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Making Evidence-Based Decision Making Ecologically Rational

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Abstract

This paper examines Evidence-Based Decision Making (EBDM) within the context of ecological rationality. It contrasts classical rationality, which prioritizes comprehensive and logical evidence utilization, with ecological rationality, which emphasizes practical decision making (DM) under real-world constraints. Our examination underscores the importance of adaptive heuristics, professional judgment, and the integration of experience and expertise in forming intuitive responses. It also examines the limitations of framing intuitive versus analytical thinking as a strict dichotomy and advocates for a balanced approach that considers context and practical constraints. Finally, the paper addresses the potential impacts of motivated reasoning and bias in decision-making. Concluding with practical recommendations, it guides practitioners in applying EBDM in an ecologically rational way, stressing the need to balance an emphasis on classical rationality with professional judgment, expertise, and the specificities of each decision context.

Keywords: Evidence-based decision making; dual-process; emotion; motivated reasoning; heuristics; intuition

A good decision is based on knowledge and not on numbers. - Plato

Decision making is relevant for all disciplines, and over the past 30 years, various disciplines have focused on more strongly emphasizing evidence in the decision-making process. Consequently, discipline-specific approaches to evidence-based decision making (EBDM) have emerged (see Table 1 for some definitions), with several resembling the definition of evidence-based medicine (from Sackett et al., 1996). This is especially the case in the definition of evidence-based management, which was conceptually introduced by Rousseau (2006), defined by Barends et al. (2014), and discussed in further detail by Barends and Rousseau (2018): "making decisions through the conscientious, explicit and judicious use of the best available evidence from multiple sources… to increase the likelihood of a favorable outcome" (Barends et al., 2014, p. 4). While the Barends et al. definition is most applicable to organizational practitioners, a central element of EBDM for all disciplines is "attention to evidence quality in decision and action" (Rousseau & Gunia, 2016, p. 667).

Because the use of *quality* evidence is a defining characteristic of EBDM, it is does not strictly adhere to classical rationality, which would focus on "logical consistency, coherence, and an effort to incorporate *all* available pieces of information" (Todd et al., 2000, p. 376, emphasis added). EBDM eschews the use of all evidence in favor of the *best available* evidence, which often requires starting with a larger evidence scope and narrowing the evidence down to the best available (Hulpke & Fronmueller, 2022). Both Morrell and Learmonth (2015) and Berg (2019), coming out of related but different fields (management and clinical psychology), further argued that an emphasis on the best available evidence can lead practitioners toward a form of scientocentrism, the belief that scientific evidence – particularly evidence derived from

randomized controlled trials and meta-analyses – trumps all other forms of evidence and that decisions made without the conscious use of scientific evidence cannot be evidence based. The same concern was raised by Wright et al. (2016) and Hulpke and Fronmueller (2022), who both argued that evidence-based management can lead to such a focus on scientific evidence that it underappreciates the relevance and utility of experts' professional judgment.

Most forms of EBDM, including evidence-based management, acknowledge and even emphasize the use of multiple sources of evidence, so a focus strictly on scientific evidence is not at issue (at least in the way it is generally discussed). However, most also eschew reliance solely on professional judgment, treating it as a low-quality source of evidence (Barends & Rousseau, 2018). In practice, this can lead to a default tendency to collect a sizeable amount of information before deciding, without necessarily considering which evidence or how much evidence would benefit the decision. Such an approach can lead to a decision-making process that ends up resembling a classically rational one.

However, EBDM – especially as it concerns organizational practitioners – should also consider ecological rationality (Gigerenzer & Todd, 1999), which is "concerned with making useful decisions in the real world…" and relies on strategies that are as "simple, economical, and robust" as needed to make "reasonable decisions given the constraints [decision makers] face" (Todd et al., 2000, p. 376-377). Making an ecologically rational decision involves basing decisions on evidence (i.e., cues, information) of sufficient quality to aid in differentiating decision options that are good enough from those that are not (Gigerenzer, 2021; Gigerenzer & Todd, 1999; Luan et al., 2019).

As such, when it comes to practitioner attempts to apply EBDM, in many situations there may exist a tension between the motivation to apply a more classically rational approach (i.e.,

considering more evidence so as to determine the most accurate decision choice) and the motivation to apply an ecologically rational one (i.e., relying only on the evidence needed to identify an accurate enough decision choice). When applications of classically rational approaches disregard ecological concerns, decision strategies may produce questionable cost-benefit trade-offs (e.g., allocating a lot of time, effort, and even money that produce limited benefit).

However, defaulting to professional judgment is not, ipso facto, a recipe for ecological rationality, which is what causes the tension. The purpose of this paper is to discuss an ecologically rational approach to EBDM with an emphasis on organizational practitioners (hence, our focus on evidence-based management). Our perspective is not meant to contradict or rebut the current theoretical conceptualization of EBDM, given that multiple sources of evidence and a more expansive inclusion of evidence are often required. Instead, we aim to integrate ecological rationality into EBDM by emphasizing the potential benefits of skilled intuition (which is based on one's mastery) and the practical advantages of strategically expanding the search for evidence. As a result, our goal is to assist organizational practitioners in establishing their own heuristic rules about when it makes sense to decide based on practitioner judgment, when it makes sense to expand the scope of evidence to be more inclusive, and how to expand it.

We begin by examining the intuitive versus analytical dichotomy of dual-process perspectives, emphasizing its limitations in capturing the complex, context-dependent nature of real-world decision making. By addressing these limitations, we highlight the need for a more adaptive approach – one grounded in ecological rationality. We then discuss the advantages and limitations of starting with a limited evidence scope before expanding outward as needed, as compared to a more classically rational approach that begins with a broader scope before

narrowing it down. We also address the issue of the 'best available evidence' and discuss how it varies based on the decision situation as well as the potential role of published research (academic or otherwise, originating outside the organization) in practical decision situations. We conclude by offering a framework for practitioners to apply EBDM in an ecologically rational way, balancing the trade-offs between evidence use, decision-making constraints, and organizational goals. This framework suggests that the scope of evidence should be guided by the practitioner's level of relevant mastery and the specific utility that different evidence sources offer for informing the ultimate decision.

<h3 style="text-align:center">**Intuitive vs. Analytical Thinking**</h3>

The application of a more classically rational approach to EBDM results in practitioners focusing on a larger amount of evidence to enhance decision accuracy. Although EBDM focuses on the best available evidence rather than all the evidence – thus differentiating it from classical rationality – it still often entails collecting a sizeable amount of evidence before whittling it down to the best available. This process typically requires increased conscious, analytical processing and aligns with the prevalent dual-process perspective in the existing decision literature. Dual-process perspectives (e.g., Evans, 1984; Wason & Evans, 1974), popularized by Kahneman (2011), generally distinguish between a fast, error-prone, and largely unconscious intuitive system (System 1) and a slower, less error-prone, and more conscious, analytical system (System 2). Practitioner judgment is generally positioned as being part of System 1, whereas the consideration of other forms of evidence, such as published research, requires more conscious analytical processing (i.e., System 2; Kahneman & Klein, 2009). The implication for EBDM is that intuition is less evidence-based and more error-prone, necessitating conscious analytical

thinking to override errors (Barends & Rousseau, 2018; Hulpke & Fronmueller, 2022; Wright et al., 2016).

Asserting that EBDM stems only from conscious, analytical thought implies that decisions can be segmented into those that occur solely through intuition and those that occur solely through conscious deliberation. This assertion, though, contradicts how human decision making actually occurs. The distinction between unconscious intuitive (System 1) and conscious analytical (System 2) decision making is not clear-cut (De Neys, 2021; Grayot, 2020; Julmi, 2019; Melnikoff & Bargh, 2018), and neither is the point at which a decision ceases to be strictly intuitive and has become analytical (Julmi, 2019; Melnikoff & Bargh, 2018; Pennycook et al., 2015). Prietula and Simon (1989) argued that "intuition grows out of experiences that once called for analytical steps" (p. 122), and Simon (1993) concluded there is "absolutely no evidence" that "there is analytic thinking and intuitive thinking" (p. 405). The issue, therefore, is not whether a decision relies on intuitive or analytical processing but the degree to which the utilization of each is appropriate to the situation.

