A Cognitive Computational Framework for Aiding Decision-Making Research

Authors: Luo Haocheng, Du Wei, 魏琏厅, Zhou Xiaolin, Gao Xiaoxue, Gao Xiaoxue

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Abstract

When facing intractable problems, individuals must weigh the costs and benefits to decide whether or to whom they should proactively seek help to obtain assistance from others. This help-seeking decision-making is a critical foundation for human cooperation and adaptation. However, previous fragmented and non-quantitative research perspectives and methods have hindered the construction of a systematic knowledge system and made it difficult to quantitatively analyze the trade-off and integration processes of core cognitive components. Consequently, the cognitive computational and neural mechanisms of help-seeking decision-making remain unclear.

Adopting an integrated and quantitative perspective, this paper proposes a cognitive computational framework for help-seeking decision-making research: (1) by reviewing theoretical and empirical studies, we extract core cognitive components and identify three key stages of help-seeking research: the generation of decisions, dynamic adjustments, and the modulation by characteristics of both interacting parties; (2) by deepening and extending rational and bounded rationality decision theories to help-seeking research, we construct a systematic set of candidate cognitive computational model hypotheses; (3) we propose key scientific questions and research method outlooks for future investigations into the mechanisms of help-seeking decision-making.

Full Text

A Cognitive Computational Framework for Help-Seeking Decision-Making

School of Psychology and Cognitive Science, East China Normal University; Shanghai Key Laboratory of Mental Health and Crisis Intervention, Shanghai

200062, China School of Psychological and Cognitive Sciences, Peking University, Beijing 100871, China

When faced with intractable problems, individuals must weigh the costs and benefits to decide whether to proactively seek help from others. This help-seeking decision-making process serves as a critical foundation for human cooperation and adaptation.

Previous research in this area has been fragmented and non-quantitative, which hinders the construction of a systematic knowledge base and makes it difficult to elucidate the trade-offs and integration processes of various decision components. Consequently, the cognitive computational mechanisms underlying help-seeking decisions remain unclear. By adopting an integrated and quantitative perspective, this paper proposes a cognitive computational framework for help-seeking decision-making research. Through a review of existing empirical studies, we extract core cognitive components and analyze the generation, dynamic adjustment, and modulation of help-seeking decisions by the characteristics of both parties involved in the interaction. Furthermore, we discuss the application of rational and bounded rationality decision-making theories to help-seeking research and construct a systematic set of candidate cognitive computational model hypotheses. Finally, we provide an outlook on key scientific questions and research methodologies for future investigations into the mechanisms of help-seeking decision-making.

Keywords

help-seeking decision-making, cognitive computational framework, decision generation, dynamic adjustment, dyadic interaction features

1.1 The Significance of Help-Seeking Decision-Making Research

Adam Smith noted in *The Wealth of Nations* that in civilized society, humans constantly require the cooperation and assistance of many. Help-seeking, as the initiating act of cooperation, determines how individuals obtain resources from others to better survive in society, carrying profound significance for human survival and adaptation [?, ?]. Ubiquitous in daily social interactions, help-seeking is an interpersonal request process based on reciprocal exchange, actively initiated by individuals attempting to leverage external resources to resolve personal dilemmas or increase personal gains [?, ?, ?]. At the individual level, help-seeking is the foundation of survival, success, and well-being [?, ?, ?, ?]. At the social level, help-seeking can stimulate altruistic behavior in others, promote reciprocal behavior in the seeker, and ultimately strengthen cooperation between interpersonal groups [?, ?, ?].

Individuals often avoid seeking help due to potential costs, such as the risk of rejection or the psychological burden felt after receiving assistance, which can result in heavy personal and social burdens [?, ?, ?]. Consequently, the decision-making process regarding "whether" or "from whom" to seek help has become a central scientific question across multiple fields, including social psychology [?, ?, ?], organizational and managerial psychology [?, ?, ?], educational psychology [?, ?, ?], and clinical psychology [?, ?, ?]. The decision of "whether to seek help" is essentially a choice of coping strategy.

