

Social Psychological Bulletin

Strategic Ambiguity in the Social Sciences

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Social Psychological Bulletin, 2023, Vol. 18, Article e9923, <https://doi.org/10.32872/spb.9923>

Received: 2022-07-22 • Accepted: 2022-10-14 • Published (VoR): 2023-##-##



Handling Editors: Simine Vazire, Melbourne School of Psychological Sciences, University of Melbourne, Melbourne, Australia; Brian Nosek, University of Virginia, Charlottesville, VA, USA

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Abstract

In the wake of the replication crisis, there have been calls to increase the clarity and precision of theory in the social sciences. Here, we argue that the effects of these calls may be limited due to incentives favoring ambiguous theory. Intentionally or not, scientists can exploit theoretical ambiguities to make support for a claim appear stronger than it is. Practices include theory stretching, interpreting an ambiguous claim more expansively to absorb data outside of the scope of the original claim, and post-hoc precision, interpreting an ambiguous claim more narrowly so it appears more precisely aligned with the data. These practices lead to the overestimation of evidence for the original claim and create the appearance of consistent support and progressive research programs, which may in turn be rewarded by journals, funding agencies, and hiring committees. Selection for ambiguous research can occur even when scientists act in good faith. Although ambiguity might be inevitable or even useful in the early stages of theory construction, scientists should aim for increased clarity as knowledge advances. Science benefits from transparently communicating about known ambiguities. To attain transparency about ambiguity, we provide a set of recommendations for authors, reviewers, and journals. We conclude with suggestions for research on how scientists use strategic ambiguity to advance their careers and the ways in which norms, incentives, and practices favor strategic ambiguity. Our paper ends with a simple mathematical model exploring the conditions in which high-ambiguity theories are favored over low-ambiguity theories, providing a basis for future analyses.



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Keywords

strategic ambiguity, theory development, formal modeling, incentive structures, theory stretching, post-hoc precision, RAPPING

Highlights

- Current incentives favor strategic ambiguity (i.e., deploying ambiguity to achieve self-interested goals).
- Researchers exploit the flexibility that theoretical ambiguity affords, intentionally or not, using practices like theory stretching and post-hoc precision, which result in the overestimation of evidentiary support for theoretical claims.
- Scientists should aim for transparency when ambiguity is unavoidable in the short run and aim for increased clarity in the long run.
- We provide recommendations for authors, editors, and funders on how to restructure incentives to disfavor strategic ambiguity and favor clarity.

1 “You who are so good with words
2 And at keeping things vague”
3 Joan Baez (1975), *Diamonds & Rust*

4 In the wake of the replication crisis, there have been numerous calls to increase the
5 clarity and precision of theory in the social sciences. A popular solution calls for the
6 ‘formalization’ of theory, expressing theory in the language of mathematics (Borsboom,
7 2013; Borsboom et al., 2021; Frankenhuis et al., 2013; Fried, 2020; Guest & Martin, 2021;
8 Muthukrishna & Henrich, 2019; Navarro, 2021; Robinaugh et al., 2021; Smaldino, 2020a;
9 van Rooij & Baggio, 2021). Formalizing theory can promote clarity and precision, for
10 instance, by requiring the scientist to specify all constructs and their relations, make
11 assumptions explicit, and logically deduce predictions. Of course, formal models are no
12 panacea, and may be of limited use when they rely upon questionable assumptions. In
13 some cases, a well-articulated verbal theory may be sufficient. The key point is that
14 scientists should strive for more rigorous, clear, and precise theory.

15 Such calls for increased theoretical rigor are not new. Similar calls, in fact, predate the
16 replication crisis (Epstein, 2008; Farrell & Lewandowsky, 2010; Gibbs, 1987; Harris, 1976),
17 as do more general manifestos cataloguing the immature state of theory in the social sci-
18 ences (Gigerenzer, 1998; Meehl, 1978; Mischel, 2008; Rozin, 2001). It is unknown whether
19 the application of formal theory is actually increasing in response to these calls. Regard-
20 less, formal and precise theory remains rare in the social sciences—disciplines studying
21 human behavior, including but not limited to psychology, anthropology, criminology,
22 and sociology—though exceptions exist in several subfields. And where formalization is
23 absent, ambiguity can flourish (Smaldino, 2017).

24 The persistence of ambiguous theory raises uncomfortable questions: Are social sci-
25 entists aware of the problem? If so, do they see this as only a minor issue? Could it
26 be that some researchers in some cases *prefer* ambiguous theory? A naïve explanation
27 of the prevalence of ambiguous theory might be that producing formal and precise
28 theory requires advanced mathematical and programming techniques that are beyond
29 the skillset of the typical social scientist. But this cannot be the whole story. After all, so-
30 cial scientists routinely use equally advanced methodological and statistical techniques.
31 Might there be structural and systemic factors—rules, norms, and institutions—limiting
32 the spread of formal and precise theory?

33 The Incentives Made Me Do it

34 “I have 3 recent experiences where I am publishing counter-evi-
35 dence and the editor sends the ms directly to the author of the theo-
36 ry I am addressing and that person says, no, not counter-evidence at
37 all because **my theory can be stretched to cover that data.**”

38 Susan Rvachew (2021, emphasis added)

39 In this paper, we argue that current incentives favor *strategic ambiguity* in the develop-
40 ment and presentation of theory. By ‘strategic ambiguity’ we mean the use of ambiguity
41 to achieve self-interested goals (Eisenberg, 1984). Any statement or set of statements,
42 including a theory or hypothesis, is ‘ambiguous’ to the degree that it is open to multiple
43 interpretations (Eisenberg, 1984; Gambetta, 2011; Lee & Pinker, 2010). Like everyone else,
44 scientists sometimes strategically deploy ambiguity for the flexibility it affords—flexibil-
45 ity which can be used to obscure weaknesses, deny specific interpretations, and accom-
46 modate unexpected data. In these and other ways, ambiguous theories are harder to
47 falsify than their precise counterparts (Popper, 1963; Smaldino, 2017). Although previous
48 research has discussed the difficulty of falsifying flexible theory (Szollosi & Donkin, 2019,
49 2021), there has been less research on how scientists employ ambiguity strategically in
50 formulating theory and on the incentives that make this possible. Analyzing strategic
51 ambiguity in communication, Eisenberg (1984) noted: “The more ambiguous the message,
52 the greater the room for projection. When an individual projects, he or she fills in the
53 meaning of a message in a way which is consistent with his or her own beliefs” (p. 233).
54 In science, ambiguous theories are more prone to confirmation bias—the tendency to
55 search for, favor, interpret, and remember information in a way that confirms or supports
56 one’s prior beliefs (Nickerson, 1998)—and are therefore more resistant to falsification
57 when compared to clear and precise theories. As a result, the use of strategic ambiguity
58 by scientists may come at the cost of scientific progress.

