Supporting Information

NB: All data and analyses reported in this paper are publicly accessible via the Harvard Dataverse at [http://dx.doi.org/10.7910/DVN/JZZIYU](http://dx.doi.org/10.7910/DVN/JZZIYU) (Montero-Melis, 2016)

A. Description of target stimuli

Table 1

Full description of target items.

<table>
<thead>
<tr>
<th>item</th>
<th>Path</th>
<th>MannerCause</th>
<th>MannerObject</th>
<th>Direction</th>
<th>Object</th>
<th>Ground</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>across</td>
<td>pull</td>
<td>roll</td>
<td>left-right</td>
<td>pram</td>
<td>street</td>
</tr>
<tr>
<td>2</td>
<td>across</td>
<td>pull</td>
<td>roll</td>
<td>right-left</td>
<td>pram</td>
<td>road</td>
</tr>
<tr>
<td>3</td>
<td>across</td>
<td>pull</td>
<td>slide</td>
<td>left-right</td>
<td>rocking horse</td>
<td>street</td>
</tr>
<tr>
<td>4</td>
<td>across</td>
<td>pull</td>
<td>slide</td>
<td>right-left</td>
<td>rocking horse</td>
<td>road</td>
</tr>
<tr>
<td>5</td>
<td>across</td>
<td>push</td>
<td>roll</td>
<td>left-right</td>
<td>cart wheel</td>
<td>road</td>
</tr>
<tr>
<td>6</td>
<td>across</td>
<td>push</td>
<td>roll</td>
<td>right-left</td>
<td>cart wheel</td>
<td>street</td>
</tr>
<tr>
<td>7</td>
<td>across</td>
<td>push</td>
<td>slide</td>
<td>left-right</td>
<td>apple basket</td>
<td>road</td>
</tr>
<tr>
<td>8</td>
<td>across</td>
<td>push</td>
<td>slide</td>
<td>right-left</td>
<td>apple basket</td>
<td>street</td>
</tr>
<tr>
<td>9</td>
<td>down</td>
<td>pull</td>
<td>roll</td>
<td>left-right</td>
<td>wheelbarrow</td>
<td>hill</td>
</tr>
<tr>
<td>10</td>
<td>down</td>
<td>pull</td>
<td>roll</td>
<td>right-left</td>
<td>wheelbarrow</td>
<td>snowy hill</td>
</tr>
<tr>
<td>11</td>
<td>down</td>
<td>pull</td>
<td>slide</td>
<td>left-right</td>
<td>trunk</td>
<td>hill</td>
</tr>
<tr>
<td>12</td>
<td>down</td>
<td>pull</td>
<td>slide</td>
<td>right-left</td>
<td>trunk</td>
<td>snowy hill</td>
</tr>
<tr>
<td>13</td>
<td>down</td>
<td>push</td>
<td>roll</td>
<td>left-right</td>
<td>ball</td>
<td>snowy hill</td>
</tr>
<tr>
<td>14</td>
<td>down</td>
<td>push</td>
<td>roll</td>
<td>right-left</td>
<td>ball</td>
<td>hill</td>
</tr>
<tr>
<td>15</td>
<td>down</td>
<td>push</td>
<td>slide</td>
<td>left-right</td>
<td>suitcase</td>
<td>snowy hill</td>
</tr>
<tr>
<td>16</td>
<td>down</td>
<td>push</td>
<td>slide</td>
<td>right-left</td>
<td>suitcase</td>
<td>hill</td>
</tr>
<tr>
<td>17</td>
<td>into</td>
<td>pull</td>
<td>roll</td>
<td>left-right</td>
<td>shopping cart</td>
<td>cave</td>
</tr>
<tr>
<td>18</td>
<td>into</td>
<td>pull</td>
<td>roll</td>
<td>right-left</td>
<td>shopping cart</td>
<td>barn</td>
</tr>
<tr>
<td>19</td>
<td>into</td>
<td>pull</td>
<td>slide</td>
<td>left-right</td>
<td>chair</td>
<td>barn</td>
</tr>
<tr>
<td>20</td>
<td>into</td>
<td>pull</td>
<td>slide</td>
<td>right-left</td>
<td>chair</td>
<td>cave</td>
</tr>
<tr>
<td>21</td>
<td>into</td>
<td>push</td>
<td>roll</td>
<td>left-right</td>
<td>wheel</td>
<td>cave</td>
</tr>
<tr>
<td>22</td>
<td>into</td>
<td>push</td>
<td>roll</td>
<td>right-left</td>
<td>wheel</td>
<td>barn</td>
</tr>
<tr>
<td>23</td>
<td>into</td>
<td>push</td>
<td>slide</td>
<td>left-right</td>
<td>table</td>
<td>barn</td>
</tr>
<tr>
<td>24</td>
<td>into</td>
<td>push</td>
<td>slide</td>
<td>right-left</td>
<td>table</td>
<td>cave</td>
</tr>
<tr>
<td>25</td>
<td>up</td>
<td>pull</td>
<td>roll</td>
<td>left-right</td>
<td>toy car</td>
<td>dune</td>
</tr>
<tr>
<td>item</td>
<td>Path</td>
<td>MannerCause</td>
<td>MannerObject</td>
<td>Direction</td>
<td>Object</td>
<td>Ground</td>
</tr>
<tr>
<td>------</td>
<td>------</td>
<td>-------------</td>
<td>--------------</td>
<td>------------</td>
<td>-------------</td>
<td>--------</td>
</tr>
<tr>
<td>26</td>
<td>up</td>
<td>pull</td>
<td>roll</td>
<td>right-left</td>
<td>toy car</td>
<td>roof</td>
</tr>
<tr>
<td>27</td>
<td>up</td>
<td>pull</td>
<td>slide</td>
<td>left-right</td>
<td>bag</td>
<td>dune</td>
</tr>
<tr>
<td>28</td>
<td>up</td>
<td>pull</td>
<td>slide</td>
<td>right-left</td>
<td>bag</td>
<td>roof</td>
</tr>
<tr>
<td>29</td>
<td>up</td>
<td>push</td>
<td>roll</td>
<td>left-right</td>
<td>rubber ring</td>
<td>dune</td>
</tr>
<tr>
<td>30</td>
<td>up</td>
<td>push</td>
<td>roll</td>
<td>right-left</td>
<td>rubber ring</td>
<td>roof</td>
</tr>
<tr>
<td>31</td>
<td>up</td>
<td>push</td>
<td>slide</td>
<td>left-right</td>
<td>gift</td>
<td>dune</td>
</tr>
<tr>
<td>32</td>
<td>up</td>
<td>push</td>
<td>slide</td>
<td>right-left</td>
<td>gift</td>
<td>roof</td>
</tr>
</tbody>
</table>
B. Norming study (participant descriptions of the events)

