

1 An individual differences perspective on pragmatic abilities in the preschool years

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Abstract

35

36 Pragmatic abilities are fundamental to successful language use and learning. Individual
37 differences studies contribute to understanding the psychological processes involved in
38 pragmatic reasoning. Small sample sizes, insufficient measurement tools, and a lack of
39 theoretical precision have hindered progress, however. Three studies addressed these
40 challenges in three- to five-year-old German-speaking children ($N = 228$, 121 female).
41 Studies 1 and 2 assessed the psychometric properties of six pragmatics tasks. Study 3
42 investigated relations among pragmatics tasks and between pragmatics and other cognitive
43 abilities. The tasks were found to measure stable variation between individuals. Via a
44 computational cognitive model, individual differences were traced back to a latent
45 pragmatics construct. This presents the basis for understanding the relations between
46 pragmatics and other cognitive abilities.

47 *Keywords:* Pragmatics, language development, individual differences, cognitive
48 modeling

49 Word count: 7995

50 An individual differences perspective on pragmatic abilities in the preschool years

51 **Introduction**

52 Communication predates productive language. Before children produce their first
53 words, they communicate with the world around them using vocalizations and gestures
54 (Bates, Benigni, Bretherton, Camaioni, & Volterra, 1979; Bruner, 1974). The process of
55 language learning recruits many of the social-cognitive processes that underlie pre-verbal
56 communication (Bohn & Frank, 2019; E. V. Clark, 2009; Tomasello, 2009). Even for
57 proficient language users, communication is not reducible to the words being exchanged.
58 The common thread running through the different aspects of human communication is its
59 inferential nature: what a speaker means – verbal or otherwise – is underdetermined by the
60 parts that make up the utterance. It takes contextual social inferences, often referred to as
61 *pragmatic* inferences, to recover the intended meaning (Bohn & Köymen, 2018; H. H.
62 Clark, 1996; Grice, 1991; Levinson, 2000; Sperber & Wilson, 2001).

63 The development of pragmatics has been widely studied in recent years (for a recent
64 review see Bohn & Frank, 2019). This research covers a range of different phenomena
65 ranging from so-called *pure pragmatics* (Matthews, 2014) in non-verbal communication in
66 infancy to sophisticated linguistic inferences developing much later (Huang & Snedeker,
67 2009; Papafragou & Skordos, 2016). A growing portion of this work is devoted to studying
68 individual differences (Lorge, 2019; Matthews, Biney, & Abbot-Smith, 2018; O'Neill, 2007;
69 A. Wilson & Bishop, 2022; E. Wilson & Katsos, 2021). The motivation behind the move to
70 study individual variation is twofold: first, individual differences offer insights into the
71 underlying psychological processes. If two phenomena (e.g. pragmatic reasoning and
72 executive functions) vary together this is consistent with shared cognitive processes (Kidd,
73 Donnelly, & Christiansen, 2018; Matthews et al., 2018; A. Wilson & Bishop, 2022), though
74 it is not definitive evidence for such a claim. Second, deficits in pragmatic abilities have
75 been linked to maladaptive behavioral patterns and forms of language impairment

76 (Helland, Lundervold, Heimann, & Posserud, 2014). However, research on individual
77 differences comes with some unique challenges.

78 In their recent review, Matthews et al. (2018) identified three issues that significantly
79 limit what we can learn from individual differences research on pragmatic abilities. First,
80 most studies have insufficient sample sizes so that small and medium-sized correlations
81 among pragmatics tasks and between pragmatics tasks and measures for other cognitive
82 abilities cannot be reliably detected (mirroring issues in estimating correlations across
83 other fields, Schönbrodt & Perugini, 2013). Second, the tasks used to assess pragmatic
84 abilities often have poor or unknown psychometric properties. For example, many tasks
85 only have a single trial and are therefore unable to capture variation between children (see
86 also Enkavi et al., 2019). Furthermore, reliability is not assessed, making it unclear if the
87 task captures stable characteristics (Flake & Fried, 2020; Norbury, 2014; Russell & Grizzle,
88 2008). Third, the cognitive processes underlying pragmatic inferences in a particular task
89 are underspecified. As a consequence, there is often no clear rationale for why a particular
90 pragmatic task should correlate with another cognitive measure.

91 In search of a better understanding of individual variation in pragmatic ability, the
92 studies presented here directly address these issues. We identified six pragmatic reasoning
93 tasks in children between three and five years of age and investigated their psychometric
94 properties, in particular, their re-test reliability. Reliable tasks are a necessary precondition
95 for meaningful individual differences research (Enkavi et al., 2019; Fried & Flake, 2018;
96 Hedge, Powell, & Sumner, 2018). Next, we investigated the relations among different
97 pragmatic reasoning tasks as well as between pragmatic reasoning and other cognitive
98 abilities in a sample large enough to detect small to medium-sized correlations. Finally, we
99 introduced computational cognitive models of pragmatic reasoning to the study of
100 individual differences. Our model formalizes the cognitive processes that could underlie
101 pragmatic reasoning and provides a substantive theoretical account of why certain
102 pragmatic reasoning tasks should be related to one another. Here, we use the formalism

103 introduced by the Rational Speech Act (RSA) framework (Frank & Goodman, 2012;
104 Goodman & Frank, 2016). RSA models see pragmatic inferences as a special case of
105 (Bayesian) social reasoning. A pragmatic listener interprets an utterance by assuming it
106 was produced by a cooperative speaker. The speaker tries to be informative, that is, they
107 provide messages that would increase the probability that the listener will recover their
108 intended meaning. The informativeness of an utterance arises from an inference process
109 during which the effects of multiple – plausible — utterances are compared. We assume
110 that this inference process is shared by some of the pragmatics tasks involved in this study
111 and can thus be used to account for individual differences (see below).

112 The six tasks we selected were developmental adaptations of referential
113 communication games inspired by research in experimental pragmatics (Noveck & Reboul,
114 2008; Noveck & Sperber, 2004). They all share a common trial-by-trial structure in which
115 the test event always involved an agent producing an ambiguous utterance that the child
116 had to resolve using pragmatic reasoning. This structure allowed us to run multiple trials
117 per task, increasing reliability. We grouped the tasks into two broad categories (Figure 1).
118 *Utterance-based tasks* asked children to derive inferences from the words and gestures the
119 speaker produced in context. *Common ground/discourse-based tasks* asked children to
120 derive inferences from the social interaction that preceded the utterance.

121 For the utterance-based category, we selected mutual exclusivity, informativeness
122 inference, and ad-hoc implicature tasks. “Mutual exclusivity” describes the phenomenon
123 that children tend to map a novel word to an unknown object (Bion, Borovsky, & Fernald,
124 2013; E. V. Clark, 1988; Halberda, 2003; Lewis, Cristiano, Lake, Kwan, & Frank, 2020;
125 Markman & Wachtel, 1988; Merriman, Bowman, & MacWhinney, 1989). Following Lewis
126 et al. (2020), we use the term “mutual exclusivity” as a convenient term to denote a
127 specific task. This term is also related to a particular theoretical account of the
128 phenomenon (Markman, 1990), but we do not presuppose that specific account. Here, we
129 take a pragmatic perspective on this phenomenon and assume that children identify a novel

130 object as the referent of a novel word by assuming that the speaker would have used a
131 different utterance (a familiar word) to refer to another potential referent present in
132 context (a familiar object). Informativeness inferences describe situations in which children
133 identify the referent of a novel word by assuming that the speaker is trying to be
134 informative. Being informative translates to using words that reduce ambiguity and help
135 the listener to recover the intended meaning (Frank & Goodman, 2014). Ad-hoc
136 implicature describes inferences that ask the child to contrast an utterance with
137 alternatives that the speaker could have used but did not (Katsos & Bishop, 2011; Stiller,
138 Goodman, & Frank, 2015; Yoon & Frank, 2019). Taken together, we assume that
139 pragmatic inferences in all three utterance-based tasks involve a comparison of possible
140 utterances. The tasks differ in how these possible utterances are constructed. We formalize
141 the task-specific and shared processes in the RSA model described below.