To more closely align dual-process systems with the way humans actually make decisions, Pennycook et al. (2015) presented a 3-stage model that introduced the idea of conflict monitoring (see Figure 1 with our additions shaded). In their model, decision situations possess cues (information that may impact decision making), and their salience (the degree to which they are noticed and attended to) elicits one or more intuitive responses (IRs)[1]. If the salient cues are consistent with IR1 (or conflict among cues is undetected[2]), IR1 is the likely response. If a

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[1] There may be cases in which no IRs are generated, which is different from cases in which IRs are generated but we lack confidence in any of them. In such instances, an obvious conflict will be detected because a decision cannot be made if someone legitimately has no intuitive reaction to the cues present in the decision situation. In such cases, it is likely that more effortful analytical processes will be initiated to generate one or more decision options.

[2] Our expanded model differentiates between situations in which a conflict is present from situations in which one is not, which will become more relevant when we discuss motivated reasoning.

conflict is detected between IR1 and one or more cues, the decision maker either proceeds with IR1, justifying it post hoc (i.e., rationalizing), or chooses an alternative response (i.e., decoupling) upon engaging more analytical thinking (resulting in the choice of IR2, IRn, or a choice not intuitively derived).

Intuitive responses are products of the *adaptive toolbox*, which contains "cognitive heuristics, their building blocks and the core capacities (e.g., recognition memory) they exploit" (Gigerenzer & Gaissmaier, 2011, p. 456). The building blocks provide rules for searching (i.e., the information attended to), stopping (i.e., when enough information is obtained), and deciding (i.e., how the choice is made). These rules are applied via heuristics, which are "strateg[ies] that ignore part of the information, with the goal of making decisions more quickly, frugally, and/or accurately than more complex methods" (Gigerenzer & Gaissmaier, 2011, p. 454). In the case of intuitive responses, decision makers recognize information in the current situation that matches patterns from prior decision situations, and this pattern matching results in intuitive responses (i.e., recognition heuristic; Klein, 2015). In other words, it can be a form of constrained EBDM.

Although heuristics are commonly associated with System 1 in the literature and instrumental in intuitive responses, heuristics are applied both consciously and unconsciously (meaning they are not unique to System 1 or System 2). For example, while fast-and-frugal trees are often employed intuitively to apply quick procedural rules (such as how to complete a series of everyday work tasks), a fast-and-frugal tree could also be applied consciously to ensure all appropriate steps are taken before hiring a job candidate. The distinction between heuristic and nonheuristic approaches is arbitrary since all strategies involve some level of information selection (Gigerenzer & Gaissmaier, 2011). For example, a heuristic approach for a manager hiring a new team member might focus on just a few selected factors, such as relevant

experience and cultural fit, but some information is still going to be ignored even if a longer list of factors is considered. The issue is not whether a heuristic is used (as they often are), but whether the amount of information used and how it is used are helpful for distinguishing sufficiently satisfactory from unsatisfactory decision choices. In this context, a satisfactory decision choice refers to one that adequately meets the goals and criteria set for the decision, given the constraints and available resources. An unsatisfactory decision choice, conversely, fails to meet these goals or introduces unacceptable risks or trade-offs.

The quantity of information considered and the sophistication of the decision strategy generally determine how quickly or frugally decisions can be made. Defaulting to IR1 requires less information and a less sophisticated decision strategy than does engaging more evidence before deciding. Generally, less information and simpler decision strategies mean less time and effort, but quicker or more frugal decisions do not always compromise accuracy (Callaway et al., 2022; Gigerenzer & Brighton, 2009; Gigerenzer & Gaissmaier, 2011; Gigerenzer et al., 2022). For example, Luan and Reb (2017) showed that heuristics (specifically fast-and-frugal trees) were as effective for making bonus-related decisions and more effective for termination decisions than were logistic regression models, and, more broadly, Gigerenzer et al. (2022) offered multiple examples of where heuristics outperform more sophisticated decision strategies within organizations. Moreover, investing more time and cognitive resources does not guarantee better decisions, especially if the additional time and cognitive effort is used merely to justify or rationalize an intuitive response (Callaway et al., 2022; Evans, 2019; Melnikoff & Bargh, 2018).

All decision making, therefore, relies on heuristics, as even the most conscious, analytical decisions involve some degree of information selection. Heuristics are employed to generate intuitive responses (i.e., recognition heuristic), engage in procedural tasks (i.e., fast-and-frugal

trees), differentiate good enough from unsatisfactory options (i.e., satisficing), and ultimately decide among various choice options (e.g., take-the-best, tallying). Contrary to a more classically rational approach of starting with an extensive amount of information and reducing it down to the best available evidence, Pennycook et al.'s model suggests that most decision making begins with less information (i.e., only the information that produced the intuitive response) and expands based on situational factors (e.g., conflict among cues/information, a lack of sufficient acceptability of intuitive responses). This expansion might include gathering more evidence, exploring alternative options, or using more advanced strategies before deciding. As such, an ecologically rational approach to EBDM would expand beyond mere reliance on the intuitive response (and defaulting to it), but only to the degree necessary to derive a sufficiently accurate conclusion. This may involve more consciously considering the intuitive response before deciding or incrementally expanding the evidence scope until a sufficiently satisfactory decision can be reached. Conversely, a classically rational approach would involve more expansive evidence at the outset before seeking to make a choice, assuming it will lead to a more accurate conclusion. Although what is ecologically and classically rational may converge, the degree of convergence would be affected by the quality of the intuitive responses, which will be influenced by the decision maker's expertise and experience.

Expertise & Experience

Defaulting to IR1 without any further consideration equates to relying on one's initial judgment, but judgment (including practitioner judgment) and expertise are not synonymous. While judgment and experience has been characterized as "low-quality evidence" (Barends et al., 2014, p. 5) and as "unsystematic" to the point where it should be "parse[d] out" (Sherman, 1998, p. 4), an ecologically rational approach more closely echoes Klein's (2015) argument that

mastery-based professional judgment should not be automatically deemed low quality.

Practitioner judgments, though, do not necessarily reflect corresponding expertise (i.e., tacit

knowledge of a subject/topic) or relevant experience (i.e., the range of situations in which

knowledge has been acquired, applied, or adapted; Kahneman & Klein, 2009); therefore,

effective application of ecologically rational EBDM necessitates awareness of one's relevant and

valid expertise and experience (Klein, 2015).

Although they are related, expertise and experience play distinct roles in EBDM.

Expertise refers to deep subject knowledge, whereas experience encompasses application of this

knowledge across various situations (Kahneman & Klein, 2009). For example, an experienced

marketing analytics expert may not apply those skills as effectively to unfamiliar fields (e.g.,

competitive sports), potentially leading to more errors. There is evidence to suggest that

expertise alone is often what distinguishes performance levels in professional judgment

(Camerer & Johnson, 1991; Rousseau & Gunia, 2016; Thomas & Lawrence, 2018), but greater

experience can also result in the development of configural rules/heuristics (i.e., if-then

exceptions to more general rules) that apply to specific decision situations (even if those

heuristics only concern where and how to collect additional quality evidence; Klein, 2008;

2015). This was recently shown by Germer et al. (2022), who found that therapists with more

experience did not produce better outcomes than those with less experience, but they produced

those same outcomes in fewer sessions.

