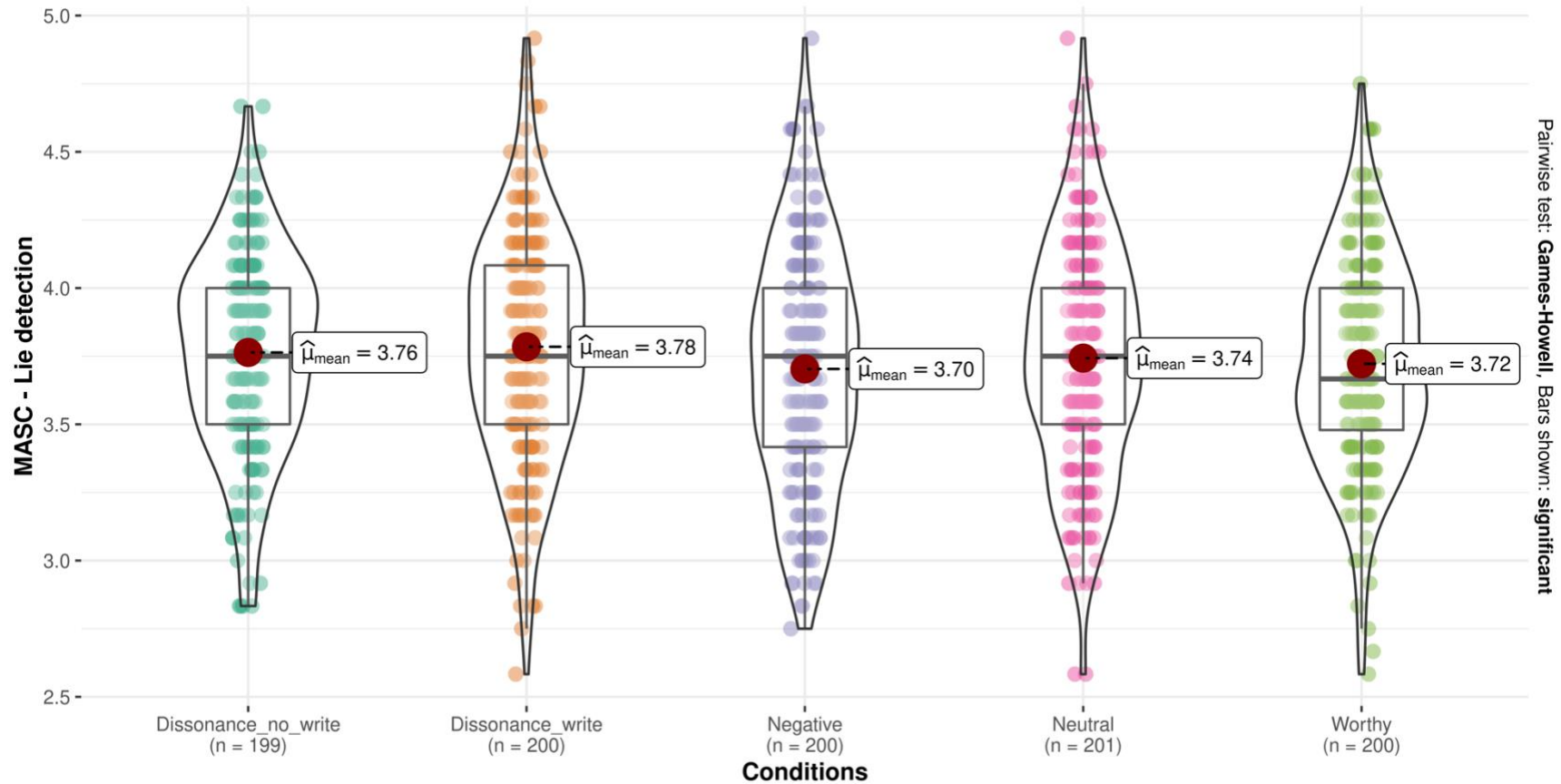
F	df1	df2	p
2.4402	4	995	0.04536

```
ANOVA_study3_MASC2 <- lm(MASC_set2 ~ condition, data = cleaned_df)
```

```
ggstatsplot::ggbetweenstats(
  data = cleaned_df, y = MASC_set2, x = condition,
  originaltheme = TRUE,
  ylab = "MASC - Lie detection", xlab = "Conditions",
  title = "Multi Aspect Scale of Cheating (MASC) - Interpreting common excuses as a lie")
```

Multi Aspect Scale of Cheating (MASC) - Interpreting common excuses as a lie

$F_{\text{Welch}}(4, 497) = 1.21, p = 0.31, \hat{\omega}_p^2 = 1.64\text{e-}03, \text{CI}_{95\%} [0.00, 1.00], n_{\text{obs}} = 1,000$



$\log_e(\text{BF}_{01}) = 5.80, \hat{R}_{\text{Bayesian}}^2 = 0.00, \text{CI}_{95\%}^{\text{HDI}} [0.00, 0.00], r_{\text{Cauchy}}^{\text{JZS}} = 0.71$

```
apa.aov.table(ANOVA_study3_MASC2, filename = "Exp3 MASC set2 ANOVA.doc", table.number = 6)
ggsave(
  "MASC2_Lie_plot.png", plot = last_plot(),
  width = 9, height = 5.5, dpi = 600)
```

MASC set 3

```
jmv::ANOVA(  
  formula = MASC_set3 ~ condition,  
  data = cleaned_df,  
  effectSize = "eta",  
  modelTest = TRUE,  
  homo = TRUE,  
  postHocES = "d",  
  postHocEsCi = TRUE,  
  #emMeans = ~ condition,  
  emmTables = TRUE)
```

ANOVA - MASC_set3

	Sum of Squares	df	Mean Square	F	p	η^2
Overall model	2.1368	4	0.53421	0.25837	0.90460	
condition	2.1368	4	0.53421	0.25837	0.90460	0.00104
Residuals	2057.2709	995	2.06761			

ASSUMPTION CHECKS
Homogeneity of Variances Test (Levene's)