142 For the discourse-based category, we selected speaker preference, discourse novelty
143 and discourse continuity tasks. In the speaker preference task, the child had to track the
144 preference of a speaker in order to identify the referent of a novel word (Saylor, Sabbagh,
145 Fortuna, & Troseth, 2009). Discourse novelty refers to a situation in which the child tracks
146 the temporal appearance of objects and expects the speaker to refer to objects that are
147 new in context (Akhtar, Carpenter, & Tomasello, 1996; Diesendruck, Markson, Akhtar, &
148 Reudor, 2004). In the discourse continuity task, the child had to infer and track the topic
149 of an ongoing conversation to resolve ambiguity (Akhtar, 2002; Bohn, Le, Peloquin,
150 Köymen, & Frank, 2021). Taken together, we assume that pragmatic inferences in these
151 three tasks involve tracking shared interactions with the speaker. They differ in the aspect
152 of the interaction that needs to be tracked.

153 In addition to the pragmatics tasks, we also included two additional cognitive tasks:
154 one measuring executive functions (Zelazo, 2006) and the other analogical reasoning
155 (Christie & Gentner, 2014). Executive functions refer to a family of top-down mental
156 processes that enable us to inhibit automatic or intuitive responses and allow us to

157 concentrate and focus attention on particulars (Diamond, 2013). Executive functions are in
158 focus because pragmatic language use and comprehension are thought to involve, for
159 example, the inhibition of one's own perspective or focusing on contextual variables that
160 are communicatively relevant. A substantial body of research has investigated the link
161 between executive functions and pragmatics – with mixed results (Matthews et al., 2018;
162 Nilsen & Graham, 2009). Based on our reading of this literature, we expected positive
163 correlations between executive functions and our pragmatics tasks. Analogical reasoning
164 refers to the ability to reason about abstract relations between stimuli (Carstensen &
165 Frank, 2021). To our knowledge, this ability has not been specifically linked to pragmatics.
166 This task serves as a control to show that the correlation between executive functions and
167 pragmatics is not due to all of the tasks measuring general mental abilities; if this were the
168 case, then analogical reasoning should correlate with the pragmatics tasks in the same way
169 as executive functions.

170 Study 1 and 2 explored the re-test reliability of the pragmatics tasks and found it to
171 be relatively good. Study 3 tested a larger sample of children to investigate relations
172 between the three utterance-based tasks. We focused on these tasks for theoretical reasons:
173 as noted above, we assume that – computationally – they share a common inference
174 process. We formalize these assumptions in a computational cognitive model which we
175 then use to study individual differences in this alleged process. Study 3 also included tasks
176 for executive functions and analogical reasoning. Across analytical approaches, we found
177 systematic relations among the pragmatics tasks as well as between pragmatics and
178 executive functions, but not analogical reasoning. In the discussion, we use the structure of
179 the cognitive model to speculate about the psychological processes shared between
180 pragmatics and executive functions.

Study 1

181
182 Study 1 focused on the psychometric properties of four pragmatics tasks, in
183 particular, their re-test reliability. We chose our sample size so that we would detect re-test
184 correlations larger than .5 with sufficient power. Two of the tasks were from the
185 utterance-based group and two from the common ground/discourse-based group. This
186 design allowed us to explore whether tasks within one group are more related to one
187 another than between groups. As a fifth task, we included a measure of executive
188 functions. Methods and sample size were pre-registered at <https://osf.io/6a723>. All
189 analysis scripts and data files can be found in the following repository:
190 <https://github.com/manuelbohn/pragBat>. The same repository also contains the code to
191 run the experiments.

192 Participants

193 For Study 1, we collected data from 48 children ($m_{age} = 3.99$, $range_{age}: 3.10 - 4.99$,
194 23 girls), of whom 41 were tested twice. For most children, the two test sessions were two
195 days apart; the longest time difference was six days. Children came from an ethnically
196 homogeneous, mid-size German city (~550,000 inhabitants, median income €1,974 per
197 month as of 2020); were mostly monolingual and had mixed socioeconomic backgrounds.
198 The study was approved by an internal ethics committee at the Max Planck Institute for
199 Evolutionary Anthropology Data was collected between November 2019 and January 2020.

200 Material and Methods

201 The study was presented as an interactive picture book on a tablet computer (Frank,
202 Sugarman, Horowitz, Lewis, & Yurovsky, 2016). The tasks were programmed in
203 HTML/JavaScript and run in a web browser. Pre-recorded sound files were used to address
204 the child (one native German speaker per animal). Children responded by touching objects

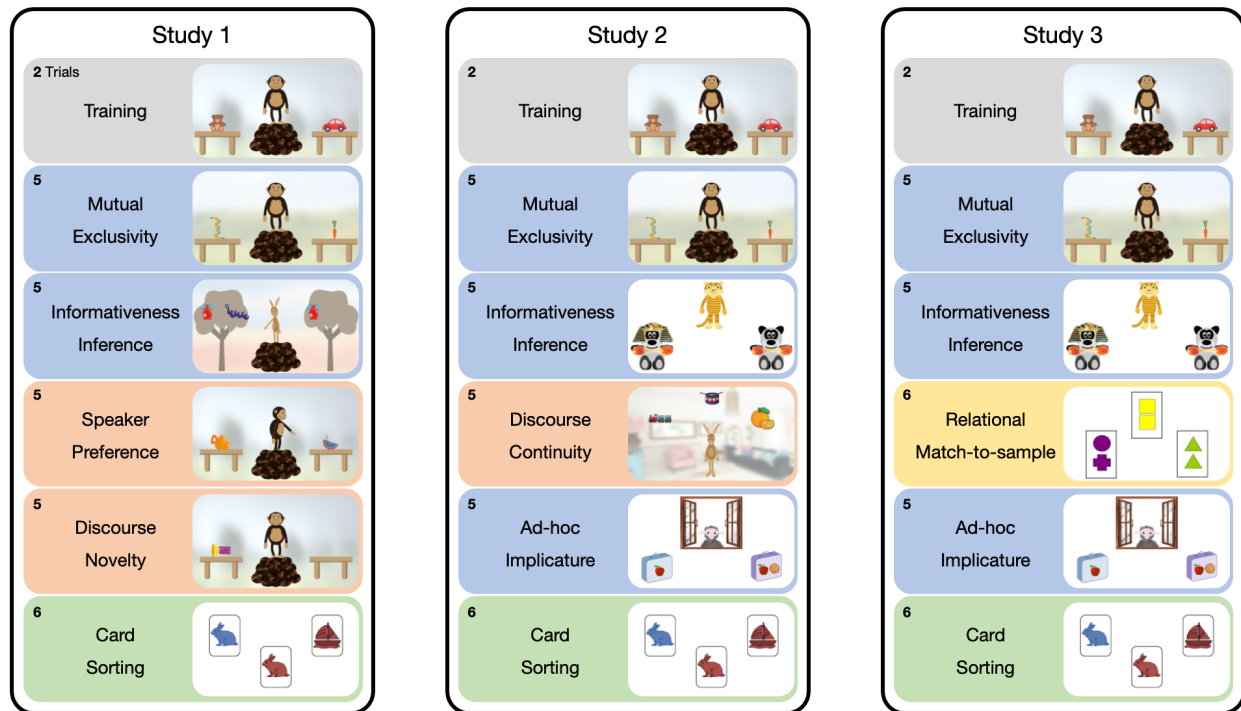


Figure 1. Overview of the tasks used in Study 1 to 3. Pictures show screenshots from each task. The vertical order corresponds to the order of presentation in each study. The colors group the tasks along the (assumed) cognitive processes involved. Blue: utterance-based inferences. Red common ground/discourse-based inferences. Green: Executive functions. Yellow: Analogical reasoning. Bold numbers show the number of trials per task.