The quality of intuitive responses produced is often affected by the amount of relevant

expertise and experience the decision maker possesses (henceforth, we refer to the combination

of expertise and experience as mastery for the sake of ease and because it is often difficult to

tease the two apart). Figure 2 highlights where mastery is likely to influence the 3-stage model

from Figure 1. Decision makers with greater mastery, because they are more proficient at identifying relevant evidence, will be more likely to produce valid intuitive responses than those with less mastery. Additionally, in the presence of conflicts, those with greater mastery will be more adept at expanding their information scope, knowing what information is needed, where to look for it, and how to acquire it. The utility of relevant mastery for producing reasonably valid intuitive responses aligns with the recognition-primed decision (RPD) model, an outgrowth of Naturalistic Decision Making (NDM; Klein, 2008). Pennycook et al.'s (2015) original model, though, implies that if a conflict is detected and IR1 is still chosen, then rationalizing occurs, irrespective of whether the conflict is recognized but ignored or further analyzed before concluding IR1 is still a satisfactory choice. To accommodate this nuance (which will be relevant in our discussion of motivated reasoning), we added a third option, called reinforcement (see both Figures 1 and 2), allowing for scenarios where decision makers, after re-evaluation, still find IR1 appropriate. This approach differentiates between overlooking a flawed IR1 and consciously reaffirming it as an appropriate choice, factoring in the decision maker's mastery.

This does not, however, mean that rapidly activated intuitive responses are necessarily more valid, as recognition is based on perceived familiarity rather than actual relevance. A failure to stay up to date with one's expertise can adversely affect decision quality, and after a point, increased experience ceases to add value (Rousseau & Gunia, 2016). Kang and Kim (2022) also showed that experts can sometimes dig their heels in, doubling down on their decisions even if they are incorrect. Still, experts with diverse experience are generally better at identifying accurate cues and managing potential conflicts in decision situations than nonexperts, a skill Kahneman and Klein (2009) refer to as skilled intuition. This skilled intuition is important in determining the applicability of intuitive responses and might require a blend of intuitive and

analytical thinking for effective execution (Klein, 2008). The efficacy of EBDM could be compromised, though, by motivated reasoning.

Bias, Motivated Reasoning, and EBDM

Bias and motivated reasoning are closely interconnected, so a discussion of the latter requires a brief overview of the former. Though bias has come to mean a systematic error in processing, Aronson (2018) pointed out that it originally referred to an "inclination, tendency, or propensity, and hence a predisposition, predilection, or prejudice" (para. 7). It was not until the term was introduced into statistics in the 20th century that it came to signify a "systematic distortion" (para. 8). The concept was extended to decision making through the heuristics and biases (HB) research paradigm, typically discussed in the context of "systematic errors and inferential biases" (Kahneman & Tversky, 1982, p. 124).

Bach and Schenke (2017), though, argued that biases are general tendencies, predictions, or expectations people make based on prior knowledge and experience. Biases are more likely to become problematic when they are based on flawed reasoning or are strong enough to override identification and consideration of conflicting cues in the decision situation. Hence, biases are not necessarily harmful, and, as both Kahneman (2011) and Gigerenzer and Brighton (2009) argued (via two different perspectives), they can be beneficial. Haselton et al. (2009) further argued that some biases are adaptive, serving as unconsciously applied heuristics that expedite decision making (consistent with RPD). If X is recognized, then Y results, where X represents a stimulus or set of stimuli and Y represents one or more intuitive responses. Rather than treating every decision as completely novel, biases provide a probable starting point for conclusions. Situations in which biases are weak or conflict exists among cues may prompt an expanded

evidence search (Felin & Koenderink, 2022). The precise evidence needed, though, will vary based on the situation.

Consider a cybersecurity scenario where network anomalies act as initial cues to be interpreted based on the security analyst's expertise. The analyst's recognition of these anomalies as indicative of a specific threat (e.g., Threat A) or multiple potential threats (e.g., Threat A, B, C) will result in one or more intuitive responses that serve as potential threat assessments. These responses, guided by the analyst's recognition heuristic, create a bias that serves as a starting point for investigation, potentially saving time in incident response. In cases with multiple potential threats, the analyst may expand the evidence search (e.g., conducting deeper log analysis, consulting threat intelligence feeds) before finalizing the threat assessment. Here, the biased responses (i.e., the intuitive responses) aid the investigation process, acting as a "gut feeling" to guide it, especially when the situation is ambiguous or uncertain (Schaltegger et al., 2024).

Biases may introduce errors in some cases, though Haselton et al. (2009) argued most of these errors occur in (1) situations poorly suited to human cognition (e.g., overly complex problems, probability-based reasoning, Gigerenzer, 2018) or (2) novel situations where prior knowledge or experience are inadequate (Kruglanski & Gigerenzer, 2011). Highly complex situations and/or a lack of mastery can lead to erroneous intuitive responses or a failure to detect cue conflicts. These types of situations would, therefore, lend themselves to EBDM that is more aligned with classical rationality.

But there is less evidence that failure to expand the evidence search or engage in analytical decision making explains rationalizing, such as when evidence consistent with IR1 is given more weight than conflicting evidence. Contrary to many dual-process theories, which

view rationalizing as a failure to correct an incorrect IR1 due to insufficient System 2 engagement - as Pennycook et al. (2015) do - there is evidence that error-inducing biases affect both intuitive and analytical processes (Felin & Koenderink, 2022; Melnikoff & Bargh, 2018). Moreover, neither high complexity nor limited mastery explains all cases where conflicts between IR1 and situational cues exist but go undetected (Kang & Kim, 2022). Such situations can result from confirmation bias (Nickerson, 1998), where decision makers, regardless of mastery, either (1) default to IR1 with little conscious thought (when it should be rejected, what Pennycook et al., 2015, originally called rationalizing), or (2) more consciously rationalize the choice of IR1 (when it should be rejected). This confirmation bias shows up as motivated reasoning. For example, a manager who has a strong bias toward a given decision choice may use the expansion of evidence (i.e., a more thorough information search) to seek out evidence that merely supports the biased conclusion.

Motivated reasoning occurs when decision makers prioritize their interests for a desired conclusion or intuitive response ahead of decision accuracy (Epley & Gilovich, 2016; Kunda, 1990), creating a bias toward the desired conclusion or intuitive response, even if some other choice would be more accurate. Kunda (1990) argued such reasoning occurs only when decision makers can construct "a justification of their desired conclusion that would persuade a dispassionate observer" (pp. 482-483). IR1 is more cognitively frugal (requires fewer cognitive resources) than responses derived from more expansive search, stop, or decision rules. If decision makers have a strong preference for or against a given decision choice, this preference may be the impetus for IR1; or it may cause decision makers to fail to detect an existing conflict (i.e., failure to identify cues/evidence misaligned with initial expectations), ignore an existing conflict and default to IR1 with post-hoc justification (i.e., rationalizing), or initiate a relatively

low-resource approach to analytical thinking (an a priori approach to rationalizing; Melnikoff &

Bargh, 2018; Pennycook et al., 2018; Tavers et al., 2016; see also Figure 2, which visually

represents these influences on the 3-stage process).

Implication for EBDM Practice in Organizations

Classical rationality posits that more information improves decision making, and more

information subsequently requires more conscious analysis. It involves collecting a greater

amount of information before whittling it down to a decision choice. Ecological rationality,

however, posits that a decision benefits from only as much information as is needed to identify a

sufficiently satisfactory choice. It involves starting with less information and then expanding as

needed to make a satisficing choice. To apply a more classically rational approach to EBDM by

default comes with trade-offs – more expansive use of evidence will necessarily increase the

time and effort required to decide with no guaranteed increase in meaningful decision accuracy

over a more frugal decision process.

Whether it is ecologically rational to expand the search for evidence beyond the scope of

the cues that initiated the intuitive response(s) will often also depend on the actual mastery of the

decision maker and the potential consequences of a more or less expanded information search

(i.e., the consequences of being satisfied with the intuitive response vs. the consequences of

increasing the time and effort involved in decision making). While there are decision situations

in which mastery produces sufficiently valid intuitive responses to warrant acting upon with no

further evidence, many decision situations will require expanding beyond one's professional

judgment. How much expansion is needed will often be a function of the amount of validity

underlying the intuitive responses and the degree to which significant adverse consequences can

result from a faulty decision.

