**Bounded rationality and human development**

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**Author note**

## Abstract

Although multi-scale, multi-directional feedback between genes, brain, cognition, and behaviour is the cornerstone of well-evidenced interactionist models of human development (e.g., Gottlieb, 2007), contemporary theories of neurodevelopmental variation and disorder characteristically describe only unidirectional cascades across this hierarchy. To complement this view, I present a new theory of the cognitive and behavioural origins of individual differences in human development. This account is grounded in the ideas of restricted search and satisficing that are central to bounded rationality (Simon, 1955, 1956, 1990), and which set this account apart from claims that adaptive agents optimise utility functions or maximise their learning. Using the foundational model of bounded rationality (Simon, 1955) as a reference point, I integrate a broad contemporary literature on adaptive, restricted search and satisficing, and reciprocal influences on development and learning. This work motivates the novel position that, although adaptive, restricted search and satisficing not only amplify neurodevelopmental differences beyond their primary genetic and neurobiological origins but also provide a route by which disparate primary causal processes are anchored to common phenotypes. While the focus of this paper is on early developmental variation and conditions of clinical significance, I argue that bounded rationality offers a general paradigm through which to understand the emergence of individual differences across the lifespan, from psychopathology to expertise. The recommendation of this report is that cognitive and behavioural feedback should be embedded more widely into causal process models of the origins of individual differences in human development.

*Keywords*: Neurodevelopmental variation, individual differences, bounded rationality, search, adaptive behaviour

**Bounded rationality and human development**

A major aim for developmental science is to identify the causal origins of individual differences in human development, including conditions of clinical significance like developmental language disorder, dyslexia, dyscalculia, and autism spectrum condition. Well-established accounts of developmental differences like these characteristically centre on functionally discrete 'core deficits', for instance in the working memory system (Ellis Weismer et al., 2017; Gray et al., 2019), the procedural learning system (Ullman & Pierpont, 2005; West et al., 2017), auditory perception (S. D. Jones et al., 2023; Richards & Goswami, 2015), visual control (Stein, 2001), or the so-called social brain network (Elsabbagh & Johnson, 2016; see Astle & Fletcher-Watson, 2020, for review). However, after over half a century of research in this direction, the message of what has been termed the transdiagnostic revolution is that the neural and cognitive signatures of developmental variation are often subtle, distributed across the brain, inconsistent within diagnostic groups, unstable in ontogenetic time, and underpinned by a highly complex genetic basis rather than a handful of candidate genes (Astle et al., 2022).

While contemporary theories of the origins of neurodevelopmental variation keenly embrace this complexity, the causal processes that they describe characteristically remain unidirectional, charting a one-way cascade of effects from a complex genetic basis to a complex neural architecture, to a multiple-deficit model of cognitive function and behaviour (see Astle et al., 2023). In this way, contemporary theories of neurodevelopmental variation apparently overlook one of the cornerstones of well-evidenced interactionist models of human development such as probabilistic epigenesis (Gottlieb, 2007) and neuroconstructivism (Westermann et al., 2007); the idea that cognition and behaviour – like all levels of the emergent, interactional hierarchy – play an active, reciprocal role in shaping a developmental trajectory (Figure 1). My aim in this Theoretical Note is to develop a new programme of research that appeals to bounded rationality (Simon, 1955) to explain how adaptive cognition

and behaviour – an agent's choices, actions, and habits – actively shape rather than merely reflect neurodevelopmental variation (S. D. Jones et al., 2024, 2025).

**Bounded rationality**

Bounded rationality (Simon, 1955, 1956, 1990) motivates a descriptive rather than normative approach to the study of intelligent behaviour guided by the fact that environments are complex and human sensation, cognition, and motor control are constrained. This makes it implausible that agents optimise or observe the axioms of neoclassical expected utility theory[1] in authentic decision spaces. Indeed, many authentic decision problems may be computationally intractable. Accordingly, bounded rationality holds that agents generally use approximating procedures involving mental models – known variously as *simplifying schemas* or *construals* – that render the complex decision problems they face tractable given their limited resources and environmental pressures[2]. *Rationality* is defined, therefore, not in terms of logical cohesion and the computation of maxima, as it is in neoclassical economics and normative approaches to human behaviour (e.g., Lieder & Griffiths, 2025; Figure 2, Panel A), but instead in terms of adaptive behaviour that is appropriate given the agent's aims and constraints; a definition echoed in contemporary treatments of natural and artificial intelligence (e.g., Chollet, 2019). Two closely related ideas are central:

> *Limited search.* Given bounded sensory, neurocognitive and motor
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> resources, environmental complexity, and time pressure, agents consider
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> only a limited amount of the decision-relevant information in principle

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[1] For instance, Ramsey (2013), Von Neumann and Morgenstern (2007), and Savage (1972). Note that this landmark neoclassical work took an unequivocally *instrumentalist* rather than *realist* position, and recognised its own limitations outside of the 'small world' of idealised omniscient agents with unlimited powers of computation. See Hampton (1994) and Tversky (1975) for critiques.

[2] Expert decision makers in domains from the everyday to the unconventional (e.g., expert mathematicians, chess players) draw on a wealth of prior experience, and intuitive recognition of the problem at hand may – in limited, highly structured settings – guide relatively systematic search and the discovery of ideal solutions (Simon, 1990).

available to them. Search is heuristic, or based on 'rule of thumb', rather

than exhaustive.

*Satisficing.* Search halts when a 'good enough' aspiration level is met, not

when the agent has all decision-relevant information (including knowledge

of all options and their orderable utilities and probabilities) required to

compute a unique optimum. Agents generally do not maximise utility or

their learning progress.

Limited search may be understood in terms of a means-ends analysis in which agents

represent the difference between their current state and a desired state and selectively search

for cues and mental operations or behaviours that reduce or eliminate that difference, halting

once a satisfactory rather than optimal outcome is discovered (Figure 2, Panel B). Search may

be environmental, referring to physical exploration and to transformation of the environment –

for instance asking questions, opening boxes to reveal options, or experimenting with objects

to test hypotheses about their function – or it may be mental, referring to retrieval and processes

of learning by thinking including simulation and analogy (Fawcett et al., 2014; Hills et al.,

2015; Lombrozo, 2024). Search incorporates model-based and model-free, habitual or cached,

processes, which complement each other as a function of development, expertise, and setting

(Daw, 2012; Huys et al., 2012; Keramati et al., 2016; Van Opheusden et al., 2023).

The foundational work on bounded rationality largely abandoned the formal rigour of

neoclassical economics, including axiomisation and the optimisation functions that continue to

influence models of agentive behaviour. However, Simon (1955) provides a minimal account

(Table 1). Agents consider a set of actions, $\mathring{A} \subseteq A$, and a set of future states, $s \in S$, associated

with a value, $V(s)$[3]. Each action $a \in \mathring{A}$ is associated with a subset of states $s_a \subseteq s$ that might

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[3] Simon (1955) emphasises that value can be read in terms of goal-directed utility or information gain, neatly
reconciling instrumental and non-instrumental search.

occur if that action pursued. The mapping $a \rightarrow s_a$ represents the agent's learned mental model of its environment, that is, actions, states, and causal contingencies. This includes memories of stimuli (e.g., spoken language, text, numbers, objects, or social cues), attentional and motor procedures, and outcomes previously elicited through those procedures. The behaviour '*attend to an expert peer*' might, for instance, might map to the valued outcome '*attain knowledge of how to solve current problem*'.

Bounded rationality involves heuristic, value-guided search. Agents search for the subset of outcomes meeting an aspiration level, $k$, rather than a global optimum, that is, $S' \subseteq S$ where $V(s) \geq k$ for all $s$ in $S'$. This allows the agent to identify behavioural alternatives, $a \in Å$, believed from experience to reliably predict outcomes within $S'$ meeting the aspiration level (i.e., $s_a \subseteq S'$). Search therefore depends on the veracity of the mental model mapping behaviours to states, which must be learned incrementally through trial and error. Search halts with the discovery of a behaviour, $a$, which satisfies $V(S_a) \geq k$. Although there may be no unique solution to this constrained search problem, if a behaviour can be found then it is guaranteed to result in a satisfactory outcome with minimal computational cost relative to exhaustive search. Failure to find a satisfactory action, $a$, in the considered set of actions $Å \subseteq A$ prompts either renewed search across $A$ for possible alternatives with which to augment $Å$ or the reduction of the agent's aspiration level.