205 on the screen. Children were tested in a quiet room in their daycare or in a separate room
 206 in a child laboratory. An experimenter guided the child through the study, selecting the
 207 different tasks and advancing within each task. In the beginning of the study, children
 208 completed a touch training to familiarize themselves with selecting objects. After a short
 209 introduction to the different animal characters, children completed the following six tasks.
 210 Figure 1 shows screenshots for each task and the order in which they were presented.

211 **Training.** An animal was standing on a pile between two tables. On each table, a
 212 familiar object was located. The animal asked the child to give them one of the objects
 213 (e.g., “Can you give me the car”). The objects were chosen so that children of the youngest

214 age group would easily understand them (car and ball). This procedure familiarized the
215 child with the general logic of the animals making requests and the child touching objects.
216 There were two training trials.

217 **Mutual exclusivity.** This task was adapted from Bohn, Tessler, Merrick, and
218 Frank (2021). The task layout and the procedure was the same as in the training. In each
219 trial, one object was a novel object (drawn for the purpose of this study) while the other
220 one was likely to be familiar to children. Both object types changed from trial to trial.
221 Following Bohn, Tessler, et al. (2021), the familiar objects varied in terms of the likelihood
222 that they would be familiar to children in the age range (carrot, duck, eggplant, garlic,
223 horseshoe). For example, we assumed that most 3-year-olds would recognize a carrot,
224 whereas fewer children would recognize a horseshoe. The animal always used a novel
225 non-word (e.g., gepsa) in their request. We reasoned that children would identify the novel
226 object as the referent of the novel word because they assumed the animal would have used
227 the familiar word if they wanted to request the familiar object. Children’s response was
228 thus coded as correct if they selected the novel object. There were five trials, with the side
229 on which the novel object appeared pseudo-randomized.

230 **Informativeness inference.** The task was adapted from Bohn, Tessler, Merrick,
231 and Frank (2022). The animal was standing between two trees with objects hanging in
232 them. In one tree, there were two objects (type A and B) and in the other tree there was
233 only one (type B). The animal turned to the tree with the two objects and labeled one of
234 the objects. It was unclear from the animal’s utterance, which of the two objects they were
235 referring to. We assumed that children would map the novel word onto the object of type
236 A because they expected the animal to turn to the tree with only the object of type B if
237 their intention was to provide a label for an object of type B. Next, the trees were replaced
238 by new ones, one of which carried an object of type A and the other of type B. The animal
239 then said that one of the trees had the same object as they labeled previously (using the
240 same label) and asked the child to touch the tree. We coded as correct if the child selected

241 the tree with the object of type A. The first two trials were training trials, in which there
242 was only one object in each tree. There were five test trials. The location of the tree with
243 the two objects in the beginning of each trial was pseudo-randomized and so was the
244 location of the objects when the new trees appeared.

245 **Speaker preference.** This task was also adapted from Bohn et al. (2022). The
246 animal was standing between the two tables, each of which had a novel object (drawn for
247 the purpose of the study) on it. The animal turned to one table, pointed at the object and
248 said that they very much liked this object (using a pronoun instead of a label). Next, the
249 animal turned to the other table and said that they really did not like the object (again,
250 using a pronoun and no label). Then the animal turned towards the participant and used a
251 novel label to request an object in an excited tone. We assumed that children would track
252 the animal's preference and identify the previously liked object as the referent. Thus, we
253 coded as correct if the child selected the object the animal expressed preference for. There
254 were five test trials. The location of the preferred object as well as whether the animal first
255 expressed liking or disliking was pseudo-randomized across trials

256 **Discourse novelty.** This task was adapted from Bohn, Tessler, et al. (2021). Once
257 again, the animal was standing between the two tables. One table was empty whereas there
258 was a novel object on the other table. The animal turned towards the empty table and
259 commented on its emptiness. Next, the animal turned to the other table and commented
260 (in a neutral tone) on the presence of the object (not using a label). The animal then
261 briefly disappeared. In the absence of the animal a second novel object appeared on the
262 previously empty table. Then the animal returned and, facing the participant, asked for an
263 object in an excited tone. We assumed that children would track which object was new to
264 the ongoing interaction and identify the object that was new in context as the referent. We
265 coded as correct when children selected the object that appeared later. There were five test
266 trials. The location of the empty table and whether the animal first commented on the
267 presence or absence of an object was pseudo-randomized across trials

268 **Card sorting.** This task was modeled after Zelazo (2006). The child saw two
269 cards, a blue rabbit on the left and a red boat on the right. The experimenter introduced
270 the child to the color game they would be playing next. In this game, all blue cards
271 (irrespective of objects depicted) would go to the left card and all red cards to the right.
272 Next, a third card appeared in the middle of the screen (red rabbit or blue boat) and the
273 experimenter demonstrated the color sorting by moving the card to the one with the same
274 color. After a second demonstration trial, the child started to do the color sorting by
275 themselves. After six trials, the experimenter said that they were now going to play a
276 different game, the shape game, according to which all rabbits would go to the card with
277 the rabbit (left) and all boats to the card with the boat (right). The experimenter repeated
278 these instructions once and without any demonstration the child continued with the sorting
279 according to the new rule. There were six test trials. The shape on the card was
280 pseudo-randomized across trials. We only coded the trials after the rule change and coded
281 as correct when the child sorted according to shape.

282 Each child received exactly the same version of each task and completed the tasks in
283 the same order, with the same order on the two days. This ensured comparability of
284 performance across children.

285 **Analysis**

286 We analyzed the data in three steps. First we investigated developmental effects in
287 each task, then we assessed re-test reliability, and finally, we looked at relations between
288 the tasks. All analyses were run in R (R Core Team, 2018) version 4.1.2. Regression models
289 were fit as Bayesian generalized linear mixed models (GLMM) using the function `brm` from
290 the package `brms` (Bürkner, 2017). We used default priors for all analysis.

291 To estimate developmental effects in each task, we fit a GLMM predicting correct
292 responses (0/1) by age (in years, centered at the mean) and trial number (also centered).

293 The model included random intercepts for each participant and random slopes for trial
294 within participants (model notation in R: `correct ~ age + trial + (trial|id)`). We
295 pre-registered the inclusion of random intercepts for item. We deviate from this here
296 because the order of items was fixed and the same for all participants so that trial and item
297 were confounded for each task. For each task, we inspected and visualized the posterior
298 distribution (mean and 95% Credible Interval (CrI)) for the age estimate.

299 We assessed re-test reliability in two ways. First, for each task we computed the
300 proportion of correct trials for each individual in the two test sessions and then used
301 Pearson correlations to quantify re-test reliability. Second, we used a GLMM based
302 approach suggested by Rouder and Haaf (2019). Here, a GLMM was fitted to the
303 trial-by-trial data for each task with a fixed effect of age (in years, centered at the mean), a
304 random intercept for each participant and a random slope for test day (`correct ~ age +`
305 `(0+test_day|id)`). The notation `0+test_day` yields a separate intercept estimate for each
306 test day and subject. The model also estimates a correlation between test days which can
307 be interpreted as the re-test reliability. This approach has several advantages. First, it uses
308 trial-by-trial data and avoids information loss that comes with data aggregation. Second, it
309 uses hierarchical shrinkage to obtain better participant-specific estimates. Finally, it allows
310 us to get an age-independent estimate for reliability. One worry when assessing re-test
311 reliability in developmental studies is that re-test correlations can be high because of
312 domain general cognitive gains and not because of task-specific individual differences. By
313 including age as a fixed effect in the model, the estimates for each participant are
314 independent of age and so is the correlation between estimates for the two test days – the
315 re-test reliability.