When individuals realize that their own abilities are insufficient to solve a problem, they must choose among at least five different coping mechanisms: active help-seeking [?], autonomous persistence [?], task abandonment [?], passive waiting [?], and procrastinatory avoidance [?]. Previous research has largely focused on the binary decision of "whether to seek help" by comparing active help-seeking against other coping strategies. However, the decision of "whom to seek help from" is a distinct choice of target; once an individual decides to initiate a request, they must determine the optimal recipient to effectively resolve their problem while mitigating potential costs, such as rejection or reciprocity anxiety [?].

Help-seeking decisions possess unique characteristics that distinguish them from other social behaviors. First is their complexity: they span various social contexts—including academic, professional, emotional, and health domains [?, ?, ?, ?]. Second is situational specificity: help-seeking often occurs under high time pressure or depleted cognitive resources, leading individuals to adopt fast, resource-efficient bounded rationality heuristics [?]. Providing a systematic answer to this question is significant because help-seeking serves as a critical starting point for reciprocity and cooperation [?].

Constructing a cognitive computational framework is a critical path toward understanding help-seeking decisions. Following David Marr' s tri-level framework [?], researchers need to address the computational level (goals), the algorithmic level (cognitive processes), and the implementation level (neurobiological basis). Identifying core cognitive components and translating them into computational models allows for the quantitative characterization of how individuals weigh and integrate these components. This modeling approach serves as the key link connecting the three levels of mechanistic research [?, ?, ?, ?, ?, ?, ?, ?, ?, ?].

2.1 Refinement of Core Cognitive Components Based on Theoretical and Empirical Research

As described in previous research [?, ?, ?], the decision-making process for seeking help involves three key stages: the perception of need, the interpersonal request, and reciprocal exchange. Through a systematic review, it is evident that the psychological variables emphasized in traditional theories are closely associated with these stages. Specifically, the perceived benefits of help, the fear of social rejection, and repayment anxiety constitute the core cognitive components. Perceived benefit acts as a cognitive driver, while social rejection and repayment anxiety serve as barriers. Furthermore, the characteristics of both parties involved in the interaction are important factors that moderate these components.

2.2 Generation, Dynamic Adjustment, and Modulation of Help-Seeking Decisions

How do individuals apply these core cognitive components? This paper proposes three critical stages: decision generation, dynamic adjustment, and the modulation of characteristics between interacting parties.

Regarding decision generation: according to self-support and self-threat theories [?, ?], individuals decide whether or to whom to seek help by weighing expected benefits against social rejection and reciprocity anxiety costs. Regarding dynamic adjustment: according to the threat to self-esteem model [?, ?], individuals adjust subsequent decisions based on the benefits and costs actually experienced. Regarding modulation: the characteristics of the seeker and the potential helper influence the weighting of benefits and costs during both generation and adjustment. Analyzing generation and adjustment determines the "depth" of the research, while analyzing moderating effects determines its "breadth."

3 Cognitive Computational Model Hypotheses for Help-Seeking Decision-Making

According to rational decision-making theory, individuals weigh and integrate benefit and cost factors through value computation [?, ?, ?, ?, ?, ?, ?, ?]. However, under time pressure or high cognitive load, individuals may rely on bounded rationality heuristics [?, ?]. This paper constructs a systematic set of candidate cognitive computational model hypotheses to lay a foundation for future empirical research [?].

3.1 Help-Seeking Decisions Under the Rational Decision-Making Framework

3.1.1 Decision Generation The generation of help-seeking decisions is grounded in value-based theory [?, ?, ?, ?, ?, ?, ?]. For each option, the Subjective Utility ($Value$) is formed by the difference between weighted benefits and costs:

$$Value_{potential\_helper} = w_{Benefit} \cdot Benefit - w_{Rejection} \cdot Rejection - w_{Repayment} \cdot Repayment$$

