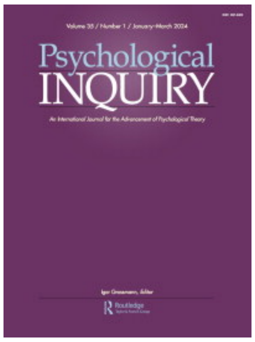


Psychological Inquiry

An International Journal for the Advancement of Psychological Theory

ISSN: (Print) (Online) Journal homepage: www.tandfonline.com/journals/hpli20


# The Inductive Reasoning Model: A Step Forward into the Future or a Step Back into the Past?


Constantine Sedikides & John J. Skowronski

PSYCHOLOGICAL INQUIRY
2024, VOL. 35, NO. 1, 56–61
https://doi.org/10.1080/1047840X.2024.2366803

COMMENTARIES

# The Inductive Reasoning Model: A Step Forward into the Future or a Step Back into the Past?

Constantine Sedikides[a] and John J. Skowronski[b]

[a]Center for Research on Self and Identity, School of Psychology, University of Southampton, Southampton, UK; [b]Northern Illinois University, DeKalb, Illinois

We begin our commentary on the Krueger et al. article by highlighting its main goals. Despite the article's virtues, we outline two reasons why we think the proposed theoretical model, the inductive reasoning model (IRM), might be taking a step backward than forward. We conclude with epistemological reflections.

## Highlighting the Article's Goals

The target article pursues two key goals. One is content-based, as it attempts to advance understanding of social psychological findings on the self. This goal is reflected in the statement, "Using only two empirically-based inputs, namely, the positivity of a person's self-image and the strength of social projection, the model predicts the direction and extent of four higher-order phenomena." The first of these phenomena is intergroup accentuation, defined in terms of the tendency to perceive group differences as greater than they are. The second is self-enhancement, defined as the tendency to think that one is better (i.e., has more positive and fewer negative traits) than the average person. The third is ingroup favoritism, defined as the tendency to describe one's own groups more favorably than other groups. The fourth phenomenon is differential accuracy, defined as the tendency for ingroup stereotypes to be more accurate than outgroup stereotypes. In addition to individually predicting these phenomena, the model predicts interrelations among them—a noteworthy novelty.

The second key goal of the article relates to philosophy of science. The authors champion the effectiveness of the IRM over other theoretical approaches, because their model is grounded in mathematical equations that predict specific "point values" for a measured outcome variable or for relations among outcome variables. These point predictions allow for hypothesis testing that is "stronger" than the "theoretically meek" hypothesis testing often used in social psychological research.

Construction of comprehensive and coherent theories in the area of the self is hard. We know this first-hand from our own attempts to do so (Sedikides et al., 2021). Hence, we appreciate the authors' diligent and well-informed effort to theorize about the self and how it is implicated in social judgments. We also appreciate the authors' attempt to discuss how various self-related phenomena might be linked.

The relations the authors describe and predict were, given the assumptions laid out, logical and well-considered. Also, the predictions they made would provide a fine starting point for a research program. Hence, the IRM might serve as a guide to interesting and informative research that examines the self, the social judgments that involve the self, and the associations among those social judgments.

## Why the Inductive Reasoning Model Might Be Taking a Step Backward

In some ways, however, the IRM appears to take a step backward rather than a step forward. We detail the reasons underlying this perception.

### The Model Ignores Mental Process, Mental Structures, and Mental Motives

The authors' theorizing echoes approaches that infused social psychology theory and research approximately 50 years ago. A relevant example is information integration theory (Anderson, 2013). Researchers from this tradition examined the extent to which judgments that required the integration of information conformed to mathematical functions such as adding, averaging, or multiplying the values of the stimuli presented. Researchers would proceed to declare as a winner the model that best fit the data.

This reasoning reminded us of information integration theory, because the authors suggested that the IRM could serve as a "baseline model" against which the data could be evaluated. They also proposed that, in this way, the IRM could be generative. In particular, it could be adjusted to incorporate discrepant data, thus spawning research. This is similar to the approach pursued by information integration theory researchers, which contributed to the theory's long run as foundation for a research program. The IRM, then, might similarly have long legs as a springboard for self-related theory and research.

