Search under Uncertainty: Cognitive Biases and Heuristics

A Tutorial on Testing, Mitigating and Accounting for Cognitive Biases in Search Experiments

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ABSTRACT

Understanding how people interact with search interfaces is core to the field of Interactive Information Retrieval (IIR). While various models have been proposed (e.g., Belkin's ASK, Berry picking, Everyday-life information seeking, Information foraging theory, Economic theory, etc.), they have largely ignored the impact of *cognitive biases* on search behaviour and performance. A growing body of empirical work exploring how people's cognitive biases influence search and judgments, has led to the development of new models of search that draw upon Behavioural Economics and Psychology. This full day tutorial will provide a starting point for researchers seeking to learn more about information seeking, search and retrieval under uncertainty. The tutorial will be structured into three parts. First, we will provide an introduction of the biases and heuristics program put forward by Tversky and Kahneman [60] which assumes that people are not always rational. The second part of the tutorial will provide an overview of the types and space of biases in search [5, 40], before doing a deep dive into several specific examples and the impact of biases on different types of decisions (e.g., health/medical, financial). The third part will focus on a discussion of the practical implication regarding the design and evaluation human-centered IR systems in the light of cognitive biases – where participants will undertake some hands-on exercises.

CCS CONCEPTS

• **Information systems → Search interfaces**; *Task models*; *Retrieval tasks and goals*; • **Human-centered computing → HCI theory, concepts and models**; *Graphical user interfaces.*

KEYWORDS

Search Behaviour, Cognitive Bias, Bounded Rationality, User Models, Search Evaluation, Bias Mitigation, GenIR

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1 MOTIVATION AND OBJECTIVES

Interactive Information Seeking and Retrieval (IS&R) encompasses the processes of searching, discovering, and retrieving relevant, valuable, and trustworthy information [22]. This multifaceted journey involves various factors that impact how individuals participate in this process, influence their search intentions and behaviours [45, 48], and affect their search and learning experiences under varying tasks [44, 47, 61]. To understand ISR comprehensively, a variety of conceptual and descriptive models have been proposed. These models, such as Bates' Berry Picking Model [8] and the ISR framework presented by Ingwersen and Kalvero [23], provide valuable insights into the intricacies of information seeking and retrieval. Moreover, researchers have explored a diverse array of determinants in this field, including user characteristics, such as expertise, background, topic knowledge, and cognitive abilities [30, 39, 46]. They have also investigated system functionalities, such as interface design, presentation, and quality, along with task attributes like difficulty, complexity, and topicality [29, 33]. These models and determinants collectively contribute to a deeper understanding of the dynamic nature of information seeking and retrieval, shedding light on the complex interplay between users, systems, and the information itself. However, they have been largely agnostic of the cognitive biases that impact people's search behaviour.

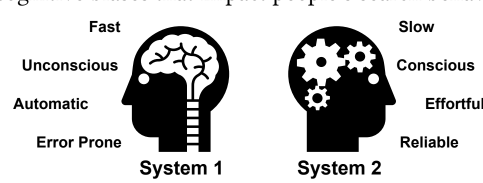

Figure 1: Thinking, Slow and Fast [25]: Cognitive biases [60], or simple heuristics that make us smart? [59]

Over the past decade there has been growing interest in understanding the influence of cognitive biases on IS&R and their consequences for information processing, knowledge acquisition, and decision-making. This concern is particularly relevant in an era marked by instant access to vast information volumes, as well as the potential exploitation of cognitive biases by search engines, content creators, and Artificial Intelligence (AI) systems [6, 11]. Moreover, questions arise about the potential interaction between cognitive biases and biases present in search engines, algorithms, and content, and whether these biases may contribute to or reinforce one another, creating a "*bias begets bias*" cycle [6]. The amalgamation of system- and user-sided biases can mutually amplify effects, both positively and negatively [37, 41]. As an increasing portion of the population relies on search and recommender systems for essential life decisions, such as medical, political, social, personal, and financial choices, understanding and mitigating the (negative) impact of cognitive biases is of considerable economic and societal significance and is also essential for building, implementing, and evaluating human-centered, responsible information systems in high-stakes decision contexts [12, 41]. Thus, this tutorial aims to bring attention to this growing body of research and applications, provide participants with an overview of cognitive biases in search, and facilitate the discussions on the potential opportunities, challenges, and practical implications of research on bias-aware IS&R. With the knowledge about human biases, we hope to provide a psychologically more realistic foundation for user models, IR evaluation measures and bias mitigation techniques in search interactions [40].