To test for between-language differences in the likelihood of expressing the three key event components manipulated in the study, we fitted three separate logistic mixed models (Jaeger, 2008), one for each of the dependent variables Path, Manner of cause and Manner of object. Analyses were run in R (R Development Core Team, 2013) using the glmer function from the lme4 package (Bates, Maechler, Bolker, & Walker, 2014). The model formulae were:

\[
\text{PathMention} \sim 1 + \text{language} + (1 | \text{subject}) + (1 | \text{item}) + (0 + \text{language} | \text{item}) \\
\text{MannerCauseMention} \sim 1 + \text{language} + (1 | \text{subject}) + (1 + \text{language} | \text{item}) \\
\text{MannerObjectMention} \sim 1 + \text{language} + (1 | \text{subject}) + (1 + \text{language} | \text{item})
\]

The models above were the maximal models that converged (Barr, Levy, Scheepers, & Tily, 2013). In the path model, a model analogous to the ones for Manner of cause and Manner of object did not converge, so we removed the by-item random correlation between the intercept and language (see difference in by-item random effects in model formulae above).

Because the analyses involved multiple tests on the same data, one for each semantic component, we Bonferroni-corrected the \( p \) values by multiplying the original \( p \) values by 3 (the number of models), to stay at the nominal level of \( \alpha = .05 \). Table 2 summarizes the results of each model.

Table 2

<table>
<thead>
<tr>
<th>Model</th>
<th>Dependent variable</th>
<th>Predictor</th>
<th>Coef. ( \hat{\beta} )</th>
<th>SE(( \hat{\beta} ))</th>
<th>( z )</th>
<th>( p )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Path</td>
<td>Spanish (intercept)</td>
<td>4.20</td>
<td>0.66</td>
<td>6.39</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Swedish vs. Spanish</td>
<td>3.03</td>
<td>1.46</td>
<td>2.08</td>
<td>=.113</td>
</tr>
<tr>
<td>2</td>
<td>Manner of cause</td>
<td>Spanish (intercept)</td>
<td>0.32</td>
<td>0.50</td>
<td>0.65</td>
<td>=1</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Swedish vs. Spanish</td>
<td>5.01</td>
<td>1.36</td>
<td>3.67</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>3</td>
<td>Manner of object</td>
<td>Spanish (intercept)</td>
<td>-5.06</td>
<td>0.87</td>
<td>-5.79</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Swedish vs. Spanish</td>
<td>2.55</td>
<td>0.89</td>
<td>2.88</td>
<td>=.018</td>
</tr>
</tbody>
</table>

Note. For each separate model, the table shows coefficient estimates \( \hat{\beta} \) (in log-odds), standard errors SE(\( \hat{\beta} \)), associated Wald’s \( z \) score (\( \hat{\beta} / \text{SE}(\hat{\beta}) \)), and Bonferroni-adjusted significance level \( p \) for predictors (i.e., original \( p \) values multiplied by three with upper bound 1).