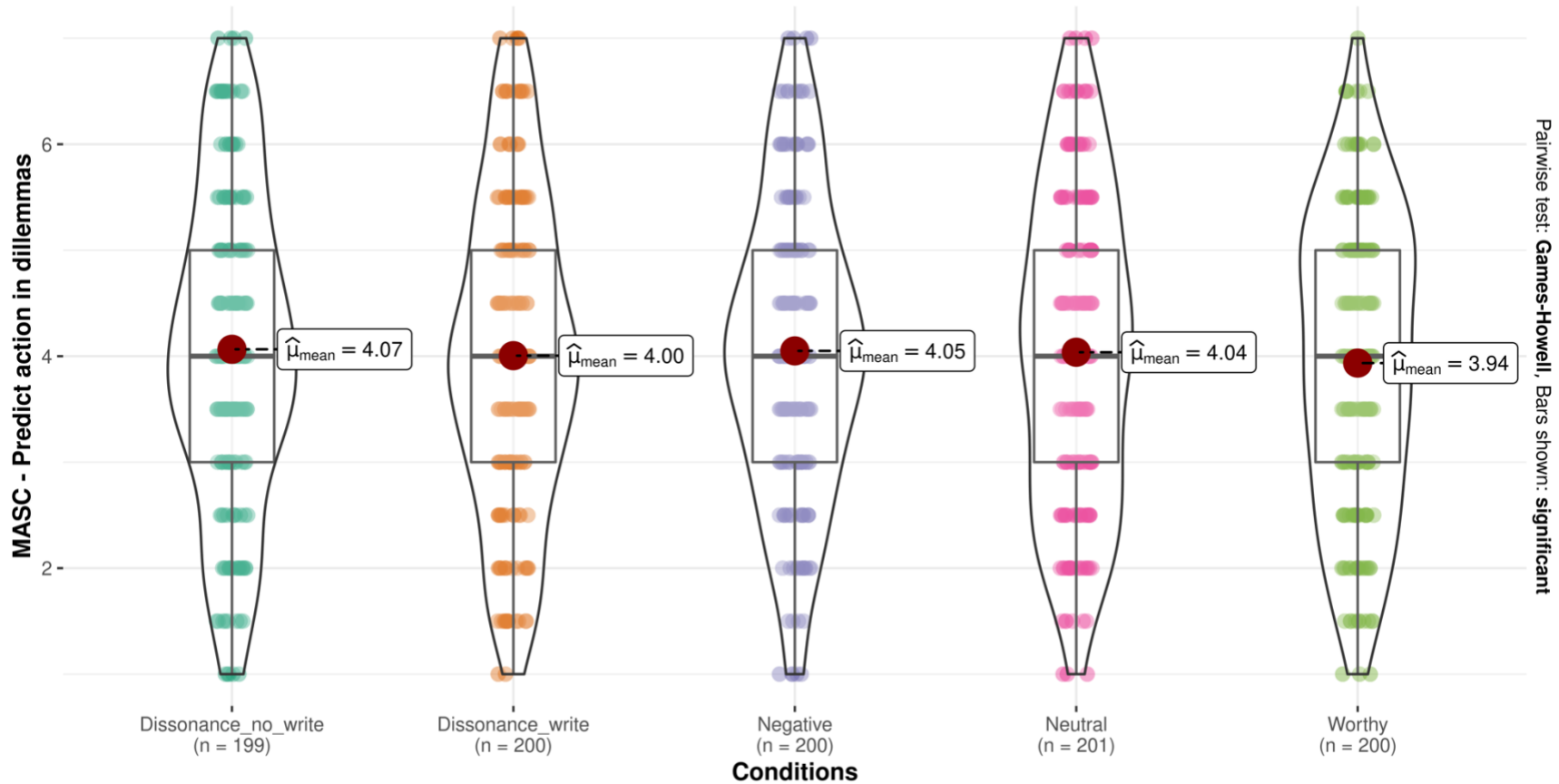
F	df1	df2	p
0.68175	4	995	0.60467

```
ANOVA_study3_MASC3 <- lm(MASC_set3 ~ condition, data = cleaned_df)
```

```
ggstatsplot::ggbetweenstats(
  data = cleaned_df, y = MASC_set3, x = condition,
  originaltheme = TRUE,
  ylab = "MASC - Predict action in dilemmas", xlab = "Conditions",
  title = "Multi Aspect Scale of Cheating (MASC) - Likelihood of actors to behave dishonestly in dilemmas")
```

Multi Aspect Scale of Cheating (MASC) - Likelihood of actors to behave dishonestly in dilemmas

$F_{\text{Welch}}(4, 497.38) = 0.27, p = 0.90, \hat{\omega}_p^2 = -5.88\text{e-}03, \text{CI}_{95\%} [0.00, 1.00], n_{\text{obs}} = 1,000$



$\log_e(\text{BF}_{01}) = 7.71, \hat{R}_{\text{Bayesian}}^2 = 0.00, \text{CI}_{95\%}^{\text{HDI}} [0.00, 0.00], r_{\text{Cauchy}}^{\text{JZS}} = 0.71$

```
apa.aov.table(ANOVA_study3_MASC3, filename = "Exp3 MASC set3 ANOVA.doc", table.number = 7)
ggsave(
  "MASC3_dilemmas_plot.png", plot = last_plot(),
  width = 9, height = 5.5, dpi = 600)
```

