



A framework for Understanding heuristic shifts and adaptation

Matteo Cristofaro¹

Received: 16 April 2025 / Accepted: 10 September 2025 / Published online: 23 September 2025
© The Author(s) 2025

Abstract

Heuristic research has developed along three major traditions: heuristics-as-biases, fast-and-frugal tools, and simple rules. While each has contributed substantially, they remain theoretically fragmented, offering limited insight into how heuristics change over time, across contexts, or between levels of analysis. This conceptual article addresses that gap by introducing the *Heuristic Spectrum*—a novel framework that conceptualizes heuristics not as fixed types, but as positionally fluid cognitive logics. Heuristics are mapped across four core dimensions: cognitive effort, intentionality, domain specificity, and goal alignment. Shift from one logic to another is theorized not as a categorical transformation but as a movement along this spectrum, shaped by mechanisms such as feedback and performance monitoring, socialization and knowledge transfer, codification and institutionalization, and contextual pressures and scaling demands. This dynamic, multidimensional framework advances Simon’s vision of bounded rationality as adaptive behavior under constraint. By enabling comparisons, the framework bridges paradigmatic divides and offers practical tools for the design, evaluation, and evolution of heuristics in strategy, AI, and public policy.

Keywords Heuristics · Biases · Ecological rationality · Simple rules · Bounded rationality · Evolution

1 Introduction

Heuristics – commonly (*but not unanimously*) described as “rules of thumb” or cognitive shortcuts – have long been central to studying decision-making under bounded rationality. Originating in early psychology (Köhler 1925), formalized in George

✉ Matteo Cristofaro
matteo.cristofaro@uniroma2.it

¹ University of Rome Tor Vergata, Rome, Italy

Pólya's (1945) problem-solving principles, and conceptually crystallized by Herbert Simon's theories of satisficing, search, and procedural rationality (Newell and Simon 1972; Simon 1955), heuristics have been interpreted as pragmatic strategies for navigating complex environments under constraints of time, information, and computational capacity. Across disciplines – including cognitive psychology, economics, artificial intelligence, neuroscience, and management and organization studies – heuristics have become foundational tools for understanding how agents make decisions in the real world (e.g. Bazerman and Moore 2012; Cristofaro et al. 2025; Gigerenzer et al. 2011; Kahneman, 2003; Kahneman et al. 1982; Katsikopoulos et al. 2022; Marewski et al. 2010a, b; Mousavi and Gigerenzer 2014).

Yet, despite their pervasiveness, the concept of heuristics has grown increasingly fragmented. As recent reviews underscore (Atanasiu et al. 2025; Pavićević et al. 2025; Vuori et al. 2024), different research traditions offer conflicting assumptions, levels of analysis, and epistemic commitments—often with limited theoretical cross-communication. The heuristics-and-biases tradition views heuristics as cognitive shortcuts prone to systematic error and misjudgment (Kahneman 2011; Tversky and Kahneman 1974). By contrast, the fast-and-frugal heuristics tradition positions them as ecologically rational tools—efficient, frugal strategies that adapt to environmental structures (Gigerenzer and Gaissmaier 2011; Gigerenzer and Todd 1999; Luan et al. 2019). A third stream, emerging from behavioral strategy (Cristofaro et al., 2025; Lovallo et al. 2023), understands heuristics as simple rules: deliberately crafted, experientially grounded, and strategically embedded (Bingham and Eisenhardt 2011; Cavarretta 2021; Davis et al. 2009; Eisenhardt and Sull 2001). This conceptual fragmentation is particularly pronounced in organizational research, where heuristics are alternately portrayed as unconscious biases, deliberate routines, or culturally diffused practices. Foundational disagreements persist across paradigms—normative vs. descriptive, individual vs. collective, biological vs. social—and are mirrored in methodological divides, from laboratory experiments to ethnographic fieldwork to computational simulation. Consequently, the same term may refer to a recognition-based judgment shortcut (Pachur et al. 2008), an inference procedure in an AI system (Langley et al. 2014), or a tacit business rule embedded in decision routines (Guercini and Milanese 2020).

Amid this conceptual disarray, recent contributions have made important strides toward theoretical integration. Cavarretta (2021) offers a classification system based on two axes: encoding source (genetic vs. social) and change dynamics (evolutionary vs. agentic), highlighting how heuristics can emerge biologically or socially and change either gradually or intentionally. Atanasiu et al. (2025), meanwhile, develop a process model of heuristic emergence, focusing on how heuristics are abstracted, enacted, and institutionalized through learning and formalization. These works share a crucial insight: what evolves over time is not necessarily the type of heuristic but its functional logic—a recurring configuration of simplification, bounded rationality, and goal-directed reasoning. When framed as evolving logics rather than static artifacts, heuristics become more intelligible across domains and more responsive to contextual pressures.

Despite this progress, many heuristic frameworks continue to treat the phenomenon as categorical or fixed—defined by essential characteristics like frugality,

speed, or error proneness. Few frameworks account for how heuristics are discovered, refined, codified, adapted, or de-formalized in practice. As several scholars note (Abatecola 2014; Guercini 2022; Hodgkinson and Sadler-Smith 2018; Vuori et al. 2024), what is missing is a dynamic theory of heuristic repositioning—one that explains how heuristics shift through feedback loops, organizational learning, institutionalization, or environmental turbulence. While bounded rationality is increasingly understood as a principle of adaptation (Gigerenzer et al. 2022; Marewski et al. 2024), the mechanisms of heuristic movement—between actors, across settings, and over time—remain undertheorized (Katsikopoulos, 2011).

This conceptual article responds by introducing the *Heuristic Spectrum*—a multidimensional, spectrum-based framework for analyzing how heuristic logics shift across four key dimensions: cognitive effort, intentionality, domain specificity, and goal alignment. Rather than classifying heuristics by fixed types, the framework treats them as positionally fluid constructs—logics of reasoning and acting that vary according to how they are enacted, justified, and embedded in context. This reconceptualization yields four key contributions. First, it enables comparative positioning across paradigms without collapsing ontological distinctions. Second, it supports context-sensitive theorizing, highlighting how the same heuristic may function differently across cognitive, organizational, or technological environments. Third, it lays the foundation for a constructive research program on heuristic dynamics, including variation, codification, adaptation, and decay (Atanasiu et al. 2025; Cavarretta 2021; Marewski and Schooler 2011).

In short, this work shifts the focus of heuristic theory from static categorization to dynamic spectrum positioning. It contributes a common analytical space to interpret how heuristics shift in function, application, and institutional form. In doing so, it extends Simon's (1947) legacy into a more pluralistic and temporally grounded science of decision-making—one that sees heuristics not as cognitive artifacts, but as evolving tools for boundedly rational action.

The remainder of the work proceeds as follows. Section 2 revisits the three dominant traditions in heuristic research, reinterpreting them as functional logics rather than fixed types. Section 3 presents the structure and logic of the Heuristic Spectrum, illustrating how heuristics can be mapped and understood through movement across four conceptual dimensions. Section 4 explores the theoretical, practical, and methodological implications of this framework. Section 5 concludes by advocating for a shift from static typologies to spectrum-based positioning, offering a path toward a more integrative, reflexive, and evolution-oriented science of heuristics.

2 Theoretical premises

2.1 Three foundational approaches to heuristics

The study of heuristics spans decades and multiple research traditions, each with distinct assumptions about what heuristics are, how they operate, and under what conditions they succeed or fail. This section synthesizes three major foundational perspectives—heuristics-as-biases, fast-and-frugal heuristics, and simple rules—not

as rigid types of heuristics, but as *distinct functional logics* that emphasize different epistemic goals, environmental assumptions, and mechanisms of action. While historically divergent, these logics are not mutually exclusive. All assume bounded rationality (Simon 1955) as a starting point and share the premise that heuristics simplify complex decision-making tasks through information reduction and effort economization (Shah and Oppenheimer 2008). Yet, they diverge in their focal concerns: normative evaluation, ecological adaptation, and strategic instrumentalization, respectively.