2 RELEVANCE TO SIGIR COMMUNITY

This tutorial is highly relevant to the core research interests of the SIGIR community and can bring to the forefront the nuanced interplay between human cognition and interactive information retrieval (IR) systems in varying task contexts. This initiative is not just timely but pivotal in an era where AI-assisted information ecosystems are becoming increasingly sophisticated and integral to societal functions. Our exploration into cognitive biases and heuristics sheds light on the often-overlooked psychological dimensions of search behaviors and offers a lens through which we can re-evaluate existing IR models and systems. By delving into the foundational theories of Tversky and Kahneman among others, and their application in the context of IS&R, this tutorial will present and discuss the insights regarding boundedly rational users and their interaction and evaluation strategies. This is critical for the development of next-generation search technologies that are not only technologically advanced but are also attuned to the complex tasks and cognitive processes of their users. This tutorial represents a bridge between the computational and cognitive realms of IR, presenting ideas and methodologies to better model, understand, and support users' interactions with information and IR systems.

3 SCHEDULE AND MATERIALS

The first half of this in-person tutorial will focus on the background theory from cognitive psychology, and the second half will be focus on providing examples in the context of interaction modeling, evaluation and bias mitigation. Our learning goals and reference materials are available at our tutorial website: https://beiir.github.io/.

3.1 Detailed Schedule

Part 1 - Session 1: Biases and Heuristics (1.5h). To kick off the tutorial, we will first organize a "*How biased are you?*" activity, where we will hand out some *standard survey questions* known to reveal cognitive biases, as a fun way to get participant actively engaged in understanding different biases and reflecting on the possible impact of biases in information search, IR evaluation, and decision-making.

Then, we will introduce the findings and implications on the role of cognitive biases in judgment and decision-making under uncertainty from classical behavioural experiments [e.g. 24, 58].

Part 2 - Session 2: Cognitive Biases in Search and Evaluation (1.5h). After the coffee break, we will do a deep dive into the role and impact of human cognitive biases in search interactions, document judgments, and whole-session evaluation in IS&R, and discuss the methodological challenges and practical implications of modeling search interactions from a behavioral economics perspective [5, 40].

- Cognitive Biases in Query Formulation [54, 67].
- Biases in Evaluation of Search Engine Result Pages (SERPs) [50].
- Biases, in-situ Evaluation and Retrospective Evaluation [12, 43].
- Biases in Health Information Search [53, 64, 65].
- Study Design and Methodological Challenges.

After introducing IS&R research on cognitive biases, we will ask participants to discuss in groups and propose relevant open questions, theoretical and methodological challenges, and possible practical applications they have in mind. During the discussions, we will also offer Table 1 as a checklist for tutorial participants to look up relevant papers under different domains and phases of search processes in order to facilitate their discussions.

Part 2 (cont) - Session 3: Bias Mitigation Strategies (1.5h). After lunch break, we will discuss the approaches and techniques applied to mitigating human cognitive biases in information judgments and decision-making. Our presentation will cover relevant research from IR, Recommender Systems as well as broader HCI fields on both explicit interventions (e.g. recommendation, re-ranking) and reminders and implicit nudging on interfaces [10, 14].

Part 3 - Session 4: Cognitive Biases and GenIR (1.5h). Large language models (LLM) are able to generate customized human-like responses to users' prompts, tasks, and preferences [62], and thus may cause harmful behavioral impacts when the responses trigger and reinforce users' existing biases. After coffee break, we will first discuss the potential opportunities and challenges in understanding cognitive biases in human-AI interactions and mitigating the risks of cognitive behavioral manipulation in Generative IR.