316 Finally, we used aggregated data from both test days for each participant and task to
317 compute Pearson correlations between the different tasks. Given the small sample size in
318 Study 1, this part of the analysis was mostly exploratory.

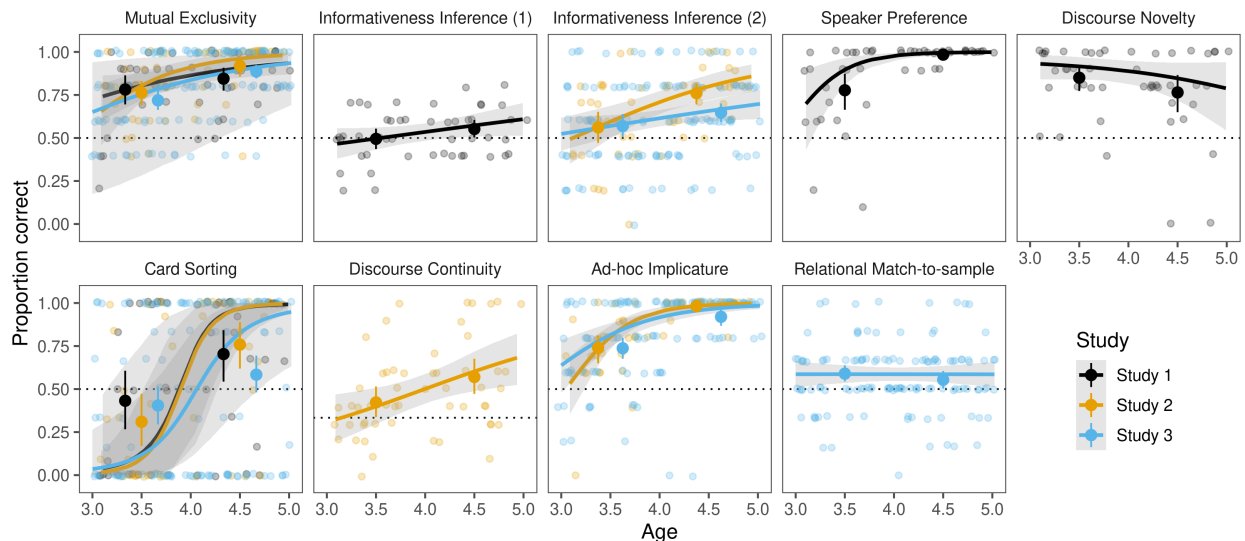
319 **Results**

Figure 2. Results by task for studies 1 to 3. Each panel shows the results for one task. Regression lines show the predicted developmental trajectories (with 95% CrI) based on by-task GLMMs, with the line type indicating the study. Colored points show age group means (with 95% CI based on non-parametric bootstrap) with the different shapes corresponding to the different studies. Light shapes show the mean performance for each subject by study. Dotted line shows the level of performance expected by chance.

320 We found developmental effects in most of the tasks. Figure 2 shows the data and
 321 visualizes the developmental trajectories based on the model. Figure 3 shows the model
 322 estimates for age. In the mutual exclusivity task, performance was reliably above chance
 323 level and increased with age. For informativeness inference, the pattern was quite different:
 324 Performance was at chance level with only minor developmental gains. In the speaker
 325 preference task, performance was again clearly above chance with developmental gains
 326 resulting in a ceiling effect for older children. In the discourse novelty task, performance
 327 was also above chance with no clear developmental effects. The card sorting task showed
 328 the strongest developmental effects with younger children performing largely below chance
 329 and older children performing above chance.

330 Re-test reliability was high for most tasks (see Figure 4). Raw correlation between
 331 the two test sessions was above .7 for mutual exclusivity, speaker preference and discourse
 332 novelty, though it was slightly lower for card sorting (.62). The model based – age
 333 independent – reliability estimates yielded similar results suggesting that the tasks did
 334 capture task specific individual differences. A notable exception was the informativeness
 335 inference task, which was not reliable according to any of the methods of computing re-test
 336 reliability (Figure 4). We suspected the overall low variation in performance to be
 337 responsible for this.

338 Most correlations between the tasks were low and ranged between $r = -0.2$ and 0.2
 339 (see Figure 2). A notable exception was the correlation between mutual exclusivity and
 340 card sorting ($r = 0.31$, 95% CI[0.03 - 0.55]).

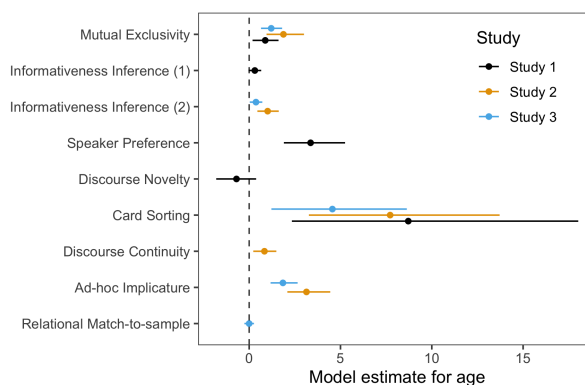


Figure 3. Model estimates (with 95% CrI) for age (in years, centered at the mean) based on GLMMs for each task and study.

341 Discussion

342 Study 1 showed that the different tasks were – for the most part – age appropriate
 343 and reliable. A notable exception was the informativeness inference task which generated
 344 no systematic variation in the age range we studied here. Correlations between the tasks
 345 were generally low, with the exception of the relation between mutual exclusivity and card

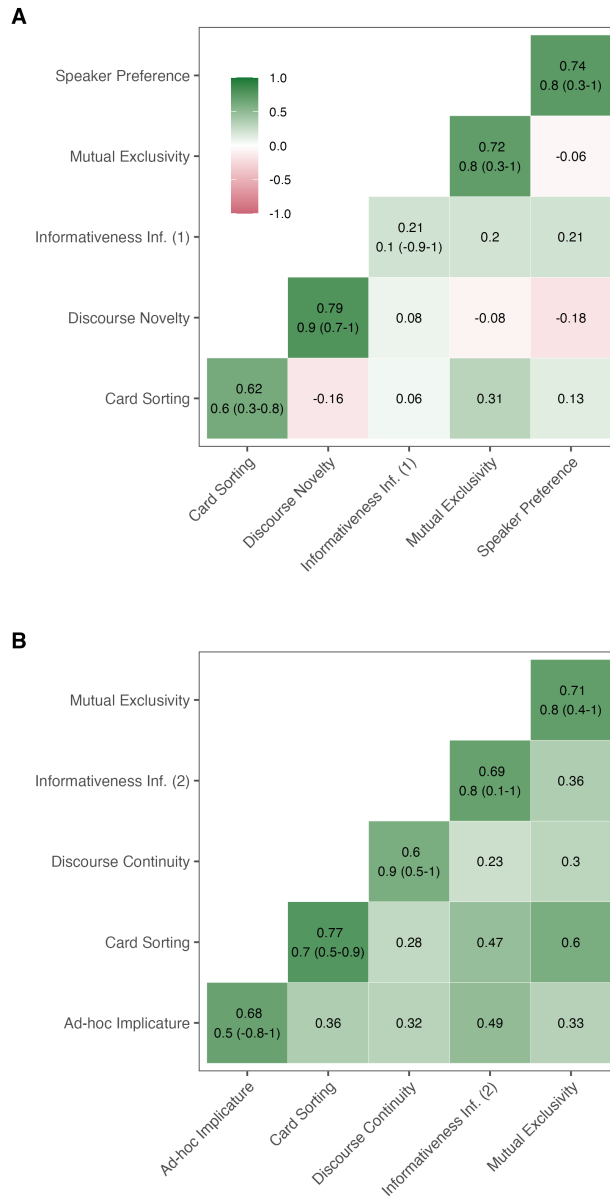


Figure 4. Re-test and task correlations for Study 1 (A) and, 2 (B). The diagonal in shows the re-test reliability based on aggregated raw test scores (top row) and based on a GLMM that accounted for participant age. Numbers in parenthesis are 95% CrI for the model based estimate. (see main text for details).

