Supplemental Online Materials, Reviewed Material

Causal Depth Analyses

To calculate causal centrality based on the causal depth of a feature, we used the dependency model of causal centrality (Sloman et al., 1998). According to this iterative model, c_i, the centrality of feature *i*, is determined (at each time step) by summing across the centrality of the concept's other features (at time, *t*), $c_{j,t}$, multiplied by how dependent each feature, *j*, is on feature *i*, d_{ij}:

$$c_{i,t+1} = \sum_j d_{ij} c_{j,t}. \quad (1)$$

The implementation of the model is a repeated matrix multiplication that converges on a stable ranking within a small number of iterations (Sloman et al., 1998; Kim & Park, 2009). The ConceptBuilder software (Kim & Park, 2009) used in the pilot experiment (see SOM-U) performs 15 iterations and the initial centrality of all features (at time 0) is set to 0.5. All causal depth analyses follow this convention.

As d_{ij} is a positive value when feature *i* causes feature *j*, according to this model, the deeper a feature is in the causal chain, the more defining it is to the concept. In the concept map task and the listing causal relationships task, the dependence, d_{ij}, is the value (1 = weak, 2 = moderate, 3 = strong) that participants assigned to the strength of each causal relationship they drew or reported.

Causal Depth Analysis – Experiment 1

The results of the causal depth correlational analyses revealed a similar pattern to the causal connections analyses. The overall correlation between causal depth and disruption to identity was significant in the close-other condition, and marginally significant in the self and generic-other conditions (see Table S1). The results of the individual-level analysis revealed that the Spearman correlation for causal depth was positive for all conditions (M_{self} = .26, $M_{close\text{-}other}$ = .32, $M_{generic\text{-}other}$ = .22), $t(78) = 5.14$, $t(78) = 6.61$, $t(80) = 4.78$, ps < .001[1]. The majority of participants in all conditions had a positive individual-level correlation between features' causal depth and rated disruptiveness of change (72%, 80%, and 72% in the self, close-other, and generic-other conditions, respectively). A one-way ANOVA revealed that the mean Spearman correlation did not differ by condition, $F(2, 238) = 1.14$, p >.250, suggesting that the relationship between casual depth and disruption to identity was similar across conditions (see Table S1).

Table S1

Correlations Between a Feature's Causal Depth and Ratings of How Disruptive Change in that Feature Would Be

	Causal Depth Approach	
Condition	Aggregate Spearman Correlation	Individual Spearman Correlation
Self	$r_s = .49$, $p = .05$	mean $r_s = .26$, t(78) = 5.15, $p < .001$, 95% CI = [.16, .36]
Close-other	$r_s = .65$, $p = .01$	mean $r_s = .32$, t(78) = 6.61, $p < .001$, 95% CI = [.22, .42]
Generic-other	$r_s = .42$, $p = .11$	mean $r_s = .22$, t(80) = 4.79 $p < .001$, 95% CI = [.13, .31]

Note. T-tests in Individual Correlations column are one-sample t-tests of the mean Spearman rho (with Fisher transformation) against 0.

Causal Depth vs. Causal Connections Approaches – Experiment 1

To examine the relative impact of the two forms of causal centrality on disruption to identity scores, for each subject, we regressed identity disruption ratings on both measures of causal centrality (all measures z-scored within subject). We performed a 3 (condition: self, close-other,

[1] Fisher transformations were performed prior to t-tests.

generic-other) × 2 (causal centrality approach: causal connections vs causal depth) ANOVA on the resulting betas. Neither the main effect of condition, $F(2, 236) = 1.08$, $p > .250$, nor the condition × causal centrality approach interaction, $F(2, 236) = .71$, $p > .250$, were significant, suggesting that condition did not influence the predictive value of these two causal centrality measures.

We found a main effect of causal centrality approach, $F(1, 236) = 36.13$, $p < .001$. For all conditions the mean regression coefficient for the causal connections term ($M_{self} = .26$, $M_{close\text{-}other} = .32$, $M_{generic\text{-}other} = .31$) was significantly positive, *t*s > 5.45, *p*s < .001, and greater than the mean coefficient for the causal depth term ($M_{self} = .04$, $M_{close\text{-}other} = .03$, $M_{generic\text{-}other} = -.05$), *t*s > 2.8, *p*s < .01 (see Table S2). The mean coefficient for the causal depth term was not significantly positive for any condition, *t*s < 1.03, *p*s > .250. The regression analysis suggests that the causal depth approach does not significantly add to the predictive power of a model that includes the number of causal connections.