59 The “motte-and-bailey fallacy” (Shackel, 2005), a pernicious rhetorical trick named
60 after a medieval castle design, illustrates the use and usefulness of strategic ambiguity.

61 Here, the speaker first advances an indefensible claim (the ‘bailey’). When challenged,
62 the speaker retreats to a more modest claim (the ‘motte’) that shares some similarities
63 with the indefensible claim. In this way, the speaker can argue that the original (and
64 indefensible) claim has not been refuted without ever having to defend it! Worse, the
65 speaker can accuse the challenger of being unreasonable. As Boudry and Braeckman
66 (2011) note, “A skilled pseudoscientist switches back and forth between different versions
67 of his theory, and may even exploit his own equivocations to accuse his critics of
68 misrepresenting his position” (p. 150).

69 Ambiguity at any stage of the research process can impede scientific progress
70 (Rohrer, 2021). For instance, during statistical hypothesis testing, ambiguity in prereg-
71 istrations affords degrees of freedom that researchers might exploit by running differ-
72 ent analyses and selectively reporting those that yield desired outcomes. One solution
73 for removing this ambiguity is to make preregistrations machine readable (Lakens &
74 DeBruine, 2021; van Lissa, 2022). Here, we focus on ambiguity in theory formation and
75 communication. We build on a previous blogpost on this topic (Frankenhuis et al., 2021),
76 an earlier book chapter (Smaldino, 2017), and a recent talk on the properties of theories
77 that promote their proliferation (Hussey, 2022). Though we draw our examples primarily
78 from psychology, we believe the problem of strategic ambiguity is widespread across
79 much of the social sciences (for a recent discussion of ambiguity in criminological theory,
80 see Niemeyer et al., 2022).

81 **The Natural Selection of Ambiguous Theories**

82 Scientists are, of course, motivated to discover the truth and thereby help the scientific
83 enterprise succeed. But, being humans, scientists are also motivated to have impact
84 and thereby help *themselves* succeed. Impact results from having ideas widely cited and
85 discussed. One way of achieving impact is to propose theories that accurately describe
86 known phenomena and explain and predict novel phenomena. In this case, the interests
87 of scientists and the scientific enterprise converge. Another way is to propose theories
88 that can be interpreted in many different ways and thereby *appear* to describe known
89 phenomena and predict novel phenomena. The ability of ambiguous verbal models to
90 accommodate a wide range of findings and their resistance to falsification might increase
91 their impact on the scientific community. If the motivation for impact is strong enough,
92 scientists might prefer the flexibility afforded by ambiguous verbal models over the
93 rigidity imposed by precise formal models. Intentionally or not, scientists can use this
94 flexibility to create the appearance of consistent support and progressive research pro-
95 grams, which may be rewarded by journals, funding agencies, hiring committees, and the
96 press.

97 The problem of detecting ambiguous theories masquerading as clear ones is made
98 worse as gatekeepers, including scholarly journals, funding agencies, and university
99 departments, crave impact, too. These gatekeepers also benefit from ambiguous theories

100 if those theories produce research that raises a journal's impact factor, increases a
101 funder's media visibility, or boosts a department's ranking. Intentionally or not, scholarly
102 journals, funding agencies, and university departments may be contributing to the prolif-
103 eration of ambiguous theory. And so there may be many potential levers for improving
104 incentives. In this paper, we focus on the incentives that push scientists, rather than
105 scientific institutions, toward strategically ambiguous theory.

106 We should note that our discussion of strategic ambiguity does not require *intentional*
107 ambiguity. Although intentional ambiguity certainly occurs, incentives can favor scien-
108 tists who use ambiguous theories over scientists who use precise, well-specified theories
109 without scientists being aware of the incentive structures nor consciously choosing to
110 be more ambiguous (Hussey, 2022; Smaldino & McElreath, 2016; Stewart & Plotkin,
111 2021). For example, consider that some scientists criticize the use of formal models for
112 the unrealistic assumptions they demand. This is a valid criticism in some cases. But
113 it is also possible that this criticism rationalizes a preference for verbal models and
114 the ambiguity they afford. Perhaps there is also the concern that formal models will
115 reduce the impact of—or even replace—familiar verbal models, especially a researcher's
116 own. Some researchers may well be aware of their goals, but not the extent to which
117 these goals end up shaping their beliefs. Our claim is that ambiguous theory proliferates
118 especially widely in disciplines where verbal models predominate due to ambiguities in
119 natural language, regardless of whether scientists act in good faith. We will also argue
120 that reshaping incentives to favor transparency about ambiguity will require intentional,
121 goal-directed action by scientists. These actions need to be supported throughout the
122 scientific system, including scholarly journals, funding agencies, and university depart-
123 ments.

124 **Outline of the Paper**

125 We begin by arguing that there is nothing inherently wrong with theoretical ambiguity.
126 In fact, in the early stages of theory construction, ambiguity may be inevitable—and
127 may even be useful. But we also argue that this ambiguity should be transparent—and
128 that scientific institutions should be designed to promote this kind of transparency.
129 And so, in the subsequent section we provide recommendations for authors, reviewers,
130 and journals to bring about transparency in the presentation of ambiguous theory. For
131 instance, we provide a set of questions that can help to evaluate the extent to which a
132 theory is ambiguous, akin to empirically-oriented checklists (Aczel et al., 2020; Flake &
133 Fried, 2020). We conclude with suggestions for research on how scientists use strategic
134 ambiguity to advance their careers and which norms, incentives, and practices favor
135 strategic ambiguity. Our paper ends with a simple mathematical model exploring the
136 conditions in which high-ambiguity theories are favored over low-ambiguity theories.
137 This model illustrates that incentives for credit can favor low-quality, high-ambiguity
138 science, and provides a basis for future formal analyses.

