*Philosophy of Science* (2026), **00**, 1–10
doi:10.1017/psa.2026.10247

DISCUSSION NOTE

# Object-Induction and Pool-Determination in the Meta-Inductive Approach. A Reply to Bakshi

Gerhard Schurz

Philosophy, HHU: Heinrich-Heine-Universitaet Duesseldorf, Duesseldorf, Germany
Email: schurz@hhu.de

(Received 16 October 2025 UTC; revised 20 June 2026 UTC; accepted 23 June 2026 UTC)

## Abstract

This note offers a response to Bakshi's critical discussion of Schurz's claim that meta-induction provides a noncircular justification of object-induction (induction at the object-level of events). Bakshi raises two issues: (1) the problem of identifying object-inductive methods and (2) the problem of determining the pool of simultaneously accessible prediction methods. In this reply, a solution to the identification problem is offered, based on existing work. Concerning the problem of pool-determination, induction-independent criteria are proposed that justify disregarding Goodman-type methods.

The first two sections of Bakshi (2025) provide a concise introduction and a valuable discussion of the meta-induction approach (Schurz 2019). This approach consists of two steps:

1) The a priori justification of attractivity-weighted meta-induction (aMI) through the provable optimality of aMI with respect to all prediction methods that are simultaneously accessible to a given epistemic agent. Thereby, aMI tracks the success records of all such prediction methods and predicts an optimally weighted average of them, with weights determined by the predictive successes of the methods (so-called attractivities). The optimality results is universal in the sense that it holds for all possible event sequences and finite sets of methods.
2) The meta-inductive a posteriori justification of object-induction (induction at the object-level of events), abbreviated as OI, based on the fact that OI methods have thus far been significantly more successful than noninductive methods. This fact, by meta-induction, justifies the use of object-inductive methods for

© The Author(s), 2026. Published by Cambridge University Press on behalf of Philosophy of Science Association. This is an Open Access article, distributed under the terms of the Creative Commons Attribution licence (https://creativecommons.org/licenses/by/4.0/), which permits unrestricted re-use, distribution and reproduction, provided the original article is properly cited.

https://doi.org/10.1017/psa.2026.10247 Published online by Cambridge University Press

future prediction tasks without committing a circularity because meta-induction has an independent a priori justification.

A predictive success evaluation in which aMI and finitely many prediction methods $M_1, \ldots, M_m$ (the "pool of methods") are iteratively predicting the "next event" $e_{n+1}$ of an infinite series of events $e_1, e_2, \ldots$, is called a *prediction game*. Regarding the first step, it can be demonstrated mathematically (based on theorems in machine learning) that in all prediction games, the predictive success rate (average success) of aMI is optimal in the long-run, with tight upper-bounds on initial short-run losses that become vanishingly small as n (the number of predicted events) grows larger than m (the number of competing methods). More precisely, where $suc_n(M)$ denotes the success rate of method M at time n, it holds that:[1]

(i) For all $n$, $suc_n(aMI) \geq \max(\{suc_n(M_1), \ldots, suc_n(M_m)\}) - 1.77\sqrt{\ln(m)/n}$, and
(ii) $\lim_{n\to\infty} suc_n(aMI) \geq \max(\{suc_n(M_1), \ldots, suc_n(M_m)\})$.

Bakshi (2025, 1) mentions two limitations of this optimality result, which, however, can be overcome: (1) The previously mentioned theorem holds only for convex loss functions, but a generalization—expressed in terms of the optimal expected success of a randomized aMI and the optimal average success of a group of aMIs—exists that applies to all loss functions (Schurz 2019, § 6.7). (2) The theorem assumes a fixed, finite pool of accessible methods, but it can be generalized to a dynamically expanding pool: A universal optimality theorem has been proven for unboundedly growing sets of methods, under the restriction that the number of accessible methods grows slower than exponentially over time (Schurz 2021, theorem 4).

