A survey on the impact of AI-based recommenders on human behaviours: methodologies, outcomes and future directions

LUCA PAPPALARDO, Institute of Information Science and Technologies at National Research Council (ISTI-CNR), Italy and Scuola Normale Superiore of Pisa, Italy
EMANUELE FERRAGINA, Sciences Po, France
SALVATORE CITRARO, GIULIANO CORNACCHIA, MIRCO NANNI, GIULIO ROSSETTI, Institute of Information Science and Technologies at National Research Council (ISTI-CNR), Italy
GIZEM GEZICI, FOSCA GIANNOTTI, MARGHERITA LALLI, Scuola Normale Superiore of Pisa, Italy
DANIELE GAMBETTA, GIOVANNI MAURO, VIRGINIA MORINI, VALENTINA PANSANELLA, DINO PEDRESCHI, Department of Computer Science at University of Pisa, Italy

Recommendation systems and assistants (in short, recommenders) are ubiquitous in online platforms and influence most actions of our day-to-day lives, suggesting items or providing solutions based on users' preferences or requests. This survey analyses the impact of recommenders in four human-AI ecosystems: social media, online retail, urban mapping and generative AI ecosystems. Its scope is to systematise a fast-growing field in which terminologies employed to classify methodologies and outcomes are fragmented and unsystematic. We follow the customary steps of qualitative systematic review, gathering 144 articles from different disciplines to develop a parsimonious taxonomy of: methodologies employed (empirical, simulation, observational, controlled), outcomes observed (concentration, model collapse, diversity, echo chamber, filter bubble, inequality, polarisation, radicalisation, volume), and their level of analysis (individual, item, model, and systemic). We systematically discuss all findings of our survey substantively and methodologically, highlighting also potential avenues for future research. This survey is addressed to scholars and practitioners interested in different human-AI ecosystems, policymakers and institutional stakeholders who want to understand better the measurable outcomes of recommenders, and tech companies who wish to obtain a systematic view of the impact of their recommenders.

CCS Concepts: • **Information systems** → *Collaborative filtering*; **Recommender systems**.

Additional Key Words and Phrases: recommendation systems, human-AI coevolution, human-centered AI, social impact, collaborative filtering, personalised recommendations

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Authors' addresses: Luca Pappalardo, luca.pappalardo@isti.cnr.it, Institute of Information Science and Technologies at National Research Council (ISTI-CNR), Via G. Moruzzi 1, Pisa, , Italy, 56124 and Scuola Normale Superiore of Pisa, Piazza dei Cavalieri, 7, Pisa, , Italy, 56126; Emanuele Ferragina, Sciences Po, , Paris, France, emanuele.ferragina@sciencespo.fr; Salvatore Citraro, Giuliano Cornacchia, Mirco Nanni, Giulio Rossetti, Institute of Information Science and Technologies at National Research Council (ISTI-CNR), Via G. Moruzzi 1, Pisa, Italy; Gizem Gezici, Fosca Giannotti, Margherita Lalli, Scuola Normale Superiore of Pisa, Piazza dei Cavalieri, 7, Pisa, , Italy, 56126; Daniele Gambetta, Giovanni Mauro, Virginia Morini, Valentina Pansanella, Dino Pedreschi, Department of Computer Science at University of Pisa, Largo Bruno Pontecorvo 3, Pisa, Italy.

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1 INTRODUCTION

Recommendation systems and assistants (from now on, *recommenders*) – algorithms suggesting items or providing solutions based on users' preferences or requests [99, 105, 141, 166] – influence through online platforms most actions of our day to day life. For example, recommendations on social media suggest new social connections, those on online retail platforms guide users' product choices, navigation services offer routes to desired destinations, and generative AI platforms produce content based on users' requests. Unlike other AI tools, such as medical diagnostic support systems, robotic vision systems, or autonomous driving, which assist in specific tasks or functions, recommenders are ubiquitous in online platforms, shaping our decisions and interactions instantly and profoundly. The influence recommenders exert on users' behaviour may generate long-lasting and often unintended effects on human-AI ecosystems [131], such as amplifying political radicalisation processes [82], increasing CO_2 emissions in the environment [36] and amplifying inequality, biases and discriminations [120]. The interaction between humans and recommenders has been examined in various fields using different nomenclatures, research methods and datasets, often producing incongruent findings. Consequently, the current understanding of the impact of this interaction remains fragmentary and unsystematic.

In this survey, we analyse the impact of recommenders in four largely studied human-AI ecosystems, i.e., social media, online retail, urban mapping and generative AI ecosystems. Online platforms within these four ecosystems recommend users to follow or items to consume (social media and online retail recommenders) and provide a range of solutions to users' requests (urban mapping and generative AI recommenders). These ecosystems are characterised by a pervasive influence of AI and are prototypical instances that help investigate how recommenders influence human behaviour. Therefore, their study is a vantage point for broadly understanding user-recommender interactions.