The compound analysis revealed that Spanish speakers relied more than Swedish speakers on ground when judging similarity. Is this mirroring a greater tendency by Spanish speakers to include ground information in their descriptions? In fact, speakers of both languages were almost at ceiling with respect to ground mentions: 96% of Spanish and 97% of Swedish descriptions mentioned this component. We fitted a mixed logistic regression model analogous to the ones...
above. The results showed no language differences in speakers’ tendency to mention ground
\( \text{Language}_{\text{Swedish-vs-Spanish}}: \hat{\beta} = 2.08, SE = 1.31, z = 1.31, p > .10 \), see Table 3.

**Table 3**

Model summary for mentions of ground in norming study. The table shows coefficient estimates \( \hat{\beta} \) (in log-odds), standard errors \( \text{SE}(\hat{\beta}) \), associated Wald’s \( z \) score \( (=\hat{\beta} / \text{SE}(\hat{\beta})) \), and significance level \( p \) for predictors.

<table>
<thead>
<tr>
<th>Dependent variable</th>
<th>Predictor</th>
<th>Coef. ( \hat{\beta} )</th>
<th>SE(( \hat{\beta} ))</th>
<th>( z )</th>
<th>( p )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ground</td>
<td>Spanish (intercept)</td>
<td>5.28</td>
<td>1.12</td>
<td>4.69</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td></td>
<td>Swedish vs. Spanish</td>
<td>2.08</td>
<td>1.31</td>
<td>1.59</td>
<td>.011</td>
</tr>
</tbody>
</table>

Model formula in R: GroundMention ~ 1 + language + (1 | subject) + (1 + language | item)

Finally, we summarize the mean proportion of descriptions that encoded each of the six event dimensions that varied in the stimuli. Table 4 shows by-subject means and standard errors.

**Table 4**

Proportion of mentions of each event component in norming study by language. Values indicate by-subject means and standard errors.

<table>
<thead>
<tr>
<th></th>
<th>Spanish (±0.02)</th>
<th>Swedish (±0.01)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Path (e.g. into)</td>
<td>0.95</td>
<td>0.99</td>
</tr>
<tr>
<td>Manner of cause (e.g., push)</td>
<td>0.55 (±0.07)</td>
<td>0.78 (±0.02)</td>
</tr>
<tr>
<td>Manner of object (e.g., roll)</td>
<td>0.10 (±0.03)</td>
<td>0.29 (±0.03)</td>
</tr>
<tr>
<td>Direction (e.g., left)</td>
<td>0.07 (±0.04)</td>
<td>0.02 (±0.02)</td>
</tr>
<tr>
<td>Ground (e.g., hill)</td>
<td>0.96 (±0.02)</td>
<td>0.97 (±0.03)</td>
</tr>
<tr>
<td>Object (e.g., ball)</td>
<td>1.00 (±0.00)</td>
<td>0.99 (±0.00)</td>
</tr>
</tbody>
</table>
C. Experiments 1–3 (linear mixed effects regression models)

All models were fitted in R (R Development Core Team, 2013) using the *lmer* function from the *lme4* library (Bates et al., 2014). The models for Experiments 1-3 all had the same structure:

\[
\text{Similarity} \sim 1 + (P + MC + MO + Di)^2 \ast \text{Language} + \text{Gr} \ast \text{Language} + \text{Ob} \ast \text{Language} + (1 + (P + MC + MO + Di)^2 + \text{Gr} + \text{Ob} | \text{Subject}) + (1 | \text{Item})
\]

(P = Path, MC = Manner of Cause, MO = Manner of Object, Di = Direction left/right, Gr = Ground, Ob = Object)

A description of the predictors that went into the models is shown in Table 5. All predictors were centred with a difference of 1, so that the reported coefficients represent the estimated difference in similarity ratings between the two levels of the predictor. Collinearity among predictors in the analyses for Experiments 1–3 was small, \( \kappa < 5 \) (cf. Baayen, 2008, p. 182). The fixed-effects estimates for each experiment are shown in Table 6 to Table 8. Significance codes were determined using the *confint.merMod* function from the *lme4* library (method = “Wald”, nsim = 10000).

Table 5
Input variables in linear mixed models for Experiments 1–3.