The *heuristics-as-biases* (HAB) tradition introduced several canonical heuristics that remain central to research in judgment and decision-making. These include the representativeness heuristic, where judgments are based on similarity to prototypes rather than statistical base rates (Tversky and Kahneman 1974); the availability heuristic, where the ease with which instances come to mind is used to judge frequency or likelihood (Tversky and Kahneman 1973); and anchoring and adjustment, where individuals make estimates by starting from an initial value (the anchor) and insufficiently adjusting from it (Tversky and Kahneman 1974). These heuristics are widely accepted as foundational constructs in the cognitive psychology of decision-making and are considered canonical precisely because of their enduring influence across decades of empirical research and interdisciplinary applications. Crucially, this tradition often treats bounded rationality as a source of error, emphasizing violations of coherence standards such as logical consistency and probabilistic reasoning (Hammond 1996). For instance, the conjunction fallacy and base-rate neglect are seen as diagnostic of flawed intuitive processes. Methodologically, the focus is on laboratory experiments comparing heuristic outcomes to normative benchmarks, often abstracted from real-world constraints. This mainly error-centric logic has profoundly shaped fields such as law (Jolls et al., 1998), behavioral finance (Barberis and Thaler 2003), and public policy (Thaler and Sunstein 2008), underpinning the widespread use of “nudges” to counteract cognitive limitations (Sunstein 2015).

However, contrary to caricatured interpretations, this tradition does not assume heuristics are inherently flawed. It acknowledges their adaptive value – and so, their effectiveness – in many everyday settings but focuses its analytic lens on conditions under which they fail—a methodological choice, not a philosophical indictment (Kelman 2011; Polonioli 2013). Indeed, Shah and Oppenheimer (2008) argue that heuristics function by reducing the effort required for information search, encoding, or decision selection. What distinguishes this logic is its commitment to identifying the trade-offs between effort reduction and normative accuracy, often through controlled experiments and quantifiable performance outcomes.

Yet, the heuristics-as-biases view has faced sustained critique. Gigerenzer (1991, 1996) and others argue that it imposes narrow normative standards and fails to account for the adaptive value of heuristics in ecologically valid settings. Empirical findings show that many biases disappear when task framings or informational cues are modified (Marewski et al. 2010a, b; Guercini 2012). Moreover, the tradition’s static portrayal of heuristics neglects how decision-makers learn, revise, or institutionalize heuristics over time (Hodgkinson and Sadler-Smith 2018; Vuori et al. 2024). Despite these limitations, this tradition remains foundational for understand-

ing how intuitive heuristic logics manifest in individual cognition under pressure, complexity, or ambiguity (Artinger et al. 2015; Cristofaro et al. 2025).

Emerging as a direct response to the bias-centric paradigm, the *fast-and-frugal heuristics* (FFH) approach recasts bounded rationality in adaptive and ecological terms. Led by Gigerenzer and colleagues (Gigerenzer and Gaissmaier 2011; Gigerenzer and Todd 1999), this tradition emphasizes that simple heuristics can be functionally superior to complex algorithms when they exploit the statistical structure of the environment. Here, rationality is assessed not through internal coherence, but through ecological correspondence—the fit between a heuristic’s structure and the task environment (Hammond 1996; Marewski et al. 2010a, b). Heuristics are deemed “fast” because they operate under severe constraints, and “frugal” because they rely on minimal information. Examples include the recognition heuristic, which infers value based on familiarity (Goldstein and Gigerenzer 2002), and take-the-best, which scans cues in order of validity and stops at the first discriminating one (Gigerenzer and Goldstein 1996). These heuristics exemplify a reduction-of-effort logic: they bypass integrative reasoning, ignore most available cues, and prioritize computational efficiency in real-world conditions (Shah and Oppenheimer 2008).

The ‘adaptive toolbox’ metaphor suggests that individuals and organizations carry a repertoire of heuristics that are deployed selectively based on task demands (Gigerenzer 2008). Empirical studies show that fast-and-frugal logics can outperform complex models in fields such as medicine, finance, and entrepreneurship (Cristofaro and Giannetti 2021; Gigerenzer et al., 2008). For instance, fast-and-frugal trees have been used successfully in medical triage and legal judgments, offering transparent, high-performing alternatives to statistical models (Gigerenzer et al. 2007, 2022).

However, this approach has drawn critique for under-specifying how heuristics are selected or learned. Without a mechanism for updating or adapting the toolbox, the metaphor risks becoming descriptively vague (Luan et al. 2019). Critics also point to overclaims of generalizability, especially in environments with compensatory cue structures or high volatility (Newell et al. 2003; Oppenheimer 2003). Additionally, the tradition largely centers on individual cognition, overlooking how heuristic logics become routinized, shared, or contested within organizations (Atanasiu et al. 2025; Vuori et al. 2024). Nonetheless, it has significantly expanded the conceptual horizon of heuristics by introducing a performance-oriented, environment-sensitive logic of simplification.

The *simple rules* (SR) tradition shifts focus from individual cognition to strategic decision-making in organizations. Pioneered by Eisenhardt and colleagues (Bingham and Eisenhardt 2011; Brown and Eisenhardt 1997; Eisenhardt and Sull 2001), this view defines heuristics as intentionally constructed, codified rules-of-thumb that help firms navigate turbulent environments. Simple rules are often articulated by leaders and embedded in organizational practices, enabling decentralized coordination without sacrificing strategic coherence. These heuristics are grouped into categories such as selection rules (e.g., “enter English-speaking markets”), procedural rules (e.g., “use joint ventures for market entry”), temporal rules, and priority rules (Furr et al. 2020; Guercini and Milanese 2020). Unlike cognitive biases or fast-and-frugal tools, simple rules are typically the result of organizational learning, shaped by context, experience, and strategic feedback (Flyvbjerg 2024). Their logic emphasizes

deliberate simplification—a way to structure choices while preserving flexibility and responsiveness in volatile contexts (Bingham and Eisenhardt 2011).

While evidence shows that simple rules improve decision speed, coordination, and performance (Bingham et al. 2007; Davis et al. 2009), they are not immune to decay. Over time, heuristics can become rigid or decoupled from the context that once made them effective (Vuori et al. 2024). In such cases, codified logics risk turning into strategic routines, stifling innovation (Heimeriks et al. 2012). Furthermore, the mechanisms by which simple rules are abstracted, refined, and scaled remain under-specified (Bingham et al. 2019; Suarez and Montes 2019). In digital and data-driven environments, these logics may be shaped by algorithmic platforms or AI tools, raising new concerns about opacity, over-automation, and the erosion of managerial judgment (Guercini 2022; 2023).

In sum, the simple rules tradition offers a view of heuristics as intentionally crafted, strategically embedded logics that reduce effort, enhance agility, and coordinate distributed action. It extends the study of heuristics beyond the mind, toward the organizational and institutional domains where heuristic logics are codified, contested, and transformed.

2.2 Reconciling divergent heuristic traditions: toward a functional synthesis

Despite their shared interest in decision-making under bounded rationality, the three dominant traditions of heuristic research have evolved largely in isolation. This fragmentation is not only disciplinary or historical but stems from deeper divergences in their epistemological premises, methodological orientations, and ontological assumptions about the nature and function of heuristics. Table 1 (see below) outlines these differences. Yet recent work suggests that an integrative perspective is both feasible and necessary. Two recent contributions—Cavarretta (2021) and Atanasiu et al. (2025)—offer particularly promising entry points for such a reconciliation.

Cavarretta (2021) proposes a classification of heuristics based on two core axes: (1) the source of encoding (biological vs. social) and (2) the mode of change (evolutionary vs. agentic). This typology transcends conventional distinctions by theorizing not what heuristics are, but how they emerge, stabilize, and adapt over time. For instance, heuristics like the recognition heuristic are biologically encoded and evolutionarily stable, whereas others—such as organizational routines—are socially encoded and agentially altered through learning or leadership decisions. Cavarretta's (2021) framework thus shifts attention from static categories to dynamic genealogies of heuristics, enabling scholars to ask not only how heuristics function but how they are acquired, contested, and transformed.