Study 3 - BIDR

Calculate ANOVA, generate APA style ANOVA table, and plot ggstatsplot.

```
## BIDR - self deceptive
jmv::ANOVA(
  formula = BIDR_self_deceptive ~ condition,
  data = cleaned_df,
  effectSize = "eta",
  modelTest = TRUE,
  homo = TRUE,
  postHocES = "d",
  postHocEsCi = TRUE,
  #emMeans = ~ condition,
  emmTables = TRUE)

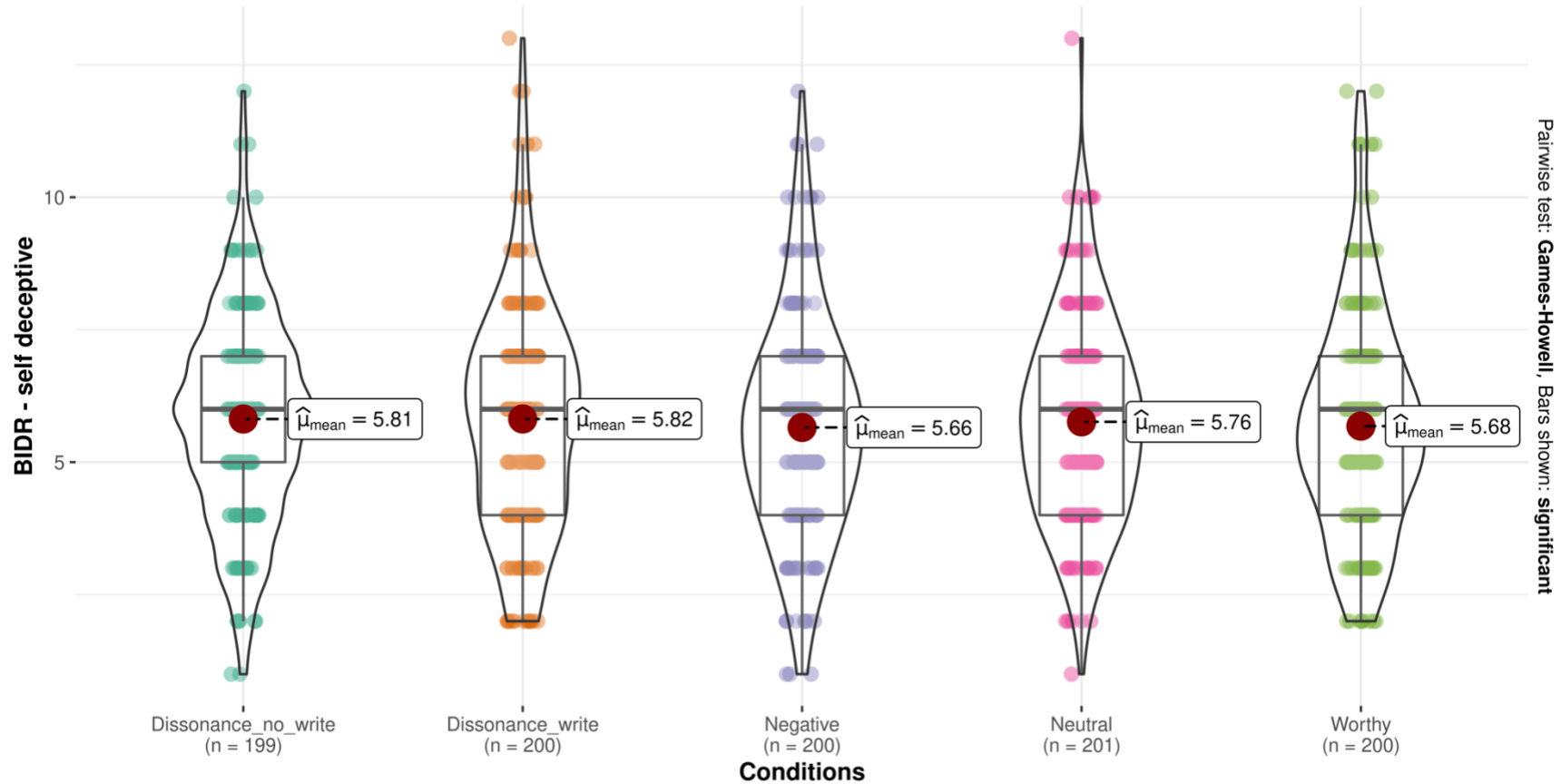
## ANOVA - BIDR_self_deceptive
##
## Sum of Squares    df    Mean Square    F    p    η²
##
## Overall model      4.4471     4      1.1118    0.26840  0.89836
## condition          4.4471     4      1.1118    0.26840  0.89836  0.00108
## Residuals        4121.5279   995      4.1422
##
## ASSUMPTION CHECKS
## Homogeneity of Variances Test (Levene's)
##
## F    df1    df2    p
##
## 0.71281    4    995    0.58323
```



```
ggstatsplot::ggbetweenstats(
  data = cleaned_df, y = BIDR_self_deceptive, x = condition,
  originaltheme = TRUE,
  ylab = "BIDR - self deceptive", xlab = "Conditions",
  title = "Balanced Inventory of Desirable Responding - Self Deceptive Score")
```

Balanced Inventory of Desirable Responding - Self Deceptive Score

$F_{\text{Welch}}(4, 497.23) = 0.26, p = 0.90, \hat{\omega}_p^2 = -5.93\text{e-}03, \text{CI}_{95\%} [0.00, 1.00], n_{\text{obs}} = 1,000$



$\log_e(\text{BF}_{01}) = 7.69, \hat{R}_{\text{Bayesian}}^2 = 0.00, \text{CI}_{95\%}^{\text{HDI}} [0.00, 0.00], r_{\text{Cauchy}}^{\text{JZS}} = 0.71$

```
apa.aov.table(ANOVA_study3_BIDR1, filename = "Exp3 BIDR1 ANOVA.doc", table.number = 8)
ggsave(
  "BIDR_SelfDeceptive_plot.png", plot = last_plot(),
  width = 9, height = 5.5, dpi = 600)
```

BIDR - impression management

```
jmv::ANOVA(  
  formula = BIDR_impre_manage ~ condition,  
  data = cleaned_df,  
  effectSize = "eta",  
  modelTest = TRUE,  
  homo = TRUE,  
  postHocES = "d",  
  postHocEsCi = TRUE,  
  #emMeans = ~ condition,  
  emmTables = TRUE)
```

```
## ANOVA - BIDR_impre_manage
```

	Sum of Squares	df	Mean Square	F	p	η^2
Overall model	0.76096	4	0.19024	0.047435	0.99577	
condition	0.76096	4	0.19024	0.047435	0.99577	0.00019
Residuals	3990.43004	995	4.01048			

```
##
```

```
## ASSUMPTION CHECKS
```

```
##
```

```
## Homogeneity of Variances Test (Levene's)
```

```
##
```