<table>
<thead>
<tr>
<th>Predictors</th>
<th>Type</th>
<th>Levels a</th>
</tr>
</thead>
<tbody>
<tr>
<td>Path</td>
<td>Within-subject</td>
<td>Same (e.g., both scenes \textit{into}), different (e.g., one scene \textit{into}, other \textit{up})</td>
</tr>
<tr>
<td>Manner of cause</td>
<td>Within-subject</td>
<td>Same (e.g., both scenes \textit{push}), different (e.g., one scene \textit{push}, other \textit{pull})</td>
</tr>
<tr>
<td>Manner of object</td>
<td>Within-subject</td>
<td>Same (e.g., both scenes \textit{roll}), different (e.g., one scene \textit{roll}, other \textit{slide})</td>
</tr>
<tr>
<td>Direction</td>
<td>Control (within-subject)</td>
<td>Same (e.g., both scenes \textit{left-right}), different (e.g., one scene \textit{left-right}, other \textit{right-left})</td>
</tr>
<tr>
<td>Ground</td>
<td>Control (within-subject)</td>
<td>Same (e.g., both scenes \textit{cave}), different (e.g., one scene \textit{cave}, other \textit{barn})</td>
</tr>
<tr>
<td>Object</td>
<td>Control (within-subject)</td>
<td>Same (e.g., both scenes \textit{tyre}), different (e.g., one scene \textit{tyre}, other \textit{table})</td>
</tr>
<tr>
<td>Language</td>
<td>Between-subject</td>
<td>Swedish, Spanish</td>
</tr>
</tbody>
</table>

a All predictors were centred: the first level was positive and the second level was negative.
### Table 6
Results Experiment 1: linguistic encoding condition. Output of mixed-effects model used to analyse the similarity arrangement task: Coefficient estimates $\hat{\beta}$, standard errors $SE(\hat{\beta})$, associated $t$ value, and significance values.

<table>
<thead>
<tr>
<th>Predictor</th>
<th>Coef. $\hat{\beta}$</th>
<th>SE($\hat{\beta}$)</th>
<th>$t$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>0.55</td>
<td>0.01</td>
<td>94.12 ***</td>
</tr>
<tr>
<td>P</td>
<td>0.18</td>
<td>0.02</td>
<td>8.43 ***</td>
</tr>
<tr>
<td>MC</td>
<td>0.08</td>
<td>0.02</td>
<td>4.74 ***</td>
</tr>
<tr>
<td>MO</td>
<td>0.04</td>
<td>0.01</td>
<td>3.88 ***</td>
</tr>
<tr>
<td>Di</td>
<td>0.04</td>
<td>0.02</td>
<td>2.22 *</td>
</tr>
<tr>
<td>Language</td>
<td>0.02</td>
<td>0.01</td>
<td>1.67</td>
</tr>
<tr>
<td>Gr</td>
<td>0.04</td>
<td>0.01</td>
<td>2.47 *</td>
</tr>
<tr>
<td>Ob</td>
<td>0.06</td>
<td>0.02</td>
<td>2.60 **</td>
</tr>
<tr>
<td>P:MC</td>
<td>0.05</td>
<td>0.02</td>
<td>2.87 **</td>
</tr>
<tr>
<td>P:MO</td>
<td>0.01</td>
<td>0.02</td>
<td>0.55</td>
</tr>
<tr>
<td>P:Di</td>
<td>0.03</td>
<td>0.01</td>
<td>1.93</td>
</tr>
<tr>
<td>MC:MO</td>
<td>0.03</td>
<td>0.01</td>
<td>1.98 *</td>
</tr>
<tr>
<td>MC:Di</td>
<td>0.00</td>
<td>0.01</td>
<td>0.22</td>
</tr>
<tr>
<td>MO:Di</td>
<td>0.00</td>
<td>0.01</td>
<td>-0.04</td>
</tr>
<tr>
<td>P:Language</td>
<td>-0.02</td>
<td>0.04</td>
<td>-0.58</td>
</tr>
<tr>
<td>MC:Language</td>
<td>0.05</td>
<td>0.03</td>
<td>1.54</td>
</tr>
<tr>
<td>MO:Language</td>
<td>0.04</td>
<td>0.02</td>
<td>2.28 *</td>
</tr>
<tr>
<td>Di:Language</td>
<td>-0.05</td>
<td>0.03</td>
<td>-1.56</td>
</tr>
<tr>
<td>Language:Gr</td>
<td>-0.03</td>
<td>0.02</td>
<td>-1.32</td>
</tr>
<tr>
<td>Language:Ob</td>
<td>0.03</td>
<td>0.03</td>
<td>0.96</td>
</tr>
<tr>
<td>P:MC:Language</td>
<td>0.01</td>
<td>0.03</td>
<td>0.49</td>
</tr>
<tr>
<td>P:MO:Language</td>
<td>0.00</td>
<td>0.02</td>
<td>0.11</td>
</tr>
<tr>
<td>P:Di:Language</td>
<td>-0.03</td>
<td>0.02</td>
<td>-1.48</td>
</tr>
<tr>
<td>MC:MO:Language</td>
<td>0.02</td>
<td>0.02</td>
<td>0.92</td>
</tr>
<tr>
<td>MC:Di:Language</td>
<td>-0.01</td>
<td>0.01</td>
<td>-1.36</td>
</tr>
<tr>
<td>MO:Di:Language</td>
<td>0.00</td>
<td>0.01</td>
<td>-0.07</td>
</tr>
</tbody>
</table>

*Note. Significance codes: * $p < .05$, ** $p < .01$, *** $p < .001$

*Legend: P = Path, MC = Manner of Cause, MO = Manner of Object, Di = Direction left/right, Gr = Ground, Ob = Object*
Table 7
Results Experiment 2: free encoding condition. Output of mixed-effects model used to analyse the similarity arrangement task: Coefficient estimates $\hat{\beta}$, standard errors SE($\hat{\beta}$), associated $t$ value, and significance values.