In his critical discussion, Bakshi grants the first step of the meta-inductive account, the a priori optimality of meta-induction in regard to the pool of accessible methods. Rather, he raises two important challenges to the second step, the a posteriori justification of object-induction based on its superior track record: (1) The problem of identifying object-inductive methods and (2) the problem of determining the pool of methods. In the following response, a solution to the identification problem is first presented based on existing work. Second, induction-independent criteria are proposed that justify disregarding Goodman-type methods, which could otherwise undermine the meta-inductive justification of object-induction. Before turning to the two problems, it should be noted that step 2 of the meta-inductive account has also been criticized in the literature for another reason. As pointed out by Pitts (2023), the superiority of object-inductive over noninductive methods does not apply to mixed methods that normally predict like object-inductive methods but intermittently employ noninductive ones—a point that must be acknowledged.[2]

[1] This theorem holds for exponentially weighted aMI (Schurz 2019, sec. 6.6.2; 2024, 166), which has better short-run loss bounds that the simple version of aMI that was introduced in Schurz (2008) and is used by Bakshi. There are two unintended mistakes in Bakshi's presentation: (a) In equation (5) on p. 4, the greater-equal sign (≥) must be replaced by a the smaller-equal sign (≤), and (b) in fn. 6, Bakshi writes that I would use concave loss functions, but the previously mentioned theorem assumes convex loss functions.

[2] A reply to Pitts (2023) is found in Schurz (2023, §3).

https://doi.org/10.1017/psa.2026.10247 Published online by Cambridge University Press

## 1. The identification problem: Defining object-induction

How could one define object-induction? In his discussion of this question, Bakshi (2025, 5) assumes that a general formal characterization of object-inductive methods is not possible. Instead, he analyzes *local* and domain-specific ways of characterizing object-induction, building on Norton's material theory of induction (Norton 2003, 2021). He discusses the proposal to identify object-induction (OI) with those domain-specific inductive methods in science that have been successfully applied within their respective domain. Bakshi (2025, 6) rightly criticizes this proposal. What should be added is that this proposal falls prey to the charge of *circularity*. If we were to subsume under "OI" only those purportedly inductive methods in science that have been successfully applied in their domains, then an unbiased comparison between inductive and noninductive prediction methods would become impossible because the success of object-induction would already be presupposed. For an unbiased investigation we need an *independent* characterization of "OI." Moreover, such a characterization must be *general* and domain-independent; otherwise we would end up with a variety of domain-specific scientific methods, without being able to say what they have in common.

The material theory of induction claims that there can be no general definition of (object-)induction. This claim is clearly rejected within the theory of meta-induction. A general characterization of induction can be derived from proposals in Schurz (2019). It is Bakshi's credit to have drawn attention to this rarely discussed element of the meta-inductive approach. From the outset, the meta-inductive approach makes clear that induction is understood in the narrow Humean sense—meaning that a certain regularity observed among past events or data $e_1, \ldots, e_n$ (within a given domain) is projected onto new, future or unobserved instances ($e_{n+1}, e_{n+2}, \ldots$) for the purpose of predicting these new instances (Schurz 2019, 1f.). This narrow sense of induction is contrasted with the broader notion of inference to the best explanation, which allows one to infer theoretical models about unobserved causes from observations—for instance, inferring the gravitational attraction of the sun from the orbits of the planets. In Schurz (2024, ch. 10) it is shown that while meta-induction can provide an instrumentalist justification of theoretical models in terms of explanatory and predictive success, their realist justification—in the sense of high theoretical truthlikeness—requires epistemological principles that go beyond meta-induction.

Given this clarification, Schurz (2019) characterizes object-inductive prediction methods based on the observation that "object-induction is not just one method but an unboundedly large *family* of—simply or increasingly refined—inductive methods" (ibid., 208f.), in which simple or arbitrarily complex properties are transferred from observed past instances to future instances (ibid., 225). These properties are formally described in terms of the values of a given variable X, which are ordered by magnitude (e.g., weight in pounds)[3]; binary variables $X_{\pm F}$ take the values 1 (property F occurs) and 0 (F does not occur). A method M is called "unconditionalized" if it predicts the future values of X based only on the observed past values of X (where "n" denotes the present time point); M is "conditionalized" if it uses the observed values of another, possibly complex, reference variable Z to predict the values of X.