Another program of research with a similar flavor to the IRM was based on theories of attribution (Forsterling, 2001;

CONTACT Constantine Sedikides cs2@soton.ac.uk Center for Research on Self and Identity, School of Psychology, University of Southampton, Southampton SO17 1BJ, UK

Weiner, 2008). For example, Kelley (1967) proposed that, when making causal attributions for an action, perceivers are informed by actor knowledge of consensus information (did others do it?), consistency information (does the actor do this in this situation all the time?), and distinctiveness information (does the actor do this across situations?). Taking a somewhat different approach to attributions, Jones and Davis (1965) advocated that perceivers analyze behaviors in the context of the situation in which they occurred. As such, perceivers would sometimes discount a person's internal characteristics (e.g., traits, motives) as the cause of the behavior, because the situation provided a sufficiently powerful explanation for that behavior.

Though neither of these attributional conceptions was accompanied by a formal mathematical presentation, the expected mathematics of judgment were often implicitly incorporated into the ensuing research designs. For instance, early tests of Kelley's attribution model were conducted via factorial designs simultaneously manipulating some combination of consensus, consistency, and distinctiveness information (McArthur, 1972; Orvis et al., 1975). The researchers' expectation was that each of Kelley's contributors to causal attributions would have a roughly equal impact on those attributions, which corresponds to the averaging rule implicated by information integration theorists scholars. The power of this averaging expectation is illustrated by the researchers' conclusion that perceivers often "underutilize" consensus information. This conclusion was based on finding that the observed impact of information on judgment was lower for consensus information than for the other information types (McArthur, 1972, 1976). A similar expectation, that input stimuli would somehow be mentally averaged, led to the conclusion by researchers pursuing Jones and Davis's (1965) ideas that perceivers evinced a "correspondence bias" or that they made a "fundamental attributional error." These two labels reflect the observation that perceivers often make attributions that fit with the trait implications of actor behavior, even when that behavior is constrained by the situation (Snyder & Jones, 1974; Trope & Gaunt, 1999).[1]

Social psychology's experiences with information integration theory and attribution theory reinforce the possibility that the IRM be useful and generative. Indeed, though somewhat modified in form, research into information integration and attributions continues to this day (Lyu et al., 2024; Pereira & Oliveira, 2021).

However, information integration theory and attribution theory were part of the research context that contributed to a seismic shift in social psychology. Scholars became dissatisfied with the field, because it—including information integration theory and attribution theory—operated largely at a descriptive level; that is, they were primarily concerned with what happened, not why it happened. In particular, prevailing theories offered relatively little guidance into the mental structures (e.g., types of knowledge and how these types are organized), mental mechanisms (e.g., attention, automatic processing and controlled processing, judgment heuristics, how memory informs judgments), and motivations (e.g., self-enhancement, self-protection) that might be involved in, and contribute to, judgments.

This dissatisfaction led to the emergence of the social cognition approach (Hamilton & Carlston, 2013; North & Fiske, 2012). This approach moved from the strict focus on the outcomes of mental processes (e.g., judgments) and propelled theories and methods which offered insight into the mental structures, mental processes, and motivations that contributed to how one thinks about the social world. We incorporated many of these ideas into the Egocentric Tactician Model of the Self that we proposed (Sedikides et al., 2021).

The IRM seems like a step backward, because of the arguably simplistic view of the self and social judgment that it depicts. This model uses only two variables, self-positivity and projection, as inputs. It uses these two inputs to predict only a few outputs: four judgments and patterns of correlations among the judgments. In light of the many variables known to influence the self and how the self affects social judgments (Baumeister, 2023; Dunning, 1999; Schmader & Sedikides, 2018; Sedikides, 2021; Sedikides et al., 2021), this simplicity gives the IRM the feel of being somewhat out of sync with existing theory and research surrounding the self.