Value-guided heuristic search and satisficing enable resource-limited agents to find solutions in authentic problem spaces with high complexity, and for this reason the principles of bounded rationality have been instrumental in shaping search algorithms since the mid-20th century[4] (see Mattar & Lengyel, 2022, for review). Monte Carlo Tree Search, known for its application in recent landmark systems like AlphaGo, uses value-guided stochastic search to

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[4] A search-and-satisfice procedure is, for instance, illustrated in the application of *Logic Theorist* (Newell & Simon, 1956) to the proofs of 38 of the first 52 theorems in chapter two of Whitehead and Russell's *Principia Mathematica* (1910-1913; Whitehead & Russell, 1992).

simulate action-state possibilities through a process known as *rollout* that is used to guide learning and the initialisation of favourable action (see Hills et al., 2015, and Mattar & Lengyel, 2022, for neurobiological evidence of the simulation of possible future states via *hippocampal rollout* or *replay*, and associated planning deficits in lesion studies). While bounded rationality rejects the idea that human decision-making involves optimisation procedures of the sort integrated with algorithms like Monte Carlo Tree Search, the general similarities of value-guided, depth-limited search and satisficing are unmistakable.

**Limited search and satisficing characterise human behaviour**

There is good evidence that human problem solving is characterised by value-guided, depth-limited search which is adaptive to both the constraints of the agent and the nature of the environment.[5] Whether with respect to search of external or internal cognitive resources, agents normally base their judgements on less information than is in principle available to them, a satisficing regime explained in terms of the constraints of the agent and environment and the diminishing returns of information sampling (Eluchans et al., 2025; Hertwig & Pleskac, 2010; Huys et al., 2012; Karasik et al., 2011). Child and adult decision-making is characterised by greedy, myopic search (i.e., *temporal discounting*), rather than sophisticated long-term planning (Cheyette et al., 2023; Gabaix & Laibson, 2017; Gershman & Bhui, 2020; Loewenstein et al., 2003; Meder et al., 2019). Still, the description of such behaviour as rational is warranted despite possible long-term costs given the importance of meeting immediate goals and the combinatorial challenges of deep planning. Although in the aggregate human performance might appear optimal, individual search and decision-making routinely deviate from the predictions of optimal modelling and expected utility theory, and the introduction of constraints is essential to mitigating this disparity (Callaway et al., 2022; Cheyette et al., 2023;

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[5] This section reviews cognitive and behavioural evidence for value-guided, depth-limited search and satisficing. The reader is directed to Hills et al. (2015), Kobayashi and Kable (2024), and Mattar and Lengyel (2022) for reviews of the neurobiological literature.

Goodman et al., 2008; Lieder & Griffiths, 2025; Stanovich & West, 2000; Todd & Gigerenzer, 2000; Tversky & Kahneman, 1974).

Search is guided by expected value, with high-value options attracting preferential resource allocation (Anderson, 2016; Anderson et al., 2011, 2021; Bourgeois et al., 2016; Gatzke-Kopp et al., 2018; Gershman & Burke, 2022; Jia et al., 2025; Pearson et al., 2022; Tomov et al., 2023). Evidence that agents sub-optimally inhibit search in response to a cost – a phenomenon that has been termed *Pavlovian pruning* (Huys et al., 2012) – illustrates not only satisficing but the role that 'simple' processes including associative learning and contrast effects play in complex decision spaces[6] (Fawcett et al., 2014; Hills, 2006; Simon, 1962). Limited search and satisficing work because of the statistical structure of the environment (Simon, 1956, 1962). The principle of *near decomposability* means that complex systems can be modelled in part rather than as a whole (Simon, 1962) and limited information solutions are advantageous because they amplify environmental correlations and help to navigate the bias-variance trade-off; features which might be particularly valuable in early development (Gigerenzer & Brighton, 2009; Hertwig & Pleskac, 2010; Kareev, 1995; Katsikopoulos et al., 2010; Lichtenberg & Şimşek, 2017; Todd & Gigerenzer, 2000). Relatedly, spatiotemporal autocorrelation means that learned search and decision strategies often generalise well (Fawcett et al., 2014).