Expanding Beyond Professional Judgment

Mastery serves as a primary source of intuitive responses, which constitute one's initial professional judgment. Even though existing EBDM perspectives generally view the best available evidence as beyond the scope of professional judgment alone (Barends et al., 2014) - treating it as a lesser form of evidence (Morrell & Learmonth, 2015) - there are many situations where that judgment is grounded in sufficient relevant mastery to warrant acting upon (Klein, 2015). For example, managers often possess sufficient mastery to rely on their intuitive responses to make decisions that are required in the course of their work. Though their mastery could sometimes benefit from additional evidence in those situations, whether the benefit of expanding the search for evidence will provide sufficient return on investment may be questionable.

In many other situations, though, mastery may be limited (Klein, 2015; Rousseau & Gunia, 2016), there may be conflict among cues (Pennycook et al., 2105), or the decision may be consequential enough (Kahneman, 2011) that it warrants a more expansive consideration of evidence. Kahneman (2011), for example, argued that more conscious, analytical decision making is beneficial to "avoid significant mistakes when the stakes are high" (p. 28), which implies that when the stakes are high (i.e., where a poor decision could result in regretful consequences), relying solely on professional judgment may be insufficient. Most EBDM perspectives presented in Table 1, including evidence-based management, advocate for using the "best available evidence" or similar phrasing (e.g., "current best evidence," "best available research"), and sometimes professional judgment is neither the best available evidence nor evidence that should be considered good enough to act upon without considering other evidence sources. However, even when expanding beyond professional judgment, that judgment remains a

vital component of EBDM, as it plays a central role in determining which additional evidence is relevant and how that evidence will contribute to the decision at hand (or what Wright et al., 2016, refer to as situated expertise). Therefore, while it may be insufficient on its own as the basis for the decision, it will still inevitably serve an important function in the decision-making process.

Although it may be tempting for practitioners to assume that incorporating evidence beyond professional judgment necessitates defaulting to a much more classically rational approach, doing so overlooks the relevance of cost-benefit trade-offs (Glimcher, 2022) that are omnipresent in EBDM. The more evidence included in the process, the more time and effort will generally be required before making the decision. While extensive evidence may benefit some decisions, assuming it *will* lead to better outcomes can result in poor cost-benefit trade-offs. This is especially likely when the goal (implicit or explicit) is to maximize accuracy. As Simon (1955) argued, accuracy maximization assumes the decision maker possesses nearly complete "knowledge of the relevant aspects of his environment," a "stable system of preferences," and the computational skills to "calculate… which [action] will permit him to reach the highest attainable point on his preference scale" (p. 99).

Savage (1949) and Simon (1955) both argued that seldom do decision makers possess sufficient knowledge of all potential costs and benefits to determine an optimal choice. While the assumption of omniscience (or at least enough knowledge) may be valid for isolated decisions (what Savage, 1954, referred to as small-world problems), most decisions entail alternatives, consequences, or probabilities that cannot be known (i.e., there is too much uncertainty). Thus, maximization or optimization is practically impossible. Instead, Simon (1956) contended that people "are concerned only with finding a choice mechanism that will lead [them] to pursue a

'satisficing' path, a path that will permit satisfaction at some specified level of all of [their]

needs" (p. 136)[3]. For most decisions, people merely seek a sufficiently satisfactory (satisficing)

option to meet their needs. To identify such an option requires heuristics that guide the expansion

of evidence (i.e., how much evidence, which evidence; see also Figure 3). One way to approach

this would be to default to a classically rational approach (starting at the largest of the concentric

circles in Figure 3). But such an approach may be costly from a resource perspective, and it may

not provide sufficient benefit to justify those costs (and, in some cases, it might actually

adversely affect decision making; Gigerenzer et al., 2022). Instead, the heuristics that guide the

expansion of evidence should focus on the evidence needed to differentiate between satisfactory

and unsatisfactory choices. Which evidence is useful in this regard will often depend on the goals

and criteria used to decide and the specific decision context.

Relevance of Goals, Criteria, and Context

A satisficing decision choice depends on prioritizing specific goal(s). Hence, which

evidence is useful cannot be determined without knowing the intention of the decision maker and

the criteria used to decide. Consider, for example, a situation in which city leaders wish to make

decisions about improving local parks. If beautification is the goal, decision criteria might focus

on aesthetics and visual enhancement. Conversely, for expanding park space, criteria might

include green space adequacy and land acquisition options. Subsequently, the best (or useful)

evidence varies according to the goals and criteria. In cases where leaders aim to achieve

multiple goals, trade-offs are necessary, with each goal's components weighted differently, often

subjectively.

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[3] Gerd Gigerenzer, in many of his works, has pointed out that many modern-day theorists and practitioners mistakenly believe that Simon's (1956) conceptualization of satisficing is synonymous with optimization, but the distinction between the two is quite important. Simon (1956) contended that "the organism…has neither the senses nor the wits to discover an 'optimal' path — even assuming the concept of optimal to be clearly defined…" (p. 136).

Decisions often involve elements that are subjective, decision-dependent, and contingent on various trade-offs (Callaway et al., 2022). This variability makes it nearly impossible to specify any universal claims about when to expand beyond professional judgment and which evidence will be best or useful for deriving a satisficing decision choice. However, practitioners can be cognizant of (1) what it is they are trying to achieve, (2) which criteria they have explicitly or implicitly set for determining a satisficing decision choice, (3) the value their professional judgment does or does not offer, and (4) which additional evidence would be helpful for identifying a satisficing decision choice.

Deciding whether to seek more evidence often depends on the initial confidence placed in IR1, the relative perceived benefit of expanding beyond IR1, and the risks of not doing so. The initial confidence in IR1 represents the degree to which a decision maker believes IR1 is an ecologically rational response (one that is satisficing). The greater the confidence, the less likely that person is to revise the response based on evidence that may conflict with it (Bach & Schenke, 2017). As confidence approaches 100%, the propensity to stick with IR1 increases.

Pennycook et al. (2015) postulated that confidence will be influenced by how many intuitive responses are generated (e.g., IR1 only vs. IR1, 2, and 3) – which could be likened to the generation of a primary hypothesis (IR1) and alternative hypotheses (IR2, IR3) – and the fluency (i.e., speed) with which these different responses come to mind. For example, if only one solution to a problem is quickly thought of, higher confidence in that solution is likely. Conversely, if multiple solutions are rapidly considered, confidence may decrease, prompting further information gathering. Yet, the relationship between mastery and the number of intuitive responses generated is unclear. Having more varied experiences could result in a single response representing a close match between a current situation and a prior one – and higher confidence -

or it could result in multiple intuitive responses – and lower confidence. As such, the relationship between evidence, mastery, confidence, and ecological rationality is murky.

Many studies have found that both experts and nonexperts are prone to overconfidence (e.g., Lambert et al., 2012; McKenzie et al., 2008), with expert judgments often suffering from what is known as the process-performance paradox (Camerer & Johnson, 1991; Thomas & Lawrence, 2018), wherein their judgments tend to be noisy (i.e., possess a large degree of variability; Kahneman et al., 2021). As both Camerer and Johnson (1991) and Kahneman et al. (2021) noted, it may be due to reliance on (1) cues that, while they showed some utility in past situations, do not generalize to a later situation (lacking validity) and/or (2) heuristics (the rules used to make decisions, including configural rules discussed earlier) that are misaligned with a given decision situation. Therefore, both experts and nonexperts can benefit from not placing so much confidence in IR1 that it overrides the willingness to revise their decision based on new or conflicting information. Those with greater mastery, though, should possess the competence to expand their evidence search more cost-effectively than those with less mastery (i.e., knowing where and how to effectively access additional evidence; Germer et al., 2022).