[3] In probabilistic games, X refers to probabilities of the values of another variable X′.

https://doi.org/10.1017/psa.2026.10247 Published online by Cambridge University Press

(1) *Definition of object-inductive prediction methods* (for unconditionalized methods, simply omit the underlined clauses): M is a conditionalized prediction method iff: M predicts the value(s) of the next instance (or future instances) of a possibly complex variable X, based on the inductive transfer of observed averages of X's past values conditional on the value of another variable Z (applying to one or several preceding events), where the value M predicts for the next instance(s) increases monotonically with an increasing average of past X-values, conditional on the observed values of Z.

For example, for binary event-sequences ($e_i = 1$ or 0), the simplest object-inductive method ($OI_s$), known as maximum-rule, predicts $X_{n+1} = 1$ if the observed frequency of 1s, $f_n(1)$, exceeds 0.5, and otherwise $X_{n+1} = 0$. The next simplest object-inductive method, known as average-induction ($OI_a$), predicts $X_{n+1} = f_n(1)$. In the limiting case of 100%-frequencies, both OI-rules coincide with the rule of *strict induction*: "All observed Fs were Gs; therefore, the next F is G." A more complex, conditionalized method is Markov induction of 1st order ($OI_{M1}$), which conditionalizes the projected frequencies on the preceding event; here the observed frequency $f_n(1_{i+1}|1_i)$ is projected to future instances (thus, $Z_{n+1} = X_n$). In *curve fitting* it is assumed that there is a (typically polynomial) function f such that $X = f(Z) + n(\sigma)$ (where $n(\sigma)$ is as normally distributed error variable), and the prediction $X_{n+1} = f_n(Z_{n+1}) + n(\sigma)$ is computed using the optimal estimation $f_n$ of f's parameters based on the observed data $\{(X_i,Z_i):1 \leq i \leq n\}$.

It may be objected that this abstract characterization of an object-inductive method (whose abstractness is necessary for sufficient generality) is far removed from real scientific inductions. This is not the case. For example, versions of average-induction underlie scientific predictions of financial markets (cf. Douven and Schurz 2026). In particular, curve fitting methods are the alpha and omega of scientific inductions. Langley et al. (1987, ch. II) have rigorously demonstrated how formally characterizable curve-fitting methods are exemplified in a variety of famous historical cases: Johannes Kepler's 1618 induction of the third law of planetary motion from telescopic observations by Tycho Brahe; Robert Boyle's 1660 induction of his empirical gas law from a series of gas measurements; Georg Ohm's 1826 induction of his law of electric currents from measurements of electrical circuits; and many more.

It is important that in *inductive* prediction methods, the *same* observed property (or its average value) is projected to future instances, while in noninductive methods, a different property is transferred. In *counterinductions*, for example, the *opposite* of the observed property (or average) is projected to future instances. Other nonnductive methods include blind guessing, dogmatic prediction of a constant value, or reliance on a material "oracle," such as a purported clairvoyant.

Different object-inductive prediction methods can be in competition and may yield contradicting predictions of the next event. For example, if the binary sequence (011011011011) has been observed, then $OI_s$ predicts $X_{n+1} = 1$ because $f_n(1) = 2/3 \geq 0.5$, while the complex method $OI_{3\text{-block}}$ predicts 0 because it projects the observation that the sequence is a strict repetition of three-blocks "011" to the future, that is, $f_n((X_{i+2},X_{i+1},X_i) = (0,1,1) \mid i \text{ is a multiple of } 3) = 1$. This fact is important, as it clarifies why meta-induction is not only needed to justify inductive over noninductive methods but also to identify the best among competing inductive methods in science.

https://doi.org/10.1017/psa.2026.10247 Published online by Cambridge University Press

Different fields of research differ markedly with respect to which inductive methods are most successful within them—in this important observation, Norton's material theory of induction is clearly right. Moreover, there are many domains (governed by chance or chaos) in which even inductive methods fail to succeed. For this reason, the a posteriori justification of object-induction (OI) is formulated as follows (cf. Schurz 2019, 209):

(2) *A posteriori justification of object-induction*: According to the presently available evidence, OI methods have significantly dominated non-OI methods in the sense that, in many fields, some OI method has been significantly more successful than every non-OI method, although in no field has any non-OI method been significantly more successful than all OI methods.