139 **Clarity and Ambiguity Each Have Their Place**

140 “Preliminary operationalizations and fuzzy inferences are not a
141 crime, but a normal starting point of scientific discovery. Yet to
142 progress toward precise claims, the initial vagueness must be recog-
143 nized and tackled in subsequent studies.”

144 Anne Scheel (2022, p. 3)

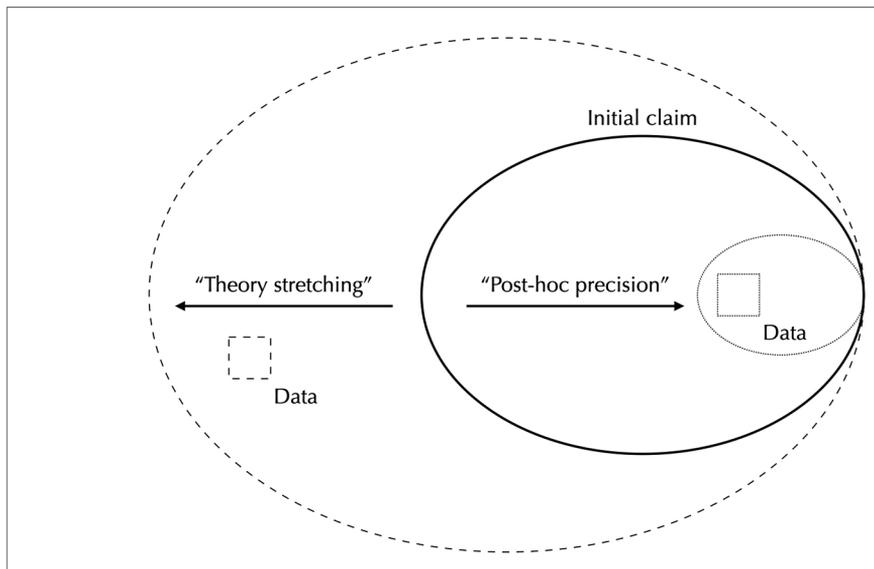
145 At this point, some readers might complain, “But psychology [or sociology, or anthropol-
146 ogy, or ...] is a young science!” or “Human behavior is too complex to ever have precise
147 theories like physics!” Depending on the details of the argument, we may be sympathetic
148 to these complaints. There are deep and fundamental differences between physics and
149 the social sciences (Fodor, 1974). But we think these kinds of objections, in general, miss
150 the mark. We are not arguing that ambiguity has no place in scientific inquiry. Instead,
151 we argue that while the transparent use of ambiguity can benefit scientific inquiry, we
152 should not tolerate ambiguity used strategically to benefit the scientist at the expense of
153 the scientific enterprise.

154 Of course, the study of human behavior faces special challenges. There is often a
155 yawning gap between theoretical concept and empirical measurement, especially when
156 compared to a science like physics. Physicists largely agree on how to define and
157 measure the motion and mass of matter, while psychologists often disagree on how
158 to define, let alone measure, the mental states and motivations of minds. Realistically,
159 these kinds of challenges are unlikely to be resolved any time soon. Perhaps they never
160 will. Nevertheless, at the level of theory—concepts and their relations—social scientists
161 can and should aim for clarity.

162 Despite its benefit to the scientific enterprise, clear theory will not settle every
163 dispute. For instance, scientists may disagree over which empirical unit (estimated from
164 observed data) best captures a given theoretical unit (Lundberg et al., 2021; Rohrer, 2021).
165 Nevertheless, this kind of debate will be more productive when scientists operate within
166 a shared framework of transparent ideas and logic, rather than a wild west world of
167 ambiguous intuition. We highlight two specific ways in which strategically ambiguous
168 theory can be detrimental to scientific inquiry. There are certainly others.

169 **Theory Stretching and Post-Hoc Precision**

170 Intentionally or not, scientists might leverage theoretical ambiguity to serve their own
171 strategic ends. Figure 1 illustrates two different ways in which scientists might exploit
172 the wiggle room afforded by ambiguity to make the evidence for a theoretical claim
173 appear stronger than is warranted.

174 **Figure 1**175 *Illustration of how Ambiguity Affords Inferential Wiggle Room*

176

177 *Note.* The rectangle represents a hypothetical space. The medium-sized, solid ellipse represents an initial
 178 theoretical claim. Encompassing a set of different hypotheses rather than just one, this claim is ‘ambiguous’ as
 179 it is open to multiple interpretations. Now, suppose data supports a hypothesis outside of the initial claim,
 180 represented by the dashed square. The large, dashed ellipse represents ‘theory stretching’ as the scientist
 181 swallows up data that was outside the scope of the original claim. Suppose, instead, the data supports one
 182 specific hypothesis within the scope of the original claim, represented by the dotted square. The small, dotted
 183 ellipse represents ‘post-hoc precision,’ in which the scientist narrows the original claim to more precisely align
 184 with the data. Both theory stretching and post-hoc precision lead to the overestimation of evidence for the
 185 original theoretical claim.

186 First, a scientist might engage in ‘theory stretching,’ interpreting an ambiguous claim
 187 more expansively to absorb data outside the scope of the original claim. Susan [Rvachew](#)
 188 (2021, April 17) describes this phenomenon in the epigraph above. Theory stretching
 189 may become a repeated pattern, with each revised and expanded claim serving as the ba-
 190 sis from which to further revise and expand, thereby swallowing up more and more data
 191 that was outside the scope of the original claim. Second, a scientist might use ‘post-hoc
 192 precision,’ interpreting an ambiguous theoretical claim narrowly so that it appears more
 193 precisely aligned with the data. For instance, a scientist might initially, and ambiguously,
 194 claim that people living in neighborhoods characterized by resource “variability” act
 195 more impulsively. Now, suppose the data support this claim only for temporal variability
 196 (fluctuating resources across time), but not spatial variability (different city blocks having

197 different levels of resources, which remain stable over time). They might redraw their
198 claim to apply only to temporal variability—crucially, without being explicit about this
199 shift.

200 Theory stretching and post-hoc precision both lead to the overestimation of evidence
201 for the original claim. Note that these practices differ from HARKing—Hypothesizing
202 After Results are Known (Kerr, 1998)—which does not start with a theoretical claim, but
203 rather with a search for statistically significant results. One way theory stretching and
204 post-hoc precision can be kept on a leash is when, *prior to conducting a study*, researchers
205 make precommitments (e.g., in a Registered Report) about which specific outcomes count
206 as support for and against a theory or hypothesis (Nosek & Errington, 2020).