Table S2

Summary of Experiment 1 Regression Results

	Mean Coefficient		
Condition	Causal Connections Term, *M (SD)*	Causal Depth Term, *M (SD)*	t-tests Comparing Terms
Self	.26 (.42) 95% CI=[.16, .35]	.04 (.37) 95% CI=[-.05, .11]	$t(78) = 2.89$, $p = .005$
Close-other	.32 (.42) 95% CI=[.23, .42]	.03 (.45) 95% CI=[-.07, .13]	$t(78) = 3.43$, $p = .001$
Generic-other	.31 (.45) 95% CI=[.21, .41]	-.05 (.46) 95% CI=[-.16, .05]	$t(80) = 4.03$, $p < .001$

Causal Depth Analysis – Experiment 2

Using causal depth as an alternative measure of causal centrality, we again found that causal information influenced identity judgments. The Spearman rank correlation coefficient was positive for the majority of participants in the self and close-other conditions (76% and 70%, respectively). The average correlation coefficient was positive between causal centrality and disruption to identity for both conditions (M_{self} = .25, 95% CI = [.18 .32]; $M_{\text{close-other}}$ = .24, 95% CI = [.16 .32]), $t(91) = 6.8$, $t(96) = 5.78$, ps < .001.

An independent-samples t-test revealed that the mean Spearman correlation did not differ by condition, $t(187) = .25$, p >.250, suggesting that the relationship between casual depth and disruption to identity was similar across conditions.

Causal Depth vs. Causal Connections Approaches – Experiment 2

To examine the relative impact of the two forms of causal centrality on disruption to identity, for each subject, we regressed identity disruption ratings on both measures of causal centrality (all measures z-scored within subject). We performed a 2 (condition: self, close-other) × 2 (causal centrality approach: causal connections vs causal depth) ANOVA on the resulting betas. The main effect of condition was not significant, $F(1, 187) = .66$, $p > .250$, nor was the condition × causal centrality approach interaction, $F(1, 187) = .57$, $p > .250$, suggesting that condition did not influence the predictive value of these two causal centrality measures.

There was no main effect of causal centrality approach, $F(1, 187) = 1.64$, $p = .202$, suggesting the predictive value of the two causal centrality approaches did not differ. Overall, the mean coefficient for the causal connections term (M = .15, 95% CI = [.08 .21]) and the causal depth term (M = .07, 95% CI = [.01 .13]) were both significantly positive, $t(188) = 4.29$, p<.001, $t(188) = 2.25$, p<.025. (See Table S3 for detailed results.)

Table S3

Summary of Experiment 2 Regression Results

Condition	Mean coefficient		
	Causal Connections Term, *M (SD)*	Causal Depth Term, *M (SD)*	t-tests Comparing Terms
Self	.17 (.50) 95% CI=[.07, .28]	.06 (.43) 95% CI=[-.02, .15]	$t(92) = 1.22, p = .225$
Close-other	.12 (.44) 95% CI=[.03, .21]	.08 (.43) 95% CI=[-.01, .16]	$t(96) = .60, p > .250$

Level of Description Analysis – Experiment 2

The features of identity reported in Experiment 2 varied on how abstract of concrete they are as well as whether they were plural or singular. To ensure that these factors did not influence our results, we had an independent coder (blind to the hypotheses) indicate whether each feature participants listed was best characterized as singular or plural, as well as how specific/concrete vs. generic/abstract it was[2]. We performed a partial correlation for each subject to determine the relationship between causal connections and disruption to identity while controlling for level of abstraction and plurality. The results revealed that when controlling for these variables the Spearman correlation coefficients were significantly positive for both approaches to causal centrality for both experiments (see Table S4).

[2] For coding, a scale of 1 to 5 was used where 1 meant that the listed feature was "not at all specific and could apply to anyone/is not a tangible feature" and 5 meant that the listed feature was "extremely specific to the participant/is a concrete feature."

Table S4

Summary of Experiment 2 Partial Correlation Results

Condition	Causal Connections	Causal Depth
Self	mean r_s = .22, t(91) = 5.39, $p < .001$, 95% CI = [.14, .30]	mean r_s = .24, t(91) = 6.04, $p < .001$, 95% CI = [.16, .32]
Close-other	mean r_s = .19, t(96) = 4.68, $p < .001$, 95% CI = [.11, .28]	mean r_s = .17, t(96) = 3.96, $p < .001$, 95% CI = [.08, .25]

Note. T-tests are one-sample t-tests of the mean Spearman rho (with Fisher transformation) against 0.

Plausibility Analysis – Experiment 3

Because different causal structures may also differ in how natural they appear to be (Ahn, 1999), we also examined the plausibility of the two different types of causal structures. The common cause and common effect vignettes were rated as equally plausible ($M_{commoncause}$ = 74.2, $M_{commoneffect}$ = 72.5, $t(11) = .47$, $p > .250$). So, the observed difference in selections between the two conditions cannot be explained by a difference in the believability of the two causal structures.

References

Ahn, W. (1999). Effect of causal structure on category construction. *Memory & Cognition*, *27*, 1008-1023.

Kim, N. S., & Park, E. Y. (2009). ConceptBuilder: An open-source software tool for measuring, depicting, and quantifying causal models. *Behavior Research Methods*, *41*, 128-136.

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