We believe that the explication of object-inductive methods in (1), in combination with formulation (2) of the meta-inductive justification of OI, provides a robust solution to Bakshi's identification problem. The critical points raised by Bakshi stem primarily from his (in our view incorrect) assumption that the explication of object-induction should be based on the material view of induction, rather than on the general characterization given in (1) in the preceding text. We conclude our reply to Bakshi's identification problem with a few remarks on the points he raised.

In Schurz and Thorn (2020), it is claimed that Norton's material account and the account of meta-induction are complementary. Bakshi (2025, 7) points out that this claim is mistaken because the two accounts are in strong tension. Bakshi is right, and when Schurz and Thorn (2020) spoke of "complementarity," they understood this notion in analogy to the wave-particle dualism in quantum mechanics. Here, complementarity is claimed despite underlying contradictions, meaning that some components of one theory can be reconciled with the other theory as a useful complement, whereas others remain in contradiction. The material theory of induction contradicts the meta-inductive approach in two respects: First, it denies that there is a general, domain-independent characterization of OI, whereas the meta-inductive account assumes this. Second, it ignores the problem of circularity, while for the meta-inductive account the avoidance of circularity in justifications is crucial.

Bakshi points out that for the material account of induction, a domain-specific type of inductive prediction or inference is *not* justified by the past track record of its instances, but rather by the "background facts of the domain . . . which warrant the goodness of an inductive inference" (ibid., 7). Bakshi cites Norton's (2021) example of Marie Curie's inference: From a few observations of instances of radium chloride, she predicted that, in general, radium chloride has the same crystalline form as barium chloride. Curie's prediction which was not justified by the observed success of previous inferences of this kind, but rather by a local "background fact," more precisely by an accepted general principle, namely the weakened Haüy's principle, which (in Norton's formulation) states that "each crystalline substance has a single characteristic crystallographic form" (ibid., ch. 1). Haüy's principle entails that if a few instances of radium chloride have the same crystallographic form as barium chloride, then this must hold for radium chloride in general.

It is true that in 1904 Curie's prediction was not inductively justified by its success rate, but it was deductively justified by Haüy's principle. Nevertheless this fact can

https://doi.org/10.1017/psa.2026.10247 Published online by Cambridge University Press

readily be accommodated within the meta-inductive framework. We just have to ask: *How did Haüy and his collaborators acquire knowledge about Haüy's general principle?* The answer is: by strict induction from observation and measurement. This is demonstrated in the work of Usselmann (1986) and Mascarenhas (2020), who show in detail how Haüy's principle follows inductively from his observations of the forms of various crystals (belonging to different chemical types) and the measurement of their angles using goniometers. Haüy's inductions did not rely on any further general background facts about crystals, which solves the circularity inherent in Norton's account.

The fact that Marie Curie's prediction was confirmed by deduction from a general principle that was inductively supported is not at odds with the meta-inductive approach. Nowhere in the theory of meta-induction is it claimed that confirmation by meta-induction over predictive success rates is the only way in which hypotheses are confirmed in science (cf. Schurz 2019, sec. 8.1.1). Meta-induction is rather the epistemologically most fundamental (regress-stopping) method within the overall network of deductive, inductive and abductive justifications in science (Schurz 2024, sec. 2.8). Moreover, Haüy's principle is not a simple "fact" but a *theoretical* principle. Scientific theories have multiple areas of application—in the case of Haüy's principle, these include all kinds of inorganic salts (all having a crystalline solid form). In the meta-inductive evaluation of theories, predictive success in each area of application is aggregated into an overall success score (as described in Schurz 2024, ch. 10.1). For this reason, theories can make *novel* predictions about new areas of application in which they do not yet have any empirical track record—because their hypotheses have been confirmed through predictive success in other areas. In this sense, Marie Curie's inference was a novel prediction, justified by a deduction from Haüy's theoretical principles whose meta-inductive support in application to well-known crystals such as table salt (sodium chloride) *carried over* to Curie's prediction.