<table>
<thead>
<tr>
<th>Predictor</th>
<th>Coef. $\hat{\beta}$</th>
<th>SE($\hat{\beta}$)</th>
<th>$t$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>0.54</td>
<td>0.00</td>
<td>117.03 ***</td>
</tr>
<tr>
<td>P</td>
<td>0.11</td>
<td>0.02</td>
<td>6.66 **</td>
</tr>
<tr>
<td>MC</td>
<td>0.12</td>
<td>0.02</td>
<td>5.45 ***</td>
</tr>
<tr>
<td>MO</td>
<td>0.04</td>
<td>0.01</td>
<td>3.11 **</td>
</tr>
<tr>
<td>Di</td>
<td>0.14</td>
<td>0.02</td>
<td>5.63 ***</td>
</tr>
<tr>
<td>Language</td>
<td>0.01</td>
<td>0.01</td>
<td>0.92</td>
</tr>
<tr>
<td>Gr</td>
<td>0.03</td>
<td>0.01</td>
<td>1.92</td>
</tr>
<tr>
<td>Ob</td>
<td>0.04</td>
<td>0.02</td>
<td>1.61</td>
</tr>
<tr>
<td>P:MC</td>
<td>0.05</td>
<td>0.01</td>
<td>3.43 ***</td>
</tr>
<tr>
<td>P:MO</td>
<td>0.01</td>
<td>0.01</td>
<td>0.76</td>
</tr>
<tr>
<td>P:Di</td>
<td>0.06</td>
<td>0.02</td>
<td>4.00 ***</td>
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<tr>
<td>MC:MO</td>
<td>0.03</td>
<td>0.01</td>
<td>2.27 *</td>
</tr>
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<td>0.02</td>
<td>0.01</td>
<td>1.96</td>
</tr>
<tr>
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<td>0.00</td>
<td>0.01</td>
<td>0.23</td>
</tr>
<tr>
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<td>0.03</td>
<td>0.87</td>
</tr>
<tr>
<td>MC:Language</td>
<td>0.03</td>
<td>0.04</td>
<td>0.70</td>
</tr>
<tr>
<td>MO:Language</td>
<td>0.05</td>
<td>0.02</td>
<td>2.27 *</td>
</tr>
<tr>
<td>Di:Language</td>
<td>-0.08</td>
<td>0.05</td>
<td>-1.67</td>
</tr>
<tr>
<td>Language:Gr</td>
<td>-0.05</td>
<td>0.02</td>
<td>-1.89</td>
</tr>
<tr>
<td>Language:Ob</td>
<td>0.03</td>
<td>0.03</td>
<td>1.05</td>
</tr>
<tr>
<td>P:MC:Language</td>
<td>0.01</td>
<td>0.02</td>
<td>0.59</td>
</tr>
<tr>
<td>P:MO:Language</td>
<td>0.02</td>
<td>0.01</td>
<td>1.08</td>
</tr>
<tr>
<td>P:Di:Language</td>
<td>-0.08</td>
<td>0.03</td>
<td>-3.05 **</td>
</tr>
<tr>
<td>MC:MO:Language</td>
<td>0.03</td>
<td>0.02</td>
<td>1.61</td>
</tr>
<tr>
<td>MC:Di:Language</td>
<td>-0.01</td>
<td>0.01</td>
<td>-0.50</td>
</tr>
<tr>
<td>MO:Di:Language</td>
<td>0.00</td>
<td>0.01</td>
<td>0.10</td>
</tr>
</tbody>
</table>

*Note. Significance codes: * $p < .05$, ** $p < .01$, *** $p < .001$  
Legend: P = Path, MC = Manner of Cause, MO = Manner of Object, Di = Direction left/right, Gr = Ground, Ob = Object*
Table 8
Results Experiment 3: verbal interference condition. Output of mixed-effects model used to analyse the similarity arrangement task: Coefficient estimates $\hat{\beta}$, standard errors SE($\hat{\beta}$), associated $t$ value, and significance values.