346 sorting. Given the small sample size, we avoid overly strong claims, however, it was
347 interesting to see that the relation between the two tasks tapping into discourse-based
348 inferences (speaker preference and discourse novelty) were – if anything – negatively
349 correlated.

350 **Study 2**

351 The goal of Study 2 was to assess the re-test reliability in a new set of tasks. We
352 retained the mutual exclusivity and card sorting tasks because of the interesting relation
353 between the two found in Study 1. We simplified the informativeness inference task to be
354 more age appropriate with the hope of inducing more variation in performance. We
355 removed the speaker preference and discourse novelty tasks – despite their excellent re-test
356 reliability – because they seemed to be unrelated to one another and also unrelated to the
357 other tasks. We also added new tasks focused on ad-hoc implicature and discourse
358 continuity. As noted in the introduction, we had theoretical reasons to expect the ad-hoc
359 implicature task to be related to the mutual exclusivity and informativeness inference
360 tasks. We had no such strong predictions for the discourse continuity task.

361 Methods and sample size were pre-registered at <https://osf.io/hp9f7>. Data, analysis
362 scripts and experiment code can be found in the associated online repository.

363 **Participants**

364 Participants for Study 2 were recruited from the same general population. We
365 collected data from 54 children ($m_{age} = 3.97$, $range_{age}$: 3.09 - 4.93, 24 girls), of whom 40
366 were tested twice. The two test sessions were again two days apart; the longest time
367 difference was 14 days. Data was collected between March and October 2020.

368 **Material and Methods**

369 The general setup and mode of presentation was the same as in Study 1. We added
370 two new tasks and modified the informativeness inferences task, which we will describe in
371 detail below. The training, mutual exclusivity and card sorting tasks were the same as in
372 Study 1.

373 **Informativeness inference.** The structure and coding of the task was the same as
374 in Study 1, however, we replaced the stimuli from Bohn et al. (2022) with those used
375 originally by Frank and Goodman (2014). Instead of objects in trees, these new stimuli
376 featured a range of different objects with different properties (e.g., a bear with a club and a
377 crown vs. a bear with just a club) The first two trials were training trials, in which each
378 object only had one property. There were five test trials. The location of the object with
379 the two properties in the beginning of each trial was pseudo-randomized and so was the
380 location of the properties when the new objects appeared.

381 **Discourse continuity.** This task was adapted from Bohn, Le, et al. (2021).
382 Children were told that they were going to visit the animals in their home. An animal
383 greeted the child and told them that they would show them their things. During exposure
384 trials, the child saw three objects from three different categories (e.g., train (vehicle), drum
385 (instrument), orange (fruit); see Figure 1). The animal named one of the objects and asked
386 the child to touch it. On the next exposure trial, the child saw three new objects but from
387 the same categories (e.g., bus (vehicle), flute (instrument), apple (fruit)). The animal asked
388 the child to touch the object from the same category as previously (only naming the
389 object, not the category). There were 5 such exposure trials. On the following test trial,
390 the animal used a pronoun to refer to one of the objects (i.e., can you touch *it*). We
391 assumed that children would use the exposure trials to infer that the animal was talking
392 about a certain category and would use this knowledge to identify the referent of the
393 pronoun. Children received five test trials, each with a different category as the target.

394 The position of the objects in exposure trials as well as test trials was pseudo-randomized.

395 **Ad-hoc implicature.** This task used the general procedure and stimuli developed
396 in Yoon and Frank (2019). The animal was located in a window, looking out over two
397 objects (see Figure 1). Both objects were of the same kind, but had different properties. As
398 properties we chose objects that were well known to children of that age range. One object
399 had one property (A), while the other had two (A and B). For example, objects were lunch
400 boxes, one with an orange and the other with an orange and an apple. The animal then
401 asked the child to hand them their object which was the one with the property that both
402 objects shared (A). We assumed that children would pick the object with only property A
403 because they expected the animal to name property B if they had wanted to refer to the
404 object with both properties. There were five test trials, preceded by two training trials in
405 which the objects did not share a common property. The positioning of the objects (left
406 and right) was pseudo-randomized.

407 **Analysis**

408 We used the same methods to analyze the data as in Study 1.

409 **Results**

410 We found substantial developmental gains in all five tasks (Figure 2 and 3). For
411 mutual exclusivity and ad-hoc implicature performance was above chance across the entire
412 age range. For the informativeness inference and discourse continuity tasks, performance
413 was close to chance for younger children and reliably above it for older children. Like in
414 Study 1, we found the strongest developmental effect for card sorting, with performance
415 below chance for 3-year-olds and above chance for 4-year-olds.

416 Re-test reliability based on aggregated data was good for all tasks with most
417 estimates around 0.7. The model-based reliability estimates were similar, with lower values

418 for ad-hoc implicature and higher ones for discourse continuity. Notably, the revised
419 informativeness inference task showed a much-improved re-test reliability compared with
420 the estimate from Study 1.

421 Correlations between tasks were generally higher compared to Study 1. In fact,
422 confidence intervals for correlation coefficients were not overlapping with 0 except for the
423 correlation between the discourse continuity and informativeness inference tasks (Figures 4.
424 Once again, we found the strongest relation between card sorting and mutual exclusivity (r
425 = 0.60, 95% CI[0.40 - 0.75]). Other notable relations were those between card sorting and
426 informativeness inference ($r = 0.47$, 95% CI[0.23 - 0.65]) as well as between ad-hoc
427 implicature and informativeness inference ($r = 0.49$, 95% CI[0.25 - 0.67]).

428 Discussion

429 In Study 2 we found good results from a measurement perspective: all tasks had
430 acceptable re-test reliability. This result extended to the informativeness inference task,
431 which had very low reliability in Study 1. Higher average performance and increased
432 variability both suggest that our changes to the stimuli made the task easier for children.

433 As in Study 1, we found a relatively strong correlation between the mutual
434 exclusivity and card sorting tasks. This finding supports the idea that these tasks share
435 common processes. We also found substantial relations between the three utterance-based
436 inference tasks (mutual exclusivity, ad-hoc implicature, informativeness inference). The
437 correlations between these tasks and the discourse continuity task were numerically lower.

438 Study 3

439 In Study 3, we focused explicitly on the relations between the different tasks. In
440 particular, we explored the idea that the three utterance-based inference tasks share
441 common cognitive processes. Once again, we also included the card sorting task and added

442 a new task of analogical reasoning as a control for which we did not expect strong relations
443 with the other tasks. To be able to test predictions about cross-task variation, we collected
444 data from a comparatively larger sample of children.