F	df1	df2	p
1.1472	4	995	0.33282

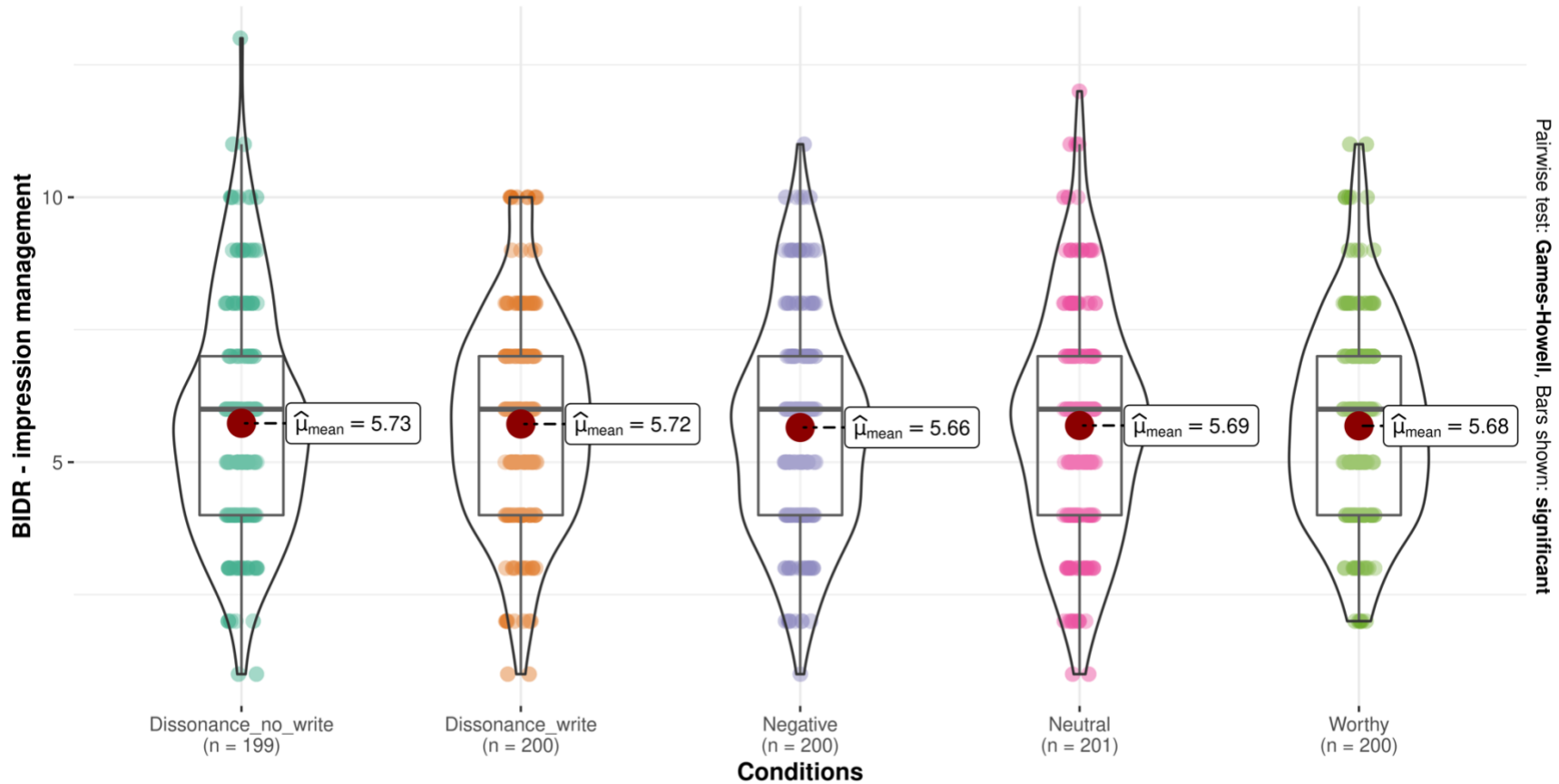
```
##
```

```
ANOVA_study3_BIDR2 <- lm(BIDR_impre_manage ~ condition, data = cleaned_df)
```

```
ggstatsplot::ggbetweenstats(
  data = cleaned_df, y = BIDR_impre_manage, x = condition,
  originaltheme = TRUE,
  ylab = "BIDR - impression management", xlab = "Conditions",
  title = "Balanced Inventory of Desirable Responding - Impression Management Score")
```

Balanced Inventory of Desirable Responding - Impression Management Score

$F_{\text{Welch}}(4, 497.09) = 0.05, p = 1.00, \hat{\omega}_p^2 = -7.65\text{e-}03, \text{CI}_{95\%} [0.00, 1.00], n_{\text{obs}} = 1,000$



$\log_e(\text{BF}_{01}) = 8.12, \hat{R}_{\text{Bayesian}}^2 = 0.00, \text{CI}_{95\%}^{\text{HDI}} [0.00, 0.00], r_{\text{Cauchy}}^{\text{JZS}} = 0.71$

```
apa.aov.table(ANOVA_study3_BIDR2, filename = "Exp3 BIDR2 ANOVA.doc", table.number = 9)
ggsave(
  "BIDR_ImpressionManagement_plot.png", plot = last_plot(),
  width = 9, height = 5.5, dpi = 600)
```