The parameters $w_{Benefit}$, $w_{Rejection}$, and $w_{Repayment}$ represent the weights assigned to each component. A Softmax function converts these values into a probability distribution:

$$P_i = \frac{e^{\beta \cdot Value_i}}{\sum_{j=1}^{n} e^{\beta \cdot Value_j}}$$

Alternative models include the Selective Value Model (focusing on a single dominant factor) and the Non-linear Value Model (based on diminishing marginal utility):

$$Value_{potential\_helper} = w_{Benefit} \cdot Benefit^{\alpha_{Benefit}} - w_{Rejection} \cdot Rejection^{\alpha_{Rejection}} - w_{Repayment} \cdot Repayment^{\alpha_{Repay}}$$

3.1.2 Dynamic Adjustment Dynamic adjustment can be conceptualized as value-driven reinforcement learning. According to the Rescorla-Wagner model [**?**], individuals update value estimates based on prediction errors (PE):

$$V_{Benefit} \leftarrow V_{Benefit} + \alpha_{Benefit} \cdot PE_{Benefit}$$
$$V_{Rejection} \leftarrow V_{Rejection} + \alpha_{Rejection} \cdot PE_{Rejection}$$
$$V_{Repayment} \leftarrow V_{Repayment} + \alpha_{Repayment} \cdot PE_{Repayment}$$

As the number of options increases, individuals may adopt exploration-exploitation strategies [**?**]. Exploitation involves choosing the target with the highest historical returns, while exploration involves attempting new options to acquire information.

3.2 Help-Seeking Decisions Under the Bounded Rationality Framework

3.2.1 Decision Generation Heuristics represent decision-making procedures suited for uncertainty [**?**, **?**]. - **Single-Cue Decision Making:** Relying on one key cue (e.g., "Can this person provide benefits?"). - **Equality (Tallying):** Summing binary judgment cues and comparing them against a threshold T. - **Satisficing:** Selecting the first option that meets an acceptable "aspiration level" [**?**]. - **Social Heuristics:** Decisions based on imitation, the wisdom of crowds, or word-of-mouth [**?**].

3.2.2 Dynamic Adjustment Under constraints, individuals may use the "Win-Stay, Lose-Shift"strategy [**?**]. If a choice yields a positive outcome ($R_t = 1$), the individual stays with the same target; if negative ($R_t = 0$), they shift.

3.3 Modulation of Rationality and Bounded Rationality

Individuals dynamically shift between rational calculations and heuristics based on internal states and environments. This can be modeled using a dual-system framework [**?**, **?**, **?**]. The final decision probability (P_{Final}) is a weighted mixture of the rational system ($P_{Rational}$) and the heuristic system ($H_{Heuristics}$):

$$P_{Final} = w \cdot P_{Rational} + (1 - w) \cdot H_{Heuristics}$$

The weight w reflects the decision-maker' s degree of reliance on a specific strategy, moderated by factors like time pressure, cognitive load, and the characteristics of the interacting parties.

4 Future Outlook and Key Scientific Questions

Future research should focus on integrating adaptive function, cognitive computational mechanisms, and neural mechanisms [**?**, **?**].

4.1 Key Scientific Questions

- **Generation:** When do individuals switch between rational and heuristic modes? How does the brain represent the weighing of social costs?
- **Adjustment:** How are social emotions integrated into social learning? Does the learning of different cost factors involve distinct neural substrates?
- **Modulation:** How do personality traits (e.g., self-esteem, attachment style) modulate model parameters like learning rates and weights?

4.2 Methodological Prospects

- **Interpersonal Interaction Paradigms:** Developing tasks that quantitatively measure help-seeking decisions, such as the paradigm by Luo et al. (2024) which manipulates rejection and reciprocity rates.
- **Model Comparison:** Advancing the parallel formalization of rational and heuristic models to test their predictive validity.
- **Neuroimaging Integration:** Using model-based fMRI, EEG, and MEG to parse the neuroanatomical foundations and temporal dynamics of help-seeking [**?**, **?**, **?**].

5 Conclusion

This paper proposes a cognitive computational framework for help-seeking decision-making by extracting core cognitive components and constructing model hypotheses across rational and bounded rationality frameworks. This approach provides a systematic foundation for revealing the patterns of human mutual aid and reciprocity, and offers a scientific basis for precision-based crisis interventions in real-world contexts.

Figures

Source: ChinaXiv —Machine translation. Verify with original.

Figure 1

Figure 1: Figure 1