Some might argue that this perception of simplicity is mistaken. After all, it is often the case that simplification is a useful scientific strategy when purporting to understand a complex system (Occam's razor). That is, to begin to comprehend a given set of phenomena, a researcher can try first to examine the system in "ideal" circumstances or in "restricted" circumstances. By doing so, the researcher can eliminate a host of complicating factors that might make it difficult to observe systematicity in the data.

In support for the utility of this approach, we note that physicists endorsed it for a long time. For example, when trying to understand fluid dynamics, physicists developed models that used two simplifying assumptions: (a) the fluids were incompressible, and (b) the flow of the fluid will be laminar (i.e., without turbulence). After making these assumptions, they developed mathematical models of fluid flow that worked reasonably well at least some of the time (Riutord, 2015). Physicists knew that these models were not entirely correct, because their assumptions were often violated, but they were nevertheless willing to accept inaccuracies for gaining a partial understanding of fluid dynamics.

In the above example, however, a reasonable understanding of fluid dynamics could progress by ignoring a small number of variables. This is not the case in the IRM model, which ignores a host of variables that are likely to influence the self and social judgment. The equations modeling fluid dynamics captured a lot of that phenomenon; the IRM equations do not capture much about the self and social judgment. A great deal is excluded.

As an illustration of the claim that the IRM excludes too many variables, consider the model's assertion that the extent to which one projects the self to a group depends on

[1]The use of the term "fundamental attributional error" implies that the theory is correct, but the perceiver's judgment is erroneous—a rather controversial implication.

whether the individual perceives the group as similar to the self. Though this statement is straightforward, it likely overlooks substantial complexities involving an individual's assessment of similarity. One such complexity reflects how similarity assessments are made. Such assessments are influenced by the nature of the referent in the similarity judgment (e.g., "are they similar to me" vs. "am I similar to them"). Although the self may serve as the referent (i.e., are they similar to me) in such judgments (Catrambone et al., 1996), that may not always be the case. The extent to which projection occurs might be expected to vary across the different forms of similarity assessment (Smith et al., 2020).

Another complexity lies in that similarity judgments may also be affected by the body of self-knowledge that is activated prior to the assessment. For instance, the perceived similarity of a scholar who resides in the United States to a scholar who resides in Poland may vary depend on whether the scholar has very recently spent time reflecting on either her Polish ancestry (which may increase perceived similarity) or on the history of the United States (which may reduce perceived similarity). One might expect that similarity judgments, and hence projections, would be stronger in the Poland-reflection case than in the United States reflection case.

Further complexity comes from the idea that the context in which the assessment is made might spontaneously impact the body of self-knowledge that is activated and used in the similarity comparison. Imagine that, prior to engaging in projection, a Liverpool football (soccer) fan is assessing similarity to Manchester City football fans. That assessment may differ depending on whether it takes place while seated in the Liverpool football club stadium (Anfield) versus in the stadium (Emirates) of a common rival, the Arsenal football club. The former context will likely activate self-knowledge that would serve to minimize perceived similarities between the self and Manchester City fans (reducing projection), whereas the latter, as it represents a common foe, will likely activate self-knowledge that might serve to enhance perceived similarities between the self and Man City fans (enhancing projection).

One additional source of complexity lies in the motivation underlying the similarity judgment. To demonstrate, we will change the comparison football club to Leeds. Given that the Leeds club was relegated from the highest level of English football in 2023, thinking about the way in which Leeds fans are similar to the self might be threatening to the self. Hence, to manage this threat, a Manchester City fan might minimize the perceived similarity of the self to Leeds fans, thus weakening projection.

Yet more complexity lies in the self-positivity variable emphasized by the IRM. The model predicts that greater self-positivity will be projected onto a group perceived to be high in similarity. Under what circumstances will this be the case? Although many people habitually think about the self in positive terms (e.g., in a trait-like fashion), it is also the case that self-thought can vary widely from moment to moment (i.e., the self has state-like properties). Which self-view will be projected onto a highly similar group – the very positive trait-like view or the less positive state-like view? The IRM is silent on this issue (but, for the record, we suspect that for motivational reasons it will be the trait-like view that is projected).