Then, we will organize breakout group discussions and match each group with a specific subtopic under the theme of session 4. Each group will discuss specific research questions under the subtopic and collaborate on designing one or two user studies or experiments that can answer some of the proposed questions.

4 PRESENTER BIOGRAPHIES

Jiqun Liu is currently an assistant professor of data science and affiliated assistant professor of psychology at the University of Oklahoma. He directs the OU human-computer interaction and recommendation (HCIR) Lab where he advises students from different backgrounds on intelligent information retrieval and recommendation, human-centered computing, and socially responsible AI research. His current research focuses on the intersection of information retrieval, machine learning, and cognitive psychology. His work applies the knowledge learned about people interacting with information in user modeling, adaptive information search and recommendation, bias mitigation and human-centered system fairness evaluation. His research on bias-aware user modeling and IR evaluation received grant support from National Science Foundation (NSF) and has been published at premier venues, such as ACM SIGIR, CHIIR, CIKM, IP&M, EMNLP, and TheWebConf. His work has also been introduced in a research monograph entitled "*A Behavioral Economics Approach to Interactive Information Retrieval: Understanding and Supporting Boundedly Rational Users*" by

Table 1: A breakdown of IS&R papers investigating different cognitive biases across domains and different parts of the search process.

	Cognitive Biases	Domains			Search Process			
		Health	Political	Web	Querying	Examining	Judging	Sat.
Too Much Information	Confirmation Bias	[19] [34] [53] [55] [63] [64] [68]	[26] [36] [35]	[54]	[34] [54] [55]	[63] [64]	[19] [53] [35] [26] [36]	
	Anchoring	[38] [53]	[50] [51]	[15] [57]		[50] [51]	[15] [38] [53] [57]	
	Availability	[19] [53] [65]	[50] [51]			[50] [51]	[19] [53]	
	Framing Effects		[50] [51]			[50] [51]		
No Meaning	Bandwagon Effects	[16] [19] [20]	[15]	[9] [31]	[31]	[9]	[15] [16] [20] [19]	
	Exposure Effects	[19] [38] [53]	[35] [17]				[17] [19] [35] [38] [53]	
	Reinforcement Effects	[38]	[35] [17]				[17] [35] [38]	
Act Fast	Decoy Effects			[15]			[13, 15]	
	Ambiguity Effects		[35] [26]	[15] [21] [27]		[26]	[15] [21] [27] [35]	
	Less is More			[52]				[52]
	Dunning-Kruger Effect			[18]			[18]	
Remember	Priming Effect		[50] [51]	[32] [54] [56] [67]	[54] [67]		[50] [51] [56]	[32]
	Order Effects	[7] [38] [53] [1]	[17]	[9] [28] [49] [66]		[9] [28] [49] [66] [1]	[7] [17] [38] [53]	
	Peak End Rule			[42]				[42]

Springer Nature and presented through numerous invited talks to both academic audiences and tech industry practitioners.

Leif Azzopardi is a Associate Professor at the University of Strathclyde within the Department of Computer and Information Sciences. Leif specializes in modelling and measuring how people interact with search and recommendation systems using theory from economics to ecology. He has over 200 peer reviewed publications on Interactive Information Retrieval focus on how user behaviour (with over 7,000 citations). Key works relevant to this tutorial include his work modelling people as economic actors [2–4] and his work summarizing the different cognitive biases affecting search [5]. He has given numerous invited talks on Formal Models of Information Seeking and Retrieval throughout the world and lectured at the Information Foraging Summer School (2011, 2012 and 2013) and Symposium of Future Directions in Information Access (2007-2013). He has given various tutorials at leading conferences, such as the Economics Models and Measures of Search (SIGIR 2019, ICTIR 2016), Modelling the Costs and Benefits of Interaction, (CHIIR CHI2019, CHIIR 2017), Simulation of Interaction (SIGIR 2016), Formal Models of Search (CIKM 2015, ICTIR 2015).

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