In summary, I agree with Bakshi that Curie's inference is not a standard object-inductive inference that is meta-inductively justified by its predictive success. In my analysis, Curie's inference relies on a *chain of justifications*: (i) deduction from a general principle H, (ii) justification of H through a standard OI based on larger data sets, and (iii) justification of OI by MI. The value of the material account lies in highlighting these cases of theory-mediated justification in science. The key difference, however, is that while the material account considers the first link in this chain sufficient, the foundation-theoretic epistemology underlying Schurz's work holds that justifications based solely on (i) are insufficient, as they lead either to dogmatism, circle or infinite regress. To avoid this, one needs OI justified by MI.

## 2. The indetermination problem: Determining the pool of methods

Attractivity-weighted meta-induction aMI is predictively optimal w.r.t the "pool of all methods" that are *simultaneously* accessible to the given epistemic agent; this pool is denoted by Π. "Simultaneous accessibility" means that the finitely bounded agent must be able to represent and track all methods in Π simultaneously and compare their success rates, which requires more computational effort than accessing the methods individually. Depending on how the notion of "accessible method" is understood, this may lead to problems. If we follow Sterkenburg (2019, 989) and

https://doi.org/10.1017/psa.2026.10247 Published online by Cambridge University Press

understand the accessible methods as all those methods that have *actually* been proposed by the scientific community, then no problem arises, because this class is not too large to be tractable simultaneously. However, if we have in mind all individually accessible methods that *could* have been included in the pool Π, then their number may exceed the maximum number of methods that can be simultaneously accessed. In this case, one needs additional criteria for determining the pool Π because there may be more than one maximally large Π. Note that aMI's optimality is not affected by this fact because it holds for all choices of Π. However, the question of which methods in Π achieves greatest weight according to the present track record may depend on the choice of Π.

The problem becomes particularly pressing in light of the possibility of so-called *Goodman methods*. In analogy to Goodman's predicate "grue" = "green of observed before a future time point t and blue thereafter," a Goodman-type method $G_t$ predicts like the best object-inductive method up to an *arbitrarily* chosen future time point t (> n), after which it begins to predict counterinductively. If the pool contains the Goodman method $G_{n+1}$, then at time n the attractivity-weight of $G_{n+1}$ will be as high as that of OI, which denotes the best inductive method in the given domain. This implies that aMI's prediction will not approximate an inductive prediction, but rather an average of an inductive and a counterinductive prediction. Of course, given the event sequence is inductively uniform, then already one time point later, at time n+1, the success of the Goodman method $G_{n+1}$ will begin to decline. But what if we add a large number of Goodman methods to Π, so that at every time point in the near future there exists a Goodman method in Π with the same weight as OI, which defeats OI's prediction? Under this condition, aMI cannot be said to provide a clear a posteriori justification of OI.

The Goodman-objection to meta-induction forms the core of Bakshi's indetermination challenge. The problem has already been raised in Schurz (2019, sec. 9.2.5) and independently in Shogenji (2019, 2023). Intuitively, Goodman methods are irrational, as nobody would replace a well-established method by its opposite out of sheer arbitrariness. For this reason, no scientist has ever proposed a Goodman method. Nevertheless, for epistemological purposes we need a justification for why Goodman methods are irrational—or at least, why they can be neglected. Schurz (2019, 269) observes that Goodman methods are algorithmically more complex than qualitative (non-Goodman) methods. For this reason, he argues that qualitative methods should be preferred for inclusion in the pool, once its capacity limit is reached. Bakshi objects against this proposal on the grounds that it would face the charge of circularity because preferring simple methods would be an inductive assumption. We think this objection is unfounded: Simplicity is *not* an inductive criterion because for every simple inductive method there is an equally simple counterinductive method (as explained in the preceding text). Yet we agree with Bakshi that the simplicity criterion alone is insufficient, and a deeper epistemological justification is needed.