One final source of complexity lies in knowledge of others. The propensity to project the self onto others might sometimes be delimited by one's direct knowledge of those others. For example, it is plausible that a perceiver has relatively detailed knowledge about one's brothers. Even with perceived similarity and a strong overall tendency to project, that tendency might be limited for particular people and particular items (e.g., "my experience with him shows that my brother Juan does not share my gregariousness"). The same limitation might occur from one's knowledge of people in general. A person may think they have a positive attribute (e.g., "I am brilliant at the game of bridge") that is not widely shared by others. Even when an individual perceives a group to be highly similar to them, the known lack of consensus on this attribute may inhibit projection.

## The Theorizing is Newtonian Rather than Dynamic

The IRM can also be seen as a step backward when considering recent knowledge advances in the operation of complex systems. We provide the context for this perception. Psychologists have habitually lusted after the ability to predict human thought and behavior in ways that mimicked the Newtonian approach to physics. This approach involved the derivation of mathematical rules that would lead to precise "point predictions" about physical issues both small (e.g., acceleration of a ball down a ramp) and large (e.g., the orbits of planets in Earth's solar system).

A fitting analogy to this scientific approach treats the natural world as if it were a finely crafted watch. The behavior of such a watch can be predictably determined by knowledge of the watch's inner workings. Thus, science aimed to discover the precise workings of the watch and to express those workings in the form of mathematical equations that predicted the behavior of the watch. The better the understanding, the better the equation, and the better the equation, the better the prediction of the watch's behavior. Decisions between competing equations could be made by examining which equation afforded the optimal predictions.

The Newtonian approach to science has been qualified by recent developments in theory and research on the properties of dynamical systems. An example of such a system is climate. Many components contribute to a dynamical system, and, as it proceeds, these components can interact with each other in complex ways. Also, the output of a system at any given moment serves as an input to it. Hence, the behavior exhibited by dynamical systems not only involves the effects of many differing components, but is also characterized by the operation of one or more feedback loops (Gleick, 1988; Lorenz, 1963).

Importantly, modeling studies indicated that these dynamical systems, whose behavior can be determined by mathematical equations, can still exhibit complex behavior, such as nonlinear behavior. Here, the orderly flow of a fluid can suddenly become a maelstrom of chaos, or the interactions among sets of small ocean waves can combine to produce a rogue huge tidal wave. Also, these systems can exhibit what we call "orderliness with variability." Here, an outcome might seem to be "attracted" to a state (e.g., a given value) or a set of states. As the system evolves and changes across time, the outcome of the system might approach, but not ever reach, the attractor values. Another interesting system property has been termed "strange attractor" or "Lorenz attractor," colloquially known as "chaos." Here, in manifesting their approach behavior, the values output by the system may not ever repeat the same value twice. In all, outcomes in dynamical systems can simultaneously exhibit structure and variability. Crucially, the variability in such systems is not "extraneous variance" or "noise," as it is often treated by social psychologists. Instead, such variance can be determined by a set of equations that define the dynamic system. (For overviews, see: Gleick, 1988; Gros, 2015; Lorenz, 1963)

The brain can be viewed as a dynamical system (Izhikevich, 2007; McKenna et al., 1994), because the patterns of interconnections among neurons and among brain regions incorporate feedback loops (Damasio, 2010; Garrido et al., 2007). Indeed, researchers and theorists have been approaching the study of the brain accordingly, exploring implications of this dynamical system for human thought and behavior (Kern et al., 2018). Following from Damasio's (2010) assertion that the self emerges from interactions among brain regions, and in light of the many mechanisms likely to be involved (Dunning, 1999; Sedikides et al., 2021), we conjecture that the self, and how it affects both self-judgments and social judgments, will eventually be found to be a fit to this dynamical systems perspective (Richardson & Chemero, 2014; Schuldberg & Guisinger 2022).