Robustness check - planned contrasts for recall conditions

Study 1 - planned contrast for ANOVA

```
contrast1 = c(3, 3, -2, -2, -2)
contrast2 = c(1, -1, 0, 0, 0)
# comprehensive data
cleaned_df$condition=factor(cleaned_df$condition)
contrasts(cleaned_df$condition) = cbind(contrast1, contrast2)

#Check
contrasts(cleaned_df$condition)

##               contrast1 contrast2
## Dissonance_no_write      3         1 -0.00000000000000041633
## Dissonance_write         3        -1 -0.00000000000000026743
## Negative                 -2         0 -0.577350269189625731059
## Neutral                  -2         0  0.788675134594812865529
## Worthy                   -2         0 -0.211324865405187106715
##
## Dissonance_no_write -0.00000000000000055511
## Dissonance_write    -0.00000000000000017154
## Negative             -0.577350269189625731059
## Neutral              -0.211324865405187134471
## Worthy               0.788675134594812865529

# ANOVA command
# result in the form of regression
#summary.lm(aov1)

ANOVA_manicheck <- lm(Manicheck ~ condition, data = cleaned_df)
summary.lm(ANOVA_manicheck)

##
## Call:
## lm(formula = Manicheck ~ condition, data = cleaned_df)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.5525 -0.3858  0.0025  0.3582  1.4765
##
## Coefficients:
```

```
##               Estimate Std. Error t value      Pr(>|t|)
## (Intercept)      2.99471    0.01762  169.93 <0.0000000000000002 ***
## conditioncontrast1 0.00525    0.00720    0.73      0.466
## conditioncontrast2 0.01298    0.02790    0.47      0.642
## condition         0.01259    0.03935    0.32      0.749
## condition         0.08996    0.03940    2.28      0.023 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.557 on 995 degrees of freedom
## Multiple R-squared:  0.00606,    Adjusted R-squared:  0.00206
## F-statistic: 1.52 on 4 and 995 DF,  p-value: 0.195

ANOVA_exp1_DV1 <- lm(Exp1_prob_hiring ~ condition, data = cleaned_df)
summary.lm(ANOVA_exp1_DV1)

##
## Call:
## lm(formula = Exp1_prob_hiring ~ condition, data = cleaned_df)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -4.145 -2.040  0.015  2.055  4.120
##
## Coefficients:
##               Estimate Std. Error t value      Pr(>|t|)
## (Intercept)      4.9989    0.0827   60.43 <0.0000000000000002 ***
## conditioncontrast1  0.0220    0.0338    0.65      0.51
## conditioncontrast2 -0.0800    0.1310   -0.61      0.54
## condition         0.0885    0.1847    0.48      0.63
## condition         -0.0713    0.1850   -0.39      0.70
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.62 on 995 degrees of freedom
## Multiple R-squared:  0.00118,    Adjusted R-squared: -0.00283
## F-statistic: 0.294 on 4 and 995 DF,  p-value: 0.882

ANOVA_exp1_DV2 <- lm(Exp1_loyalty ~ condition, data = cleaned_df)
summary.lm(ANOVA_exp1_DV2)
```

```
##
## Call:
## lm(formula = Exp1_loyalty ~ condition, data = cleaned_df)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -4.240 -1.940  0.073  2.139  4.155
##
## Coefficients:
##              Estimate Std. Error t value      Pr(>|t|)
## (Intercept)    4.9601     0.0822   60.32 <0.0000000000000002 ***
## conditioncontrast1 -0.0268     0.0336   -0.80      0.43
## conditioncontrast2  0.0348     0.1302    0.27      0.79
## condition     -0.2357     0.1836   -1.28      0.20
## condition     -0.1564     0.1838   -0.85      0.39
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.6 on 995 degrees of freedom
## Multiple R-squared:  0.00308,    Adjusted R-squared:  -0.000926
## F-statistic: 0.769 on 4 and 995 DF,  p-value: 0.545

ANOVA_exp1_DV3 <- lm(Exp1_honesty ~ condition, data = cleaned_df)
summary.lm(ANOVA_exp1_DV3)

##
## Call:
## lm(formula = Exp1_honesty ~ condition, data = cleaned_df)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -4.08  -2.04  -0.04   2.02   4.29
##
## Coefficients:
##              Estimate Std. Error t value      Pr(>|t|)
## (Intercept)    4.9282     0.0809   60.93 <0.0000000000000002 ***
## conditioncontrast1  0.0273     0.0330    0.83      0.41
## conditioncontrast2  0.0301     0.1280    0.24      0.81
## condition     0.0153     0.1806    0.08      0.93
## condition     0.2594     0.1808    1.43      0.15
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
## Residual standard error: 2.56 on 995 degrees of freedom
## Multiple R-squared:  0.00281,    Adjusted R-squared:  -0.0012
## F-statistic: 0.701 on 4 and 995 DF,  p-value: 0.591

ANOVA_exp3_MASC1 <- lm(MASC_set1 ~ condition, data = cleaned_df)
summary.lm(ANOVA_exp3_MASC1)

##
## Call:
## lm(formula = MASC_set1 ~ condition, data = cleaned_df)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.1356 -0.2349 -0.0106  0.2475  1.0600
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    4.250357   0.011436  371.66 <0.0000000000000002 ***
## conditioncontrast1 -0.000861   0.004671   -0.18    0.85
## conditioncontrast2 -0.012850   0.018105   -0.71    0.48
## condition      -0.002720   0.025533   -0.11    0.92
## condition      -0.012082   0.025569   -0.47    0.64
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.362 on 995 degrees of freedom
## Multiple R-squared:  0.000775,    Adjusted R-squared:  -0.00324
## F-statistic: 0.193 on 4 and 995 DF,  p-value: 0.942

ANOVA_exp3_MASC2 <- lm(MASC_set2 ~ condition, data = cleaned_df)
summary.lm(ANOVA_exp3_MASC2)

##
## Call:
## lm(formula = MASC_set2 ~ condition, data = cleaned_df)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.201 -0.285  0.007  0.278  1.213
##
## Coefficients:
```

```
##              Estimate Std. Error t value      Pr(>|t|)
## (Intercept)      3.74335    0.01289  290.34 <0.0000000000000002 ***
## conditioncontrast1 0.01028    0.00527    1.95      0.051 .
## conditioncontrast2 -0.01038    0.02041   -0.51      0.611
## condition         0.02728    0.02879    0.95      0.343
## condition         0.00642    0.02883    0.22      0.824
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.408 on 995 degrees of freedom
## Multiple R-squared:  0.00502,    Adjusted R-squared:  0.00102
## F-statistic: 1.25 on 4 and 995 DF,  p-value: 0.286

ANOVA_exp3_MASC3 <- lm(MASC_set3 ~ condition, data = cleaned_df)
summary.lm(ANOVA_exp3_MASC3)

##
## Call:
## lm(formula = MASC_set3 ~ condition, data = cleaned_df)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -3.0653 -1.0373 -0.0373  0.9950  3.0650
##
## Coefficients:
##              Estimate Std. Error t value      Pr(>|t|)
## (Intercept)      4.01853    0.04547   88.38 <0.0000000000000002 ***
## conditioncontrast1 0.00555    0.01857    0.30      0.77
## conditioncontrast2 0.03016    0.07199    0.42      0.68
## condition         0.01430    0.10152    0.14      0.89
## condition        -0.08802    0.10166   -0.87      0.39
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.44 on 995 degrees of freedom
## Multiple R-squared:  0.00104,    Adjusted R-squared: -0.00298
## F-statistic: 0.258 on 4 and 995 DF,  p-value: 0.905

ANOVA_exp3_BIDR1 <- lm(BIDR_self_deceptive ~ condition, data = cleaned_df)
summary.lm(ANOVA_exp3_BIDR1)
```



```
##
## Call:
## lm(formula = BIDR_self_deceptive ~ condition, data = cleaned_df)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -4.814 -1.655  0.186  1.239  7.239
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    5.745053    0.064361   89.26 <0.0000000000000002 ***
## conditioncontrast1  0.023161    0.026286    0.88    0.38
## conditioncontrast2 -0.000465    0.101890    0.00    1.00
## condition         0.078469    0.143691    0.55    0.59
## condition        -0.002725    0.143898   -0.02    0.98
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.04 on 995 degrees of freedom
## Multiple R-squared:  0.00108,    Adjusted R-squared:  -0.00294
## F-statistic: 0.268 on 4 and 995 DF,  p-value: 0.898

ANOVA_exp3_BIDR2 <- lm(BIDR_impre_manage ~ condition, data = cleaned_df)
summary.lm(ANOVA_exp3_BIDR2)

##
## Call:
## lm(formula = BIDR_impre_manage ~ condition, data = cleaned_df)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -4.734 -1.685  0.266  1.308  7.266
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    5.69704    0.06333   89.96 <0.0000000000000002 ***
## conditioncontrast1  0.00993    0.02586    0.38    0.70
## conditioncontrast2  0.00683    0.10026    0.07    0.95
## condition         0.02248    0.14139    0.16    0.87
## condition         0.01594    0.14159    0.11    0.91
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
## Residual standard error: 2 on 995 degrees of freedom
## Multiple R-squared:  0.000191,    Adjusted R-squared:  -0.00383
## F-statistic: 0.0474 on 4 and 995 DF,  p-value: 0.996
```