Crucially, this perspective reveals that the three traditions studied in this conceptual work reflect different regions of this broader conceptual space. The heuristics-as-biases tradition focuses primarily on biologically encoded and relatively stable cognitive operations, often assuming minimal agentic modification. In contrast, the fast-and-frugal tradition, while still cognitively grounded, introduces ecological plasticity, allowing heuristics to adapt through experiential tuning or environmental calibration. The simple rules tradition, finally, fits squarely in the quadrant of socially encoded, agentially modifiable heuristics—explicitly designed, shared,

Table 1 Comparison of heuristic traditions

Dimension	Heuristics-as-Biases	Fast-and-Frugal Heuristics	Simple Rules
Epistemological stance	Normative (focus on deviation from logic/probability)	Ecological (fit with environmental structure)	Pragmatic–strategic (goal-directed action)
Normative benchmark	Formal rationality (logical coherence, probabilistic accuracy)	Ecological rationality (adaptive success)	Instrumental rationality (performance, coordination)
Primary focus	Identification of systematic cognitive errors	Use of minimal information for adaptive accuracy	Organizational simplification under complexity
Typical function of heuristics	Effort-saving shortcuts prone to bias	Effort-efficient, domain-specific strategies	Codified decision guidelines supporting action
Encoding source (Cavarretta 2021)	Biologically encoded	Biologically or experientially encoded	Socially encoded
Mode of change (Cavarretta 2021)	Evolutionary (cognitive hardwiring)	Mixed (experiential tuning, ecological adaptation)	Agentic and institutional (learned, abstracted, retained)
Level of analysis	Individual-level cognition	Individual in ecological context	Organizational, collective
Context sensitivity	Low (abstract, decontextualized tasks)	Moderate to high (dependent on task structure)	Very high (routines embedded in social/institutional context)
Heuristic evolution mechanism (Atanasiu et al. 2025)	Negligible; heuristics treated as stable cognitive mechanisms	Partial; adaptation through experiential feedback	Cognitive abstraction, social embedding, organizational retention
View on bounded rationality	Constraint leading to error	Adaptive strategy	Condition for strategic improvisation

and strategically refined within organizations. By situating each tradition along these axes, Cavarretta's (2011) framework clarifies both their internal coherence and their mutual incompleteness: each captures a vital aspect of heuristic function, but none alone accounts for the full range of heuristic phenomena across cognitive, social, and temporal contexts.

Complementing this, Atanasiu et al. (2025) develop a more practice-oriented model by tracing how heuristics are institutionalized in organizational settings. Drawing on longitudinal case studies, they identify three interrelated processes: cognitive abstraction (where heuristics are learned from individual experience), social embedding (where heuristics are shared, taught, and routinized), and organizational retention (where heuristics become part of the formal or informal infrastructure of decision-making). They interpret heuristic evolution as a socio-cognitive process involving actors, institutions, and cultural norms. This is particularly relevant for understanding how fast-and-frugal strategies may be stabilized through managerial codification, or how individual biases may be corrected through collective deliberation and organizational learning.

Importantly, Atanasiu et al. (2025) highlight that heuristics do not exist in isolation from organizational structures—they are politically and socially situated. For instance, the same heuristic may be preserved as a best practice in one firm, modified in another, or abandoned altogether depending on strategic priorities, power dynamics, or regulatory changes. Their work offers a critical bridge between cognitive and organizational scholarship by showing that heuristic evolution is not simply a matter of adaptation to the environment but also involves normative contestation, legitimacy seeking, and institutional alignment.

Together, these two contributions offer the theoretical scaffolding necessary to integrate the fragmented traditions of heuristic research. While the heuristics-as-biases tradition offers insight into the limits of intuitive judgment (without disregarding the effectiveness of heuristics), the fast-and-frugal tradition emphasizes ecological fit and computational parsimony, and the simple rules tradition foregrounds the strategic and institutional life of heuristics. What these perspectives lack, however, is a shared conceptual vocabulary to describe how heuristics functionally evolve across cognitive and social domains. Both Cavarretta (2021) and Atanasiu et al. (2025) implicitly suggest that what evolves is not a discrete heuristic per se, but rather the *functional logic* that underpins its use—an insight we develop further in our proposed framework.

The goal, then, is not to collapse these traditions into a single theory but to develop a spectrum-based framework that enables cross-paradigmatic comparison. By recognizing the multiple sources (biological, experiential, social), modes of change (evolutionary, agentic, institutional), and contexts (individual, ecological, organizational) in which heuristics operate, we move closer to a constructivist view of heuristic evolution. This does not reduce heuristics to errors, ecological fits, or strategic tools alone, but treats them as situated, evolving logics of action that reduce effort, enable action, and embed normative assumptions about what constitutes a “good enough” decision.

The next section introduces this *Heuristic Constructivist Evolution Framework* (HCEF), which builds on the traditions reviewed here while integrating the dynamic, context-sensitive perspectives. Through this synthesis, we aim to chart a path beyond binary distinctions between “bias” and “tool” and to offer a generative conceptual

space for understanding how heuristics adapt, shift, and evolve in contemporary decision environments.

3 The heuristic spectrum

The preceding theoretical premises illustrates that existing heuristic traditions differ not only in methodological emphasis, but in ontological stance. Some view heuristics as non-intentional cognitive shortcuts—automatic, frugal, and often unconscious responses to bounded rationality (Gigerenzer and Todd 1999; Tversky and Kahneman 1974). Others, particularly in strategic and organizational research, emphasize deliberate, experience-based construction—heuristics that are designed, articulated, and scaled to support decision-making under uncertainty (Eisenhardt and Sull 2001).

Rather than treating these views as mutually exclusive, we propose an integrative perspective: heuristics are best understood as evolving functional logics. That is, the same heuristic may function through different logics—automatic or constructed—depending on its level of abstraction, intentionality, domain scope, or alignment with organizational goals. These logics are not fixed types but dynamic states that may shift over time through feedback, learning, institutionalization, or contextual misfit (Guercini 2022; Hodgkinson and Sadler-Smith 2018; Vuori et al. 2024).

This position is informed by pragmatic constructivism (Nørreklit 2017; Nørreklit et al. 2016), which theorizes decision-making as a situated, reflexive process in which decision rules are enacted, revised, or deconstructed in relation to actors' strategic purposes and social context. From this view, heuristic change is not solely a matter of environmental selection or evolutionary drift; it is also shaped by intentional use, interpretive framing, and communicative legitimacy.

Building on this integrative foundation, we now introduce the Heuristic Spectrum—a conceptual structure for understanding how the functional logic of heuristics evolves across contexts, actors, and levels of analysis. Rather than treating heuristics as stable types—such as biases, fast-and-frugal tools, or simple rules—the Heuristic Spectrum conceptualizes them as fluid, context-sensitive positions in a multidimensional space. This space is defined by four orthogonal dimensions: intentionality, cognitive effort, domain specificity, and goal alignment.

The metaphor of a “spectrum” does not imply linear progression or fixed stages. Instead, it captures the idea that heuristics may shift dynamically—intensifying or relaxing in abstraction, becoming more or less goal-driven, or moving from unconscious habit to deliberate routine. These shifts reflect changes in the logic guiding heuristic use, not just its observable form. A rule of thumb may begin as an intuitive judgment, be formalized through organizational experience, and later become rigid or obsolete through overuse or misfit. The Heuristic Spectrum enables us to model and interpret these transformations without forcing them into static typologies.

This approach addresses a longstanding fragmentation in the field. As Marewski et al. (2024) and Vuori et al. (2024) observe, heuristic research is burdened by conceptual ambiguity and theoretical isolation. Scholars debate whether heuristics represent cognitive flaws (Tversky and Kahneman 1974), ecologically rational strategies (Gigerenzer and Gaissmaier 2011), or routinized strategic mechanisms (Bingham and

Eisenhardt 2011). Such debates often assume that heuristics belong to fixed ontological categories, rather than recognizing that they may transition between logics over time and across settings.

The Heuristic Spectrum instead proposes a multi-dimensional conceptual space in which heuristics are not defined by static type but by their current configuration across relevant dimensions. This perspective allows for intentional and non-intentional logics to coexist and evolve, acknowledging that heuristics may emerge from intuition, habit, or selection, but also be reframed, abstracted, and codified through reflective and strategic processes. Rather than collapsing distinct traditions into a single framework, the spectrum provides a shared structure for positioning and comparing them—enabling a more integrated, dynamic, and evolution-aware understanding of heuristic use in organizational and managerial contexts.