Given our viewpoint, and in the context of advances in theory and research involving these dynamical systems, it is perhaps easier to appreciate why the IRM appears to us as if it were a step backward. The model embodies the Newtonian view of the world in which precise point predictions can be confidently made once a researcher understands all the properties of the system. In contrast, the dynamical systems approach implies that such point predictions will be difficult to make, because of the complex nature of the system's behavior and because accurate prediction of that behavior requires a very precise knowledge of the conditions present at any given time in the operation of the system. Very small alterations in system conditions can lead to very large effects as the systems evolves (producing the oft-used example that the flap of a butterfly's wings in South America might cause tornadoes in the United States).

## Epistemological Reflections: On the Supposed Superiority of Point Predictions in Science

The authors claim that the IRM is superior because it provides point predictions. They ground this superiority claim in the notion that point predictions provide a baseline against which research data can be evaluated. If the data fit the prediction, then the model is supported. If the data do not fit the prediction, then the model is unsupported. Two models that make differing predictions can be examined relative to the data to find out which model best fits them. If this superiority is displayed often enough, the better-fitting model can be retained and the poorer-fitting model can be discarded.

Experience in the natural sciences provides ample evidence for the utility of this approach. One example are studies thought to verify the existence of the Higgs boson. These studies detected predicted evidence for the presence of certain types of certain sub-atomic particles that emerged in the aftermath of an atom-splitting procedure (ATLAS collaboration et al., 2012; CMS collaboration et al., 2012). Another example pitted Einstein's views of gravity against Newton's views of gravity with regard to whether the path of light is deflected around large masses. Einstein's views (verified) could accommodate the bending of light observed in the data, but Newton's views could not (Dyson et al., 1920).

Krueger et al. suggested that the IRM ought to be preferred to other models of self and social judgment, because their model's point predictions lead to "strong" hypothesis testing such as the one evinced by the Higgs boson studies and the Einsteinian light bending experiments. In contrast, they claim that most hypothesis testing in psychology is "meek," because it provides little information other than support for the conclusion that something not predicted by random chance is occurring.

We illustrate the "meekness" claim with an example. Assume one suspects that a coin has been tampered with so that results produced by coin flips are not "fair." Given this suspicion, one can conduct a coin-flipping study comparing results from 10,000 flips produced by the suspect coin to the results produced by the same number of flips of a coin known to be "fair." The Krueger et al. analysis would suggest that this exemplifies the "null-hypothesis testing" approach often employed in social psychology. The authors assert that this approach is not strong in that it can only lead a researcher to conclude either that the coin toss data from the suspect coin condition matches what would be expect from the fair coin condition or that it does not. This latter result is deemed "weak" by the authors because the fact that the coin toss data indicate lack of fairness does not necessarily implicate the coin. For example, the data in the "suspect coin" condition could be produced by the coin-tosser used in that condition, one who is skilled in producing desired coin toss results (Diaconis et al., 2007). The "unfair" result in the suspected tampering condition may also be produced by a property of the surface on which the tossed coin lands as it interacts with the coin. If the suspect coin is steel on one side and nickel on the other, it might usually produce fair results on most surfaces, but a magnetized table might tend to pull the steel side down (Diaconis & Skyrms, 2019).

We are in general agreement with Krueger et al. that it is desirable for scientific theories to make specific predictions which can be disconfirmed via research findings. However, we would qualify this desirability with a couple of cautions.

First, the value of a theory is not enhanced simply because it makes a specific point prediction. A point prediction made by a theory that is intellectually vacuous and poorly grounded in prior scholarship may be valueless. We hasten to say that this is not a criticism we level against the IRM; in our opinion, the IRM is grounded in scholarship and is well-reasoned. Instead, we are simply reacting to what we perceive in the Krueger et al. article as the claim that theories which make precise numerical predictions are to be preferred simply because they can make such predictions. Arguably, one learns very little when the prediction of an obviously valueless theory is disconfirmed. Perhaps a pithier way to express this opinion is that the capacity to produce a point prediction does not by itself make a theory good, but it can make an already good theory better.