There are two possible solutions to the problem of Goodman methods. While the first solution proposal is based on a refined method of meta-induction, the second solution proposal is based in independent epistemic reasons. The meta-inductive solution was proposed in Schurz (2021, sec. 4), building on Cesa-Bianchi and Lugosi (2006, 105). It starts from a given finite set of *qualitative* methods—the set

https://doi.org/10.1017/psa.2026.10247 Published online by Cambridge University Press

$\mathscr{B} = \{M_1, \ldots, M_m\}$ of so-called *base methods*—that are formulated solely in terms of logical combinations of qualitative predicates without reference to particular time points.[4] Goodman methods in the generalized sense are defined as *concatenations* of qualitative methods, with one or *multiple* switch points lying in the future: "Between time 1 and $n_1$ apply method $M_{i1}$; between time $n_1+1$ and $n_2$ apply $M_{i2}$; and so on." Because the number of Goodman methods increases exponentially with the number of base methods and switch points, tracking the success records of all Goodman methods soon becomes unfeasible. A solution of this problem is provided by a particular version of meta-induction: the *fixed-share* meta-induction fsMI. This method tracks only the success records of all base methods in $\mathscr{B}$, yet remains long-run optimal with respect to all Goodman methods over $\mathscr{B}$, provided the number k of switch points grows *slower than linearly* with n. The gain of this result lies in showing that the long-run optimality of meta-induction even holds in regard to the expanded pool of Goodman methods of a given set of base methods. However, this advantage comes at the cost of a significantly worsened short-run performance. Thus, for practical applications within time frames relevant to humans, a better and more fundamental solution is therefore needed.

The second solution is epistemologically deeper and can only be sketched here; an elaboration is left for future work. This solution is based on the observation that the switch points of Goodman methods are entirely *arbitrary*. More generally, a method is arbitrary iff it contains parameters whose values are entirely unrelated to (i) the set of all observed past events, and (ii) any other recognizable cues—be they intuitions of the agents or anything else.[5] However, there are only two possibilities for a prediction method M to achieve significantly greater predictive success than random guessing:

(i) Either there is a qualitative regularity inherent in the event sequence, whose observation makes it possible to transfer information from past observations to future instances, or
(ii) The sequence of events exhibits no such inherent regularity, so that learning from past observations is impossible, but the forecaster is a concrete entity, an "oracle," rather than an abstract algorithm, and this oracle is causally connected with the event to be predicted—for example, through backward causation, by which a clairvoyant "sees the future," or through a common cause, by which a "God-guided truthteller" gets informed about the truth.

In both cases, there exists a qualitative, nonarbitrary method—in case (i), a qualitative learning method, and in case (ii), the simple method of following an oracle—that makes success possible. If, however, a method is based on parameters whose values are *arbitrary*, then this method fails to satisfy both (i) and (ii). In the case of

[4] This definition is relative to a language with a given set of primitive predicates. Goodman's problem of the language-dependence of primitive predicates ("green/blue" versus "grue/bleen") is not addressed here; for a proposed solution in terms of cognitive learning cf. Schurz (2024, sec. 8.3.3).

[5] Already Clendinnen (1966) proposed nonarbitrariness as a solution to Goodman's paradox (for criticism cf. Jackson 1970).

https://doi.org/10.1017/psa.2026.10247 Published online by Cambridge University Press

Goodman methods these arbitrary parameters consist in their future switch points and in the noninductive methods that are arbitrarily selected after the switch points. Meta-induction relies on the inductive projection of success rates from past instantiations of a method into the future. However, such a projection is impossible for Goodman methods because their future instantiations are entirely different methods, chosen arbitrarily and bearing no relation to past success. Given that there are potentially infinitely many values to which an arbitrary parameter could be set, the chances that such a method achieves accidental success are vanishingly small. This is the deeper epistemological reason why Goodman methods should be excluded from the pool.

**Funding Statement.** None to declare.

**Declarations.** None to declare.

## References

Bakshi, Kabir. 2025. "Identification and Indetermination in the Meta-Inductive Approach to Induction." *Philosophy of Science* 92 (5):1427–37. https://doi.org/10.1017/psa.2025.10130.

Cesa-Bianchi, Nicolò, and Gabor Lugosi. 2006. *Prediction, Learning, and Games*. Cambridge: Cambridge University Press.

Clendinnen, F. John. 1966. "Induction and Objectivity." *Philosophy of Science* 33 (3):215–29. https://doi.org/10.1086/288095.