207 There is nothing inherently wrong with theory stretching and post-hoc precision,
208 so long as they happen transparently. After all, what is learning if not revising beliefs
209 based on observations? But if we allow ambiguous theory to masquerade as its clear
210 counterpart, surreptitiously shapeshifting to match the data, we end up overestimating
211 the evidentiary support for theoretical claims. Strategic ambiguity allows researchers to
212 observe different or even contradictory data patterns, and nevertheless interpret both
213 patterns as being consistent with the same theory (Fried, 2020; Robinaugh et al., 2021).
214 One particularly pernicious practice is making different theoretical claims in different
215 papers using the same label for each claim. By making empirical evidence seem to sup-
216 port a claim more strongly than is warranted, strategic ambiguity distorts the scientific
217 record. To prevent this, scientists should be transparent about their use of ambiguity,
218 a form of intellectual humility that benefits the scientific enterprise (Bringmann et al.,
219 2022; Frankenhuus et al., 2021; Hoekstra & Vazire, 2021).

220 **Ambiguity Might Be Inevitable—and Perhaps Even Useful**

221 Ambiguity might be unavoidable in the early stages of theory construction. When
222 scientists explore new territories, they encounter novel phenomena. They may face
223 uncertainty about how to categorize or even conceptualize these new phenomena—and
224 yet develop concepts and explanations they must (Scheel et al., 2021). And so they
225 present candidate explanations with coarse-grain mappings between the observed parts
226 of the system and the parts involved in their explanation. This can become an iterative
227 process of tinkering as it may not even be initially clear what one's hypothesis even is
228 (Kauffman, 1971). It would be counterproductive to dismiss nascent theories for being
229 ambiguous. How could they be otherwise? We cannot expect a useful map until we have
230 charted the territory! As Paul Rozin (2001) notes, “we would do well to open our eyes
231 more widely before we dig too deep a hole at one place in the broad and varied terrain of
232 human social life” (p. 13).

233 Rozin's (2001) warning of premature excavation can be interpreted in at least two
234 different ways, either about uncertainty reduction or about surveying the problem space.
235 Armed with a good map of the problem space, we can reduce uncertainty without having

236 to ask ambiguous questions. Consider the way young children often play the game 20

237 Questions:

- 238 1. Is it Ringo Starr? *No.*
- 239 2. Is it George Harrison? *No.*
- 240 3. Is it Paul McCartney? *No.*

241 It would be most impressive if this strategy correctly guessed the target, but extremely
242 unlikely as the overwhelming majority of possible solutions are not members of *The*
243 *Beatles*. As adults, we know it is better to start with broad questions:

- 244 1. Is it a human? *Yes.*
- 245 2. Is this person still living? *Yes.*
- 246 3. Is this person an artist? *Yes.*

247 In the game of 20 Questions, broad questions can be just as precise as specific ones.
248 In fact, the whole point of broad and precise questions is to quickly reduce the search
249 space. Knowing that the target is a ‘human’ dramatically narrows the space of possible
250 solutions. Whether broad or specific, there is little room to interpret what a question
251 means so long as it is clear. Playing this game is similar to how Platt (1964) discussed
252 ‘strong inference’ as a guide to scientific discovery, in which definitive experiments carve
253 up the possibility space in a finer and finer grain. When the scientific terrain has already
254 been well-mapped, definitive experiments present a powerful tool for learning about
255 how the world works.

256 But what happens when we do not already know the problem space? Trying to
257 reduce our uncertainty about a specific hypothesis would be premature. Here, we need
258 to map the problem space. This is precisely the situation in which scientists often find
259 themselves during the early stages of inquiry: Unclear about basic concepts and catego-
260 ries and unsure about the space of possible, let alone probable, hypotheses. During these
261 early stages of scientific inquiry, ambiguity may not only be inevitable—it might actually
262 be beneficial. Ambiguity affords more interpretive room, which might lead different sci-
263 entists to think about the problem in different ways, ask different types of questions, and
264 consider different kinds of evidence. The more diverse the pool of scientists studying the
265 phenomenon, the more hypothetical space they are likely to cover (Hofstra et al., 2020).
266 Some will hit upon fruitful lines of inquiry, leading others to follow. In the early stages
267 of scientific inquiry, we should heed Daniel Dennett’s (1991) warning of the ‘heartbreak
268 of premature definition,’ especially when studying elusive concepts like consciousness,
269 which remain mysterious despite sustained scientific inquiry spanning decades, if not
270 centuries.

271 To be clear, we are *not* calling for the abolition of ambiguity in science. That would
272 be both counterproductive and futile. Instead, we argue that scientists should be as clear
273 as they can be about the ambiguities lurking in their theories, whether studying novel

274 phenomena or mysterious ones, and everything in between. And, as we will discuss,
275 incentives should encourage transparent ambiguity and discourage its strategic counter-
276 part.

277 **Towards Transparency About Ambiguity**

278 “Giving a bad thing a name can help to raise awareness. For exam-
279 ple “p-hacking”. What should we call it when: detailed methods &
280 explicit models are heavily criticized while thin methods & vague
281 verbal models pass freely? Used to see this constantly on grant
282 panels.”