3.1 The four core heuristic dimensions

To meaningfully compare heuristics across traditions, domains, and levels of analysis, this work introduces four conceptual dimensions: cognitive effort, intentionality, domain specificity, and goal alignment. These dimensions form the foundation of the Heuristic Spectrum, which does not assume that heuristics transform in kind (e.g., from “bias” to “rule”), but instead maps how their functional logic shifts across contexts and applications. This view aligns with recent calls to move beyond static typologies and to better account for how heuristics are operationalized, embedded, and reinterpreted in different settings (Atanasiu et al. 2025; Cristofaro and Giannetti 2021; Vuori et al. 2024).

The selection of dimensions follows a structured synthesis of key insights from behavioral decision theory, cognitive psychology, and management and organization studies (e.g., Bingham and Eisenhardt 2011; Gigerenzer and Gaissmaier 2011; Marewski et al. 2010a, b). These dimensions meet three criteria. First, they are conceptually salient: each captures a recurring distinction used to differentiate how heuristics function in different streams of research—for example, intuitive vs. deliberative application (Kahneman 2011), implicit vs. codified forms (Bingham and Eisenhardt 2011), or domain-general vs. domain-specific fit (Luan et al. 2019). Second, they are empirically traceable. Heuristics can be observed or inferred from behavioral experiments (e.g., dual-system tasks), field research (e.g., ethnographies), or organizational documentation (e.g., protocols, algorithms) (Abatecola et al. 2018; Gigerenzer et al. 2011; Guercini and Milanese 2020; Hodgkinson and Sadler-Smith 2018). Third, they have explanatory power, helping account for how heuristics are learned, revised, codified, and transferred across actors and levels of analysis (Davis et al. 2009; Marewski et al. 2024; Suárez and Montes 2019).

Alternative dimensions—such as speed, accuracy, or structural form—were considered but excluded. These are better understood as outcomes or correlates of heuristic application rather than defining attributes. For instance, speed is often a by-product of low cognitive effort (Kahneman and Tversky 1979; Kahneman 2011; Marewski et al. 2010a, b), while accuracy is context-contingent and largely mediated by goal alignment and ecological fit (Katsikopoulos et al. 2022; Mousavi and Gigerenzer 2014). Similarly, structural forms (e.g., if-then rules) often emerge after

heuristic maturation and codification, making them secondary to more fundamental usage characteristics (Bingham et al. 2015; Guercini 2023; Suárez and Montes 2019).

The four selected dimensions enable heuristics to be positioned relationally—not by what they are, but by how they are used and interpreted. They offer a spectrum-based approach for understanding heuristic plasticity, rather than a fixed classification system.

Cognitive effort reflects the degree of mental processing, attentional demand, and representational complexity required to apply a heuristic. Shah and Oppenheimer (2008) propose that heuristics function by reducing effort across five domains: examining fewer cues, simplifying retrieval, minimizing weighting and integration, and reducing comparisons. Some heuristics operate automatically and with minimal effort—such as recognition or fluency-based strategies (Goldstein and Gigerenzer 2002; Pachur et al. 2008). Others involve greater deliberation, particularly when shaped through learning or embedded in routines (Atanasiu et al. 2025; Bingham et al. 2019). This dimension aligns with effort–accuracy tradeoffs (Payne et al. 1993), dual-process theories (Evans and Stanovich 2013), and abstraction in organizational learning (Suárez and Montes 2019). It provides a means to compare heuristics based on how they manage cognitive demand across contexts and applications.

Intentionality captures the degree of conscious awareness, deliberate selection, and reflective control associated with heuristic application. At one end, heuristics may be triggered reflexively and unconsciously; at the other, they may be explicitly chosen, monitored, and refined. This dimension integrates distinctions between procedural and declarative knowledge and connects to emerging meta-heuristic perspectives—how actors select, revise, or coordinate heuristics through experience and learning (Atanasiu et al. 2025; Bingham and Eisenhardt 2011; Guercini 2023; Marewski et al. 2024).

Domain specificity indicates the extent to which a heuristic is context-dependent versus broadly generalizable. Some heuristics, like representativeness or anchoring, are presumed to operate across many domains as part of cognitive architecture (Kahneman 2011; Tversky and Kahneman 1974). Others are domain-bound—shaped through ecological fit with specific environments, industries, or problems (Gigerenzer et al. 2011; Luan et al. 2019). This dimension is particularly salient in management contexts where decision rules may be tailored to markets, technologies, or firm cultures (Bingham et al. 2015; Guercini and Milanese 2020). It also parallels distinctions between domain-general and domain-specific strategies in artificial intelligence (Langley et al. 2014; Newell and Simon 1972).

Goal alignment refers to the degree to which heuristic use is calibrated to support particular decision objectives. Some heuristics serve as satisficing strategies, adopted under constraint to manage complexity, without deliberate alignment to goals (Kahneman 2011; Polonioli 2013; Simon 1955). Others are designed, adapted, and monitored explicitly for strategic or performance-related outcomes (Bingham and Eisenhardt 2011; Gigerenzer and Gaissmaier 2011). This dimension reflects not only the user’s intention but also organizational learning mechanisms that formalize and revise heuristics for ongoing goal-fit (Reb and Jha 2024).

Taken together, these four dimensions form a conceptual space—not of heuristic types, but of heuristic positions. Each heuristic may occupy different locations on

the spectrum depending on how it is used, interpreted, and embedded. A recognition-based heuristic, for example, may shift from automatic to intentional use as experience grows; a codified decision rule may degrade into a reflexive shortcut under conditions of institutional forgetting. The Spectrum enables researchers to capture these shifts without assuming that the heuristic itself “evolves” in kind. It is not the heuristic that changes, but its mode of use, intentionality, and contextual fit.

3.2 Positioning the three heuristic traditions along the spectrum

The Heuristic Spectrum framework enables a structured comparison of the three major heuristic traditions—heuristics-as-biases, fast-and-frugal heuristics, and simple rules—by positioning them according to their typical use characteristics along the four heuristic dimensions introduced above: cognitive effort, intentionality, domain specificity, and goal alignment. Importantly, this positioning is not ontological: it does not claim that these traditions represent fixed or sequential stages. Rather, it offers a way to compare their prevailing assumptions and usage logics without conflating structure with performance or assuming universal transitions between forms.

As illustrated in Fig. 1, each tradition spans a particular region of the heuristic spectrum based on how its heuristics are generally studied, applied, and interpreted. The aim is not to prescribe boundaries but to facilitate cross-paradigmatic dialogue on how heuristics operate in practice.

Heuristics-as-Biases. In the cognitive effort dimension, heuristics in this tradition—such as representativeness, availability, or anchoring—are typically conceptualized as low-effort, intuitive mental shortcuts (Kahneman 2011; Tversky and Kahneman 1974). They operate automatically and often unconsciously, drawing on fast, associative processes that conserve cognitive resources under bounded rational-

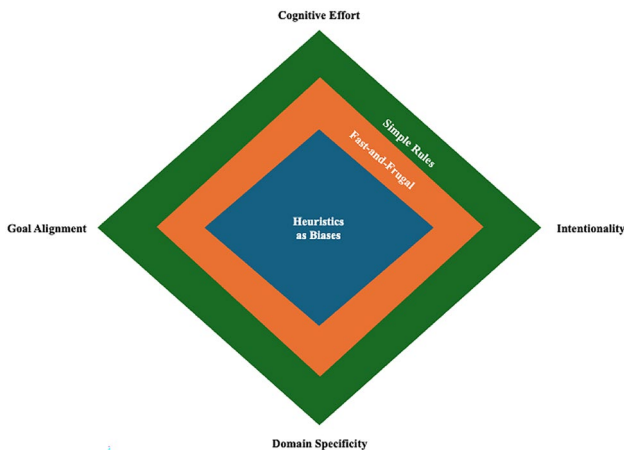


Fig. 1 Dimensional positioning of heuristic traditions on the Heuristic Spectrum *Note:* Shaded areas indicate the observed or theorized range of heuristic logics within each tradition along four core dimensions. These are not fixed types of heuristics, but rather reflect the variability in how heuristic reasoning is structured, justified, and embedded across contexts. The figure represents logics of use and interpretation

ity. In terms of intentionality, these heuristics are often non-deliberative: they arise without explicit reflection or conscious choice, triggered by environmental stimuli and embedded in cognitive architecture (Kahneman et al. 1982). Regarding domain specificity, they are often treated as domain-general tendencies—emergent from universal psychological processes, not tailored to specific environments. Their applicability across domains is assumed, although this generality is increasingly challenged by recent contextualist accounts (Kelman 2011; Polonioli 2013). Finally, on goal alignment, heuristics-as-biases are usually depicted as misaligned with normative decision standards. They can yield functional outcomes in some contexts, but they are primarily studied for their potential to produce systematic errors, such as base-rate neglect or the conjunction fallacy (Tversky and Kahneman 1974).