The second caution is that the supposed "meekness" of null hypothesis testing may be in the eye of the beholder. Sometimes, all one needs to advance theory is experiments that are well-conceived and well-designed. An example of this assertion in social psychology occurred in the context of the debate about whether experiments demonstrating "behavior influences attitude" effects were produced by consistency motivation (as suggested by cognitive dissonance theory) or by self-inference processes (as suggested by self-perception theory). The research, much of it in the form of null hypothesis testing characterized as "meek" by Krueger et al., yielded a definitive conclusion: Both theories are right, but each operates in a separate set of circumstances (Fazio et al., 1977; Olson & Stone, 2005; Preston & Wegner, 2005).

This example suggests a notion that we see as crucial: Because theory testing is a vital scientific endeavor, researchers should use theory to the extent that is possible. Just because researchers will not be able make a theory gin up a specific point prediction does not mean that they cannot effectively test theory. Instead, to advance science, researchers should do the best they can to test theories. What is "best"? That depends on the theory.

Sometimes a theory may simply imply that an outcome is not random, indicating a non-directional test against a null hypothesis. Researchers do not need a point prediction to test such a theory; they simply need a demonstration that an outcome is not as expected from randomness. To illustrate, we will return to our coin-flipping example. If an individuals is considering gambling against a street grifter, they might theorize that that the grifter has an unfair advantage that leads him to routinely beat his victims. This view can be confirmed by observing the grifter's actual success rate relative to chance expectations. Such a simple view and observational research suffice to save one's money, regardless of whether the grifter's advantage is due to the grifter's skills, the die, or the surface on which the die falls (or some combination thereof). The details are irrelevant to protecting one's pocket.

Other times a theory might be effectively tested via a directional prediction against a control condition. For example, research on spontaneous trait inference generation searched for evidence of inference generation at a rate above that observed in a control condition in which no inference generation was expected (Skowronski & McCarthy, 2023). "Meek," you say? This was exactly the kind of directional hypothesis test that led physicists to conclude they had found the Higgs boson (ATLAS collaboration et al., 2012; CMS collaboration et al., 2012). It was a "meek" enough finding to culminate to Nobel prizes being awarded to some of the physicists involved in the project.

Taken together, although we concur with Krueger et al. that theories which generate highly specific predictions can be better than theories which are less specific in their predictions, we also think that this claim needs context and qualification. Lousy theories that generate specific predictions are not to be preferred just because they make specific predictions – they remain lousy, despite such predictions. Moreover, just because a theory does not generate a highly specific numerical prediction does not mean it is a poor theory. Instead, theories that generate non-numerical predictions (e.g., an outcome is unfair, the frequency of an outcome should be above a given baseline, the frequency of an outcome should be below a given baseline) can be both worthy to consider and adequately examined in well-designed research programs. Again, trying to be pithy, in the case of theory development and use, we opine that a researcher should not "throw the baby out with the bath water."

## Disclosure Statement

No potential conflict of interest was reported by the author(s).

## References

Anderson, N. H. (2013). Unified psychology based on three laws of information integration. *Review of General Psychology*, *17*(2), 125–132. https://doi.org/10.1037/a0032921

ATLAS Collaboration et al. (2012). Observation of a new particle in the search for the Standard Model Higgs boson with the ATLAS detector at the LHC. *Physics Letters B*, *716*(1), 1–29. https://doi.org/10.1016/j.physletb.2012.08.020

Baumeister, R. F. (2023). *The self-explained: Why and how we become who we are*. Guilford Press.

Catrambone, R., Beike, D., & Niedenthal, P. (1996). Is the self-concept a habitual referent in judgments of similarity? *Psychological Science*, *7*(3), 158–163. https://doi.org/10.1111/j.1467-9280.1996.tb00349.x

CMS Collaboration et al. (2012). Observation of a new boson at a mass of 125 GeV with the CMS experiment at the LHC. *Physics Letters B*, *716*(1), 30–61. https://doi.org/10.1016/j.physletb.2012.08.021

Damasio, A. (2010). *Self comes to mind: Constructing the conscious brain*. Pantheon/Random House.