283 Richard McElreath (2021)

284 We have argued that social scientists should strive for theoretical clarity and be transpar-
285 ent about ambiguity when it is either inevitable or useful. One way to do this is to
286 construct formal models of hypotheses and theories that clearly state their meaning and
287 scope (Kauffman, 1971; Smaldino, 2017). Several tutorials exist to support non-modelers
288 in developing formalizations of theories (Frankenhuis et al., 2013; Fogarty et al., 2022;
289 Smaldino, 2020a; van Rooij & Blokpoel, 2020; Wilson & Collins, 2019). But, while model-
290 ing *is* one way to reduce ambiguity, the two issues are hardly isomorphic. So rather
291 than rehashing advice for model-building here, we instead focus on actions that authors,
292 reviewers, and journal editors can take to increase transparency about ambiguity in the
293 scientific literature. Clarity should be the goal, even if some ambiguity is inevitable and
294 perhaps useful in the early stages of theory construction. By this we mean that one
295 should be as precise as possible, given one’s current understanding, as to the *scope* of
296 a theory or hypothesis: the set of conditions under which it is or is not expected to
297 hold (Walker & Cohen, 1985). Clarity holds interpretative wiggle room on a leash, while
298 ambiguity liberates it. By making assumptions, concepts and their relations, and the
299 derivation chain from assumptions to predictions explicit, it becomes easier to decouple
300 a theory from the scientist who proposed it, making the theory a public good for all
301 to evaluate and use (Epstein, 2008; Guest & Martin, 2021; Meehl, 1990; Smaldino, 2017).
302 Clarity also makes it easier for a hypothesis to be falsified, and the rate at which
303 incorrect hypotheses are falsified influences the growth of scientific knowledge (even if
304 this growth also depends on other factors, such as the discovery of anomalies (Kuhn,
305 1970) and the development of new theory that better accounts for the data (Lakatos,
306 1970)).

307 **Rewarding Ambiguity and Penalizing Precision**

308 The epigraph above points out that, all too often, grant panels, hiring and promotion
309 committees, and journal editorial boards more harshly criticize formal and precise mod-

310 els and methods than verbal and ambiguous models and methods. Responding to McEl-
311 reath's tweet, Smaldino (2020b, November 30) proposed the term 'RAPPING' to denote
312 the practice of "rewarding ambiguity and penalizing precision". The term RAPPING is
313 general and could be used in the context of empirical work as well—for instance, when
314 grant proposals are criticized for the planned sample sizes they provide, whereas other
315 proposals that do not even state their planned sample sizes sail through. Here, our focus
316 is on theory.

317 Why would a scientist evaluating another's research reward theoretical ambiguity?
318 One could argue that evaluators, being human, are imperfect, despite being motivated
319 by good intentions. This might explain noise in evaluations, but not a bias toward
320 ambiguity. We think there is something else going on. The mapping between theory and
321 measurement is often inexact, especially in the social sciences. When scientists write
322 clearly about their models and methods, this inexactness is brought into stark relief. As
323 Julia Rohrer (2021) notes: "It is the curse of transparency that the more you disclose
324 about your research process, the more there is to criticize" (Rohrer, 2021, December
325 8). Clarity can have the perverse effect of making it easier for evaluators to identify
326 flaws that might have remained hidden in a more ambiguous description. This is espe-
327 cially detrimental if, as suggested by empirical research, grant reviewers weigh negative
328 information more heavily than positive information (Teplitskiy et al., 2022). Ambiguous
329 theory does not, of course, eliminate flaws, it merely conceals them. We hope that
330 labelling this phenomenon draws attention to it and, hopefully, encourages remediation.

331 To help researchers avoid RAPPING, we list six questions evaluators can ask of any
332 hypothesis or theory to help identify ambiguities (Table 1). For each question, we have
333 suggested a few response options, but of course it is possible to obtain more graded esti-
334 mates by rating those questions on a more finely grained scale. It is not essential that all
335 these questions be answered in the affirmative for a hypothesis or theory to be deemed
336 clear. For instance, while formal modeling makes it easier to satisfy questions 1–3 and
337 5–6, some verbal theories may be clear and precise without requiring a formal model.
338 Furthermore, clarity is but one desirable feature of a scientific theory. However, each
339 question answered in the negative should reduce the clarity assigned to the hypothesis or
340 theory being evaluated. We also note that the clarity of a theory is not synonymous with
341 its empirical testability. For example, the Hawk-Dove model has been influential in the
342 study of human and non-human conflict but was never intended to be directly testable
343 (Maynard Smith & Price, 1973). The Hawk-Dove model does, however, involve clear
344 assumptions that *can* be directly compared with empirical data to assess its applicability.
345 Thus, Table 1's question about scope directly implies questions about the specification of
346 conditions for validation or falsification. Finally, our list is not meant to be exhaustive,
347 but merely suggestive. Future work could explore its effectiveness and improve the
348 items for clarifying theoretical ambiguities through empirical research. Some journals

349 and funding agencies could even train reviewers in how to use these types of questions
 350 effectively, aiming to increase standardization in evaluations of theoretical transparency.

351 **Table 1**

352 *Six Questions to Help Evaluate Theoretical Transparency*

Question	Examples of responses
1. Is each term clearly defined?	No / some / all terms are defined
2. Are all relations between terms specified?	No / some / all relations between terms are specified
3. Are all assumptions explicitly described?	No / some / all key assumptions are discussed
4. Has the theory been formalized?	The theory does / does not have a formal basis
5. Is the scope of the theory well specified?	The conditions in which the theory does and does not apply are unstated / coarsely described / fully explicit
6. Is the theory consistent across papers?	The theory is consistent / inconsistent across papers in terms of its assumptions, scope, and predictions

353 **Evaluating Theoretical Transparency: A Worked Example**

354 We illustrate how asking these questions can help identify key ambiguities by consid-
 355 ering a specific example. We use this example not because it is a unique outlier, but
 356 because it is high-profile and representative of a widespread trend across the social
 357 sciences.

358 In a target article in the journal *Behavioral and Brain Sciences*, [Baumeister, Ainsworth,](#)
 359 [and Vohs \(2016\)](#) develop an argument for the following hypothesis: “Groups will produce
 360 better results if the members are individuated than if their selves blend into the group.”
 361 Some scientists might use this hypothesis as the basis for their empirical research. How-
 362 ever, doing so would be problematic, because as it currently stands the proposal is not
 363 falsifiable ([Smaldino, 2016](#)). Evaluating this hypothesis—as it is presented in the paper—in
 364 light of [Table 1](#) yields an answer of “no” to every single question. The hypothesis con-
 365 tains undefined terms and undefined relationships; it is laden with hidden assumptions
 366 and lacks clear scope; and the hypothesis is presented as a verbal rather than a formal
 367 model. Let us interrogate the hypothesis with Questions 1 and 5.

368 The hypothesis takes the form of a standard conditional statement (B occurs if condi-
 369 tion A holds). The antecedent clause, “the members are individuated [instead of] their
 370 selves [being] blend[ed] into the group,” involves some ambiguity, but for simplicity we
 371 will focus most of our attention on the consequent: “groups will produce better results.”

