



# Trustworthy Recommender Systems: Technical, Ethical, Legal, and Regulatory Perspectives

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## ABSTRACT

This tutorial provides an interdisciplinary overview about the topics of *fairness*, *non-discrimination*, *transparency*, *privacy*, and *security* in the context of recommender systems. These are important dimensions of trustworthy AI systems according to European policies, but also extend to the global debate on regulating AI technology. Since we strongly believe that the aforementioned aspects require more than merely technical considerations, we discuss these topics also from ethical, legal, and regulatory points of views, intertwining different perspectives. The main focus of the tutorial is still on presenting technical solutions that aim at addressing the mentioned topics of trustworthiness. In addition, the tutorial equips the mostly technical audience of RecSys with the necessary understanding of the social and ethical implications of their research and development, and of recent ethical guidelines and regulatory frameworks.

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## 1 MOTIVATION

Recommender systems (RSs) affect many aspects of our lives, deciding which content we are exposed to online, which items to buy, or which movies to watch. With the ever increasing adoption of – mostly opaque – deep learning technology in RSs, concerns about the trustworthiness of RSs have emerged. In particular, questions related to *fairness*, *non-discrimination*, *diversity*, *transparency*, *privacy*, and *security* have been the focus of the public debate and recent studies, e.g. [6, 8, 9]. At the same time, research on trustworthy RSs that ensure (at least some of) these properties has gained significant momentum in the past few years, e.g. [8, 11, 23].

Addressing the increasing interest in trustworthiness aspects of RSs, the tutorial will equip the mostly technical audience of RecSys with the necessary understanding of the ethical implications of their research and development, as well as political and legal

regulations that address the aforementioned challenges. As for these regulations, we will provide an overview of recent plans and policies to regulate AI technology, and their consequences for the various stakeholders of RSs. Since the European Union is at the forefront of regulating AI technologies (notably, by the Digital Service Act,<sup>1</sup> Digital Markets Act,<sup>2</sup> and AI Act<sup>3</sup>), we will foremost take a European perspective. Nevertheless, we will also discuss initiatives outside of Europe, in particular in the US and China. Since the topics addressed are vital and relevant on a global scale, we firmly believe that the tutorial will attract a global audience.

## 2 TUTORIAL OUTLINE

The tutorial is organized into five parts: an introduction including ethical guidelines for trustworthy AI and their adoption in regulatory approaches; three subsequent parts corresponding to the main themes addressed, i.e., fairness and non-discrimination; privacy and security; transparency and explainability; rounded off with a discussion of open challenges. Throughout the three main parts, we discuss three perspectives: the system-centric perspective, the human-centric perspective, and the legal perspective, covering technical aspects, human needs, and legislators' points of view, respectively. More precisely, the tutorial covers the following aspects and is organized accordingly:

### (1) Introduction

We provide details on the tutorial background, motivation, objectives, relevance for the scientific community, and recent political and legal regulations.

- (a) *Ethics guidelines for trustworthy AI*: We introduce the seven key requirements for trustworthy AI and discuss how they apply to RSs. We provide examples of related scientific publications and outline the specific challenges that need to be addressed.
- (b) *From ethics guidelines to regulatory approaches*: We discuss the translation of ethics guidelines to legal requirements, with a focus on current EU regulations, in particular the *AI Act* and *Digital Services Act*.

### (2) Fairness and Non-discrimination

- (a) *Stakeholders*: We discuss the various stakeholders of recommender systems, approaching the question for whom the system should be fair.
- (b) *Definition and quantification of bias and fairness*: We introduce the various kinds of bias and fairness concepts



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<sup>1</sup><https://digital-strategy.ec.europa.eu/en/policies/digital-services-act-package>

<sup>2</sup>[https://commission.europa.eu/strategy-and-policy/priorities-2019-2024/europe-fit-digital-age/digital-markets-act-ensuring-fair-and-open-digital-markets\\_en](https://commission.europa.eu/strategy-and-policy/priorities-2019-2024/europe-fit-digital-age/digital-markets-act-ensuring-fair-and-open-digital-markets_en)

<sup>3</sup><https://artificialintelligenceact.eu>

and definitions that are relevant for RSs research, along different axes (e.g., societal vs. statistical biases, model vs. presentation bias, provider vs. consumer fairness); we review the most common measures and metrics to quantify bias and fairness; we discuss their relation to political and legal regulations.