Given the complexity of authentic decision settings, claims of bounded agents maximising information gain (e.g., Poli et al., 2022) are overstated. However, agents may

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[6] An emphasis on relatively 'simple' mechanisms replayed across complex but structured environments might be contrasted with an emphasis, common to normative or *instrumentalist* accounts, on meta-reasoning about an accuracy-effort trade-off, which characteristically takes the bipartite form of the expected utility of action minus the cost of information processing (Binz et al., 2022; Lieder & Griffiths, 2020; C. A. Sims, 2003; see Figure 1, Panel A). The accuracy-effort trade-off has its origin in Carnap's (1947) *principle of total evidence* and *Good's principle* (see Ramsey, 2013). In general, it is argued that rational agents should make use of all information available to them that has a higher expected utility than the cost of procuring that information. Normative approaches to adaptive behaviour have been criticised for blurring the line between instrumentalist and descriptive positions, announcing an *'as-if'* formalism – for instance, that the constrained optimisation problem is solved by evolution, not by the decision-maker (e.g., Lieder & Griffiths, 2020) – but at times using language that suggests the complex operations outlined are performed in the brain (e.g., Rahnev, 2020).

preferentially allocate resources to interpretable information sources from which they believe they can learn, due to the perceived credibility of an informant, evidence of learning progress, or a violation of expectation, (Bazhydai et al., 2020; Dunn & Bremner, 2017; S. D. Jones et al., 2024; Kidd et al., 2012). Search is reliably shallower under time pressure, with deliberative model-based search complemented by cached habit-driven computation that may in certain cases negatively impact performance (Eluchans et al., 2025; Huys et al., 2012; Keramati et al., 2016; Mattar & Lengyel, 2022; Wu et al., 2022). Over time, decision-makers learn to adapt their search strategies to the structure of the environment, for instance making use of just one cue or integrating multiple cues as the setting dictates (i.e., depending on whether the decision space is *non-compensatory* or *compensatory* respectively; Binz et al., 2022; Callaway et al., 2022; Lieder & Griffiths, 2017; Siegler, 1999). However, the description of agents selecting discrete heuristics like *take the best* from an *adaptive toolbox* (e.g., Gigerenzer & Gaissmaier, 2011; Todd & Gigerenzer, 2012) introduces unwarranted complexity. Agents need not select an information-agnostic heuristic prior to selecting an appropriate information sub-structure but can instead select that information structure directly.[7] Put another way, *heuristic search* does not mean *the search for heuristics*, but instead *inexhaustive search* in complex problem spaces.

Motor development, for instance learning to walk, plays an essential role in facilitating environmental search and learning (Iverson, 2010; Karasik et al., 2011). Though reliably short of optimal, search becomes more efficient over developmental time (Bramley & Xu, 2023; Chai et al., 2023; Ruggeri et al., 2021; see De Simone & Ruggeri, 2022, for review). Children are, for instance, more likely than adults to ask hypothesis-scanning rather than effective constraint-seeking questions, and characteristically continue search past the point at which a

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[7] In *rational inattention* (C. A. Sims, 2003) this is interpreted as an extension of the Blackwell framework (Blackwell, 1953) in which idealised agents select an information structure subject to a mutual-information cost, effectively choosing how informative their Blackwell experiment will be.

single hypothesis remains (Ruggeri et al., 2016). Search is mediated not only by developmental change but also by individual differences (Bari & Gershman, 2024; S. D. Jones et al., 2024). Expertise and attention are positively associated with search depth (Daw, 2012; Van Opheusden et al., 2023), enabling agents to work toward long-term rewards rather than sub-optimally curtail search in response to an immediate loss (i.e., to overcome *Pavlovian pruning*; Huys et al., 2012), and to resist excessively shallow search under time pressure (Daw, 2012; Van Opheusden et al., 2017). Mood disturbance like depression may be associated with shallower search (Huys et al., 2012), while trait somatic anxiety and attention deficit hyperactivity disorder may be associated with stronger search preferences, including search for non-instrumental information, which are explained in terms of uncertainty aversion and distractibility and impulsiveness respectively (Bari & Gershman, 2025; Le Cunff, 2024).

Given that search is guided by learning progress and information interpretability, which are a function of the agent's neurocognitive profile, it is unsurprising that clinically significant developmental differences, including – though by no means limited to – developmental language disorder, dyslexia, dyscalculia, and autism spectrum condition, promote idiosyncratic search trajectories steered by the child's primary areas of difficulty (Annaz et al., 2009; Ashkenazi et al., 2009; Bogaerts et al., 2015; M. W. Jones et al., 2018; S. D. Jones et al., 2024, 2025; Kaldy et al., 2011; Leclercq et al., 2013; Muter & Snowling, 2009; Snowling et al., 2020; van Viersen et al., 2013). This might be as subtle as a dependence on serial counting versus subitising in dyscalculia (Schleifer & Landerl, 2011) or as obvious as a reduced sensitivity to social cues in autism (Moriuchi et al., 2017), and may or may not be a common feature of the cognitive and behavioural development of younger peers.