Study 2 - planned contrast for repeated ANOVA

Repeated-measures ANOVA with the afex package

```
library("afex")
```

```
## Loading required package: lme4
```

```
## Loading required package: Matrix
```

```
##
```

```
## Attaching package: 'Matrix'
```

```
## The following objects are masked from 'package:tidyr':
```

```
##
```

```
##      expand, pack, unpack
```

```
## *****
```

```
## Welcome to afex. For support visit: http://afex.singmann.science/
```

```
## - Functions for ANOVAs: aov_car(), aov_ez(), and aov_4()
```

```
## - Methods for calculating p-values with mixed(): 'S', 'KR', 'LRT', and 'PB'
```

```
## - 'afex_aov' and 'mixed' objects can be passed to emmeans() for follow-up tests
```

```
## - NEWS: emmeans() for ANOVA models now uses model = 'multivariate' as default.
```

```
## - Get and set global package options with: afex_options()
```

```
## - Set orthogonal sum-to-zero contrasts globally: set_sum_contrasts()
```

```
## - For example analyses see: browseVignettes("afex")
```

```
## *****
```

```
##
```

```
## Attaching package: 'afex'
```

```
## The following object is masked from 'package:lme4':
```

```
##
```

```
##      lmer
```

using the long format "df_s2long" created in main analysis:

planned contrast notation

```
contrast1 = c(3, 3,-2,-2,-2)
```

```
contrast2 = c(1,-1, 0, 0, 0)
df_s2long$condition <- as.factor(df_s2long$condition)
contrasts(df_s2long$condition) = cbind(contrast1, contrast2)
```

#Check

```
contrasts(df_s2long$condition)
```

```
##               contrast1 contrast2
## Dissonance_no_write      3         1 -0.00000000000000041633
## Dissonance_write         3        -1 -0.00000000000000026743
## Negative                 -2         0 -0.577350269189625731059
## Neutral                  -2         0  0.788675134594812865529
## Worthy                   -2         0 -0.211324865405187106715
##
## Dissonance_no_write -0.00000000000000055511
## Dissonance_write    -0.00000000000000017154
## Negative             -0.577350269189625731059
## Neutral              -0.211324865405187134471
## Worthy               0.788675134594812865529
```

ANOVA command

```
ANOVA_Exp2_DV1 <- afex::aov_car(Exp2_seen_wrong ~ condition*scenario + Error(ID/scenario), data=df_s2DV1)
```

```
## Converting to factor: condition
```

```
ANOVA_Exp2_DV2 <- afex::aov_car(Exp2_self_action ~ condition*scenario + Error(ID/scenario), data=df_s2DV2)
```

```
## Converting to factor: condition
```

```
ANOVA_Exp2_DV3 <- afex::aov_car(Exp2_guide_other ~ condition*scenario + Error(ID/scenario), data=df_s2DV3)
```

```
## Converting to factor: condition
```

```
summary(ANOVA_Exp2_DV1)
```

```
## Univariate Type III Repeated-Measures ANOVA Assuming Sphericity
```

```
##
##               Sum Sq num Df Error SS den Df F value      Pr(>F)
## (Intercept)      52062     1    6524    995 7940.25 <0.0000000000000002
## condition         6      4    6524    995   0.24      0.9158
## scenario          3      1    6297    995   0.50      0.4790
## condition:scenario 92      4    6297    995   3.65      0.0058
##
## (Intercept)      ***
```

```
## condition
## scenario
## condition:scenario **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

summary(ANOVA_Exp2_DV2)
## Univariate Type III Repeated-Measures ANOVA Assuming Sphericity
##
##              Sum Sq num Df Error SS den Df F value           Pr(>F)
## (Intercept)      51729      1      6487      995 7934.75 <0.0000000000000002
## condition         20       4      6487      995   0.75           0.56
## scenario          0       1      7078      995   0.02           0.89
## condition:scenario 23       4      7078      995   0.80           0.52
##
## (Intercept)      ***
## condition
## scenario
## condition:scenario
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

summary(ANOVA_Exp2_DV3)
##
## Univariate Type III Repeated-Measures ANOVA Assuming Sphericity
##
##              Sum Sq num Df Error SS den Df F value           Pr(>F)
## (Intercept)      51133      1      6634      995 7669.31 <0.0000000000000002
## condition         65       4      6634      995   2.43           0.046
## scenario          15       1      6767      995   2.16           0.142
## condition:scenario 41       4      6767      995   1.50           0.200
##
## (Intercept)      ***
## condition         *
## scenario
## condition:scenario
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Planned Additional Analysis

Investigate the order effect if we fail to find support for the original's analyses.

Study 1 - ANOVA

Only include participants that saw study 1 before study 2.