- (c) *Algorithms to mitigate biases and improve fairness*: We categorize the main strategies to mitigate harmful biases and improve fairness of RSs, e.g., into pre-, in-, and post-processing techniques; we present concrete methods for each of these categories.
  - (d) *Technical versus ethical and legal perspectives*: We discuss how the regulatory and legal frameworks align with the operationalization of fairness according to formal definitions often found in RSs research.
- (3) **Privacy and Security**
- (a) *Privacy risks in recommender systems*: We discuss the potential privacy risks associated with RSs, such as data leakage and disclosure of sensitive information.
  - (b) *Privacy-preserving techniques*: We introduce relevant privacy-preserving techniques and privacy-by-design learning paradigms, including: anonymization (e.g., k-anonymity and differential privacy to protect user identities); federated learning (different learning paradigms to protect individual user preferences); secure multi-party computation (techniques that allow collaborative computation without exposing sensitive information).
  - (c) *Security of recommendation models*: We discuss different types of attacks against RSs, including: profile injection (manipulating user profiles to influence recommendations); shilling attacks (creating fake accounts or profiles to bias recommendations); data poisoning (injecting malicious data to manipulate the recommendation algorithm); sybil attacks (creating multiple fake identities to impact recommendations); evasion attacks (manipulating the recommendation process by providing misleading or deceptive input); adversarial learning (exploiting vulnerabilities in recommendation algorithms and models).
  - (d) *Defense mechanisms*: We present various defense mechanisms and countermeasures against attacks in RSs, including robust modeling to build more resilient models, such as adversarial training and outlier detection, methods to identify and filter out malicious or low-quality data to prevent poisoning attacks, and approaches that dynamically adapt recommendations based on user feedback, mitigating the impact of adversarial attacks.
- (4) **Transparency**
- (a) *Categories of transparency*: We introduce the major aspects of transparency, as they relate to building trust in RS technology; we focus on explainability, traceability, and communication; we review and clarify the terminology.
  - (b) *Explainability and justification*: We discuss major strategies to achieve explainability of RSs technology, i.e., provide means to understand how the system works, targeting different stakeholders (e.g., developers vs. end users); we

review approaches to provide justifications, i.e., mechanisms for the system to justify why a system outputs a certain (list of) documents or items.

- (c) *Traceability and auditability*: We discuss strategies to keep track of the behavior of a system in a chronological way, in particular with the aim of facilitating auditing. We also point to recent works that discuss legal groundings and consequences of algorithmic auditing approaches, which is a still under-researched topic.
  - (d) *Communication and logs*: We discuss the importance of documenting the development process, the resulting models, system capabilities, intended use, and limitations.
- (5) **Open Challenges**
- (a) Understanding the discrepancy between (1) bias, fairness, and diversity metrics, (2) human perception of these aspects and factors influencing this perception, and (3) regulatory frameworks.
  - (b) Understanding the capabilities and limitations of existing technical solutions in terms of fairness, diversity, and transparency.
  - (c) Taking a multistakeholder perspective when developing solutions for fairness, privacy, security, and transparency in RS technology.
  - (d) Improving the communication between the different stakeholders and between relevant research communities, including computer science, law, ethics, economy, sociology, psychology, in order to foster interdisciplinarity.

The tutorial will be supported by a GitHub repository, containing all used materials: <https://github.com/socialcomplab/Trustworthy-RS-Tutorial-RecSys23>.

### 3 BIOGRAPHIES OF PRESENTERS

*Markus Schedl* (<http://www.mschedl.eu>) is a full professor at the Johannes Kepler University Linz (JKU), affiliated with the Institute of Computational Perception, leading the Multimedia Mining and Search group and the Human-centered AI group at the Linz Institute of Technology (LIT) AI Lab. His research interests include recommender systems, user modeling, information retrieval, machine learning, multimedia processing, and trustworthy AI (e.g., [8, 15, 18, 19]).

*Vito Walter Anelli* (<https://sisinflab.poliba.it/people/vito-walter-anelli>) is an assistant professor at Polytechnic University of Bari, affiliated with the Information Systems Laboratory (SisInflab). His current research interests fall in the areas of recommender systems, knowledge representation, and user modeling (e.g., [1–5, 7, 10]).

*Elisabeth Lex* (<https://elisabethlex.info>) is an associate professor at Graz University of Technology (TUG) and PI of the Recommender Systems and Social Computing Lab at the Institute of Interactive Systems and Data Science. Her research interests include recommender systems, user modeling, information retrieval, and data science (e.g., [12–14, 16, 17, 20–22, 24]).

Please also note that the presenters of the tutorial are currently co-authoring a book titled *Information Retrieval and Recommender*

*Systems: Technical, Ethical, and Regulatory Perspectives*, which is expected for publication by Springer Nature in 2024.

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