445 The reliability estimates from Study 1 and 2 helped us plan the sample size for Study
446 3. The focal tasks had a re-test reliability around 0.7. Because the highest plausible
447 correlation between two tasks is the product of their reliabilities (higher correlations would
448 mean that the task is more strongly related to a different task than to itself), the highest
449 we could expect were correlations between two tasks around $0.7 * 0.7 = 0.49$. We planned
450 our sample so that we could detect correlations between two tasks of 0.3 with 95% power.
451 The first author drafted a pre-registration and shared it with the last author but forgot to
452 register it at OSF. Thus, the study was not officially pre-registered. Data, analysis scripts
453 and experiment code can be found in the associated online repository.

454 **Participants**

455 For Study 3, we collected data from 126 children ($m_{age} = 4.00$, $range_{age}$: 3.00 - 5.02,
456 74 girls) from the same general population. Data was collected between June and
457 November 2021. Children were tested only once.

458 **Materials and Methods**

459 From Study 2, we used the mutual exclusivity, ad-hoc implicature, informativeness
460 inference and card sorting tasks. We added the relational match-to-sample task, which we
461 now describe in more detail.

462 **Relational match-to-sample.** The task was modeled after (and used the original
463 stimuli from) Christie and Gentner (2014). The child saw three cards, one on top (the
464 sample) and two at the bottom (the potential matches; see Figure 1). The experimenter
465 guided the child through the study and read out the instructions. The child was instructed

466 to match the sample card to one of the lower ones based on similarity, that is, they were
467 instructed to pick the card that was “like” the sample. All cards had two geometrical
468 shapes of the same color on them. The sample card showed two identical shapes and so did
469 one of the potential matches. The other card showed two different shapes. We assumed
470 that children would match the sample to the match that showed the same relation between
471 shapes (sameness). Children received six test trials, preceded by two training trials in
472 which one of the potential matches was identical to the sample. The position of the
473 same-match was pseudo randomized.

474 **Analysis**

475 Study 3 had only one test session. Therefore, we did not investigate re-test reliability.
476 We estimated age effects and raw correlations between tasks in the same way as in Studies
477 1 and 2. We used two additional methods to investigate the structure of individual
478 differences between tasks.

479 First, we used Confirmatory Factor Analysis (CFA). Models were fit in a Bayesian
480 framework using the R package `blavaan` (Merkle & Rosseel, 2018) using default priors. The
481 response variables were z-transformed aggregated raw scores for each participant. In the
482 associated online repository we also include models that treat the raw scores as ordinal
483 instead of continuous. These models yield the same qualitative results. As outlined above,
484 our focal model assumed that mutual exclusivity, ad-hoc implicature and informativeness
485 inference load on a common pragmatics factor. The card sorting and relational
486 match-to-sample tasks were included as separate factors. We used Posterior Predictive
487 P-Values (PPP) to evaluate model fit (Lee & Song, 2012). A good model fit is indicated by
488 a PPP close to 0.5 and should not be smaller than 0.1 (Cain & Zhang, 2019). We also fit
489 two alternative models: one including only a single factor on which all tasks loaded and a
490 second with a separate factor for each task. In the latter model, we set the correlations
491 between the pragmatics tasks to be zero so that this model represents the hypothesis that

492 the pragmatics tasks are unrelated. We compared models using WAIC (widely applicable
493 information criterion) scores and weights (McElreath, 2018). WAIC is an indicator of
494 out-of-sample predictive accuracy with lower values indicating better fit. WAIC weights
495 transform WAIC values to give the probability that a particular model (out of the models
496 considered) provides the best out-of-sample predictions. In addition, we report Bayes
497 Factors for model comparisons computed based on the marginal likelihood of the data
498 given each model. Within the focal model, we inspected the posterior estimates (with
499 95%CrI) for the factor loadings and the variance in the task explained by the factor for the
500 three pragmatics tasks. In addition, we evaluated the correlations between the pragmatics
501 factor and the other two tasks.

502 Second, we used computational cognitive models from the Rational Speech Act
503 (RSA) framework to relate the three pragmatics tasks to one another (Frank & Goodman,
504 2012; Goodman & Frank, 2016). In contrast to the CFA model above, the RSA models are
505 models of the tasks and not of the data. That is, they include a schematic representation of
506 the experimental tasks and provide a computational account of how participants make
507 inferences in this context. RSA models see pragmatic inferences as a form of Bayesian
508 social reasoning where the listener tries to infer the speaker’s meaning (here: the intended
509 referent) by assuming that the speaker is helpful and informative. Being helpful and
510 informative means that the speaker chooses a message based on the probability that it
511 would help the listener to recover the speaker’s intended meaning (i.e., select the intended
512 referent). Thus, RSA models have a recursive structure in which the listener reasons about
513 a speaker who is reasoning about the listener. To avoid an infinite regress, the speaker is
514 assumed to reason about a literal listener, who interprets utterances according to their
515 literal semantics.

516 The studies from which we took the mutual exclusivity and informativeness inference
517 tasks also formalized these tasks in an RSA-style model (Bohn, Tessler, et al., 2021; Bohn
518 et al., 2022). We refer to this earlier work for a more detailed description of the models.

519 For the present study, we formalized the ad-hoc implicature task within the same RSA
 520 framework. The common model structure is formally defined as:

$$P_{L_1}(r|u) \propto P_{S_1}(u|r) \cdot P(r)$$

521 In the above equation, the listener (P_{L_1}) is trying to infer the speaker's (P_{S_1}) intended
 522 referent r by imagining what a rational speaker would say, given the referent they are
 523 trying to communicate and the listener's prior expectations about the referent $P(r)$ (which
 524 we assumed to be uniform over potential referents). The speaker is an approximately
 525 rational Bayesian actor (with degree of rationality α) who produces utterances as a
 526 function of their informativity.

$$P_{S_1}(u|r) \propto \text{Informativity}(u; r)^\alpha$$

527 The informativity of an utterance for a referent is taken to be the probability with which a
 528 naive listener (P_{L_0}), who only interprets utterances according to their literal semantics,
 529 would select a particular referent given an utterance.

$$\text{Informativity}(u; r) = P_{L_0}(r|u)$$

530 The three models differ in the types of utterances that are being produced, however,
 531 they share the same contrastive inference process according to which the listener (P_{L_1})
 532 compares the speaker's (P_{S_1}) utterance to a set of alternative, possible utterances. As noted
 533 above, the listener expects the speaker to be informative (with degree α) that is, choose the
 534 utterance that best communicates the intended message. In the mutual exclusivity task,
 535 the speaker produced an unfamiliar word; thus, the alternative utterance for the speaker
 536 would have been to use a familiar word. In the case of the informative inference task, the
 537 speaker pointed to the object with two properties; thus, the alternative would have been to
 538 point to the object with only one property. For the ad-hoc implicature task the speaker

539 referred to the property shared by the two objects, which contrasts with referring to the
540 property that was unique to one of the objects. In all cases, these alternative utterances
541 would be better suited to communicate about the respective other referent.

542 As noted above, models for the different tasks shared one common parameter: the
543 speaker informativeness parameter α . This commonality offers a way of relating
544 performance in the three tasks to one another by constraining the three models to use the
545 same value for α . We then used Bayesian inference to estimate the posterior distribution
546 for α that best explained performance in the three tasks. To adapt this framework to the
547 study of individual differences, we allowed a separate parameter for each participant (α_i).
548 We estimated α_i in a hierarchical model as a deviation from a hyper parameter:
549 $\alpha_i \sim \mathcal{N}(\alpha_j, \sigma^\alpha)$. Given the developmental nature of our data, we defined α_j via a linear
550 regression as a function of the child's age (age_i): $\alpha_j = \beta_0^\alpha + age_i \cdot \beta_1^\alpha$. Thus, the
551 participant-specific value for α was not only constrained by the performance in the three
552 tasks but also by the child's age. The parameter can be interpreted in the following way:
553 for $\alpha = 1$, the likelihood of each referent is equal to its relative informativity. Values of $\alpha >$
554 1 amplify the preference of the most informative referent and reflect a heightened
555 expectation that the speaker chooses the best utterance. In contrast, values of $1 > \alpha > 0$
556 (lower bound) decrease the preference for the most informative referent and thus suggest
557 an expectation that the speaker is not helpful or informative.