372 First, the terms are not clearly defined. To what sort of groups does the hypothesis
 373 apply? The target article discusses a very wide range of groups, including track athletes
 374 in relays, families, universities, corporations, military organizations, and governments.
 375 Does the hypothesis apply to all groups? Kindergarten classrooms? Dutch soccer play-

376 ers? Bob Dylan fans? Or only to groups that have particular features? If so, which
377 features? Should these features occur in combination or is any one of them sufficient?

378 Second, the scope of the hypothesis is never specified. What constitutes ‘better’
379 results? For some groups, there is a relatively straightforward answer: a sports team per-
380 forms better when they win more competitions (though even here, not all competitions
381 are equivalent). For other groups, it is harder to pin down a single measure of success;
382 particularly as groups often exist for multiple reasons. An intervention could increase
383 performance on one metric while decreasing performance on another (e.g., a corporation
384 increases its profits but employee morale decreases, leading to attrition). What happens
385 when groups are nested within larger groups, or when individuals belong to multiple
386 groups with non-aligned interests? These and other ambiguities of the consequent clause
387 must be addressed before one can test whether a particular group outcome is within the
388 scope of the theory. In its stated form, the hypothesis is suggestive and can productively
389 drive research to answer these disambiguating questions but cannot be directly tested. It
390 is too ambiguous to falsify.

391 To reiterate, ambiguity is not necessarily a bad thing; it might be inevitable or even
392 useful in the early stages of theory construction. Not all research can or should be
393 driven by precise hypotheses. Instead, sometimes the purpose of research must be disam-
394 biguation rather than confirmation or falsification. Transparency about a current lack
395 of precision can and should motivate future research. However, if ambiguous theoretical
396 and empirical work is consistently supported at the expense of more precise research
397 proposals—if there is excessive RAPPING by grant panels, editorial boards, and hiring and
398 promotion committees—then science is the worse for it. We need transparency about
399 ambiguity, which helps us decide for any case whether the ambiguity is inevitable,
400 desirable, or harmful.

401 **Recommendations and Future Directions**

402 “[T]he effectiveness and the ethics of any particular communicative
403 strategy are relative to the goals and values of the communicators in
404 the situation.”

405 Eric M. Eisenberg (1984, p. 238)

406 The authors of this paper often use formal modeling. We have often heard critics argue
407 that formal models are not useful tools in theory construction. These critics often defend
408 their position by arguing that formal models make assumptions that are too simplistic,
409 too unrealistic, and too arbitrary. Instead, these critics advocate for the use of verbal
410 models, which they argue are more complex and more complicated, and therefore more
411 realistic. To this, we might respond by highlighting the ambiguities inherent in verbal
412 models, including imprecise constructs, implicit assumptions, and predictions based on

413 intuitive rather than deductive reasoning. There are, of course, merits to each side of
414 this debate (for a historically informed discussion of the mathematization of nature, see
415 Eronen & Romeijn, 2020). Our hope is that partisans in debates like this can find common
416 ground in our proposal to strive for transparency in the face of ambiguity, in much
417 the same way that proponents of more exploratory research and proponents privileging
418 confirmatory research can find common ground in the proposal to clearly delineate these
419 two types of research (Chambers & Tzavella, 2022; Frankenhuis & Nettle, 2018; Nosek et
420 al., 2018; Wagenmakers et al., 2012). How can authors, reviewers, and journals promote
421 transparency about theoretical ambiguity?

422 Recommendations

423 First and foremost, the burden should be on authors to strive for transparency about
424 ambiguities lurking in their theories. For instance, authors could write: ‘our definition
425 [of some term] is not without problems’, followed by an explanation. Or ‘there is friction
426 between one of our assumptions [about the relationship between two terms] and another
427 assumption’, followed by an explanation. If authors use ambiguity deliberately, they
428 should signal their intentions. If they do not, they may be building a Potemkin village,
429 presenting a façade of clarity that collapses on closer inspection—and takes down anyone
430 who was lured into working on its construction. Nguyen (2021) argues that epistemic
431 manipulators strategically imbue their belief system with an exaggerated sense of clarity
432 to avoid closer inspection. Whereas a sense of confusion invites us to think more, a
433 sense of clarity, whether real or imagined, encourages us to terminate our inquiries,
434 protecting the belief system. If authors believe their theories are clear and precise, they
435 should welcome scrutiny rather than assume a defensive posture. The use of transparent
436 ambiguity is fine. It is opaque ambiguity that poses risks precisely because it can be used
437 opportunistically, whether intentional or not. The goal should be transparency in the
438 face of theoretical ambiguity.

439 Reviewers should be mindful to not penalize authors for being transparent about
440 ambiguities—just as they should not penalize authors for being explicit about exploratory
441 aspects of their research. Reviewers should appreciate that transparency about ambiguity
442 is a much-needed form of intellectual humility (Hoekstra & Vazire, 2021), a move that
443 will only benefit the scientific enterprise. And just as a culture that licenses us to
444 be more open and explorative in empirical research can feel liberating (Frankenhuis
445 & Nettle, 2018), so too can a culture that acknowledges and embraces transparency
446 about ambiguity in the development and presentation of theory. In addition, reviewers
447 may consider penalizing opaque submissions—perhaps identified using Table 1—as these
448 compete with transparent submissions.

449 Journals can help to reduce the harms associated with ambiguities by encouraging
450 the formalization of theory and transparent communication about known ambiguities
451 (van Rooij, 2022; Jamieson & Pexman, 2020). They might consider publishing articles

452 or special issues in which empirical researchers collaborate with modelers to formalize
453 theories, or in which many modelers independently develop models of an influential
454 verbal theory (van Dongen et al., 2022). In addition, journals can be explicit that they
455 value transparency about ambiguity and encourage authors to be transparent about
456 ambiguity and reviewers not to penalize this kind of transparency. Additionally, funding
457 agencies can help by supporting the development of formal theory.

458 We have argued that theoretical ambiguity proliferates in disciplines in which verbal
459 models predominate. Though we have strived for clarity, we are certain that some of *this*
460 paper's content is open to multiple interpretations. We welcome criticism and hope for
461 improved clarity as we develop and test these ideas. Toward this end, we propose two
462 future directions, one empirical and one theoretical.