Fast-and-Frugal Heuristics. The fast-and-frugal program (Gigerenzer and Gaissmaier 2011; Gigerenzer and Goldstein 1996) defines heuristics as simple, cue-based rules that exploit environmental structure to generate efficient decisions under uncertainty. Importantly, this tradition is not restricted to one point on the spectrum—it spans low to moderate cognitive effort, depending on the complexity of the heuristic and the user’s experience. For instance, the recognition heuristic is often applied effortlessly, while more complex strategies (e.g., fast-and-frugal trees) may require attentional resources for encoding, cue ordering, or adaptation to context (Marewski et al. 2010a, b). In terms of intentionality, fast-and-frugal heuristics vary widely. Some, like the hiatus heuristic in marketing (Wübben and Wangenheim, 2008), are explicitly selected and refined through repeated use, while others are used implicitly and only partially accessible to introspection. Hence, their “middle-ground” positioning on this axis is not a simplification but reflects the tradition’s theoretical diversity: intentionality is a variable property, not a categorical feature. Regarding domain specificity, the FFH tradition explicitly embraces context-sensitivity through the principle of ecological rationality: the performance of a heuristic depends on how well it fits the structure of the decision environment (Gigerenzer et al. 2011; Luan et al. 2019). Some heuristics, like take-the-best, are more generalizable, while others—such as the delta rule or tallying rules—are tailored to specific domains (Katsikopoulos et al. 2022). Thus, FFHs cannot be centrally located on this axis by averaging, but must be understood as range-bound: the tradition encompasses both universal and context-specific forms. On goal alignment, FFHs are not inherently optimized, but they are designed or selected to perform well in specific environments, often under time and information constraints. Their success is conditional on fit, not on abstract optimality (Mousavi and Gigerenzer 2014). As such, FFHs are not always adaptive: when misapplied outside their ecological niche, even simple rules like take-the-best can produce biased outcomes (Gigerenzer et al. 2022). This underscores a key point: no heuristic is inherently biased or functional—it depends on match, not type.

Simple Rules. Simple rules, as theorized in the behavioral strategy literature (Eisenhardt and Sull 2001; Bingham and Eisenhardt 2011), are heuristics that emerge through deliberate abstraction of experience, codified into decision routines, protocols, or organizational practices. They typically entail higher cognitive effort during their design phase, as firms experiment, reflect, and formalize decision logics (Atanasiu et al. 2025; Bingham et al. 2015). Once established, their application may become streamlined, but their initial abstraction requires significant cognitive and

organizational resources. On intentionality, simple rules are highly deliberate: they are often consciously crafted, documented, and taught. They reflect explicit choices about what information to use and how to act in recurring decision scenarios. They may even become institutionalized, embedded in algorithms or templates (Guercini, 2023). Regarding domain specificity, simple rules are generally context-bound: they reflect situated learning within specific industries, markets, or organizational challenges (Vuori et al. 2024; Suárez and Montes, (Suarez, and Montes, 2019). Their power lies in their fit to local constraints—not in universal application. In terms of goal alignment, simple rules are among the most explicitly performance-oriented heuristics. They are selected, refined, and institutionalized to support strategic priorities—such as scaling, innovation, or consistency—and are regularly monitored for alignment with evolving goals (Reb and Jha 2024). Unlike biases or some FFHs, their justification is not just about speed or frugality but about organizational effectiveness.

In summary, the Heuristic Spectrum does not propose a linear transition from one tradition to another (e.g., from bias to rule). Rather, it offers a relational, dynamic map of how heuristics are typically positioned in use—acknowledging that the same heuristic might occupy different coordinates depending on context, user expertise, or organizational function. Fast-and-frugal heuristics do not serve as a necessary “middle stage” between bias and rules; instead, they exemplify ecologically tuned strategies whose functionality depends on fit, not form. Likewise, biased outcomes may arise from misapplication of any heuristic, including simple rules. This framework helps clarify these tensions while providing a shared vocabulary for comparing traditions without collapsing their distinct assumptions.

3.3 Heuristics in motion: plasticity across the spectrum

The Heuristic Spectrum does not propose that heuristics change in kind—for example, from a bias into a rule—but rather that the functional logic through which heuristics are used, interpreted, and institutionalized may shift over time. This repositioning occurs along four orthogonal dimensions—cognitive effort, intentionality, domain specificity, and goal alignment—as heuristics are embedded in different settings, transferred across levels of analysis, or reoriented by organizational feedback. In this sense, the framework does not describe the structural transformation of a heuristic per se but traces changes in how a given judgment strategy is operationalized, represented, and justified in practice. It builds on recent calls to examine how heuristics fluctuate in meaning, usage, and institutional salience (Atanasiu et al. 2025; Vuori et al. 2024), rather than assuming fixed categorical boundaries.

The use of examples in this section should thus not be read as documenting literal morphing from one type of heuristic to another (as the term “heuristics-as-biases” or “simple rules” might suggest), but as illustrating how a decision logic—initially used in a low-effort, unreflective manner—can become increasingly structured, goal-oriented, and intentional through organizational processes. These logics often share a common cognitive core (e.g., recognition, availability, threshold filtering) but differ in how they are triggered, refined, or institutionalized.

Four mechanisms underpin these positional shifts:

Feedback and performance monitoring. Through performance monitoring, users gain insight into whether a heuristic aligns with actual decision goals or task environments. Feedback loops support what Mousavi and Gigerenzer (2014) describe as “adaptive toolbox” refinement, where heuristics are modified, retained, or discarded based on outcome congruence. In boundedly rational settings, such learning parallels Simon’s (1955) notion of satisficing and supports increasing goal alignment over time (Abatecola et al. 2018; Gigerenzer et al. 2022).

Socialization and knowledge transfer. As heuristics circulate among individuals or units, their usage often becomes more reflective and explicit. Reb and Jha (2024) describe this as a process of behavioral scaffolding: heuristics move from tacit knowledge to semi-formal know-how, embedded in shared language, tools, or training. This shift increases intentionality and often enables contextual adaptation and refinement (Hodgkinson and Sadler-Smith 2018; Vuori et al. 2024).

Codification and institutionalization. With repeated use and validation, heuristics may become codified into protocols, playbooks, or algorithms. Bingham and Eisenhardt (2011) show how entrepreneurial firms transform repeated learning into “simple rules,” embedding decision logics into formal systems. Codification raises cognitive effort by requiring retrieval, validation, and cross-functional alignment (Suarez, and Montes, 2019), and often enhances both intentionality and goal alignment (Atanasiu et al. 2025).

Contextual pressures and scaling demands. Dynamic or volatile environments push decision-makers to reorient heuristic logic to new affordances. For instance, a general-purpose heuristic may be adapted to meet domain-specific constraints or institutional requirements (Abatecola 2014; Guercini and Milanese 2020). Such adaptation often shifts the heuristic’s domain specificity and explanatory fit within its context (Heimeriks et al. 2012).

These mechanisms tend to exert primary (but not exclusive) influence on specific spectrum dimensions. Importantly, they illustrate how a heuristic logic may shift position—not necessarily evolve ontologically—without implying that it crosses categorical boundaries in the way traditions have historically conceptualized them (e.g., Bingham and Eisenhardt 2011; Gigerenzer and Gaissmaier 2011). Figure 2 visualizes these shifts not as type transitions, but as changes in how a logic is instantiated.