```
df_s1 <- cleaned_df %>% filter(study_order == "Exp1First")
#write.csv(df_s1, "stimulated_cleaned_study1.csv",fileEncoding = "UTF-8")
```

```
# DV1 Probability of hiring the candidate
```

```
jmv::ANOVA(
  formula = Exp1_prob_hiring ~ condition,
  data = df_s1,
  effectSize = "eta",
  modelTest = TRUE,
  homo = TRUE,
  postHocES = "d",
  postHocEsCi = TRUE,
  #emMeans = ~ condition, # using ggstatsplot instead
  emmTables = TRUE)
```

```
## ANOVA - Exp1_prob_hiring
```

```
##
```

	Sum of Squares	df	Mean Square	F	p	η^2
Overall model	4.9239	4	1.2310	0.18405	0.94668	
condition	4.9239	4	1.2310	0.18405	0.94668	0.00141
Residuals	3498.0288	523	6.6884			

```
##
```

```
##
## ASSUMPTION CHECKS
```

```
## Homogeneity of Variances Test (Levene's)
```

```
##
```

F	df1	df2	p
1.1999	4	523	0.30986

```
##
```

```
ANOVA_exp1_DV1 <- lm(Exp1_prob_hiring ~ condition, data = df_s1)
```

```
#apa.aov.table(ANOVA_exp1_DV1, filename = "Exp1 DV1 ANOVA.doc",table.number = 10)
```

```
# DV2 Perceived loyalty of the candidate
```

```
jmv::ANOVA(
```

```
  formula = Exp1_loyalty ~ condition,
```

```
  data = df_s1,
```

```
  effectSize = "eta",
```

```
  modelTest = TRUE,
```

```
  homo = TRUE,
```

```
  postHocES = "d",
```

```
  postHocEsCi = TRUE,
```

```
  #emMeans = ~ condition,
```

```
  emmTables = TRUE)
```

```
## ANOVA - Exp1_loyalty
```

```
##
```

	Sum of Squares	df	Mean Square	F	p	η^2
Overall model	34.495	4	8.6237	1.2792	0.27703	
condition	34.495	4	8.6237	1.2792	0.27703	0.00969
Residuals	3525.839	523	6.7416			

```
##
```

```
##
```

```
##
```

```
## ASSUMPTION CHECKS
```

```
##
```

```
## Homogeneity of Variances Test (Levene's)
```

```
##
```

```
##
```

F	df1	df2	p
0.32806	4	523	0.85915

```
##
```

```
##
```

```
##
```

```
ANOVA_exp1_DV2 <- lm(Exp1_loyalty ~ condition, data = df_s1)
```

```
#apa.aov.table(ANOVA_exp1_DV2, filename = "Exp1 DV2 ANOVA.doc", table.number = 11)
```

```
# DV3 Perceived honesty of the candidate
```

```
jmv::ANOVA(
```

```
  formula = Exp1_honesty ~ condition,
```

```
  data = df_s1,
```

```
  effectSize = "eta",
```

```
  modelTest = TRUE,
```

```
  homo = TRUE,
```

```
  postHocES = "d",
```

```
  postHocEsCi = TRUE,
```

```
  #emMeans = ~ condition,
```

```
  emmTables = TRUE)
```

```
## ANOVA - Exp1_honesty
```

```
##
```

	Sum of Squares	df	Mean Square	F	p	η^2
Overall model	9.6951	4	2.4238	0.34810	0.84537	
condition	9.6951	4	2.4238	0.34810	0.84537	0.00266
Residuals	3641.5700	523	6.9628			

```
##
```

```
##
```

```
##
```

```
## ASSUMPTION CHECKS
```

```
##
```

```
## Homogeneity of Variances Test (Levene's)
```

```
##
```

```
##
```

F	df1	df2	p
0.083724	4	523	0.98741

```
##
```

```
ANOVA_exp1_DV3 <- lm(Exp1_honesty ~ condition, data = df_s1)
```

```
#apa.aov.table(ANOVA_exp1_DV3, filename = "Exp1 DV3 ANOVA.doc", table.number = 12)
```

Study 2 - Repeated ANOVA

Only include participants that saw study 2 before study 1.

```
df_s2 <- cleaned_df %>% filter(study_order == "Exp2First")
#write.csv(df_s2, "stimulated_cleaned_study2.csv",fileEncoding = "UTF-8")
```

```
jmv::anovaRM(
  data = df_s2,
  rm = list(
    list(
      label="scenario",
      levels=c("S1", "S2"))),
  rmCells = list(
    list(
      measure="Exp2_S1_seen_wrong",
      cell="S1"),
    list(
      measure="Exp2_S2_seen_wrong_T2",
      cell="S2")),
  bs = condition,
  effectSize = "eta",
  rmTerms = ~ scenario,
  bsTerms = ~ condition,
  leveneTest = TRUE,
  #emMeans = ~ scenario:condition,
  emmTables = TRUE,
  groupSumm = TRUE)
```

```
##
```

```
## REPEATED MEASURES ANOVA
```

```
##
```

```
## Within Subjects Effects
```

```
##
```

	Sum of Squares	df	Mean Square	F	p	η^2
scenario	0.30127	1	0.30127	0.048624	0.82557	0.00005
scenario:condition	60.67590	4	15.16897	2.448200	0.04556	0.01002
Residual	2893.51796	467	6.19597			

```
##
```

```
## Note. Type 3 Sums of Squares
```

```
##
```



```

##
## Between Subjects Effects
##
##      Sum of Squares    df    Mean Square    F        p         $\eta^2$ 
## -----
## condition            15.040      4      3.7600    0.56914    0.68516    0.00248
## Residual            3085.205    467      6.6064
## -----
## Note. Type 3 Sums of Squares
##
##
## ASSUMPTIONS
##
## Homogeneity of Variances Test (Levene's)
##
##      F      df1    df2    p
## -----
## Exp2_S1_seen_wrong    0.11592      4    467    0.97687
## Exp2_S2_seen_wrong_T2  1.47146      4    467    0.20973
## -----
##
##
## Group Summary
##
##      condition    N    Excluded
## -----
## Dissonance_no_write    97      0
## Dissonance_write      94      0
## Negative               87      0
## Neutral                95      0
## Worthy                 99      0
## -----

```

Study 2 DV2