The literature reviewed in this section highlights a decoupling of the global problem space and the adaptive agent's problem space. In general, adaptive, value-seeking agents allocate cognitive and motor resources to regions of the problem space aligned with processing

fluency or the conservation of mental effort and anticipated learning progress, switching from local search to global search for new options (i.e., from exploitation to exploration) when information sources are exhausted in a manner that highlights an evolutionary homology with animal foraging (Cheyette et al., 2023; Metcalfe & Kornell, 2003; Patzelt et al., 2019; Shenhav et al., 2017; Hills, 2006; Simon, 1955; see Hills et al., 2015, for review and a discussion of *area restricted search*). Adaptive agents are not predicted to preferentially commit limited cognitive and motor resources to searching areas of the problem space that, due to their primary neurocognitive constraints, are less valuable to them than alternatives (whether value is understood in terms of utility or valence), and this will have a substantial impact on their learning over time (S. D. Jones et al., 2024, 2025).

**Adaptive search shapes neurodevelopmental variation**

Bounded rationality is unusual among decision-theoretic frameworks for putting not only individual differences but learning and developmental dynamics front and centre (Simon, 1955, 1956). Subjective payoffs, $V(s)$, for instance, must be tuned through trial and error, and might be lowered when options are no longer reliably conducive to a desired outcome or increased in response to environmental change that makes a course of action more lucrative (see Hills et al., 2015, for evidence that less-than-expected reward affects neuromodulation and promotes exploration). Similarly, the agent's aspiration level, $k$, may rise when search and satisficing are easy but lower when search and satisficing are hard, providing near-uniqueness with respect to satisfactory solutions[8]. The dynamic updating of value and decision thresholds in response to environmental change is well-evidenced (Castro-Rodrigues et al., 2022; Ramadan et al., 2025; Schultner et al., 2025).

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[8] Simon (1955) uses aspiration level as an example of how individual differences might shape search. A persistent agent may be reluctant to lower aspirations, and this may prompt a prolonged search for satisfactory alternatives.

Most importantly for the account developed in this paper, the world model mapping from actions to states, $A \rightarrow S$, encoded by the agent's memories of previous experiences of both the primitive elements ($a$, $s$, associated stimuli) and their causal contingencies, is refined in response to experience, subject to imperfect encoding and forgetting. Simon (1955) emphasises that model refinement by agents with bounded resources is necessarily local and selective rather than complete, a position for which there is empirical evidence (see Bramley et al., 2017). Agents actively intervene on or mentally simulate interventions on the world and update their memories and hypotheses in light of the evidence that their interventions return[9] (Gopnik, 1996; Siegel et al., 2021; Tsividis et al., 2021). In this way, learning about the external world proceeds along a search trajectory that is shaped by anticipated value, that is, utility and valence, which is itself conditional on the constraints of the environment and the agent's neurocognitive profile (Anderson, 2016; Anderson et al., 2011; Bourgeois et al., 2016; Callaway et al., 2022; Goodman et al., 2008; S. D. Jones et al., 2024, 2025; Metcalfe & Kornell, 2003).

Behavioural and neurobiological evidence converges on the idea that – subject to the constraints of the agent and setting – perception, attention, and prioritisation in memory are enhanced by valence and utility (Ho et al., 2023; Itthipuripat et al., 2019; Lai & Gershman, 2021; Luo & Maunsell, 2015; Serences, 2008; C. R. Sims, 2016; Gershman & Burke, 2022). Given their limited resources, agents reliably construct simplified representations of their problem spaces that prioritise goal-relevant features, for instance during spatial navigation (Ho et al., 2022), visual classification (Bates et al., 2019), and language processing (see Frances, 2024, for review). By the same token, undesirability and low utility prompt *rational*

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[9] Bramley et al. (2017) adopt the metaphor of *Neurath's boat* popularised by Quine, (1960) to describe agents entertaining a single global hypothesis that is subject to local, intervention-driven updating.