The virtuous path: from biased logic to codified application. Consider a product manager in a technology firm who initially relies on the availability heuristic to judge which features should be prioritized for a software release. In early iterations, this decision logic is shaped by cognitive salience: features mentioned in recent meetings or reflected in recent customer complaints are overweighted due to their ease of recall. This reliance on salience operates with low cognitive effort, minimal intentionality, and broad domain generality—consistent with what the heuristics-and-biases tradition would label a biased logic (Tversky and Kahneman 1974).

However, over time, as the manager gains experience and receives performance feedback, this same logic becomes increasingly refined. She begins to notice, through informal reflection and team discussions, that certain types of feedback (e.g., from enterprise clients) are more predictive of product success than others. The availability-based heuristic is not replaced but repositioned: she now filters feedback not just by salience, but by source and recency—e.g., “prioritize requests repeated by top-tier



Fig. 2 Heuristics in Motion. Plasticity Across the Spectrum *Note:* Unlike Figure 1, Figure 2 does not display shaded areas due to graphical constraints. However, the conceptual logic remains the same: the figure represents the shifting position of heuristic logics along the four core dimensions, not discrete types of heuristics. Movement across the spectrum reflects changes in how heuristics are used, interpreted, and embedded over time

clients in the last two months.” This rule of thumb still draws on availability but becomes more context-sensitive, intentional, and goal-aligned, reflecting a fast-and-frugal logic that matches decision structure to environmental regularities (Gigerenzer and Gaissmaier 2011; Marewski et al. 2010a, b).

As the company scales and formal decision support is required, the manager collaborates with colleagues to articulate and institutionalize this heuristic. The refined logic is embedded in a CRM dashboard and codified into a rule: “In quarterly prioritization meetings, feature requests are ranked by frequency, source, and recency.” This rule—while grounded in the same underlying intuition—now carries high intentionality, higher cognitive effort (in development and integration), and clear strategic alignment. It illustrates how a decision logic, initially experienced as a biased shortcut, can be refined and codified into a formal rule through recursive use, reflection, and contextualization. Importantly, this is not a transformation of one heuristic into another, but a repositioning of the same core logic across different organizational and cognitive conditions (Abatecola et al. 2018; Bingham and Eisenhardt 2011; (Suarez, and Montes, 2019)).

The vicious path: from codified rule to degraded shortcut. Now consider a multinational consultancy that has developed a simple rule for client screening: “Only

pursue clients if projected project margin exceeds 35% and executive sponsorship is confirmed.” This rule is the product of organizational learning, experience, and deliberation—it is high in cognitive effort, intentionality, domain specificity, and goal alignment, consistent with the simple-rules tradition (Bingham and Eisenhardt 2011; Vuori et al. 2024).

As the firm expands rapidly into new markets, however, strict adherence to this rule becomes impractical. Teams in fast-growing regions begin to loosen the criteria, informally adapting it into a more flexible logic: “Pursue the client if the sponsor is well-known and the deal offers reputational value.” This shift is not a change in rule structure but a re-embedding of the same logic in a new, less formalized and more intuitive form. The heuristic becomes context-sensitive, moderately intentional, and adaptable—a fast-and-frugal logic that privileges speed and selective cues over formal analysis (Gigerenzer et al. 2022).

Eventually, as the organization experiences leadership turnover and growth fatigue, even this adapted logic erodes. New staff inherit a simplified version: “Go after flashy clients.” The original logic—balancing margin and sponsorship—fades into a vague representativeness heuristic: clients are selected based on superficial resemblance to past successes (Tversky and Kahneman 1974). This version operates with low intentionality, minimal effort, and poor goal alignment. It reflects a drift toward biased logic, not because the heuristic itself has mutated, but because its embedded use has been stripped of context, reflection, and feedback (Hodgkinson and Sadler-Smith 2018; Abatecola 2014).

These examples demonstrate that what evolves is not the intrinsic structure of a heuristic, but its *logic of application*—how it is selected, justified, and embedded in practice. The Heuristic Spectrum does not claim that biases become rules or that fast-and-frugal heuristics evolve linearly. Rather, it shows how the same core logic may be used differently as actors engage in sensemaking, formalization, or adaptation. This dynamic repositioning—across dimensions of effort, intentionality, specificity, and alignment—helps explain both the institutionalization and degradation of decision logics in organizational life.

4 Implications

This study reconceptualizes heuristics not as fixed entities, but as dynamic logics of decision-making that shift positionally across four key dimensions: cognitive effort, intentionality, domain specificity, and goal alignment. In doing so, it introduces the Heuristic Spectrum—a conceptual framework that enables scholars to analyze how heuristic *logics* are embedded, enacted, and transformed in practice, rather than how individual heuristics mutate across taxonomic types. Rather than proposing a laminar or linear progression from biases to rules, the framework situates heuristics as plural, evolving rationalities whose function and structure emerge from recursive interaction between cognition, context, and institutional embedding. This reorientation carries three main theoretical implications.

First, the Heuristic Spectrum enables a processual and position-based approach to heuristic research, grounded in situated use rather than essentialist categorization.

Building on Atanasiu et al. (2025), who distinguish heuristics based on their origin (e.g., learned vs. hardwired), level of formalization, and cognitive traceability, this framework reorients attention from “types of heuristics” to the functional logics through which they operate in context. It emphasizes that heuristic performance is inseparable from how heuristics are justified, transmitted, and aligned to goals, not from their structural essence. This view dissolves the false dichotomy between bias and tool. It foregrounds how the *same functional logic* may shift its spectrum position over time depending on feedback, codification, socialization, or decontextualization. Rather than arguing that a single heuristic “evolves,” we show how decision logics—e.g., availability-based reasoning, recognition-based prioritization—can be differently configured and embedded. This complements prior static taxonomies and introduces a vocabulary for dynamic repositioning.

Second, the framework advances a synthetic yet pluralistic theory of heuristic rationality by integrating evolutionary and constructivist foundations. While Cavarretta (2021) offers a classification of heuristics based on whether they are biologically encoded or socially constructed, and whether they operate via agentic selection or emergent evolution, the Heuristic Spectrum does not choose one ontological basis over the other. Instead, it bridges these perspectives by theorizing how agentic, situated, and sometimes institutionalized logics operate within broader ecological and social systems. It treats decision logics as neither wholly endogenous nor exogenous but co-shaped by actors, routines, and constraints. This allows the model to account for both top-down formalization (as in simple rules) and bottom-up emergence (as in intuitive biases), while retaining the ability to map hybrid and transitional forms. In contrast to frameworks that assume evolutionary path-dependence or cognitive modularity, the Heuristic Spectrum underscores flexibility, cross-domain transfer, and recontextualization—thus offering a nuanced complement to evolutionary theories and bounded rationality.

Third, the Spectrum invites a rethinking of heuristic adaptation as a socio-cognitive process involving positional drift, not categorical replacement. This addresses a persistent issue in the literature: the tendency to conflate heuristic *performance* with heuristic *identity*. As highlighted by Mortensen and Haas (2018) in related domains, what appears to be the “same” cognitive rule can serve different strategic, epistemic, or organizational purposes depending on how it is embedded and justified. The notion of “heuristics in motion” proposed here does not claim that heuristics migrate across traditions (e.g., from a bias into a rule), but rather that their *logic of application* can be refined, diffused, codified, or decontextualized—leading to shifts in cognitive effort, intentionality, domain sensitivity, and goal alignment. This perspective aligns with organizational scholarship on rule adaptation (Bingham and Haleblan, 2012; Suárez and Montes, 2019) and offers a fresh theoretical language to study how routines and rules evolve through accumulation and re-positioning in use.

In sum, the Heuristic Spectrum reframes the study of heuristics as a problem of dynamic positioning rather than static classification. It offers scholars a vocabulary and structure to theorize how heuristics—understood as bundles of reasoning logic—shift over time and across settings, reflecting the interplay between cognition, institutions, and design.

In addition to these theoretical advancements, the Heuristic Spectrum framework offers significant and actionable implications for practitioners across domains.