```
jmv::anovaRM(  
  data = df_s2,  
  rm = list(  
    list(  
      label="scenario",  
      levels=c("S1", "S2"))),  
  rmCells = list(  
    list(  
      measure="Exp2_S1_self_action",  
      cell="S1"),  
    list(  
      measure="Exp2_S2_self_action_T2",  
      cell="S2")),  
  bs = condition,  
  effectSize = "eta",  
  rmTerms = ~ scenario,  
  bsTerms = ~ condition,  
  leveneTest = TRUE,  
  #emMeans = ~ scenario:condition,  
  emmTables = TRUE,  
  groupSumm = TRUE)
```

```
##  
## REPEATED MEASURES ANOVA  
##  
## Within Subjects Effects
```

	Sum of Squares	df	Mean Square	F	p	η^2
scenario	0.79792	1	0.79792	0.11871	0.73059	0.00013
scenario:condition	24.80868	4	6.20217	0.92274	0.45041	0.00400
Residual	3138.91908	467	6.72145			

```
## Note. Type 3 Sums of Squares  
##  
##
```

Between Subjects Effects

	Sum of Squares	df	Mean Square	F	p	η^2
condition	30.109	4	7.5273	1.1667	0.32472	0.00485
Residual	3012.941	467	6.4517			

Note. Type 3 Sums of Squares

ASSUMPTIONS

Homogeneity of Variances Test (Levene's)

	F	df1	df2	p
Exp2_S1_self_action	0.35370	4	467	0.84146
Exp2_S2_self_action_T2	0.65821	4	467	0.62133

Group Summary

condition	N	Excluded
Dissonance_no_write	97	0
Dissonance_write	94	0
Negative	87	0
Neutral	95	0
Worthy	99	0

Study 2 DV3

```
jmv::anovaRM(  
  data = df_s2,  
  rm = list(  
    list(  
      label="scenario",  
      levels=c("S1", "S2"))),  
  rmCells = list(  
    list(  
      measure="Exp2_S1_guide_other",  
      cell="S1"),  
    list(  
      measure="Exp2_S2_guide_other_T2",  
      cell="S2")),  
  bs = condition,  
  effectSize = "eta",  
  rmTerms = ~ scenario,  
  bsTerms = ~ condition,  
  leveneTest = TRUE,  
  #emMeans = ~ scenario:condition,  
  emmTables = TRUE,  
  groupSumm = TRUE)
```

```
##  
## REPEATED MEASURES ANOVA  
##  
## Within Subjects Effects
```

	Sum of Squares	df	Mean Square	F	p	η^2
scenario	1.4952	1	1.4952	0.21350	0.64425	0.00024
scenario:condition	20.1721	4	5.0430	0.72011	0.57849	0.00318
Residual	3270.4550	467	7.0031			

```
##  
## Note. Type 3 Sums of Squares  
##
```

```
##
## Between Subjects Effects
##
```

	Sum of Squares	df	Mean Square	F	p	η^2
condition	37.779	4	9.4448	1.4629	0.21241	0.00595
Residual	3015.136	467	6.4564			

```
##
## Note. Type 3 Sums of Squares
##
```

```
##
## ASSUMPTIONS
##
```

```
## Homogeneity of Variances Test (Levene's)
##
```

	F	df1	df2	p
Exp2_S1_guide_other	0.58391	4	467	0.67444
Exp2_S2_guide_other_T2	0.90514	4	467	0.46071

```
##
## Group Summary
##
```

condition	N	Excluded
Dissonance_no_write	97	0
Dissonance_write	94	0
Negative	87	0
Neutral	95	0
Worthy	99	0

Testing order effect as a moderator

note: the moderator package is not yet available for the current version of R, hence we pasted all code on running moderation analysis from JAMOVI, but will provide the analysis and result in a separate .omv file.

study 1

```
install.packages("medmod")
library(medmod)
medmod::mod(
  data = cleaned_df,
  dep = Exp1_prob_hiring,
  mod = study_order_n,
  pred = Condition_n,
  ci = TRUE,
  simpleSlopeEst = TRUE,
  simpleSlopePlot = TRUE)

medmod::mod(
  data = cleaned_df,
  dep = Exp1_honesty,
  mod = study_order_n,
  pred = Condition_n,
  ci = TRUE,
  simpleSlopeEst = TRUE,
  simpleSlopePlot = TRUE,
  duplicate = 2)

medmod::mod(
  data = cleaned_df,
  dep = Exp1_loyalty,
  mod = study_order_n,
  pred = Condition_n,
  ci = TRUE,
  simpleSlopeEst = TRUE,
  simpleSlopePlot = TRUE,
  duplicate = 2)
```

study 2

```
medmod::mod(
  data = cleaned_df,
  dep = Exp2_S1_seen_wrong,
  mod = study_order_n,
  pred = Condition_n,
  ci = TRUE,
  simpleSlopeEst = TRUE,
  simpleSlopePlot = TRUE,
  duplicate = 2)

medmod::mod(
  data = cleaned_df,
  dep = Exp2_S1_self_action,
  mod = study_order_n,
  pred = Condition_n,
```

```
ci = TRUE,  
simpleSlopeEst = TRUE,  
simpleSlopePlot = TRUE,  
duplicate = 2)
```

```
medmod::mod(  
  data = cleaned_df,  
  dep = Exp2_S1_guide_other,  
  mod = study_order_n,  
  pred = Condition_n,  
  ci = TRUE,  
  simpleSlopeEst = TRUE,  
  simpleSlopePlot = TRUE,  
  duplicate = 2)
```

```
medmod::mod(  
  data = cleaned_df,  
  dep = Exp2_S2_seen_wrong_T2,  
  mod = study_order_n,  
  pred = Condition_n,  
  ci = TRUE,  
  simpleSlopeEst = TRUE,  
  simpleSlopePlot = TRUE,  
  duplicate = 2)
```

```
medmod::mod(  
  data = cleaned_df,  
  dep = Exp2_S2_self_action_T2,  
  mod = study_order_n,  
  pred = Condition_n,  
  ci = TRUE,  
  simpleSlopeEst = TRUE,  
  simpleSlopePlot = TRUE,  
  duplicate = 2)
```

```
medmod::mod(  
  data = cleaned_df,  
  dep = Exp2_S2_guide_other_T2,  
  mod = study_order_n,  
  pred = Condition_n,  
  ci = TRUE,  
  simpleSlopeEst = TRUE,  
  simpleSlopePlot = TRUE,  
  duplicate = 2)
```