*inattention*[10] and attenuated, low-fidelity memorisation (S. D. Jones et al., 2024, 2025; C. A. Sims, 2003). A parallel with the perceptual narrowing literature is apparent here (Krasotkina et al., 2021). Collectively, the idiosyncratic search and decision strategies that agents develop might be understood as a developmental niche (Ready & Price, 2021; Schrödinger, 1992) that is co-constructed by the child and their caregivers and peers and which, much like an ecological niche (e.g., nest or dam), regulates environmental pressures on the child because it is tuned to their neurocognitive profile (Constant et al., 2018; Flynn et al., 2013; Marewski & Schooler, 2011). Information sources and cues outside of that developmental niche, that is, which reside on search trajectories that are avoided or de-weighted due to low anticipated value, will be memorised in relatively low fidelity, just as language sounds and faces outside of the child's circle of experience might be memorised in low fidelity relative to familiar alternatives (Krasotkina et al., 2021).

The evidence of value-guided search, satisficing, and learning reviewed in this Theoretical Note motivates the claim that idiosyncratic, heuristic search, which is adaptive to the neurocognitive constraints of the agent, contributes unique variance to the agent's developmental trajectory over and above the effects of those constraints in and of themselves (S. D. Jones et al., 2025)[11]. This position acknowledges that neurodevelopmental variation has a basis in complex genetic and neurobiological factors but takes an interactionist view emphasising reciprocal cognitive and behavioural mediation (Figure 1). Illustrating this, S. D.

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[10] *Rational inattention* describes a normative decision-theoretic framework in which agents maximise expected utility minus information processing or procurement costs, formalised as $\max_{\pi} E[U] - \lambda I(X; S)$, where $I(X; S)$ is the mutual information between states and signals and $\lambda$ is a Lagrange multiplier on the information flow (C. A. Sims, 2003). The term *rational inattention* was used informally by S. D. Jones et al., (2024, 2025) to describe adaptive disengagement with information sources associated with low anticipated value of computation.

[11] This position is broadly continuous with the notion of a Matthew effect (Soriano-Ferrer & Morte-Soriano, 2017; Stanovich, 2009), but departs from an emphasis on reading and affective disengagement toward a general framework grounded in adaptive, value-guided search under constraints. My account is agnostic to the exact nature of neurocognitive constraint and indeed to the broader neurotypical and neurodivergent distinction.

Jones et al. (2024) demonstrated that an adaptive agent-based model with processing constraints showed significant disengagement and learning deficits relative to a non-adaptive baseline model with matched processing constraints. Disengagement and idiosyncratic search may be encouraged by any number of foundational causal processes that ultimately decrease anticipated value. At a high level, this might include, for instance, primary deficits in either perceptual encoding or working memory. For this reason, it is plausible that constrained, value-guided search not only reinforces or amplifies learning delay over and above fundamental genetic and neurobiological factors – which in some instances may themselves be subtle and confer limited direct effect – but that value-guided search also anchors diverse causal bases to common phenotypes.

**Summary**

The ideas of value-guided search, satisficing, and learning that are central to bounded rationality offer one way to think about how adaptive cognition and behaviour reciprocally shape individual differences. This Theoretical Note has surveyed evidence of value-guided search steered by simple associative mechanisms, and its implications for learning over time. Collectively this work motivates the position that adaptive search and satisficing not only amplify neurodevelopmental differences beyond their genetic and neurobiological origins but also provide a route by which disparate primary causal processes are anchored to common phenotypes. This view complements dominant accounts of the origins of individual differences centred on unidirectional structure-function cascades (Figure 1) and offers a partial explanation for variability in human development in general (e.g., including psychopathology and expertise), beyond my primary focus on conditions of clinical significance.

The implications of this work are twofold. First, it re-affirms the importance of the decoupling of the child's adaptation environment, to which search and decision strategies are tuned, and the evaluation environment in which the child is tested (Fawcett et al., 2014). Clinics

and experimental spaces often lack or distort the statistical regularities upon which the child commonly relies, preventing use of their adaptive search and decision strategies. In some cases, this may lead to error, bias, or apparently irrational behaviour that should not be mistaken for direct evidence of a fundamental deficit. Second, cognitive and behavioural feedback should be embedded more widely into causal process models of the origins of neurodevelopmental variation. Bounded rationality offers a paradigm rather than a predictive model, and new empirical work is required to better understand the nature of search and satisficing as a function of neurodevelopmental variation (see, for instance, Huys et al., 2012; Van Opheusden et al., 2023, for work in this direction). In pursuing this line of inquiry, we approach a more complete picture of the origins of individual differences in human development.