Diaconis, P., Holmes, S., & Montgomery, R. (2007). Dynamical bias in the coin toss. *SIAM Review*, *49*(2), 211–235. https://doi.org/10.1137/S0036144504446436

Diaconis, P., & Skyrms, B. (2019). *Ten great ideas about chance*. Princeton University Press.

Dunning, D. (1999). A newer look: Motivated social cognition and the schematic representation of social concepts. *Psychological Inquiry*, *10*(1), 1–11. https://doi.org/10.1207/s15327965pli1001_1

Dyson, F. W., Eddington, A. S., & Davidson, C. (1920). A determination of the deflection of light by the sun's gravitational field, from observations made at the total eclipse of May 29, 1919. *Philosophical Transactions of the Royal Society of London. Series A, Containing Papers of a Mathematical or Physical Character*, *220*, 291–333.

http://links.jstor.org/sici?sici=0264-3952%281920%29220%3C291%3AADOTDO%3E2.0.CO%3B2-W

Fazio, R. H., Zanna, M. P., & Cooper, J. (1977). Dissonance and self-perception: An integrative view of each theory's proper domain of application. *Journal of Experimental Social Psychology*, *13*(5), 464–479. https://doi.org/10.1016/0022-1031%2877%2990031-2

Forsterling, F. (2001). *Attribution: An introduction to theories, research and applications*. Psychology Press.

Garrido, M. I., Kilner, J. M., Kiebel, S. J., & Friston, K. J. (2007). Evoked brain responses are generated by feedback loops. *Proceedings of the National Academy of Sciences of the United States of America*, *104*(52), 20961–20966. https://doi.org/10.1073/pnas.0706274105

Gleick, J. (1988). *Chaos: Making a new science*. Penguin Books Ltd.

Gros, C. (2015). *Complex and adaptive dynamical systems: A primer* (4th ed.) Springer International Publishing.

Hamilton, D. L., & Carlston, D. E. (2013). The emergence of social cognition. In D. Carlston (Ed.), *The Oxford handbook of social cognition* (pp. 16–32). Oxford University Press.

Izhikevich, E. (2007). *Dynamical systems in neuroscience: The geometry of excitability and bursting*. The MIT Press.

Jones, E. E., & Davis, K. E. (1965). From acts to dispositions: The attribution process in person perception. *Advances in Experimental Social Psychology*, *2*, 219–266. https://doi.org/10.1016/S0065-2601(08)60107-0

Kelley, H. H. (1967). Attribution theory in social psychology. In D. Levine (Ed.), *Nebraska symposium on motivation* (Vol. 15, pp. 192–238). University of Nebraska Press.

Kern, D., Karwowski, W., Franco, E. G., & Murata, A. (2018). Evidence of chaos in a routine watchstanding task. *Nonlinear Dynamics, Psychology, and Life Sciences*, *22*(1), 153–171.

Lorenz, E. N. (1963). Deterministic nonperiodic flow. *Journal of the Atmospheric Sciences*, *20*(2), 130–141. https://doi.org/10.1175/1520-0469(1963)020<0130:dnf>2.0.co;2

Lyu, Y., Su, Z., Neumann, D., Meidenbauer, K. L., & Leong, Y. C. (2024). Hostile attribution bias shapes neural synchrony in the left ventromedial prefrontal cortex during ambiguous social narratives. *The Journal of Neuroscience*, *44*(9), e1252232024. https://doi.org/10.1523/JNEUROSCI.1252-23.2024

McArthur, L. A. (1972). The how and what of why: Some determinants and consequences of causal attribution. *Journal of Personality and Social Psychology*, *22*(2), 171–193. https://doi.org/10.1037/h0032602

McArthur, L. Z. (1976). The lesser influence of consensus than distinctiveness information on causal attributions: A test of the person-thing hypothesis. *Journal of Personality and Social Psychology*, *33*(6), 733–742. https://doi.org/10.1037/0022-3514.33.6.733

McKenna, T. M., McMullen, T. A., & Shlesinger, M. F. (1994). The brain as a dynamic physical system. *Neuroscience*, *60*(3), 587–605. https://doi.org/10.1016/0306-4522(94)90489-8

North, M. S., & Fiske, S. T. (2012). A history of social cognition. In A. W. Kruglanski & W. Stroebe (Eds.), *Handbook of the history of social psychology*. (pp. 81–99). Psychology Press.

