

Supplemental Materials:

Does Contextualized Attitude Change Depend on Individual Differences in

Responses to Belief-Incongruent Information?

Skylar M. Brannon & Bertram Gawronski

University of Texas at Austin

Combined Analysis

Experiments 1 and 2 collectively suggest that individual differences in PFC, NFS, and ITP do not moderate contextualized attitude change. To provide a stronger basis for drawing theoretical conclusions from non-significant effects, we combined the data from Experiments 1 and 2 ($N = 270$) to obtain greater statistical power for detecting small effects.¹ We also conducted Bayesian analyses to evaluate (1) the strength of evidence in favor of contextualized attitude change and (2) the strength of evidence against the hypothesized moderation by individual differences in PFC, NFS, and ITP.

Results. As in Experiments 1 and 2, we submitted participants' aggregated evaluation scores to separate LME models for each individual difference measure.

PFC. First, we conducted a LME analysis using the full Valence Order \times Measurement Context \times PFC model, with Measurement Context as within-subjects factor, Valence Order as a between-subjects factor, and PFC as a continuous predictor (see Table S1). The three-way interaction was not significant, and was thus removed from the model. In the reduced model, neither the two-way interaction between Valence Order and PFC nor the two-way interaction between Measurement Context and PFC were significant. These interactions were, thus, removed from the model, and the model was re-estimated. The final model revealed a significant main effect of Valence Order, which was qualified by a significant two-way interaction between Valence Order and Measurement Context. As in Experiments 1 and 2, we conducted a priori pairwise contrasts to decompose this interaction.² These contrasts suggested a significant pattern

¹ A sample size of 270 provides 80% power to detect a correlation of $r = .17$ between the two components contextualized attitude change and individual difference measures, and 95% power to detect a correlation of $r = .22$.

² Decomposition of the interaction between Valence Order and Measurement Context was conducted using the *phia* package (De Rosario-Martinez, 2015) in RStudio (RStudio Team, 2016). Effect sizes for these contrasts were calculated using the online companion for Lipsey and Wilson's (2002) guide to meta-analysis (<https://www.campbellcollaboration.org/escalc/html/EffectSizeCalculator-R5.php>).

of contextualized attitude change for both Valence Order conditions. For positive-negative targets, evaluations for positive-negative targets were more positive in the first learning context as compared to the second learning context, $\chi^2(1) = 9.88, p = .002, r = .19$. Moreover, positive-negative targets were evaluated more positively in the novel context than in the second learning context, $\chi^2(1) = 5.93, p = .015, r = .15$. Conversely, negative-positive targets were evaluated more negatively in the first learning context as compared to the second learning context, $\chi^2(1) = 25.70, p < .001, r = .31$. Moreover, negative-positive targets were evaluated more negatively in the novel context than in the second learning context, $\chi^2(1) = 4.25, p = .039, r = .13$.

NFS. The same analyses were repeated for NFS (see Table S1). In the full LME model, the three-way interaction between Valence Order, Measurement Context, and NFS was not significant, and thus removed from the model. In the reduced model, the interaction between Measurement Context and ITP was not significant. This interaction was, thus, removed from the model, and the model was re-estimated. The final model revealed significant two-way interactions between Valence Order and Measurement Context and between Valence Order and NFS. The pairwise comparisons decomposing the two-way interaction between Valence Order and Measurement Context suggested a significant pattern of contextualized attitude change for both Valence Order conditions. For positive-negative targets, evaluations for positive-negative targets were more positive in the first learning context as compared to the second learning context, $\chi^2(1) = 9.91, p = .002, r = .19$. Moreover, positive-negative targets were evaluated more positively in the novel context than in the second learning context, $\chi^2(1) = 5.96, p = .015, r = .15$. Conversely, negative-positive targets were evaluated more negatively in the first learning context as compared to the second learning context, $\chi^2(1) = 25.78, p < .001, r = .31$. Moreover, negative-

positive targets were evaluated more negatively in the novel context than in the second learning context, $\chi^2(1) = 4.26, p = .039, r = .13$.

ITP. Finally, the LME model was repeated for ITP (see Table S1). As with the other two models, the three-way interaction between Valence Order, Measurement Context, and ITP was not significant. This interaction was removed from the model, and the model was re-estimated. In the reduced model, the interaction between Measurement Context and ITP was not significant. This interaction was, thus, removed from the model, and the model was re-estimated. The final model revealed a significant main effect of Valence Order, which was qualified by significant two-way interactions between Valence Order and Measurement Context, and between Valence Order and ITP. The pairwise comparisons decomposing the two-interaction between Valence Order and Measurement Context suggested a significant pattern of contextualized attitude change for both Valence Order conditions. For positive-negative targets, evaluations for positive-negative targets were more positive in the first learning context as compared to the second learning context, $\chi^2(1) = 9.91, p = .002, r = .19$. Moreover, positive-negative targets were evaluated more positively in the novel context than in the second learning context, $\chi^2(1) = 5.95, p = .015, r = .15$. Conversely, negative-positive targets were more negatively in the first learning context as compared to the second learning context, $\chi^2(1) = 25.78, p < .001, r = .31$. Moreover, negative-positive targets were evaluated more negatively in the novel context than in the second learning context, $\chi^2(1) = 4.26, p = .039, r = .13$.