Indirect evidence of this comes from a meta-analysis by Van Iddekinge et al. (2019). Prior experience was not predictive of job performance in general ($\bar{r}$=.06), but it was moderately predictive (1) immediately after hire (i.e., those with experience start performing better sooner; $\bar{r}$=.16) and (2) for jobs with both low ($\bar{r}$=.25) and high ($\bar{r}$=.29) but not moderate ($\bar{r}$=.07) complexity. The results, especially regarding low and high complexity, align with arguments put forth by Gigerenzer and Gaissmaier (2011) and Klein (2015) that heuristics, such as those developed with greater mastery, tend to function better in situations with low and high complexity.

Expanding the amount of evidence considered, though, does not necessarily lead to higher confidence or increased decision accuracy. Reliance on more information may result in the integration of redundant information that only decreases speed and frugality, and in some cases (especially situations with low predictability or high complexity) it may result in reliance on low-quality information that decreases speed, frugality, *and* accuracy (Gigerenzer & Gaissmaier, 2011). The general priority, as Glimcher (2022) argued, is in a focus on "a precise optimization of the trade-off between the costs of increasing [DM] precision" and "the declining benefits that comes as precision increases" (p. 669). Thus, there is a need to be cognizant of what Glimcher (2022) called the "rationally imprecise strategy" of "work[ing] toward optimal efficiency" rather than "optimal rationality" (p. 669). When the costs are worth it, organizational practitioners benefit from expanding the search for and acquisition of evidence in more targeted ways so that the additional evidence effectively informs the decision. Such a strategic expansion is likely to benefit from practitioners' expertise and experience, as those with greater overall mastery should be better suited to know which evidence to collect to improve decision quality and increase confidence in the decision (Klein, 2015).

But confidence itself can be relative. As Gigerenzer et al. (2022) argued, what is an acceptable level of confidence varies based on the willingness to accept false positives (i.e., incorrectly identifying a condition or outcome as present when it is not) and false negatives (i.e., failing to identify a condition or outcome as present when it actually is). Using the example of fast-and-frugal trees in a hiring situation, they demonstrated how an incremental increase in evidence and alterations to the decision criteria (i.e., when to decide to hire/not hire the candidate) also alters the false positive and false negative rates. For example, hiring people just because they possess one beneficial quality will lead to a higher percentage of false positives

(hiring candidates who should have been rejected) than if they possess two beneficial qualities, and each increase in supportive evidence will lead to a relative decrease in false positives (assuming that evidence is of reasonable quality). At some point, though, a degree of acceptable confidence will be reached, and a decision will be made. The challenge, of course, is determining which evidence is best to consider.

Which Evidence is Best

Following Kruglanski and Gigerenzer (2011), evidence is only useful if it validly informs a specific decision. When organizational practitioners seek to expand beyond their professional judgment, the challenge lies in selecting additional evidence to include. Many EBDM definitions from Table 1 emphasize reliance on the best available evidence, but which is best often depends on the decision context. Using our example from earlier, useful evidence for deciding how to beautify existing parks will differ from useful evidence for deciding how to expand available park space.

The classification of evidence sources varies across disciplines, reflecting the different factors at play in discipline-specific decisions (e.g., clinical decisions vs. management decisions). For organizational practitioners, Barends et al. (2014) provided perhaps the broadest set of categories in their discussion of evidence-based management. They identified professional judgment (which could include the judgment of other practitioners as well), scientific evidence (evidence from published research), organizational evidence (evidence from inside the organization), and stakeholder evidence (evidence from those impacted by or impacting the decision) as sources of evidence that are useful for EBDM.

Practitioners must consider which evidence sources are relevant for a particular decision and what benefit they serve. Callaway et al. (2022) argued that some decision making involves

"iteratively considering possible future states" to "reveal the sequence of actions that maximize reward" (p. 1113). In such situations, decision makers benefit from determining which evidence (and which sources) would help to discriminate better from worse choices with the goal of determining which is the best or optimal choice. This type of decision process is likely to result in an expansive amount of evidence (Wright et al., 2016). But many decisions are made with "limited cognitive resources," and considering a large set of possible future states is "usually infeasible" (p. 1113). As such, decision makers will iteratively explore a possible future state to determine whether it provides an acceptable cost-benefit trade-off, and if so, pursue that state with the intent to identify a satisficing choice. Such a decision process is likely to expand to include the evidence needed to determine whether that future state is a satisficing choice and, as such, is likely to be less expansive than when seeking to maximize reward.

The incremental expansion of evidence that would be needed to identify a satisficing decision choice could be likened to a fast-and-frugal decision tree (Figure 4): determining whether mastery is sufficient to be confident enough to make a decision and, if not, deciding whether each source of evidence (i.e., additional practitioner evidence, organizational evidence, scientific evidence, stakeholder evidence) would be beneficial for increasing confidence in whatever decision is made. Although the order of the different sources of evidence could feasibly vary based on the specific decision and context, the end result would be an incremental expansion of specific sources of evidence (Figure 4).

Barends et al. (2014), like most EBDM perspectives, argue that scientific evidence from published research is an integral part of making evidence-based decisions, and Figure 4 incorporates scientific evidence into the incrementally expanding EBDM process (where it fits

exactly will vary). Published research, though, has strengths and limitations that organizational practitioners should keep in mind.

The Strengths & Limitations of Published Research

The use of published research as evidence often corresponds with a classically rational approach to EBDM, which starts with a bigger set of evidence to aid in making a decision choice. This involves collecting relevant studies, reviews, or other research reports that could improve the accuracy of the decision being made. But published research may not have as much obvious utility in an applied setting using a more ecologically rational approach, which starts with less evidence and expands as needed. Although EBDM is generally concerned with the best available evidence, the best available evidence is not always published research. For example, Porzsolt et al. (2003) argued that for health-related decisions, published research is seldom relevant without first understanding existing internal evidence (i.e., which is specific to the decision context). Only once the internal evidence is considered should published research be consulted, and it must be relevant to provide value[4].

This would also apply to organizational decisions, especially given that Barends et al. (2014) specifically emphasize the relevance of organizational evidence (which is why we placed it where we did in Figure 4). Organizational evidence often defines the decision situation, providing contextual information that frames the entire decision-making process. Scientific evidence, while often valuable, is better introduced after an initial understanding of the decision context has been established (Morrell & Learmonth, 2015; Wright et al., 2016). Practitioner and organizational evidence are essential for identifying specific decision-relevant questions that external evidence, whether scientific or otherwise, can help answer (Head, 2015). By narrowing

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[4] While Porzsolt et al. (2003) assumed published research would be consulted, the context of their writing was medicine, which would typically fall into the category of high-consequence decisions.

the focus to such questions, decision makers can increase the likelihood that any scientific evidence collected is both relevant and actionable, avoiding the pitfalls of overly broad or unfocused evidence searches (Head, 2015). This targeted approach enhances the efficiency of EBDM by aligning evidence with the decision context and ensures that scientific evidence effectively complements practitioner and organizational insights.

The search for relevant scientific evidence will often benefit from applying the evidence hierarchy (Guyatt et al., 2011), but Morrell and Learmonth (2015) criticized the use of such a hierarchy on the grounds that it is overly prescriptive about what constitutes quality evidence. Evidence from randomized controlled trials, meta-analyses, and systematic reviews, though, can be extremely helpful in addressing issues like average effects of an intervention (e.g., whether Intervention A or B is going to be most effective) or the average strength of an association (e.g., knowing whether some variable is predictive of some outcome). For example, a change management consultant deciding between two solutions might consult such evidence as a way to complement their professional judgment.