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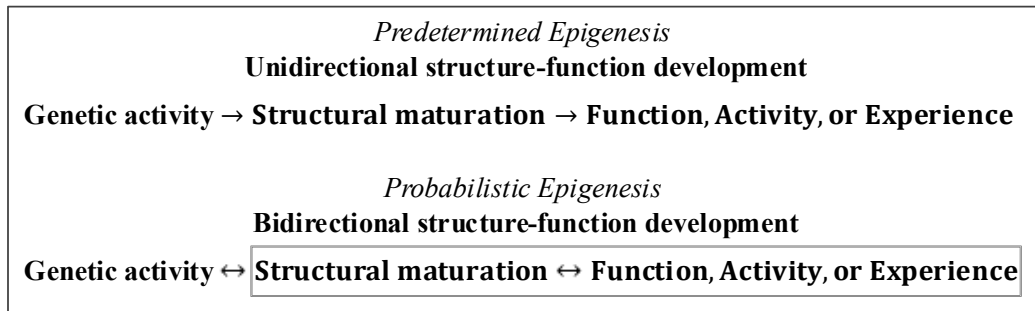
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**Figure 1**

*Predetermined and probabilistic epigenesis*



*Predetermined Epigenesis*
**Unidirectional structure-function development**

**Genetic activity → Structural maturation → Function, Activity, or Experience**

*Probabilistic Epigenesis*
**Bidirectional structure-function development**

**Genetic activity ↔ Structural maturation ↔ Function, Activity, or Experience**

*Note.* Figure adapted from Gottlieb (2005, p. 37; see also Gottlieb, 2007). Core deficit theories of neurodevelopmental variation chart a unidirectional cascade of effects from genes to brain, cognition, and behaviour, known as *predetermined epigenesis*. This stance is echoed in contemporary theories of neurodevelopmental variation that embrace complexity but omit dynamic feedback. *Probabilistic epigenesis*, in contrast, incorporates multi-scale, multi-directional feedback and non-linear dynamics across this hierarchy. The focus of this Theoretical Note is on the bi-directional dynamics of (i) the structural changes in the brain that constitute learning and (ii) the agent's cognition and behaviour (i.e., function, activity, or experience; boxed inset). See Westermann et al. (2007) for an alternative, more detailed interactionist model.

**Figure 2**

*Optimisation under constraints (A) and heuristic search, satisficing, and learning (B)*



$$\pi^*(s) = \arg\max_{a \in \mathring{A}(s)}[V(f(s,a)) - c(s,a)] \qquad \pi_k(s) \in \{a \in \mathring{A}(s) \mid V(f_M(s,a)) \geq k\}$$
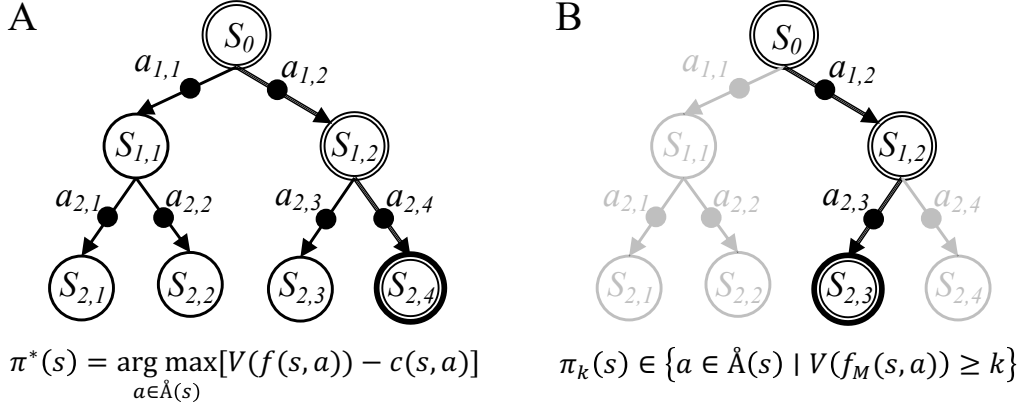
*Note.* Search may be visualised as a decision tree in which nodes indicate environmental or mental states, *s,* associated with values, $v(s)$, and edges indicate environmental or mental actions, *a*, for instance, explore, attend to, retrieve, or transform. Panel A shows exhaustive search and optimisation. All trajectories through the problem space are evaluated and a course of action, or *policy $\pi^*(s)$*, which maximises total value minus the total cost of action, $c(a)$, is initialised (note that this deterministic illustration omits the probability weightings typical in expected utility formalisms). Cost might be read variously as, for instance, an opportunity cost (e.g., Gershman & Burke, 2022; Wu et al., 2022) or a metabolic cost (Kringelbach et al., 2024). In Panel A the agent at root node $S_0$ considers all options and identifies trajectory $[S_0 \rightarrow a_{1,2} \rightarrow S_{1,2} \rightarrow a_{2,4} \rightarrow S_{2,4}]$ as the optimal policy maximising instrumental or non-instrumental utility. Exhaustive search and optimisation of this sort are impossible in complex decision spaces, and accordingly agents generally use approximating procedures including heuristic search and satisficing, illustrated in Panel B. This agent, with incomplete knowledge of the problem space, halts search upon identifying a state meeting an aspiration level, *k*, rather than performing exhaustive search and the computation of optima. (Note that costs are embedded in the value function in this example, as they are in the foundational work on bounded rationality; Simon, 1955.) Following Panel A, the theoretical optimum under complete knowledge may be $S_{2,4}$, but