Olson, J. M., & Stone, J. (2005). The influence of behavior on attitudes. In D. Albarracin, B. T. Johnson, & M. P. Zanna (Eds.), *The handbook of attitudes* (pp. 223–271). Erlbaum.

Orvis, B. R., Cunningham, J. D., & Kelley, H. H. (1975). A closer examination of causal inference: The roles of consensus, distinctiveness, and consistency information. *Journal of Personality and Social Psychology*, *32*(4), 605–616. https://doi.org/10.1037/0022-3514.32.4.605

Pereira, T., & Oliveira, A. (2021). The usefulness of the averaging rule in consumer studies: A partial replication with an eye at neuroeconomics. *European Review of Applied Psychology*, *71*(5), 100718. https://doi.org/10.1016/j.erap.2021.100718

Preston, J., & Wegner, D. M. (2005). Ideal agency: The perception of self as an origin of action. In A. Tesser, J. V. Wood, & D. A. Stapel (Eds.), *On building, defending and regulating the self: A psychological perspective* (pp. 103–125). Psychology Press.

Richardson, M. J., & Chemero, A. (2014). Complex dynamical systems and embodiment. In L. Shapiro (Ed.), *The routledge handbook of embodied cognition* (pp. 39–50). Routledge/Taylor & Francis Group.

Riutord, R. (2015). *An introduction to fluid dynamics*. Springer Nature.

Schmader, T., & Sedikides, C. (2018). State Authenticity as Fit to Environment (SAFE): The implications of social identity for fit, authenticity, and self-segregation. *Personality and Social Psychology Review*, *22*(3), 228–259. https://doi.org/10.1177/1088868317734080

Schuldberg, R., Guisinger, S., & Richards, D. (Eds) (2022). *Chaos and nonlinear psychology: Keys to creativity in mind and life*. Oxford University Press.

Sedikides, C. (2021). The homeostatic model of identity protection: Lingering issues. *Psychological Inquiry*, *32*(4), 284–288. https://doi.org/10.1080/1047840X.2021.2007703

Sedikides, C., Alicke, M. D., & Skowronski, J. J. (2021). On the utility of the self in social perception: An Egocentric Tactician Model. *Advances in Experimental Social Psychology*, *64*, 247–298. https://doi.org/10.1016/bs.aesp.2020.11

Skowronski, J. J., & McCarthy, R. J. (2023). Reflections on a 30-year-long program of research exploring perceivers' spontaneous thoughts about social targets. In E. Balcetis & G. B. Moskowitz, (Eds.), *The handbook of impression formation: A social psychological approach* (pp. 161–184). Routledge.

Smith, A. R., Windschitl, P. D., & Rose, J. P. (2020). An integrated approach to biases in referent-specific judgments. *Thinking & Reasoning*, *26*(4), 581–614. https://doi.org/10.1080/13546783.2019.1691053

Snyder, M., & Jones, E. E. (1974). Attitude attribution when behavior is constrained. *Journal of Experimental Social Psychology*, *10*(6), 585–600. https://doi.org/10.1016/0022-1031%2874%2990081-X

Trope, Y., & Gaunt, R. (1999). A dual-process model of overconfident attributional inferences. In S. Chaiken & Y. Trope (Eds.), *Dual-process theories in social psychology* (pp. 161–178). The Guilford Press.

Weiner, B. (2008). Reflections on the history of attribution theory and research: People, personalities, publications, problems. *Social Psychology*, *39*(3), 151–156. https://doi.org/10.1027/1864-9335.39.3.151