<table>
<thead>
<tr>
<th>Predictor</th>
<th>Coef. $\hat{\beta}$</th>
<th>SE($\hat{\beta}$)</th>
<th>$t$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>0.54</td>
<td>0.01</td>
<td>99.36***</td>
</tr>
<tr>
<td>P</td>
<td>0.10</td>
<td>0.02</td>
<td>6.33***</td>
</tr>
<tr>
<td>MC</td>
<td>0.07</td>
<td>0.02</td>
<td>3.46***</td>
</tr>
<tr>
<td>MO</td>
<td>0.02</td>
<td>0.01</td>
<td>2.46*</td>
</tr>
<tr>
<td>Di</td>
<td>0.11</td>
<td>0.02</td>
<td>4.49***</td>
</tr>
<tr>
<td>Language</td>
<td>0.02</td>
<td>0.01</td>
<td>1.52</td>
</tr>
<tr>
<td>Gr</td>
<td>0.02</td>
<td>0.02</td>
<td>1.51</td>
</tr>
<tr>
<td>Ob</td>
<td>0.06</td>
<td>0.03</td>
<td>1.92</td>
</tr>
<tr>
<td>P:MC</td>
<td>0.03</td>
<td>0.02</td>
<td>1.96*</td>
</tr>
<tr>
<td>P:MO</td>
<td>0.00</td>
<td>0.01</td>
<td>0.22</td>
</tr>
<tr>
<td>P:Di</td>
<td>0.08</td>
<td>0.02</td>
<td>4.32***</td>
</tr>
<tr>
<td>MC:MO</td>
<td>0.03</td>
<td>0.01</td>
<td>2.03*</td>
</tr>
<tr>
<td>MC:Di</td>
<td>0.02</td>
<td>0.01</td>
<td>2.01*</td>
</tr>
<tr>
<td>MO:Di</td>
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<td>0.01</td>
<td>-0.21</td>
</tr>
<tr>
<td>P:Language</td>
<td>-0.01</td>
<td>0.03</td>
<td>-0.32</td>
</tr>
<tr>
<td>MC:Language</td>
<td>0.00</td>
<td>0.04</td>
<td>-0.01</td>
</tr>
<tr>
<td>MO:Language</td>
<td>0.00</td>
<td>0.01</td>
<td>0.41</td>
</tr>
<tr>
<td>Di:Language</td>
<td>0.03</td>
<td>0.05</td>
<td>0.70</td>
</tr>
<tr>
<td>Language:Gr</td>
<td>-0.04</td>
<td>0.03</td>
<td>-1.35</td>
</tr>
<tr>
<td>Language:Ob</td>
<td>-0.04</td>
<td>0.04</td>
<td>-0.89</td>
</tr>
<tr>
<td>P:MC:Language</td>
<td>0.05</td>
<td>0.02</td>
<td>2.51*</td>
</tr>
<tr>
<td>P:MO:Language</td>
<td>0.01</td>
<td>0.02</td>
<td>0.66</td>
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<tr>
<td>P:Di:Language</td>
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<td>0.03</td>
<td>-0.13</td>
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<td>MC:MO:Language</td>
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<td>0.02</td>
<td>-0.54</td>
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<tr>
<td>MC:Di:Language</td>
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<td>1.41</td>
</tr>
<tr>
<td>MO:Di:Language</td>
<td>0.00</td>
<td>0.01</td>
<td>-0.22</td>
</tr>
</tbody>
</table>

Note. Significance codes: * $p < .05$, ** $p < .01$, *** $p < .001$
Legend: P = Path, MC = Manner of Cause, MO = Manner of Object, Di = Direction left/right, Gr = Ground, Ob = Object
D. Compound analysis

The model for the compound analysis was fitted in R (R Development Core Team, 2013) using the `lmer` function from the lme4 library (Bates et al., 2014). The model formula was:

\[
\text{Similarity} \sim 1 + (P + MC + MO + Di)^2 \times \text{Language} \times \text{Encoding} + Gr \times \text{Language} \times \text{Encoding} + Ob \times \text{Language} \times \text{Encoding} + (1 + P + MC + MO + Di + Gr + Ob | \text{Subject}) + (1 | \text{Item})
\]

\(P = \text{Path}, \ MC = \text{Manner of Cause}, \ MO = \text{Manner of Object}, \ Di = \text{Direction left/right}, \ Gr = \text{Ground}, \ Ob = \text{Object}\)

The same predictors as for Experiments 1 to 3 went into this models (Table 5), but we added the factor ENCODING CONDITION, with three levels: linguistic, free and interference (corresponding to Experiments 1–3, respectively). Encoding condition was forward coded, so as to compare the linguistic against the free condition, and the free condition against verbal interference. All other predictors were centred with a difference of 1, so that reported coefficients represent the estimated difference in similarity ratings between the two levels of each predictor (as for Experiments 1–3). The random effects structure differed from the models for Experiments 1–3 in that there were no by-subject random slopes for the \textit{interactions} between Path, MannerCause, MannerObject and Direction (compare model formula above with that on p. 5). This was due to non-convergence of a model that did include those terms. Therefore fixed-effect estimates involving interactions between event components might suffer from inflated \(t\)-values, leading to unreliable significance estimates for those coefficients. Collinearity among predictors was moderate, \(\kappa = 6.6 < 10\) (cf. Baayen, 2008). Fixed-effects estimates for each experiment are shown in Table 9. Significance codes were determined using the \texttt{confint.merMod} function from the lme4 library (method = “Wald”, nsim = 10000).

