Supplementary Online Material

How Do Examples Impact Divergent Thinking? The Interplay Between Associative and Executive Processes

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Table S1 Intercorrelations between the Gf task (matrix-, letter- and number-series) and the Gf composite score

		1	2	3
	Gf composite score	.76 **	.84 **	.86 **
1	Matrix-series	_	.44 **	.48 **
2	Letter-series		_	.60 **
3	Number-series			_

Notes. n = 365. ** p < .01.

Table S2

Intercorrelations between originality, fluency, cognitive load and Gf for each AUT trial (book, bottle, brick)

				•					
	Book		Bottle			Brick			
	1	2	3	4	5	6	7	8	9
Gf (composite score)	.26 **	.21 **	14 **	.19 **	.15 **	.05	.21 **	. 19 **	04
Book									
1 Originality	_	.15 **	02	.23 **	.17 **	05	.30 **	.23 **	09
2 Fluency			44 **	.07	.67 **	12 *	.03	.65 **	08
3 Cognitive load				01	21 **	.45 **	.08	23 **	.44 **
Bottle									
4 Originality					.11 *	05	.37 **	.11 *	07
5 Fluency						38 **	.07	.70 **	16 **
6 Cognitive load							.03	20 **	.49 **
Brick									
7 Originality								.11 *	01
8 Fluency									42 **
9 Cognitive load									

Notes. Mean originality scores are aggregated to the subject level for each AUT trial. * p < .05. ** p < .01.

Table S3

Intercorrelations between originality, fluency, cognitive load and Gf across AUT trials

		1	2	3
	Gf (composite score)	.30 **	.21 **	05
1	Originality	_	.19 **	04
2	Fluency		_	35 **
3	Cognitive load			_

Notes. Originality, fluency, and cognitive load scores are averages over the AUT trials (book, bottle, brick). * p < .05. ** p < .01.

Preregistered robustness checks using Structural Equation Modelling models (SEM)

As a preregistered robustness check of our findings, we started with two independent latent variables models, once regressing the latent variable of fluency on condition, and latent variables of cognitive load and reasoning (Model A), while in the second model (Model B) originality served as the dependent variable. Figure S1 provides a graphical illustration of the models. Both models were estimated using the "lavaan" package 0.6-13 (Rosseel, 2012) for R twice: first using maximum likelihood robust estimator (MLR) and second—to obtain bootstrapped standard errors and confidence intervals for indirect effect—using ML estimator. Given that models resulted in highly similar estimates, we provide ML parameters below. Table S4 contains a summary of model fit indices. In a model with fluency as the dependent variable, the basic model (Model A) was characterized by a poor fit, yet modification indices suggested that additional covariances between cognitive load and fluency at each task level (i.e., for book, brick, and bottle) improve fit. Indeed, as illustrated, model A' had an excellent fit. Latent variables were robustly loaded by its indicators (see Table S5). Condition with a remote example generated a higher cognitive load as compared to a common example ($\beta = .194$, p = .004), and a higher cognitive load resulted in lower fluency ($\beta = -.281$, p < .001). Consequently, we observed a statistically significant indirect effect: $\beta = -.054$, p = -.054.016, consistent with our mixed models analyses presented in the paper. In the case of a model with originality as a dependent variable, model fit was characterized by a mediocre fit. We did not observe cognitive load translate significantly into participants' originality. The indirect effect was not significant.

Figure S1
Schematic illustration of the SEM models estimated

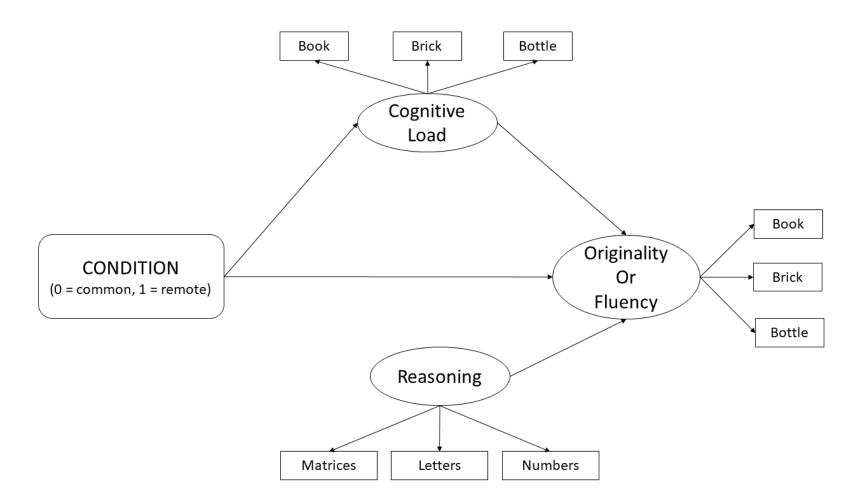


Table S4
Summary of the model fit and structural weights across SEM models

]	Originality		
Model fit	Model A	Model A'	Model B	
$\chi^2(df)$	354.50 (31)	41.03 (26)	130.05 (31)	
χ^2/df	11.436	1.578	4.195	
CFI	.766	.991	.870	
TLI	.660	.985	.811	
RMSEA (90% CI)	.169 (.153, .185)	.036 (.000, .058)	.094 (.078, .111)	
SRMR	.065	.044	.074	
Structural weights (standardized)				
Condition-Cognitive Load (CL)	.196**	.194**	.209**	
CL-DV	436***	281***	055	
Condition-DV (Direct Effect)	.007	024	.457***	
Reasoning-DV	.221***	.227***	.351**	
Condition-CL-DV (Indirect Effect)	085**	054*	012	
Total Effect (Direct + Indirect)	078	079	.446***	

Notes. Model A' includes correlated residuals between cognitive load and fluency scores at the trial level.

^{*} *p* < .05. ** *p* < .01. *** *p*< .001.

Table S5 Factor loadings for the measurement part of SEM models

	Fluency	Originality	Cognitive Load	Reasoning
Book	.787	.352	.655	
Brick	.836	.862	.691	_
Bottle	.838	.460	.691	_
Matrices	_	_	_	.598
Letters	_		_	.741
Numbers	_	_	_	.804

References

Rosseel, Y. (2012). Lavaan: An R package for structural equation modeling and more. Version 0.5–12 (BETA). *Journal of Statistical Software*, 48(2), 1–36.