

SAMPLING IN JUDGMENT AND DECISION MAKING

Sampling approaches to judgment and decision making are distinct from traditional accounts in psychology and neuroscience. While these traditional accounts focus on limitations of the human mind as a major source of bounded rationality, the sampling approach originates in a broader cognitive-ecological perspective. It starts from the fundamental assumption that in order to understand intrapsychic cognitive processes one first has to understand the distributions of, and the biases built into, the environmental information that provides input to all cognitive processes. Both the biases and restriction, but also the assets and capacities of the human mind often reflect, to a considerable degree, the irrational and rational features of the information environment and its manifestations in the literature, the Internet, and collective memory. Sampling approaches to judgment and decision making constitute a prime example of theory-driven research that promises to help behavioral scientists cope with the challenges of replicability and practical usefulness.

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