Fairness in Information Retrieval: An Economic Perspective

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Abstract

Fairness-aware information retrieval (IR) has attracted growing attention, with numerous metrics and algorithms proposed. However, the complexity of fairness and IR systems makes it challenging to systematically summarize progress and identify future directions. Economics has long studied fairness and offers a system-oriented perspective that naturally captures societal and intertemporal trade-offs. In this tutorial, we first frame IR systems as specialized economic markets and reorganize fairness algorithms along three key economic dimensions: macro vs. micro, demand vs. supply, and short-term vs. long-term. Unlike prior fairness-aware tutorials, this economic lens not only provides a structured reframing of fairness-aware IR, but also points toward new opportunities by encouraging the use of economic tools to address open problems.

CCS Concepts

• **Information systems** → **Information retrieval**.

Keywords

Recommender systems, Fairness, Economics

ACM Reference Format:
Chen Xu, Clara Rus, Yuanna Liu, Marleen de Jonge, Jun Xu, and Maarten de Rijke. 2026. Fairness in Information Retrieval: An Economic Perspective. In *International Conference on Multimedia Retrieval (ICMR '26), June 16–19, 2026, Amsterdam, Netherlands.* ACM, New York, NY, USA, 2 pages. https://doi.org/10.1145/3805622.3810981

1 Motivation and Scope

Background on Fairness in IR. Information retrieval (IR) systems such as search engines and recommender systems not only help users access information but also shape their thoughts [10]. Beyond accuracy, IR systems should address broader objectives like fairness [6] and bias mitigation [3], ensuring they neither discriminate against user groups [11] nor overlook long-tail creators and items [12]. Numerous fairness-aware IR algorithms have been proposed and categorized along multiple dimensions [5, 16]. This complexity arises from the diverse definitions of fairness [8] and the multiple stakeholders involved [1], making it difficult to systematically summarize existing work and identify future directions.

IR systems as economic markets. Drawing on economic theory, we map IR systems to a specialized market: users as consumers seeking high-quality items, providers as suppliers competing for exposure, and the platform as a central node akin to a government [14], delivering personalized services to maximize profits and user satisfaction. Resources are limited (a finite number of ranking slots), and ranking scores serve as market prices [2]. This shared structure naturally bridges fairness issues in economics and IR.

Benefits of using an economic perspective. The field of economics has long studied fairness, primarily focusing on how to allocate limited resources to best satisfy humans' unlimited desires [4]. Due to the established body of literature, an economic perspective on fairness offers a stronger theoretical and empirical foundation, allowing for a more structured analysis of complex fairness challenges in IR. Furthermore, the field of economics is concerned with interactions of different stakeholders in a system and analyzes the implications thereof over varying time spans. This systems-oriented thinking allows IR fairness to be embedded within a broader framework of societal and intertemporal trade-offs. By building on these well-established economic principles, fairness research in IR can benefit from greater coherence and avoid the proliferation of narrowly scoped or disconnected approaches.

IR fairness framework from an economic perspective. In this tutorial, we will elaborate on the following three economic dimensions: scale (macro – micro), objects (demand – supply), and time (long-term – short-term) of economic modeling to re-organize fairness-aware IR algorithms and evaluation methods. This perspective not only provides a novel and structured approach to reframing fairness-aware IR but also underscores the potential of applying economic principles and methodologies, such as game theory and taxation theory, to rethink and tackle fairness challenges in IR.

Target audience and prerequisites. This tutorial is designed for researchers, practitioners, and students focused on fairness and trustworthiness in IR systems, needing a basic understanding of IR and fairness, and no prior knowledge of economics.

2 Detailed Duration and Outline

This 3-hour (half-day) tutorial combines lectures, interactive demonstrations based on the FairDiverse environment [13], and Q&A sessions. The outline is as follows:

00:00–00:20 Introduction

- Introduction of IR systems and fairness.

ICMR '26, Amsterdam, Netherlands

ACM ISBN 979-8-4007-2617-0/26/06
https://doi.org/10.1145/3805622.3810981

- Taxonomy for fairness in IR.
- Organization of the tutorial.

00:20–00:50 An Economic View on Fairness in IR
- Introduction of fairness in economics.
- Relating IR systems to the economic markets.
- Re-framing fairness in IR through economics.

00:50–01:00 Q&A

01:00–01:30 Economic-based Fairness Mitigation Strategies I
- Objective: demand vs. supply
  – Demand (user) fairness [9].
  – Supply (provider) fairness [7].
  – Economic tools: taxation

Break, with Q&A

01:30–02:00 Economic-based Fairness Mitigation Strategies II
- Scale: macro vs. micro
  – Micro (individual) fairness [9].
  – Macro (group or amortized) fairness [12]
  – Economic tools: game theory

02:00–02:30 Economic-based Fairness Mitigation Strategies III
- Time: long-term vs. short-term
  – Long-term or dynamic fairness [15]
  – Short-term or static fairness [12]
  – Economic tools: risk theory

02:30–02:50 Open Problems, Future Directions, and Conclusions

02:50–03:00 Q&A

3 Presenters

Chen Xu (main contact) is a last-year Ph.D. student at Renmin University of China. His current research interests lie in fairness problems in IR from an economic perspective. He earned a double bachelor's degree in both computer science and economics. He has published over ten papers in top-tier IR conferences and journals. Chen Xu is the first author of the Best Paper Candidates for TheWebConf 2023 SIGIR 2024 with fairness issues.

Clara Rus is a fourth-year Ph.D. student at IRLab, University of Amsterdam. Her research focuses on fairness in IR, particularly fairness-aware learning to rank for algorithmic hiring. She has publications on the topic of fairness-aware rankings in venues such as RecSys, CIKM, and ECIR. Additionally, she delivered lectures on fairness-aware rankings as part of the FINDHR EU project.

Yuanna Liu is a fourth-year Ph.D. student at IRLab, University of Amsterdam. Her research focuses on fairness in IR. She has published papers on the topic of fairness-aware next basket recommendation at conferences such as SIGIR, RecSys, and ECIR. Additionally, she delivered lectures on evaluation of recommender systems as a teaching assistant for Recommender Systems course.

Marleen de Jonge is a second-year Ph.D. student. Her research interests focus on the application of representation learning and econometric methods for macro-financial research. She has published work on evolutionary computation and climate finance, and has taught classes in machine learning and econometrics.

Jun Xu is a Professor at Gaoling School of Artificial Intelligence, Renmin University of China. His research interests focus on applying machine learning to IR. He has given tutorials at top conferences like SIGIR, WSDM, TheWebConf and KDD on the topic of deep learning and fairness in IR.

Maarten de Rijke is a Distinguished University Professor of Artificial Intelligence and Information Retrieval at the University of Amsterdam. He has taught numerous courses at the BSc, MSc, and PhD level at the University of Amsterdam, numerous tutorials on a range of information retrieval topics at all the main conferences in our field, and has co-organized multiple summer schools in IR.

4 Materials

Slides & Bibliography. Slides and bibliography will be released on the tutorial website https://economic-fairness-ir.github.io/.
Related benchmark. We provide a benchmark that introduced fairness-aware IR algorithms, evaluation metrics, and datasets [13], available on https://github.com/XuChen0427/FairDiverse.

Acknowledgments. This work was funded by the National Natural Science Foundation of China (No. 62472426). This research was (partially) supported by the Dutch Research Council (NWO), under project numbers 024.004.022, NWA.1389.20.183, and KICH3.LTP.20.006, and the European Union's Horizon Europe program under grant agreements No. 101070212 (FINDHR) and No. 101201510 (UNITE).

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