the agent in Panel B selects a suboptimal state – perhaps the first they encounter – that meets their aspirations, $V(S_{2,3}) > k$. The agent selects trajectory $[S_0 \rightarrow a_{1,2} \rightarrow S_{1,2} \rightarrow a_{2,3} \rightarrow S_{2,3}]$ to that state, actions from which may be chunked into single procedure to reduce computational load. The agent then locally updates its mental model of the environment, $f_M$, with respect the features and outcomes observed along that search trajectory $(a, s, v(s)$, and associated cues or features), including estimates for abandoned search paths. Note that the full tree is shown in grey for reference only – using this mode of visualisation, the agent 'expands the tree' incrementally from node states through rollout, rather than 'seeing everything' and pruning unpromising branches. Note also that while this visualization shows a discrete decision process, the principles described throughout this Theoretical Note apply to both discrete and continuous search spaces. The key point is that neurocognitive constraints shape the value structure of the problem space by affecting the difficulty of initialising an action in a manner that is reliably conducive to a state meeting the agent's aspiration level. With a different value structure, for instance, one in which $a_{1,1}$ is easier to perform than $a_{1,2}$ such that $S_{1,1}$ and subsequent states are of higher value for a specific child (perhaps $a_{1,1}$ is a compensatory strategy), the learning trajectory will be very different.

**Table 1**

*A simple model of bounded rational search, satisficing, and learning*

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**Initialize** considered actions $Å \subseteq A$, states $S$ with values $V(s)$, Model $a \rightarrow S_a \subseteq S$ , and aspiration level $k$.

**Loop**:

      (a) Identify target outcomes $S' \subseteq S$ where $V(s) \geq k$ for all $s \in S'$

      (b) Search for behavioural alternatives $a \in Å$ predicted to yield $s_a \subseteq S'$

      (c) If $a$ satisfies $V(s_a) \geq k$:

            Execute $a$

            Observe outcome

            Update Model $a \rightarrow V(s_a)$ (local learning through trial and error)

            Halt search

      (d) Else (failure to find satisfactory action, $a$):

            $Å \leftarrow$ renew search across $A$ to augment $Å$

            or

            $k \leftarrow$ reduced aspiration level

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*Note.* Simon (1955) suggests that steps (a) and (b) might happen in reverse or iteratively, that is, that the agent considers an action, determines if the anticipated outcome is in $S'$, then moves on. The account developed in this Theoretical Note hinges on the idea that neurocognitive constraints affect the value structure of the agent's environment, rendering certain action-state pairs low value. In response, the adaptive agent can either lower their aspiration level or avoid these regions of the problem space and exploit and crucially learn from high-value alternatives. The opposite is also true – relatively low mental effort and high value are conducive to the development of expertise. Bounded rationality therefore offers a partial explanation for the emergence of individual differences in human behaviour generally, from expertise to delay to psychopathology.