463 Empirical Research on Strategic Ambiguity

464 Empirical research could examine which norms, incentives, and practices favor the use of
465 strategic ambiguity. This kind of research would benefit from qualitative and quantitative
466 measures of ambiguity. A first step might be to have human reviewers evaluate the
467 degree of ambiguity in theoretical claims, perhaps by using our Table 1. Another measure
468 of ambiguity could be the number of distinct interpretations that different researchers
469 provide when reading a theoretical claim. Such distinct interpretations appear to explain
470 at least part of the variation in results obtained by the different teams involved in the
471 various "Many Analysts" projects (Scheel, 2022). Specifically, a recent reanalysis of one
472 "Many Analysts" study (Silberzahn et al., 2018) suggests that teams answered different
473 versions of the underspecified research question (Auspurg & Brüderl, 2021). A more
474 quantitative approach might involve the use of a machine learning algorithm that 'reads'
475 a verbal theory and quantifies the degree of ambiguity. We are aware of one study
476 that used Flesch's reading ease score to explore whether the readability of abstracts of
477 scientific papers is associated with the evaluation of their quality. Specifically, in an
478 analysis of the Research Excellence Framework, a research impact evaluation of British
479 higher education institutions, machine learning models rated harder-to-understand ab-
480 stracts better than easier-to-understand abstracts; these models had been trained using
481 mock ratings provided by scientists (Thompson et al., 2022). This finding is consistent
482 with incentives for strategic ambiguity. We look forward to future empirical work ex-
483 ploring which norms, incentives, and practices favor strategic ambiguity in high-stakes,
484 real-world settings. Some of this work should be qualitative, investigating how grant
485 panels, hiring and promotion committees, and journal editorial boards interpret, discuss,
486 and evaluate formal and precise models versus verbal and ambiguous models.

487 More broadly, the social sciences would benefit from identifying, cataloguing, and
488 understanding the practices of theory stretching and post-hoc precision. For instance, as
489 has already been done for HARKing (John et al., 2012), survey studies could examine how
490 commonly researchers self-report engaging in theory stretching and post-hoc precision

491 (self-admission rates), what they believe the percentage of other researchers who had
492 engaged in each behavior to be (prevalence estimate), and among those researchers who
493 had, the percentage that would admit to having done so (admission estimate) (John et
494 al., 2012). In addition to providing baselines, this tool could be used to compare across
495 social science disciplines (e.g., psychology and economics) and between subfields within
496 a discipline (e.g., cognitive and developmental psychology). Such comparisons could
497 be used to identify factors which contribute to theoretical ambiguity. Tracking these
498 measures over time, and measuring their responses to interventions (e.g., changes in
499 journal policies), can provide insight into perceived theoretical progress.

500 Finally, we have not covered all the reasons why theoretical ambiguity may be
501 favored. For example, another reason might be the so-called ‘Guru effect’ (Sperber, 2010):
502 people judge profound that which they fail to grasp. If ambiguity leads people to feel
503 that they do not understand, this feeling of ignorance evokes awe, and this awe increases
504 a theory’s dissemination and success, then ambiguous theory may be favored. Such
505 a process could be studied empirically, for instance by examining whether (a) people
506 feel that they understand ambiguous theories less well than clear ones, (b) ambiguous
507 theories evoke more awe than clear ones, and (c) theories that evoke more awe are more
508 likely to proliferate. Though these ideas are interesting and perhaps worth exploring, we
509 have restricted our scope to falsifiability (rather than awe) as the mediating pathway for
510 a theory’s success.

511 **Modeling Strategic Ambiguity: A Worked Example**

512 We believe theoretical modeling would be useful in exploring the conditions that favor
513 and disfavor the strategic use of ambiguity. This kind of work could follow in the tradi-
514 tion of treating the scientific enterprise as a cultural phenomenon and applying the logic
515 of cultural evolutionary theory (McElreath & Smaldino, 2015; Smaldino & McElreath,
516 2016). Such an approach can help identify conditions in which strategic ambiguity flour-
517 ishes as well as interventions that might reduce it. Of course, this kind of research would
518 also benefit from formal definitions of strategic ambiguity in the context of scientific
519 theory. Such definitions could build on related developments in other fields, such as
520 political science and communication (e.g., Aragonès & Neeman, 2000; Jarzabkowski et al.,
521 2010; Pinker et al., 2008).

522 As a starting point, we develop a formal model to illustrate how and why theoretical
523 ambiguity might be favored. This is a toy model, intentionally simple, designed only for
524 the purpose of making clear an otherwise complex point. Like all models, this model
525 makes specific assumptions. Any conclusions drawn from this analysis only apply to
526 scenarios in which these assumptions apply.

527 Suppose scientists can choose one of two strategies determining how they produce
528 and disseminate research: A *low-ambiguity strategy* (L), in which scientists derive and
529 test precise hypotheses from clearly specified formal models, and a *high-ambiguity*

530 *strategy* (H), in which scientists use ambiguous language to shroud the vagueness and
 531 imprecision of their theories and hypotheses.

532 Scientists receive credit for their work based on value conferred by their research
 533 community. We assume that scientific inquiry involves risk, so that any individual study
 534 may fail to generate credit. A low-ambiguity researcher produces useful and repeatable
 535 results a proportion p of the time. When they do, they receive a payoff of 1. And a
 536 proportion $1-p$ of the time, the low-ambiguity researcher produces less useful results. In
 537 these cases, they receive a payoff of ε (where $\varepsilon < 1$), which without loss of generality
 538 can be set to zero. Overall, low-ambiguity researchers have an expected payoff of p .
 539 The real-world consequences of low payoffs may be severe, especially for early-career
 540 researchers, as they can result in failures to get grants, promotions, or jobs.

541 We assume that high-ambiguity researchers produce research that is of lower quality
 542 in terms of usefulness and repeatability when compared to research produced by low-
 543 ambiguity researchers. However, by its very nature, highly ambiguous research offers
 544 flexibility in its interpretation, meaning there is a lower risk that the researcher fails to
 545 receive credit compared with the low-ambiguity strategy. At the extreme, there is little
 546 risk when a theory can accommodate any finding and get away with it. We assume
 547 that high-ambiguity researchers receive an expected payoff of q , such that $0 < q < 1$.
 548 This payoff range captures two ideas. First, that ambiguous work is less valuable than
 549 low-ambiguity research that produces useful and precise results (i.e., $q < 1$). Second,
 550 because it can accommodate any finding, high-ambiguity research will be *perceived*
 551 as more valuable than low-ambiguity research when the latter fails to produce useful
 552 results (i.e., $q > 0$). Note that if $p < q$, the expected payoff (that is, the average payoff
 553 over a large number of studies) of high-ambiguity research is larger than the expected
 554 payoff of low-ambiguity research, even if useful and repeatable results obtained from
 555 low-ambiguity research are preferable to high-ambiguity research.