558 To account for differences in difficulty between the tasks due to other factors, we
559 added a scale parameter to the model that adjusted α for each task in comparison to a
560 reference task (ad-hoc implicature).

561 To validate this approach, we first applied this model to the data from Study 2
562 separately for each test session. This allowed us to compute the re-test reliability of α and
563 see if it captures individual differences equally well compared to the raw test scores. After
564 finding excellent re-test reliability, we applied it to the data from Study 3 and correlated

565 the results with the card sorting and relational match-to sample tasks. For this
566 correlational analysis, we converted the posterior distribution for each participant into a
567 single value by taking the mode (and 95% highest density interval – HDI). The cognitive
568 models were implemented in **WebPPL** (Goodman & Stuhlmüller, 2014) and the
569 corresponding code, including information on prior distributions (which we omit here for
570 space), can be found in the associated online repository.

571 **Results**

572 The age effects in Study 3 largely replicate those of Study 2 for the four overlapping
573 tasks (see Figure 2 and 3). There were no substantial developmental gains in the newly
574 added relational match-to-sample task and performance was close to chance for both age
575 groups. Thus – in the absence of information on re-test reliability – it is unclear if the
576 variation in performance reflects systematic individual differences in analogical reasoning or
577 not.

578 Overall, the correlations between the tasks were lower compared to Study 2. This was
579 to some extent expected given that there were only half the number of trials per task in
580 Study 3 and, hence less “signal” (systematic, non-error variability) for capturing individual
581 differences. Nevertheless, the overall pattern resembles that found in Study 2 (compare
582 Figure 4 and 5). We saw the strongest bi-variate relation between the mutual exclusivity
583 and the ad-hoc implicature task ($r = 0.33$, 95% CI[0.16 - 0.48]) followed by ad-hoc
584 implicature and card sorting ($r = 0.28$, 95% CI[0.11 - 0.44]). The relational
585 match-to-sample task showed no substantial correlations with any of the other tasks.

586 Next, we turn to the results of the confirmatory factor analysis. Our focal model –
587 including a latent factor for pragmatic reasoning – fit the data well (PPP = 0.50, WAIC =
588 1,753.45, se = 32.01). The one factor model also showed an acceptable fit (PPP = 0.42,
589 WAIC = 1,754.87, se = 32.26), while the model with individual factors (and correlations

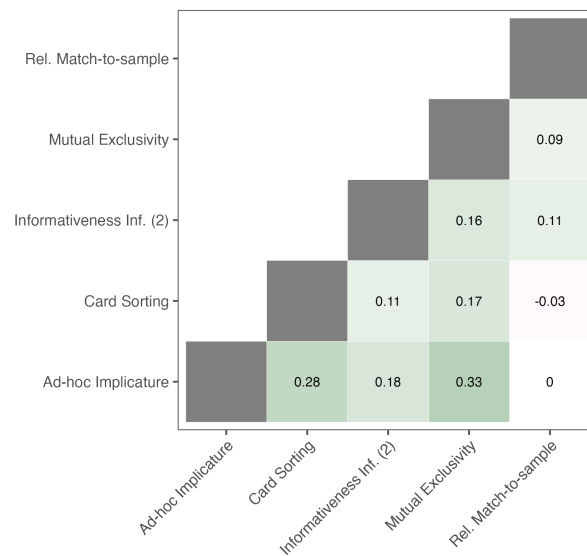


Figure 5. Correlations between tasks in Study 3 based on aggregated raw test scores.

590 between the pragmatics tasks set to zero) did not (PPP = 0.02, WAIC = 1,773.57, se =
 591 32.67). Due to this poor fit, we did not consider this model further. When directly
 592 comparing the focal model to the one factor model, we found that the focal model provided
 593 a slightly better fit (WAIC difference = -0.71, se of difference = 1.04, Bayes Factor in favor
 594 of the focal model = 8.42).

595 Figure 6 shows factor loadings for the individual tasks as well as their residual
 596 variance. The latent pragmatic reasoning factor best explained the mutual exclusivity task,
 597 followed by the ad-hoc implicature and the informativeness inference task. The correlation
 598 between pragmatic reasoning and executive functions (indicated by the card sorting task)
 599 was estimated to be reliably different from zero ($r = 0.33$; model estimate = 0.20, 95% CrI
 600 [0.01 - 0.38]). There was no systematic relation between pragmatic reasoning and analogical
 601 reasoning (as indicated by the relational match-to-sample task): $r = 0.06$; model estimate
 602 = 0.04, 95% CrI [-0.11 - 0.19]. However, the latter result should be taken with a grain of
 603 salt given the unknown psychometric properties of the relational match-to-sample task.

604 Finally, we present the results of the cognitive modeling analysis. Using the data

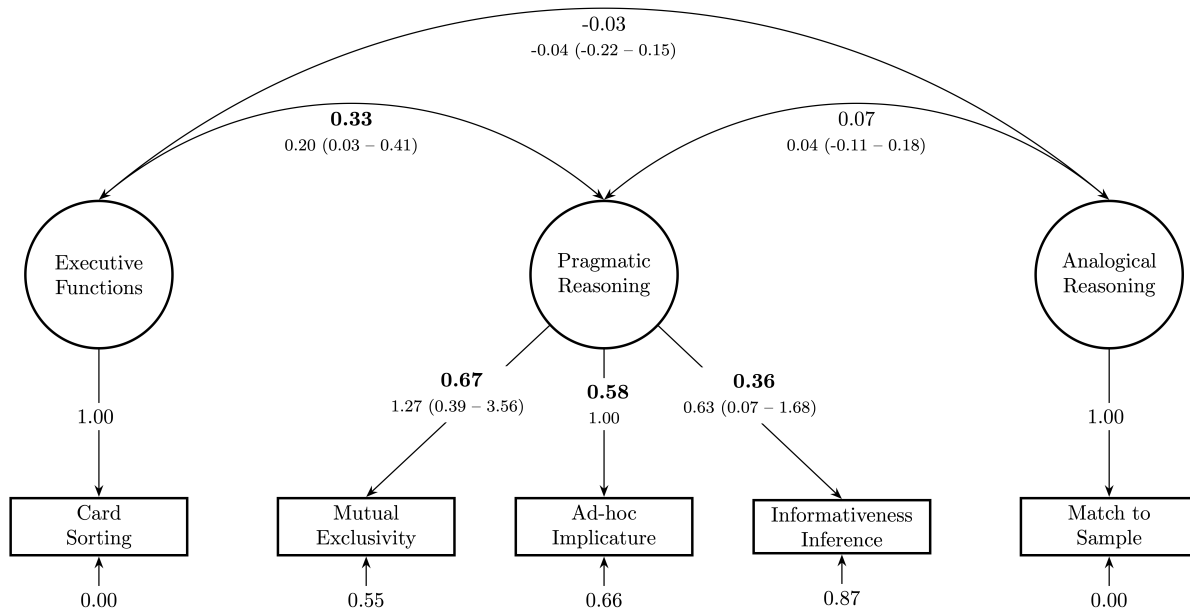


Figure 6. Graphical overview of CFA model for Study 3. Arrows from latent variable (circles) to observed variable (rectangles) show factor loadings. Bottom arrows to observed variables give the residual variance not explained by the factor. Bent arrows between latent variables show correlations. Bottom rows show model estimates with 95% CrI. Top rows show standardized estimates (bold if 95 % CrI does not include 0).