Table 9

Results from compound analysis. Output of mixed-effects model used to analyse the similarity arrangement task: Coefficient estimates \(\hat{\beta}\), standard errors SE(\(\hat{\beta}\)), \(t\) value, and significance level.

<table>
<thead>
<tr>
<th>Predictor</th>
<th>Coef. (\hat{\beta})</th>
<th>SE((\hat{\beta}))</th>
<th>(t)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Intercept)</td>
<td>0.54</td>
<td>0.00</td>
<td>162.67 ***</td>
</tr>
<tr>
<td>P</td>
<td>0.13</td>
<td>0.01</td>
<td>11.01 ***</td>
</tr>
<tr>
<td>MC</td>
<td>0.09</td>
<td>0.01</td>
<td>7.75 ***</td>
</tr>
<tr>
<td>MO</td>
<td>0.03</td>
<td>0.01</td>
<td>4.71 ***</td>
</tr>
<tr>
<td>Di</td>
<td>0.10</td>
<td>0.01</td>
<td>7.40 ***</td>
</tr>
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<td>Language</td>
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<td>0.01</td>
<td>2.47 *</td>
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<td>0.01</td>
<td>1.12</td>
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<td>Encodingfree_vs_interf</td>
<td>0.00</td>
<td>0.01</td>
<td>0.60</td>
</tr>
<tr>
<td>Gr</td>
<td>0.03</td>
<td>0.01</td>
<td>2.77 **</td>
</tr>
<tr>
<td>Ob</td>
<td>0.05</td>
<td>0.02</td>
<td>2.44 *</td>
</tr>
<tr>
<td>P:MC</td>
<td>0.04</td>
<td>0.01</td>
<td>3.62 ***</td>
</tr>
<tr>
<td>Predictor</td>
<td>Coef. $\hat{\beta}$</td>
<td>SE($\hat{\beta}$)</td>
<td>$t$</td>
</tr>
<tr>
<td>-----------------------------------</td>
<td>----------------------</td>
<td>---------------------</td>
<td>-----</td>
</tr>
<tr>
<td>P:MO</td>
<td>0.01</td>
<td>0.01</td>
<td>0.60</td>
</tr>
<tr>
<td>P:Di</td>
<td>0.06</td>
<td>0.01</td>
<td>5.72***</td>
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<td>MC:MO</td>
<td>0.03</td>
<td>0.01</td>
<td>3.19**</td>
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<tr>
<td>MC:Di</td>
<td>0.01</td>
<td>0.01</td>
<td>1.69</td>
</tr>
<tr>
<td>MO:Di</td>
<td>0.00</td>
<td>0.01</td>
<td>-0.01</td>
</tr>
<tr>
<td>P:Language</td>
<td>0.00</td>
<td>0.02</td>
<td>-0.10</td>
</tr>
<tr>
<td>MC:Language</td>
<td>0.03</td>
<td>0.02</td>
<td>1.20</td>
</tr>
<tr>
<td>MO:Language</td>
<td>0.03</td>
<td>0.01</td>
<td>3.02**</td>
</tr>
<tr>
<td>Di:Language</td>
<td>-0.03</td>
<td>0.02</td>
<td>-1.32</td>
</tr>
<tr>
<td>P:Encodingling_vs_free</td>
<td>0.07</td>
<td>0.02</td>
<td>2.97**</td>
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<td>P:Encodingfree_vs_interf</td>
<td>0.01</td>
<td>0.02</td>
<td>0.58</td>
</tr>
<tr>
<td>MC:Encodingling_vs_free</td>
<td>-0.04</td>
<td>0.03</td>
<td>-1.69</td>
</tr>
<tr>
<td>MC:Encodingfree_vs_interf</td>
<td>0.05</td>
<td>0.03</td>
<td>1.92</td>
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<tr>
<td>MO:Encodingling_vs_free</td>
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<td>0.07</td>
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<td>MO:Encodingfree_vs_interf</td>
<td>0.02</td>
<td>0.01</td>
<td>1.48</td>
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<td>0.03</td>
<td>-3.42***</td>
</tr>
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<td>0.03</td>
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<td>0.01</td>
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<tr>
<td>Language:Gr</td>
<td>-0.04</td>
<td>0.01</td>
<td>-2.71**</td>
</tr>
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<td>0.02</td>
<td>0.44</td>
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<tr>
<td>Encodingfree_vs_interf:Gr</td>
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<td>0.02</td>