First, the framework enables managers and organizational leaders to diagnose and redesign decision logics based on context–strategy alignment. By mapping decision rules across the four dimensions—cognitive effort, intentionality, domain specificity, and goal alignment—leaders can assess whether a given heuristic remains fit for purpose or has become inertial, misaligned, or overly rigid. This is especially valuable in dynamic environments where once-effective heuristics may degrade or ossify. For example, a fast-and-frugal pricing rule that worked in a stable market may require codification or contextual recalibration as the firm scales or diversifies (Bingham and Eisenhardt 2011; Guercini, 2023). The Spectrum helps identify whether a decision logic should be further institutionalized, reframed, or simplified, offering a structured alternative to reactive overhauls or passive drift.

Second, the Heuristic Spectrum informs the design of adaptive, explainable AI systems. As Atanasiu et al. (2025) argue, the effectiveness of algorithmic decision tools depends not just on their outputs but on their underlying logics—how they balance cognitive demands, intentional control, specificity, and alignment with user goals. By applying the Spectrum, designers can embed human-like heuristics into AI systems with greater precision and transparency. For example, high-goal-alignment heuristics may be suited for strategic planning tools, whereas low-effort, low-intentionality heuristics may be appropriate for front-end automation. The framework also encourages continuous monitoring and repositioning of algorithmic decision logics as user expectations, data environments, or organizational structures evolve—promoting explainability, ethical alignment, and human-in-the-loop control (Gigerenzer, 2022; Katsikopoulos et al. 2022).

Third, the framework supports behaviorally informed public policy by moving beyond static nudges toward dynamic decision scaffolds. Traditional behavioral interventions often rely on generic heuristics—defaults, simplification, and salience—applied uniformly across populations. The Heuristic Spectrum allows policymakers to design interventions that evolve with users, shifting in intentionality or domain specificity as familiarity, trust, or goals change. For instance, a low-effort health nudge (e.g., default flu shot appointment) may transition over time into a more intentional strategy (e.g., personal schedule planning) through feedback and social learning. This logic aligns with calls for “adaptive nudging” and scaffolding-based approaches that remain sensitive to evolving cognitive and contextual conditions (Reb and Jha 2024; Sunstein 2015). By positioning heuristics dynamically, rather than statically, the Spectrum ensures that behavioral interventions remain relevant, scalable, and responsive over time.

Consequently, this reconceptualization opens a rich interdisciplinary research program, inviting conceptual development and empirical exploration. Future scholarship can investigate how heuristics are enacted, stabilized, and reconfigured across diverse decision ecologies, ranging from individual cognition and organizational routines to algorithmic systems and policy interventions. The notion of positional shifts along the Spectrum enables novel empirical designs that track how performance feedback, institutional constraints, technological mediation, or cultural learning shape heuristics. Researchers can explore how intentionality or goal alignment changes affect

decision outcomes over time, or how domain specificity interacts with transferability and generalization across settings.

This agenda also invites methodological innovation. Longitudinal process studies, ethnographies of practice, machine learning audits, and simulation-based modeling could all be used to investigate the dynamic interplay of the four dimensions in real-world decision environments. Moreover, the Spectrum accommodates theoretical pluralism: it enables scholars to draw from behavioral decision theory, ecological rationality, routine dynamics, and socio-technical systems research without collapsing ontological distinctions. The Heuristic Spectrum offers a generative platform for building cumulative, context-sensitive theory by shifting focus from heuristic types to heuristic trajectories. It encourages scholars to move beyond debates about which tradition is “correct” and instead ask how heuristics acquire meaning, adaptiveness, and legitimacy across time, actors, and institutional arrangements. In this way, the Spectrum supports a more integrative and reflexive science of bounded rationality, attuned to cognitive architecture and situated practice.

5 Conclusion

This article has introduced the Heuristic Spectrum Framework to address a critical theoretical blind spot in the literature on heuristics: the lack of a systematic lens for understanding how heuristics vary, shift, and reposition across contexts. Rather than assuming that heuristics change in type (e.g., from bias to rule), the framework reconceptualizes them as positionally fluid logics—adaptive reasoning strategies that evolve across four interdependent dimensions: cognitive effort, intentionality, domain specificity, and goal alignment. These dimensions capture how heuristics are not fixed entities but embedded, enacted, and reinterpreted through practice, reflection, and learning. In doing so, the framework moves beyond static typologies and binary classifications. It bridges fragmented research traditions—heuristics-as-biases, ecological rationality, and simple rules—without reducing their foundational differences. Instead, it provides a common conceptual grammar to compare, trace, and contextualize heuristics as they are learned, codified, transferred, or degraded. It brings analytic clarity to phenomena such as transitional heuristics, hybrid decision tools, and context-induced shifts in heuristic use, which have remained undertheorized in prior work. The Heuristic Spectrum contributes both a theoretical and methodological advance: it equips researchers with a structure to investigate the dynamics of heuristic application and adaptation over time and across domains. It also gives practitioners a diagnostic tool to design and recalibrate heuristics in management, policymaking, and human–AI systems. Most importantly, it restores and extends Simon’s (1947) original insight: that bounded rationality is not a flaw to be corrected, but a logic of adaptation to real-world complexity. In this sense, the Heuristic Spectrum Framework lays the foundation for a more integrative, dynamic, and interdisciplinary science of decision-making—one that sees heuristics not as artifacts of error, but as evolving instruments of situated rationality.

Author contributions M.C. conceived the study, conducted the research, wrote and revised the manuscript.

Funding Open access funding provided by Università degli Studi di Roma Tor Vergata within the CRUI-CARE Agreement.

Data availability No datasets were generated or analysed during the current study.

Declarations

Competing interests The authors declare no competing interests.

Open Access This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit <http://creativecommons.org/licenses/by/4.0/>.

References

- Abatecola G (2014) Untangling self-reinforcing processes in managerial decision making. Co-evolving heuristics? *Manag Decis* 52(5):934–949
- Abatecola G, Caputo A, Cristofaro M (2018) Reviewing cognitive distortions in managerial decision making: toward an integrative co-evolutionary framework. *J Manage Dev* 37(5):409–424
- Artinger F, Petersen M, Gigerenzer G, Weibler J (2015) Heuristics as adaptive decision strategies in management. *J Organ Behav* 36(S1):S33–S52
- Atanasiu R, Wickert C, Khapova SN (2025) Towards a heuristic view of managerial heuristics: integrating divergent perspectives. *Int J Manag Rev* 27(1):58–80
- Barberis N, Thaler R (2003) A survey of behavioral finance. *Handb Econ Finance* 1:1053–1128
- Bazerman MH, Moore DA (2012) *Judgment in managerial decision making*. Wiley, Hoboken
- Bingham CB, Eisenhardt KM (2011) Rational heuristics: the ‘simple rules’ that strategists learn from process experience. *Strateg Manag J* 32(13):1437–1464
- Bingham CB, Eisenhardt KM, Furr NR (2007) What makes a process a capability? Heuristics, strategy, and effective capture of opportunities. *Strateg Entrep J* 1(1–2):27–47
- Bingham CB, Heimeriks KH, Schijven M, Gates S (2015) Concurrent learning: how firms develop multiple dynamic capabilities in parallel. *Strateg Manage J* 36(12):1802–1825
- Bingham CB, Howell T, Ott TE (2019) Capability creation: heuristics as microfoundations. *Strateg Entrep J* 13(2):121–153
- Brown SL, Eisenhardt KM (1997) The art of continuous change. *Adm Sci Q* 42(1):1–34
- Cavarretta FL (2021) On the hard problem of selecting bundles of rules: a conceptual exploration of heuristic emergence processes. *Manag Decis* 59(7):1598–1616
- Cristofaro M, Giannetti F (2021) Heuristics in entrepreneurial decisions: a review, an ecological rationality model, and a research agenda. *Scand J Manage* 37(3):101170
- Cristofaro M, Augier M, Lovallo D, Abatecola G, Leoni L (2025) Behavioral strategy in evolution: a review and conceptual framework. *Eur Manag J*. <https://doi.org/10.1016/j.emj.2024.10.002>
- Davis JP, Eisenhardt KM, Bingham CB (2009) Optimal structure, market dynamism, and the strategy of simple rules. *Adm Sci Q* 54(3):413–452
- Eisenhardt KM, Sull DN (2001) Strategy as simple rules. *Harv Bus Rev* 79(1):107–116
- Evans JSB, Stanovich KE (2013) Dual-process theories of higher cognition: advancing the debate. *Perspect Psychol Sci* 8(3):223–241
- Flyvbjerg B (2024) Heuristics for better project leadership: teasing out tacit knowledge. *Proj Manag J* 55(6):615–625
- Furr NR, Eisenhardt KM, Bingham CB (2020) Simple rules for a world of change: reflections on turning a process into a capability. *Strateg Entrep J* 14(4):552–561