556 Finally, we assume that research is costly in terms of time and resources. We assign
 557 a separate cost for the low and the high-ambiguity strategy: c_L and c_H , respectively.
 558 Further, we assume that producing low-ambiguity research requires greater effort than
 559 high-ambiguity research (i.e., $c_L > c_H$).

560 We can use these costs and benefits to calculate the expected payoffs for each
 561 strategy. The expected payoff of a strategy is the credit received minus the time and
 562 resources spent. The expected payoff for a low-ambiguity researcher is therefore:

$$U_L = p(1) + (1-p)(0) - c_L = p - c_L \quad (1)$$

563 Similarly, the expected payoff for a high-ambiguity researcher is:

$$U_H = q - c_H \quad (2)$$

564 We are now able to ask when the low-ambiguity strategy is favored over the high-ambiguity strategy. This happens when $U_L > U_H$. In other words, a low-ambiguity research strategy is favored when:

$$p - c_L > q - c_H \quad (3)$$

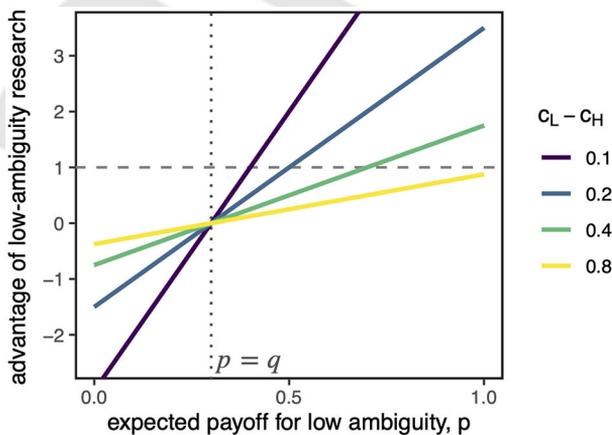
567 which can be rewritten as follows:

$$\frac{p - q}{c_L - c_H} > 1. \quad (4)$$

568 The left side of the inequality is the extent to which the expected credit advantage
569 of low-ambiguity research offsets the larger cost. Two conclusions follow from this
570 analysis. First, because the denominator is always positive, this inequality is never true if
571 the expected credit payoff of low-ambiguity research is less than that of high-ambiguity
572 research (i.e., $p < q$). Second, and perhaps more troubling, highly ambiguous research can
573 be favored even if, on average, it yields a lower payoff than less ambiguous research,
574 so long as producing the latter is sufficiently more costly. Figure 2 illustrates this relationship.
575 Note that when low-ambiguity research is much costlier than high-ambiguity
576 research, high-ambiguity is always incentivized.

577 **Figure 2**

578 *Illustration of the Mathematical Model*



579

580 *Note.* The plot shows the credit advantage to low-ambiguity research (left side of Equation 4) as a function of its
581 expected payoff, p . The differently colored lines represent different values for the added cost to low-ambiguity
582 research. The low-ambiguity strategy is favored only when the solid lines are above 1 on the y-axis. This
583 requires low-ambiguity research to pay off more reliably when such research is more costly. In this example, q
584 = 0.3.

585 Based on the logic of this simple model, we have two levers to promote greater clarity
586 and less ambiguity. First, we should decrease the credit accruing to high-ambiguity
587 research, perhaps through increased standards of scrutiny within a research community.
588 Second, we should be concerned if the cost to produce low-ambiguity research in a scien-
589 tific discipline is significantly higher than the cost to produce high-ambiguity research.
590 Otherwise, low-cost, high-ambiguity research becomes incentivized and will proliferate.

591 Conclusion

592 We are confident that increased transparency about ambiguity will benefit science, but
593 we are less clear on the value of any specific protocols for detection or enforcement. For
594 this reason, we have avoided a more specific set of guidelines for dealing with problems
595 related to strategic ambiguity. Systemic problems often require sustained scrutiny and
596 systemic solutions that focus on the system in which individuals operate, rather than
597 simply nudging individual behavior (Chater & Loewenstein, 2022). We have a long way
598 to go. A start would be to acknowledge, as some other disciplines do (e.g., physics,
599 biology), that developing theory is not something that empirical researchers can just do
600 ‘on the side’, but rather is a professional skill that requires specialized training. Where
601 are the jobs for theoreticians in our field? Where is funding for them? In our view,
602 such factors contribute to the current incentives not favoring rigorous theory. Ideally,
603 proposed solutions operate in concert, targeting multiple components of a system, as is
604 done by funder and journal partnerships rewarding transparency in empirical research
605 (Chambers & Tzavella, 2022; Munafò, 2017). The challenge of how to improve incentives
606 for better theory in the social sciences is underexplored. We hope metascience research-
607 ers will make progress on this challenge in the coming years.

608 **Funding:** WEF’s contributions have been supported by the Dutch Research Council (V1.Vidi.195.130) and the James
609 S. McDonnell Foundation (<https://doi.org/10.37717/220020502>).

610 **Acknowledgments:** We thank Balazs Aczel, Tasha Fairfield, Sander Koole, Daniel Nettle, Glenn Roisman, Anne
611 Scheel, Sven Arend Ulpts, Stefan Vermeent, Ethan Young, and one anonymous reviewer for feedback on previous
612 versions of this manuscript.

613 **Competing Interests:** The authors have declared that no competing interests exist.

614 **Author Contributions:** *Willem E. Frankenhuis*—Idea, conceptualization | Writing | Feedback, revisions | Visualization
615 (data presentation, figures, etc.) | Supervision, mentoring | Project coordination, administration. *Karthik*
616 *Panchanathan*—Idea, conceptualization | Writing | Feedback, revisions | Visualization (data presentation, figures, etc.).
617 *Paul E. Smaldino*—Idea, conceptualization | Writing | Data analysis | Feedback, revisions | Visualization (data
618 presentation, figures, etc.).

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