<td>0.34</td>
</tr>
<tr>
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<td>0.02</td>
<td>0.26</td>
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<td>0.03</td>
<td>1.03</td>
</tr>
<tr>
<td>Encodingfree_vs_interf:Ob</td>
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<td>0.03</td>
<td>-0.64</td>
</tr>
<tr>
<td>P:MC:Language</td>
<td>0.02</td>
<td>0.01</td>
<td>2.80**</td>
</tr>
<tr>
<td>P:MO:Language</td>
<td>0.01</td>
<td>0.01</td>
<td>1.10</td>
</tr>
<tr>
<td>P:Di:Language</td>
<td>-0.04</td>
<td>0.01</td>
<td>-5.13***</td>
</tr>
<tr>
<td>MC:MO:Language</td>
<td>0.01</td>
<td>0.01</td>
<td>1.74</td>
</tr>
<tr>
<td>MC:Di:Language</td>
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<td>0.01</td>
<td>-0.15</td>
</tr>
<tr>
<td>MO:Di:Language</td>
<td>0.00</td>
<td>0.01</td>
<td>-0.13</td>
</tr>
<tr>
<td>P:MC:Encodingling_vs_free</td>
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<td>0.01</td>
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</tr>
<tr>
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<td>0.02</td>
<td>0.01</td>
<td>1.92</td>
</tr>
<tr>
<td>P:MO:Encodingling_vs_free</td>
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<td>0.01</td>
<td>-0.16</td>
</tr>
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<td>P:MO:Encodingfree_vs_interf</td>
<td>0.01</td>
<td>0.01</td>
<td>0.66</td>
</tr>
</tbody>
</table>
predictor | Coef. $\hat{\beta}$ | SE($\hat{\beta}$) | t  
---|---|---|---
P:Di:Encodingling\_vs\_free | -0.04 | 0.01 | -4.50 ***
P:Di:Encodingfree\_vs\_interf | -0.01 | 0.01 | -1.53
MC:MO:Encodingling\_vs\_free | 0.00 | 0.01 | -0.05
MC:MO:Encodingfree\_vs\_interf | 0.00 | 0.01 | -0.35
MC:Di:Encodingling\_vs\_free | -0.02 | 0.01 | -2.49 *
MC:Di:Encodingfree\_vs\_interf | 0.00 | 0.01 | -0.07
MO:Di:Encodingling\_vs\_free | 0.00 | 0.01 | -0.37
MO:Di:Encodingfree\_vs\_interf | 0.00 | 0.01 | 0.57
P:Language:Encodingling\_vs\_free | -0.05 | 0.05 | -1.09
P:Language:Encodingfree\_vs\_interf | 0.04 | 0.05 | 0.74
MC:Language:Encodingling\_vs\_free | 0.02 | 0.05 | 0.33
MC:Language:Encodingfree\_vs\_interf | 0.03 | 0.05 | 0.58
MO:Language:Encodingling\_vs\_free | -0.01 | 0.03 | -0.50
MO:Language:Encodingfree\_vs\_interf | 0.05 | 0.03 | 1.80
Di:Language:Encodingling\_vs\_free | 0.03 | 0.06 | 0.47
Di:Language:Encodingfree\_vs\_interf | -0.11 | 0.06 | -1.88
Language:Encodingling\_vs\_free:Gr | 0.01 | 0.03 | 0.44
Language:Encodingfree\_vs\_interf:Gr | -0.01 | 0.03 | -0.32
Language:Encodingling\_vs\_free:Ob | 0.00 | 0.05 | -0.04
Language:Encodingfree\_vs\_interf:Ob | 0.07 | 0.05 | 1.25
P:MC:Language:Encodingling\_vs\_free | 0.00 | 0.02 | 0.11
P:MC:Language:Encodingfree\_vs\_interf | -0.04 | 0.02 | -1.82
P:MO:Language:Encodingling\_vs\_free | -0.01 | 0.02 | -0.64
P:MO:Language:Encodingfree\_vs\_interf | 0.00 | 0.02 | 0.18
P:Di:Language:Encodingling\_vs\_free | 0.05 | 0.02 | 2.89 **
P:Di:Language:Encodingfree\_vs\_interf | -0.07 | 0.02 | -4.17 ***
MC:MO:Language:Encodingling\_vs\_free | -0.01 | 0.01 | -0.65
MC:MO:Language:Encodingfree\_vs\_interf | 0.04 | 0.02 | 2.63 **
MC:Di:Language:Encodingling\_vs\_free | -0.01 | 0.01 | -0.62
MC:Di:Language:Encodingfree\_vs\_interf | -0.02 | 0.01 | -1.65
MO:Di:Language:Encodingling\_vs\_free | 0.00 | 0.01 | -0.13
MO:Di:Language:Encodingfree\_vs\_interf | 0.00 | 0.01 | 0.24

Note. Significance codes: * p < .05, ** p < .01, *** p < .001
Legend: P = Path, MC = Manner of Cause, MO = Manner of Object, Di = Direction left/right, Gr = Ground, Ob = Object
Getting the ball rolling

References