Bayesian analysis. As in Experiments 1 and 2, we also conducted Bayesian analyses for each effect in the LME models (see Table S1). These analyses provided decisive evidence for contextualized attitude change, as captured by the two-way interaction between Valence Order and Measurement Context. Moreover, there was very strong evidence that the two-way

interaction between Valence Order and Measurement Context was not qualified by higher-order interactions with PFC, NFS, or ITP.

Table S1

LME Model Results and Bayes Factors, Combined Data from Experiments 1 and 2

Model	Predictor	Model	Residual	<i>F</i>	<i>p</i>	<i>R</i> _p ²	<i>BF</i> ₁₀	<i>BF</i> ₁₀ Interpretation
		<i>df</i>	<i>df</i>					
PFC								
	Valence Order	1.00	1345.00	14.30	<.001	.011	60.83	Very strong evidence for H ₁
	Measurement Context	2.00	1345.00	1.53	.218	.002	0.03	Very strong evidence for H ₀
	PFC	1.00	268.00	2.66	.104	.010	0.23	Substantial evidence for H ₀
	Valence Order × Measurement Context	2.00	1345.00	16.91	<.001	.025	206650.40	Decisive evidence for H ₁
	Valence Order × PFC	1.00	1342.00	0.05	.821	.000	0.09	Strong evidence for H ₀
	Measurement Context × PFC	2.00	1342.00	1.81	.165	0.003	0.06	Strong evidence for H ₀
	Valence Order × Measurement Context × PFC	2.00	1340.00	0.35	.708	.001	0.03	Very strong evidence for H ₀
NFS								
	Valence Order	1.00	1344.00	3.06	.081	.002	60.83	Very strong evidence for H ₁
	Measurement Context	2.00	1344.00	1.53	.217	.002	0.03	Very strong evidence for H ₀
	NFS	1.00	268.00	0.09	.762	.000	0.07	Strong evidence for H ₀
	Valence Order × Measurement Context	2.00	1344.00	16.97	<.001	.025	204760.40	Decisive evidence for H ₁
	Valence Order × NFS	1.00	1344.00	6.03	.014	.004	1.69	Anecdotal evidence for H ₁

CONTEXTUALIZED ATTITUDE CHANGE

7

Measurement Context × NFS	2.00	1342.00	0.12	.890	.000	0.01	Very strong evidence for H ₀
Valence Order × Measurement Context × NFS	2.00	1340.00	0.16	.851	.000	0.03	Very strong evidence for H ₀
ITP							
Valence Order	1.00	1344.00	10.12	.002	.007	60.83	Very strong evidence for H ₁
Measurement Context	2.00	1344.00	1.53	.217	.002	0.03	Very strong evidence for H ₀
ITP	1.00	268.00	0.08	.781	.000	0.07	Strong evidence for H ₀
Valence Order × Measurement Context	2.00	1344.00	16.96	<.001	.025	204885.10	Decisive evidence for H ₁
Valence Order × ITP	1.00	1344.00	5.13	.024	.004	1.08	Anecdotal evidence for H ₁
Measurement Context × ITP	2.00	1342.00	1.06	.346	.002	0.03	Very strong evidence for H ₀
Valence Order × Measurement Context × ITP	2.00	1340.00	0.36	.696	.001	0.03	Very strong evidence for H ₀

Note. LME analyses were conducted using the lmerTest package (Kuznetsova, Brockhoff, & Christensen, 2016) in RStudio (RStudio Team, 2016) using Kenward-Roger approximated degrees of freedom. Residual degrees of freedom for each effect reflect removal of non-significant higher order effects, which were removed from the model for a more accurate estimation of lower order interactions and main effects (e.g., Kutner, Nachtsheim, Neter, & Li, 2005). Bayes factors were obtained using the BayesFactor package (Morey & Rouder, 2015) in RStudio (RStudio Team, 2016). To obtain the Bayes factor, a model including only lower level effects (or an empty model for the main effects) was compared to a model containing both the lower level effects and the effect of interest. Evidence category labels for Bayes Factors follow recommendations from Wetzels and Wagenmakers (2012).