However, many studies categorized at the top of the evidence hierarchy are misleading due to variable quality of the evidence that was used to produce them (Ioannidis et al., 2017; Morrell & Learmonth, 2015). As such, some skepticism is warranted when seeking to apply those studies. Barends and Rousseau (2018) argue for the grading of studies underlying meta-analyses and then adjusting one's confidence in those meta-analyses based on the quality of studies they included. For example, meta-analyses based on a large number of studies of questionable quality are not likely to be as informative as meta-analyses that include a smaller number of higher-quality studies (DeSimone et al., 2020). Therefore, reliance on published

research is not a simple replacement for informed practitioner judgment; it should complement it (Wright et al., 2016).

Additionally, a limitation of evidence that exists at the top of the hierarchy is that it often provides an average effect or association (Lau et al., 1998). These types of studies are constrained by the number of relevant moderators or other context-specific factors that are not tested (e.g., due to space limitations or lack of studies assessing specific contextual factors). Even when studies at the top of the hierarchy are relevant and of reasonable quality, decision makers still need to determine whether relevant situational cues may limit their applicability (Rousseau & Gunia, 2016). Otherwise, they may run the risk of making an ecological fallacy. Some tools may offer the long-term potential to more easily curate locally relevant evidence from more global datasets, such as Shackelford et al.'s (2021) dynamic meta-analysis or more AI-driven tools like Elicit (n.d.) or Consensus (n.d.). Such tools, though, are still relatively early in their development and may require a baseline level of expertise to guide their use and evaluate the quality of evidence they produce.

Finally, while evidence at the top of the hierarchy is often considered higher quality, the evidence hierarchy focuses on traditional scientific evidence. In some decision situations, though, evidence lower in the hierarchy (e.g., industry reports) or from other sources (e.g., organizational and stakeholder evidence) may be equally or more informative (Morrell & Learmonth, 2015). For example, scientific evidence might indicate the effectiveness of certain interventions, but without considering the fit within a specific organization or how it may be perceived by those affected by the intervention, the chosen intervention could fail. Therefore, in certain scenarios, alternative forms of evidence may be just as or more important than scientific

evidence to identify satisficing choices, demonstrating that the 'best' or 'most useful' evidence varies depending on the decision situation[5].

Implications for EBDM Practice in Organizations

Decisions typically result from either (1) being confident enough in a choice to accept its costs and benefits (i.e., concluding a choice is accurate enough) or (2) defaulting to the status quo (i.e., inaction). A more classically rational approach to EBDM differs from a more ecologically rational approach in terms of its starting point (narrower vs. broader), whether accuracy is prioritized over other concerns (like time and effort), and how much evidence is assumed to be needed to derive a decision choice. In revisiting Figure 4, a more classically rational approach would default to collecting evidence from all sources and then whittle it down to only the evidence that is relevant and of sufficient quality.

There are two general scenarios in which the classically rational and the ecologically rational should converge in organizations. The first is when a decision maker lacks relevant mastery; in such situations the decision would likely benefit from expanding the amount of evidence (perhaps extensively) before deciding. The second is when the decision maker has some relevant mastery, but the decision is one that is likely to have significant adverse consequences or potential benefits to justify the added costs (time, effort) required to collect a lot more information.

In certain cases, the costs of expanding beyond professional judgment may not be worth the benefits, making an ecologically rational approach to EBDM more cost-effective than a classically rational one, especially in terms of time and effort. A manager, for example, can make

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[5] An important meta-skill in EBDM involves identifying which evidence is likely to provide value in a given situation. This is what Callaway et al. (2022) recently referred to as a metalevel problem.

many sufficiently accurate decisions by relying on expertise-driven heuristic rules (especially fast-and-frugal trees; Artinger et al., 2014; Luan et al., 2019). If sufficient accuracy can be achieved, then there is little reason to expand the search for evidence.

In other cases, situational constraints may limit how much evidence can be used (Wright et al., 2016). Even if the decision would benefit from increased evidence, it may be infeasible (e.g., due to situational pressures or lack of beneficial evidence). For example, consider a project manager overseeing a critical deadline for a new product launch. The manager may have some evidence to guide decision making, such as previous project timelines and current team capacity, but might need to adapt to unexpected challenges, such as last-minute design changes or supply chain disruptions. Therefore, the connection between evidence expansion and a satisficing decision choice will vary based on the decision context (as different decisions will benefit from different types of evidence), the amount of mastery guiding the production of intuitive responses (and whether those responses are sufficient to ascertain a good enough decision choice), the costs and benefits of expanding beyond one's professional judgment, and situational constraints (e.g., which may constrain how expansive the search for evidence can be).

Summary and Implications for Practice

Throughout the preceding sections, we emphasized that ecologically and classically rational approaches to EBDM do not necessarily converge fully. Most decisions people make begin with the production of intuitive responses based on their recognition of similarities between the present decision situation and past situations, which conflicts with a classically rational approach. Defaulting to a more expansive search for evidence in the presence of these intuitive responses can subsequently lead to poor cost-benefit trade-offs, especially given that doing so does not necessarily improve accuracy.

However, much of our argument is geared toward practitioners who possess relevant mastery so that there is a modicum of validity underlying the intuitive responses that are elicited. In the absence of relevant mastery, organizational practitioners would be advised to start with a more expansive search for evidence, especially when errors carry significant consequences. Ignoring the limits of one's mastery may contribute to overconfidence, leading to lower-quality decision making (e.g., Camerer & Johnson; 1991; Kahneman et al., 2021; Lambert et al., 2012; McKenzie et al., 2008).

In situations where a more expansive search is necessary, practitioners should apply a strategic approach to that expansion. Being cognizant of the goal(s) to be accomplished and the criteria used to identify satisficing options can aid in (1) identifying value-added evidence and (2) deciding whether its potential benefits are worth the costs of obtaining it. More consequential decisions may necessitate obtaining higher-quality evidence or a higher standard of confidence before deciding, even if that means incurring sizable costs (in terms of time, effort, or even money).

In summary, the determination of whether a decision process is an ecologically rational application of EBDM depends on the decision maker's relevant mastery, the decision context (including goal(s) and decision criteria), and the stakes involved in the decision (i.e., low or high). An ecologically rational application of EBDM involves tailoring the decision-making process to align with practical constraints and the specific demands of the decision context, leveraging the decision-maker's relevant mastery and additional quality evidence to achieve satisficing outcomes. There is no recipe for effective EBDM, especially in organizations, and a lot depends on whether decision makers have employed enough evidence and of sufficient quality to make decisions they are confident enough to act on. Thus, whether the process is broad

or narrow, EBDM ultimately comes down to the trade-offs decision makers are willing to make

before making a decision.

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Table 1. *Examples of the Use of "Evidence-Based" in Various Disciplines*

Domain	Definition	Key References
Medicine	"The conscientious, judicious, and explicit use of current best evidence in making decisions about the care of individual patients...integrating individual clinical expertise with the best available external clinical evidence from systematic research."	Sackett, D. L., Rosenberg, W. M., Gray, J. A., Haynes, R. B., & Richardson, W. S. (1996). Evidence based medicine: What it is and what it isn't. *BMJ, 312,* 71-72. https://doi.org/10.1136/bmj.312.7023.71
Policing	"Evidence-based policing is the use of the best available research on the outcomes of police work to implement guidelines and evaluate agencies, units, and officers."	Sherman, L. W. (1998, July). Evidence-based policing. *Ideas in American Policing.* Washington, DC: Police Foundation. https://www.cebma.org/wp-content/uploads/Sherman-Evidence-Based-Policing.pdf
Management	"Evidence-based practice is about making decisions through the conscientious, explicit and judicious use of the best available evidence from multiple sources… to increase the likelihood of a favorable outcome."	Barends, E., Rousseau, D. M., & Briner, R. B. (2014). *Evidence-based management: The basic principles.* Center for Evidence-Based Management. https://www.cebma.org/wp-content/uploads/Evidence-Based-Practice-The-Basic-Principles.pdf
Nursing	"An ongoing process by which evidence, nursing theory and the practitioners' clinical expertise are critically evaluated and considered, in conjunction with patient involvement, to provide delivery of optimum nursing care for the individual."	Scott, K. & McSherry, R. (2009). Evidence based nursing: Clarifying the concepts for nurses in practice. *Journal of Clinical Nursing, 18*(8), 1085-95. https://doi.org/10.1111/j.1365-2702.2008.02588.x
Psychology	"Evidence-based practice is the integration of the best available research with clinical expertise in the context of patient characteristics, culture and preferences."	American Psychological Association (2005, August). Policy statement on evidence-based practice in psychology. https://www.apa.org/practice/guidelines/evidence-based-statement
Policymaking	"Evidence-based policymaking has two goals: to use what we already know from program evaluation to make policy decisions and to build more knowledge to better inform future decisions."	Evidence-Based Policymaking Collaborative (2016, September). *Principles of evidence-based policymaking.* https://www.evidencecollaborative.org/principles-evidence-based-policymaking