Douven, Igor, and Gerhard Schurz. 2026. "Reinforcement Learning as Meta-induction." *Minds and Machines* 36:23. https://doi.org/10.1007/s11023-026-09764-1.

Jackson, Frank. 1970. "Discussion: A Reply to 'Induction and Objectivity.'" *Philosophy of Science* 37 (3):440–43. https://doi.org/10.1086/288319.

Langley, Pat, Herbert A. Simon, Gary L. Bradshaw, and Jan M. Zytkow. 1987. *Scientific Discovery. Computational Explorations of the Creative Process*. Cambridge, MA: MIT Press.

Mascarenhas, Yvonne P. 2020. "Crystallography Before the Discovery of X-ray Diffraction." *Revista Brasileira de Ensino de Física* 42:e20190336. https://doi.org/10.1590/1806-9126-RBEF-2019-0336.

Norton, John D. 2003. "A Material Theory of Induction." *Philosophy of Science* 70 (4):647–70. https://doi.org/10.1086/378858

Norton, John D. 2021. *The Material Theory of Induction*. Calgary, Alberta: University of Calgary Press.

Pitts, J. Brian 2023. "Does Meta-induction Justify Induction: Or Maybe Something Else?" *General Journal of the Philosophy of Science* 54:393–419. https://doi.org/10.1007/s10838-022-09620-7.

Schurz, Gerhard 2008. "The Meta-Inductivist's Winning Strategy in the Prediction Game: A New Approach to Hume's Problem." *Philosophy of Science* 75 (3):278–305. https://doi.org/10.1086/592550.

Schurz, Gerhard. 2019. *Hume's Problem Solved: The Optimality of Meta-Induction*. Cambridge, MA: MIT Press.

Schurz, Gerhard. 2021. "Meta-Induction over Unboundedly Many Prediction Methods: A Reply to Arnold and Sterkenburg." *Philosophy of Science* 88 (2):320–40. https://doi.org/10.1086/711587.

Schurz, Gerhard. 2023. "In Search for Optimal Methods: New Insights About Meta-Induction." *General Journal of the Philosophy of Science* 54:491–522. https://doi.org/10.1007/s10838-023-09649-2.

Schurz, Gerhard. 2024. *Optimality Justifications*. Oxford: Oxford University Press.

Schurz, Gerhard, and Thorn, Paul. 2020. "The Material Theory of Object-Induction and the Uni-versal Optimality of Meta-Induction: Two Complementary Accounts." *Studies in History and Philosophy of Science* 82:88–93. https://doi.org/10.1016/j.shpsa.2019.11.001.

Shogenji, Tomoji. 2019. "Hume's Problem Solved: The Optimality of Meta-Induction, by Gerhard Schurz" (Book Review). *International Studies in the Philosophy of Science* 32:229–31. https://doi.org/10.1080/02698595.2020.1767892.

https://doi.org/10.1017/psa.2026.10247 Published online by Cambridge University Press

Shogenji, Tomoji. 2023. "A Twofold Tension in Schurz's Meta-Inductive Solution to Hume's Problem of Induction." *Journal of the General Philosophy of Science* 54:79–392. https://doi.org/10.1007/s10838-023-09654-5.

Sterkenburg, Tom. 2019. "Meta-Inductive Justification of Induction. The Pool of Strategies." *Philosophy of Science* 86 (5):981–92. https://doi.org/10.1086/705526.

Usselman, Melvyn C. 1986. "The Reflective Goniometer and Its Impact on Chemical Theory." In *The History and Preservation of Chemical Instrumentation* (Chemists and Chemistry Vol. 8), edited by John T. Stock and Mary V. Orna, 33–40. Dordrecht: Springer. https://doi.org/10.1007/978-94-009-4690-3_4.

**Cite this article:** Schurz, Gerhard. 2026. "Object-Induction and Pool-Determination in the Meta-Inductive Approach. A Reply to Bakshi." *Philosophy of Science*. https://doi.org/10.1017/psa.2026.10247

https://doi.org/10.1017/psa.2026.10247 Published online by Cambridge University Press