605 from Study 2, we saw that participant specific speaker informativeness parameters (α) were
 606 highly reliable (Figure 7B). The scale parameter suggested that the mutual exclusivity task
 607 was easier and the informativeness inference task was harder compared to the ad-hoc
 608 implicature task (Figure 7C). When correlating α with performance in the other two tasks,
 609 the cognitive modeling approach yielded similar conclusions compared to the confirmatory
 610 factor analysis (Figure 7A): There was a substantial correlation with the card sorting ($r =$
 611 0.31 , 95% CI[$0.15 - 0.47$]) but not the relational match-to-sample task ($r = 0.03$, 95%
 612 CI[$-0.15 - 0.20$]). The same limitations apply to the latter result as for the confirmatory
 613 factor analysis.

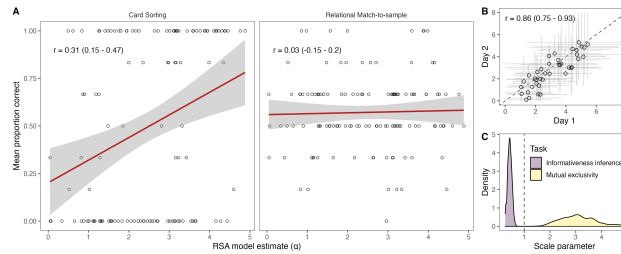


Figure 7. Results of cognitive model analyses. A: Correlation between the speaker informativeness parameter α and the performance in the card sorting and relational match to sample tasks. Regression line (with 95% CI) is based on a linear model. B: Re-test reliability for α based on the data from Study 2. C: Scale parameter for α in relation to the ad-hoc implicature task. Values below 1 indicate a more difficult task, values above 1 an easier task. Correlation coefficients show Pearson correlation with 95% CI.

614 Discussion

615 Using a diversity of analytical tools, we found that performance in the three
 616 utterance-based pragmatic inference tasks was related in a way that points to shared
 617 cognitive processes. In the confirmatory factor analysis, we found that a model including a
 618 latent pragmatic reasoning factor fit the data well and better compared to alternative
 619 models. The latent factor explained substantial portions of the variance in each of the
 620 three tasks. The cognitive modeling approach provides an explicit theory of what the
 621 shared cognitive processes may look like: according to the model, the pragmatic inference
 622 in each task was driven by contrasting the utterance the speaker produced and alternative
 623 utterances. Individual differences were thought to arise from differential expectations
 624 about how informative the speaker is.

625 Both analytic strategies point to systematic relations between pragmatic reasoning
 626 and executive functions as indicated by the card sorting test. We found no such relations
 627 with analogical reasoning as indicated by the relational match-to-sample task. However,
 628 given the unknown psychometric properties of the latter task, this result should be

629 interpreted with caution.

630

General Discussion

631 In this paper, we explored the development of pragmatic inferences in the preschool
632 years. We identified six tasks covering a broad range of pragmatic phenomena. We found
633 them to have generally good re-test reliability. We then selected three utterance-based
634 inference tasks for a well-powered study of relations among different types of pragmatic
635 abilities and between pragmatics and other cognitive abilities. The results showed
636 systematic relations between the utterance-based tasks, consistent with a latent cognitive
637 construct. We used a computational cognitive model of pragmatic reasoning to formalize
638 the cognitive processes we believed the tasks to share. Finally, we found pragmatic abilities
639 to be related to a task of executive functions.

640 One of the main contributions of this paper is that it presents six pragmatic inference
641 tasks that are highly robust and reliable. Whenever we used a task in two studies (mutual
642 exclusivity, informativeness inference, ad-hoc implicature), we found developmental results
643 that replicated previous findings. In Study 1 and 2, all tasks showed good re-test reliability
644 – even when corrected for age. A notable exception was the informativeness inference task
645 in Study 1. However, after making some procedural changes, it turned out to be robust
646 and reliable as well. Taken together, the tasks are suitable for individual differences
647 research, advancing the agenda of Matthews et al. (2018). These materials are freely
648 available via the associated online repository.

649 We grouped our pragmatics tasks into utterance-based and common
650 ground/discourse based. This grouping broadly captured the kind of information that we
651 assumed to be relevant to compute the inference. For Study 3, we focused on the three
652 utterance-based tasks. The main reason was theoretical. We were able to build on earlier
653 work (Bohn, Tessler, et al., 2021; Bohn et al., 2022) and formalize the inferences involved

654 in these tasks in a common computational framework. We specified the structural overlap
655 between the tasks and identified a parameter in the model that we used to capture
656 individual differences. The shared structural features involve a recursive social inference
657 process according to which the listener expects the speaker to select the most informative
658 of a set of possible utterances. The individual difference parameter captured how
659 informative the listener expected the speaker to be. Previous accounts would not have
660 predicted such an overlap. In particular, theoretical accounts of mutual exclusivity as
661 arising from heuristics or principles unconnected with pragmatic reasoning (reviewed in
662 Lewis et al., 2020) do not make the prediction of correlations with other pragmatic tasks.

663 Our formal model also allowed us to speculate about why we saw a systematic
664 relation across the three studies between pragmatic inference and the card sorting task as a
665 measure of executive functions. Before we do so, we want to emphasize that the model is
666 first and foremost a computational description of the tasks and not a model of a
667 psychological process (cf. Goodman & Frank, 2016). Here we speculate, assuming a bit
668 more psychological realism in our interpretation of the RSA model than previous authors
669 have. The card sorting task asks the child to switch between rules after having practiced
670 the first rule over the course of several trials. This switch requires inhibiting a pre-potent
671 response and attending to different features of the cards. Similarly, pragmatic inference in
672 the RSA model involves contrasting the observed utterance with alternative plausible
673 utterances. This process, too, could be described as requiring inhibiting available, plausible
674 interpretations and contrasting different interpretations before making a response. To
675 pursue this connection further, the next step should be to model card sorting and the
676 pragmatics tasks jointly to substantiate such a verbal analysis.

677 **Limitations**

678 The studies we presented here have important limitations. Our focus on the
679 utterance-based pragmatic inference tasks meant that we did not study or analyze the

680 common ground/discourse-based tasks with the same level of detail. That is, we did not
681 formalize them in a cognitive model and did not study relations between them in a larger
682 sample. Future research should address these shortcomings. Nevertheless, the work
683 presented here is an important first step because it showed that the common
684 ground/discourse tasks themselves have good psychometric properties and are therefore
685 suitable for individual differences research.

686 Finally, we only studied one sample of children from a Western, affluent setting.
687 Thus, it is unclear if and how the results would transfer to other settings (Nielsen, Haun,
688 Kärtner, & Legare, 2017). The tasks used here were largely developed and tested with
689 English-speaking children in the US. The fact that they transferred well to the German
690 setting of the current studies is at least a small hint that they might also be suitable to
691 study pragmatic inference in other cultural and linguistic settings. Future research will
692 hopefully test whether that is the case.

693 **Conclusion**

694 The studies reported here addressed some fundamental challenges in the study of
695 individual differences in pragmatic abilities (Matthews et al., 2018). We developed and
696 validated new methodological and theoretical tools that helped to study the relations
697 between different types of pragmatic inferences as well as between pragmatics and other
698 cognitive abilities in a more reliable and valid way. This approach emphasizes the
699 interdependent nature of theoretical and methodological progress and provides a roadmap
700 for future work.

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