Figure 1. Adaptation of Pennycook et al.'s (2015) three-stage dual-process model.
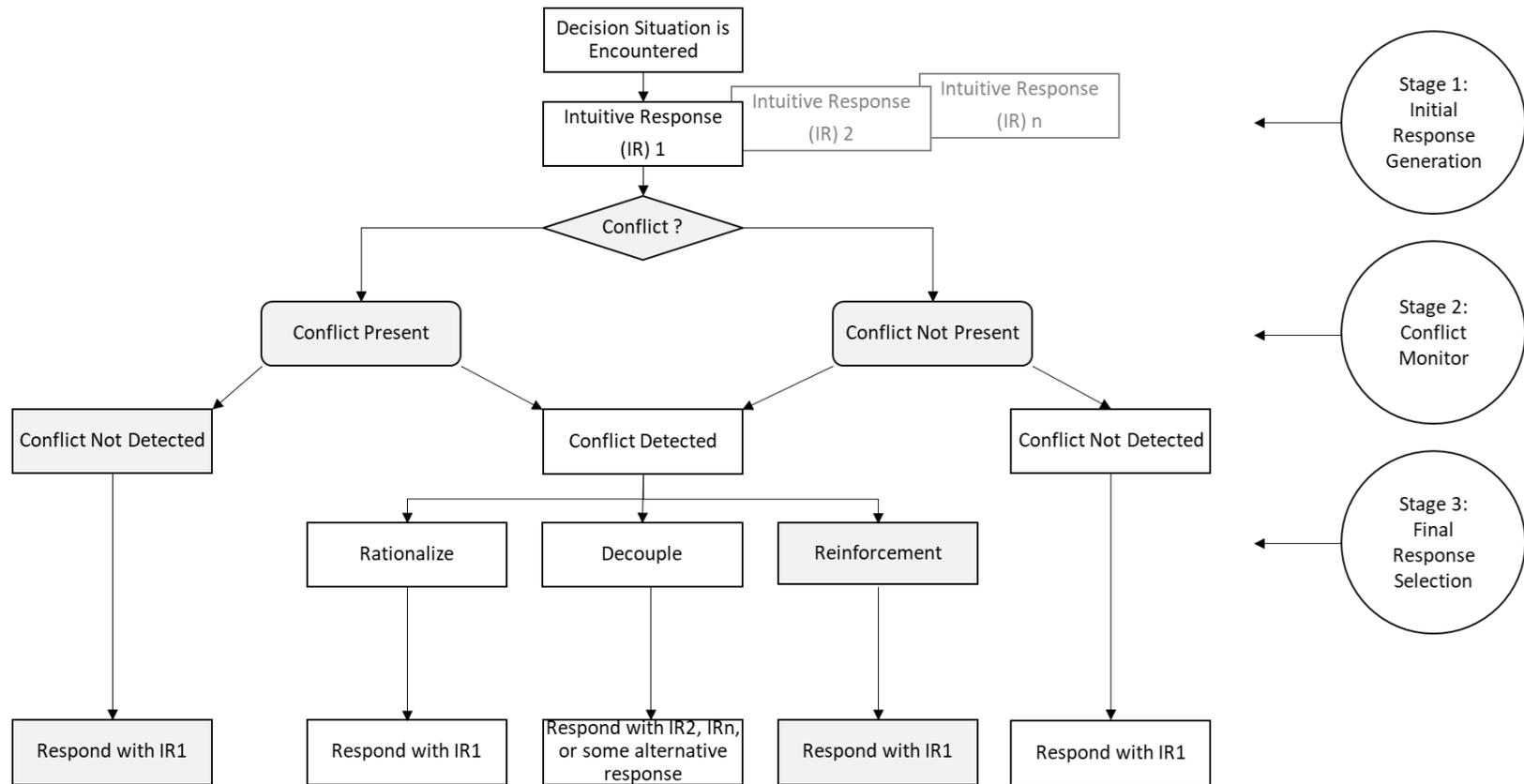
Expansion of Model Presented by Pennycook et al. (2015); shaded boxes represent revisions to the original model.

Figure 2. Expanded Model Showing Influence of Mastery and Motivated Reasoning.
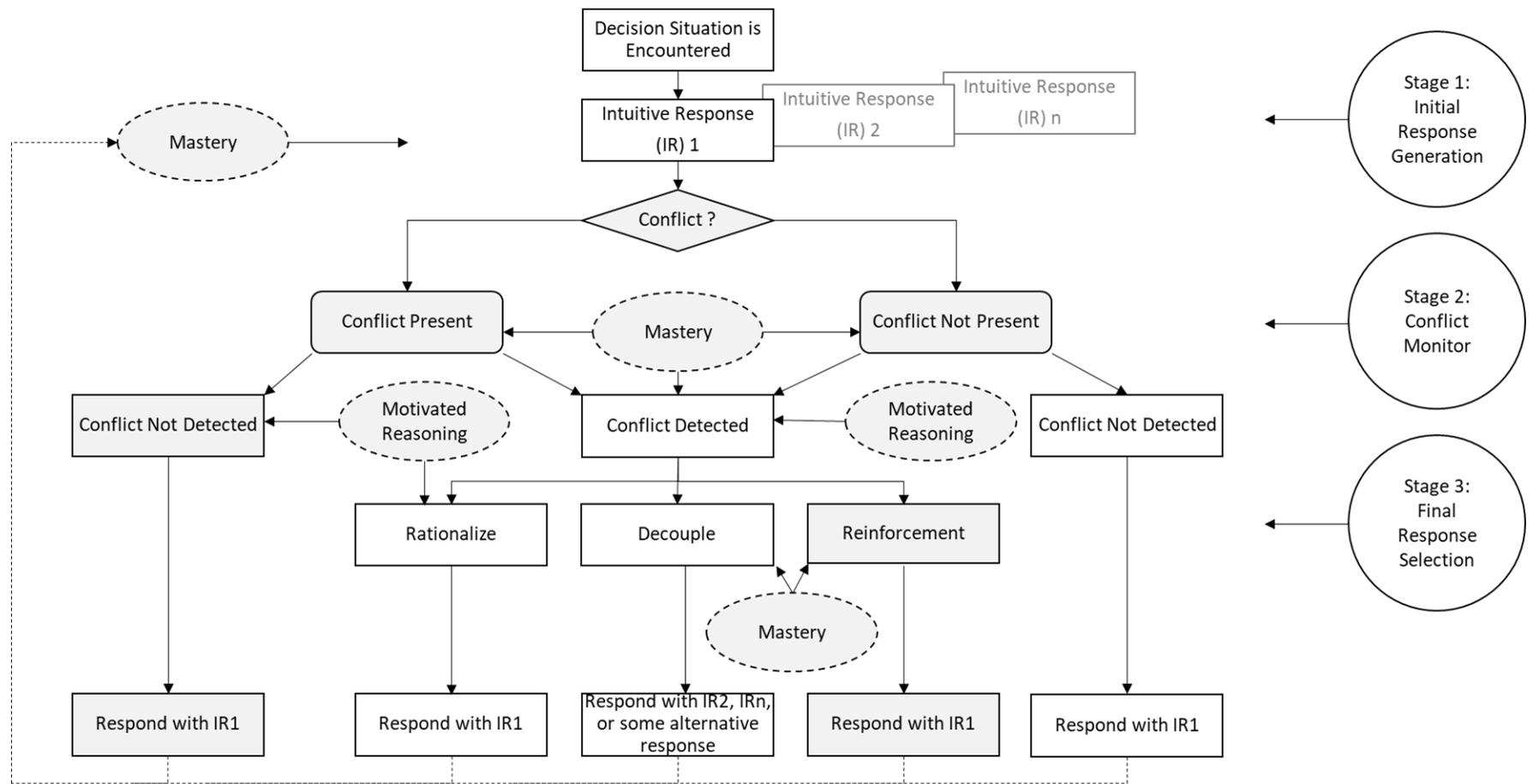
Expansion of Figure 1 showing where mastery and motivated reasoning may affect the decision-making process.