- Gigerenzer G (1991) How to make cognitive illusions disappear: beyond heuristics and biases. *Eur Rev Soc Psychol* 2(1):83–115
- Gigerenzer G (2008) Why heuristics work. *Perspect Psychol Sci* 3(1):20–29
- Gigerenzer G, Gaissmaier W (2011) Heuristic decision making. *Annu Rev Psychol* 62:451–482
- Gigerenzer G, Goldstein DG (1996) Reasoning the fast and frugal way: models of bounded rationality. *Psychol Rev* 103(4):650–669
- Gigerenzer G, Gaissmaier W, Kurz-Milcke E, Schwartz LM, Woloshin S (2007) Helping doctors and patients make sense of health statistics. *Psychol Sci Public Interest* 8(2):53–96
- Gigerenzer G, Reb J, Luan S (2022) Smart heuristics for individuals, teams, and organizations. *Annu Rev Organ Psychol Organ Behav* 9(1):171–198
- Gigerenzer G, Todd PM (1999) Fast and frugal heuristics: the adaptive toolbox. Simple heuristics that make Us smart. Oxford University Press, pp 3–34
- Gigerenzer G, Hertwig RE, Pachur TE (2011) Heuristics: the foundations of adaptive behavior. Oxford University Press
- Goldstein DG, Gigerenzer G (2002) Models of ecological rationality: the recognition heuristic. *Psychol Rev* 109(1):75–90
- Guercini S (2012) New approaches to heuristic processes and entrepreneurial cognition of the market. *J Res Mark Entrep* 14(2):199–213
- Guercini S (2022) Scope of heuristics and digitalization: the case of marketing automation. *Mind Soc* 21(2):151–164
- Guercini S (2023b) Marketing automation and decision making: the role of heuristics and AI in marketing. Edward Elgar Publishing
- Guercini S, Milanese M (2020) Heuristics in international business: a systematic literature review and directions for future research. *J Int Manag* 26(4):100782
- Hammond KR (1996) Upon reflection. *Think Reason* 2(2–3):239–248
- Heimeriks KH, Schijven M, Gates S (2012) Manifestations of higher-order routines: the underlying mechanisms of deliberate learning in the context of postacquisition integration. *Acad Manage J* 55(3):703–726
- Hodgkinson GP, Sadler-Smith E (2018) The dynamics of intuition and analysis in managerial and organizational decision making. *Acad Manage Perspect* 32(4):473–492
- Kahneman D (2003) Maps of bounded rationality: psychology for behavioral economics. *Am Econ Rev* 93(5):1449–1475
- Kahneman D (2011) Thinking, fast and slow. Farrar, Straus and Giroux, New York
- Kahneman D, Tversky A (1979) Prospect theory: an analysis of decisions under risk. *Econometrica* 47(2):263–291
- Kahneman D, Slovic P, Tversky A (eds) (1982) Judgment under uncertainty: heuristics and biases. Cambridge University Press, Cambridge
- Katsikopoulos KV (2011) Psychological heuristics for making inferences: definition, performance, and the emerging theory and practice. *Decis Anal* 8(1):10–29
- Katsikopoulos KV, Egozcue M, Garcia LF (2022) A simple model for mixing intuition and analysis. *Eur J Oper Res* 303(2):779–789
- Kelman MG (2011) The heuristics debate. Oxford University Press, Oxford
- Köhler W (1925) An aspect of gestalt psychology. *Pedagog Semin J Genet Psychol* 32(4):691–723
- Langley P, Pearce C, Barley M, Emery M (2014) Bounded rationality in problem solving: guiding search with domain-independent heuristics. *Mind Soc* 13:83–95
- Lovallo D, Cristofaro M, Flyvbjerg B (2023) Governing large projects: a three-stage process to get it right. *Acad Manag Persp* 37(2):138–156
- Luan S, Reb J, Gigerenzer G (2019) Ecological rationality: fast-and-frugal heuristics for managerial decision making under uncertainty. *Acad Manag J* 62(6):1735–1759
- Marewski JN, Schooler LJ (2011) Cognitive niches: an ecological model of strategy selection. *Psychol Rev* 118(3):393–437
- Marewski JN, Gaissmaier W, Gigerenzer G (2010a) Good judgments do not require complex cognition. *Cogn Process* 11:103–121
- Marewski JN, Schooler LJ, Gigerenzer G (2010b) Five principles for studying people’s use of heuristics. *Acta Psychol Sin* 42(1):72–87
- Marewski JN, Katsikopoulos KV, Guercini S (2024) Simon’s scissors: meta-heuristics for decision-makers. *Manag Decis* 62(13):283–308
- Mousavi S, Gigerenzer G (2014) Risk, uncertainty, and heuristics. *J Bus Res* 67(8):1671–1678

- Newell A, Simon HA (1972) *Human problem solving*. Prentice-Hall, Englewood Cliffs
- Newell BR, Weston NJ, Shanks DR (2003) Empirical tests of a fast-and-frugal heuristic: not everyone takes-the-best. *Organ Behav Hum Decis Process* 91(1):82–96
- Nørreklit H, Raffinsoe-Møller M, Mitchell F (2016) A pragmatic constructivist approach to accounting practice and research. *Qual Res Acc Manage* 13(3):266–277
- Nørreklit H (ed) (2017) *A philosophy of management accounting: A pragmatic constructivist approach*. Taylor & Francis
- Oppenheimer DM (2003) Not so fast (and not so frugal!): rethinking the recognition heuristic. *Cognition* 90(1):B1–B9
- Pachur T, Bröder A, Marewski JN (2008) The recognition heuristic in memory-based inference: is recognition a non-compensatory cue? *J Behav Decis Mak* 21(2):183–210
- Pavičević S, Keil T, McNamara G (2025) Debiasing the literature on executive decision-making biases. *Acad Manag Ann*. <https://doi.org/10.5465/annals.2022.0152>
- Payne JW, Bettman JR, Johnson EJ (1993) *The adaptive decision maker*. Cambridge University Press
- Polonioli A (2013) Reflecting on Gigerenzer's critique of optimisation. *Mind Soc* 12:245–256
- Pólya G (1945) *How to solve it*. Princeton University Press, Princeton
- Reb J, Jha N (2024) Smart heuristics in business relationships: toward a typology. *Manag Decis* 62(11):3457–3472
- Shah AK, Oppenheimer DM (2008) Heuristics made easy: an effort-reduction framework. *Psychol Bull* 134(2):207
- Simon HA (1947) *Administrative behavior*. Macmillan, New York
- Simon HA (1955) A behavioral model of rational choice. *Q J Econ* 69(1):99–118
- Suarez FF, Montes JS (2019) An integrative perspective of organizational responses: routines, heuristics, and improvisations in a Mount Everest expedition. *Organ Sci* 30(3):573–599
- Sunstein CR (2015) The ethics of nudging. *Yale J Regul* 32:413–450
- Thaler R, Sunstein CR (2008) *Nudge: improving decisions about health, wealth and happiness*. Yale University Press, New Haven
- Tversky A, Kahneman D (1973) Availability: a heuristic for judging frequency and probability. *Cogn Psychol* 5(2):207–232
- Tversky A, Kahneman D (1974) Judgment under uncertainty: heuristics and biases. *Science* 185(4157):1124–1131
- Vuori N, Burkhard B, Laamanen T, Bingham C (2024) Heuristics in organizations: toward an integrative process model. *Acad Manag Ann* 18(2):670–711
- Wübben M, Wangenheim FV (2008) Instant customer base analysis: Managerialheuristics often “get it right”. *J Market* 72(3):82–93

Publisher's note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.