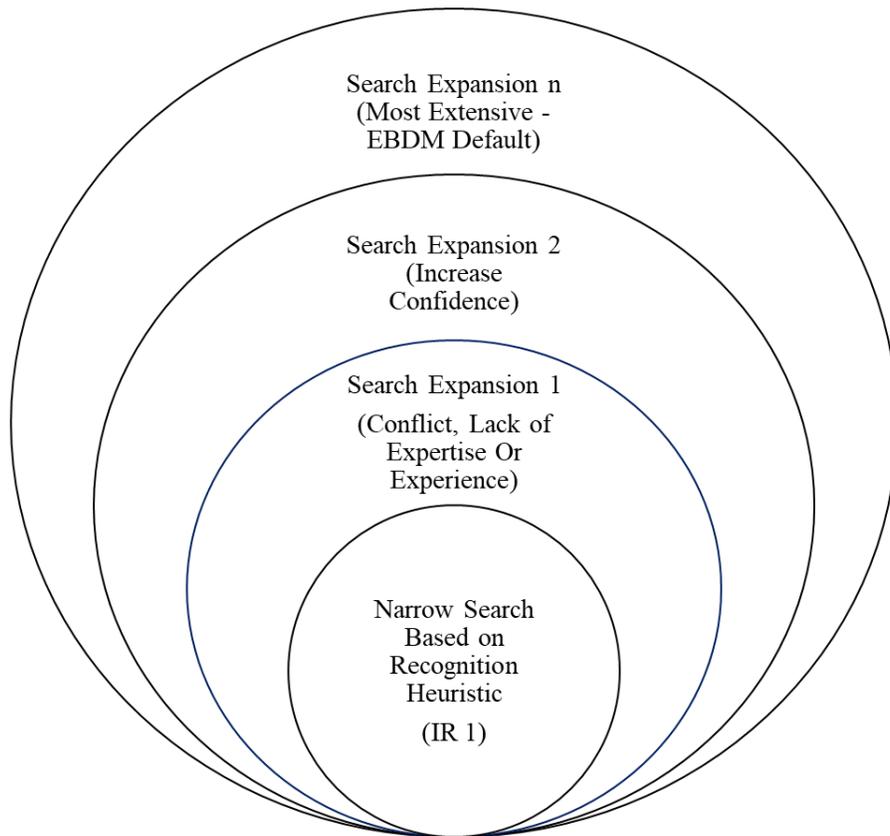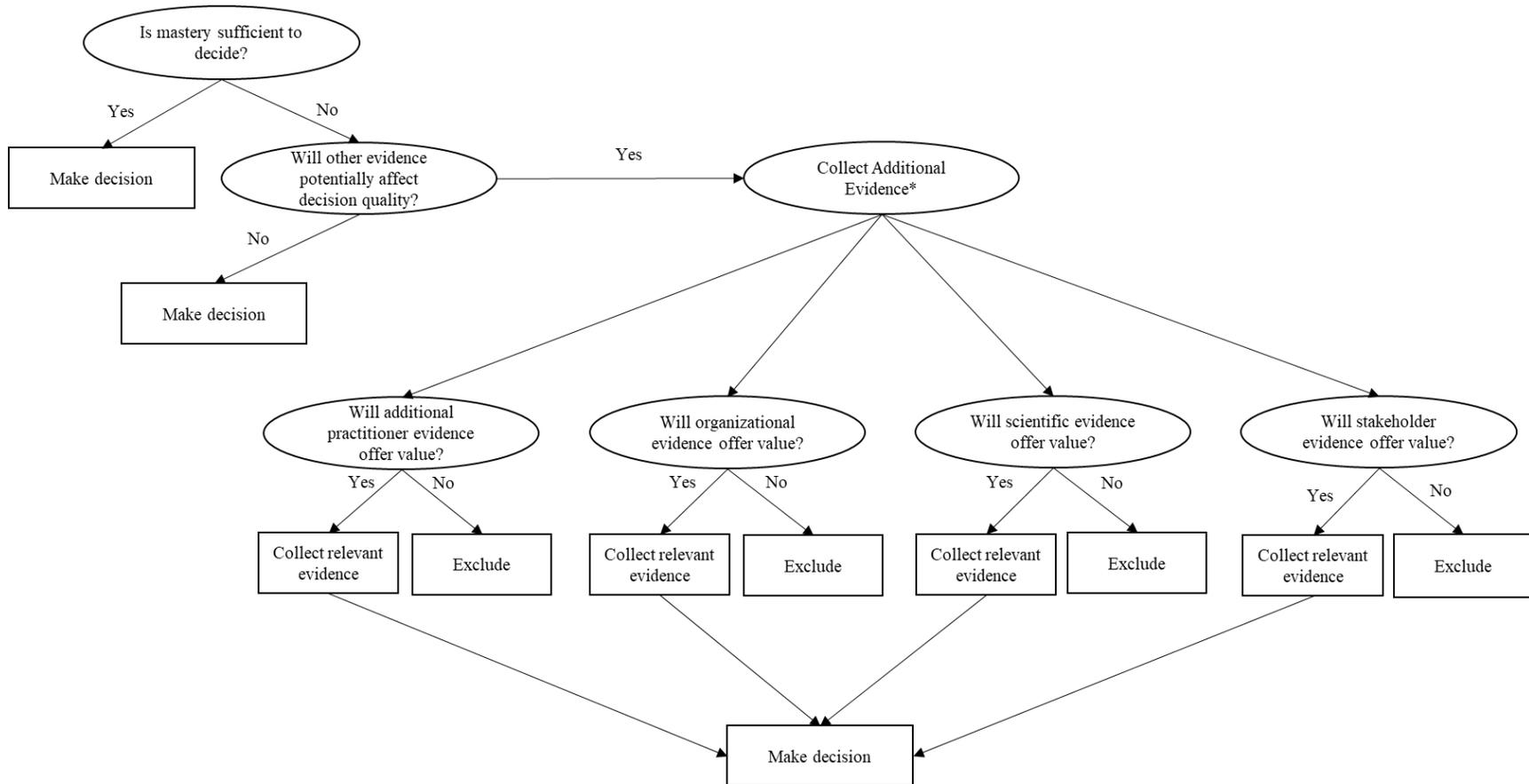**Figure 3. Expansion of Search and Stop Rules.**

Search Expansion n
(Most Extensive -
EBDM Default)

Search Expansion 2
(Increase
Confidence)

Search Expansion 1
(Conflict, Lack of
Expertise Or
Experience)

Narrow Search
Based on
Recognition
Heuristic

(IR 1)

Figure 4. Expanding Evidence Use Based on Potential Value.

* Process will be iterative based on which evidence sources are deemed to add value