Although the attention of the literature in this regard is growing fast [27, 131, 133], the terminologies employed to define the outcomes and the methods deployed to measure them are highly fragmented. To bridge this gap, our survey provides a holistic overview of recent advances in the literature:

(1) It categorises the methodologies employed to assess the influence of recommenders on users' behaviour (empirical, simulation, observational and controlled studies) in four prominent human-AI ecosystems (social media, online retail, urban mapping, and generative AI ecosystems) ;
(2) It gathers the outcomes observed in the literature (collapse, concentration, diversity, echo chamber, filter bubble, inequality, polarisation, radicalisation, volume) and standardises the terminologies in a new parsimonious taxonomy;
(3) It disentangles the level at which the outcomes are measured (individual, item, model, and systemic levels);
(4) It suggests new avenues for future research and unveils some technical and methodological gaps in the literature from a holistic point of view.

Several surveys on recommenders have been published recently, systematising domains like explainable recommendations, knowledge-based recommendations, and deep learning-based recommendations [155, 166, 167], applications of recommenders [105] and how to evaluate them [149], the impact of diversity in recommenders [91], and bias/debias in recommenders [27]. To the best of our knowledge, this is the first work that reviews recommenders' outcomes at various levels in different human-AI ecosystems, as well as the methodologies employed to assess these impacts.

Our survey can be helpful to several public and private stakeholders. First, scholars and practitioners may obtain guidance on recent advancements in different ecosystems. Second, policymakers and institutional stakeholders may better understand measurable outcomes of actual or potential recommenders and their societal consequences, such as polarisation, congestion, segregation, etc. Third, tech companies employing recommenders may obtain a systematic view of the impact of their services to increase revenues and contribute to societal development.

The remainder of the paper is organised as follows. Section 2 details how we collected and classified the articles and built our taxonomy. In Sections 3-6, we discuss the methodologies employed and the outcomes in the four human-AI ecosystems under investigation. In Section 7, we summarise our survey findings and suggest new avenues for future research.

2 CONSTRUCTION OF THE SURVEY

2.1 Articles collection

We gathered 144 articles from different disciplines (e.g., complexity science, computational social science, computer science, marketing, management, network science, urban studies) in leading journals, conferences as well as recent unpublished material on the basis of the customary steps of qualitative systematic reviews [66]. Studies were collected from Google Scholar, Web of Science, EBSCO, and JSTOR by scanning titles and abstracts for keywords related to recommenders' outcomes in social media, online retail, urban mapping and generative AI ecosystems.

Our original results were refined by four additional steps. First, we browsed all issues of journals where the original articles were gathered in the initial search. Second, we cross-checked the bibliography of each selected article. Third, we called upon the expertise of two senior scholars and presented the article selection in a group meeting with all authors. Fourth, we eliminated the articles that did not fit our search definition after the initial classification process (see Section 2.2). Note that we only consider articles that measure the effect of recommenders on human-AI ecosystems; therefore, we exclude those only aiming to improve recommenders' performance.

2.2 Classification process

We classified each article through the following process. We split the pool of authors into four teams, one for each ecosystem. Each article was assigned to two coders, who independently read the paper, evaluated its relevance for the survey, and classified it based on a preliminary taxonomy. Ecosystem teams discussed each article, solving disagreements on the coders' classification. This step allowed each team to present a preliminary classification of the articles to the entire research group. During this presentation, the ecosystem teams illustrated doubts concerning the keywords employed and the articles that were difficult to classify under the preliminary taxonomy. These doubts were progressively solved through a series of meetings to build the final taxonomy. Our outcomes and their definitions are summarised in Table 1.

2.3 Taxonomy

We designed a taxonomy that classifies articles based on the methodologies employed (Figure 2) and the outcomes measured with their level of analysis (Table 1). We built the taxonomy through a consensus exercise among the authors. Initially, the taxonomy was built through a deductive process based on the characteristics of a sample of articles already known by the authors. All these articles have been then reclassified by the authors to validate or question each category in the taxonomy. The iterative nature of the process allowed us to progressively improve the initial taxonomy, proposing, in the end, a robust and comprehensive framework for the analysis of recommenders' outcomes.

Human-AI Ecosystems. We gather articles from four human-AI ecosystems: social media, online retail, urban mapping, and generative AI ecosystems (see Figure 1). Articles in the social media ecosystem examine recommenders that filter and suggest content or users to follow. Platforms in this ecosystem include Facebook, Google News, Apple News, Instagram, X, Reddit, Gab, YouTube, and TikTok. Research in the online retail ecosystem primarily focuses on recommenders suggesting products and services for consumption, encompassing consumer goods, songs and movies. Platforms in this ecosystem include e-commerce and streaming giants like Amazon, Alibaba, eBay, Netflix, and Spotify. Studies within the urban mapping ecosystem focus on recommenders

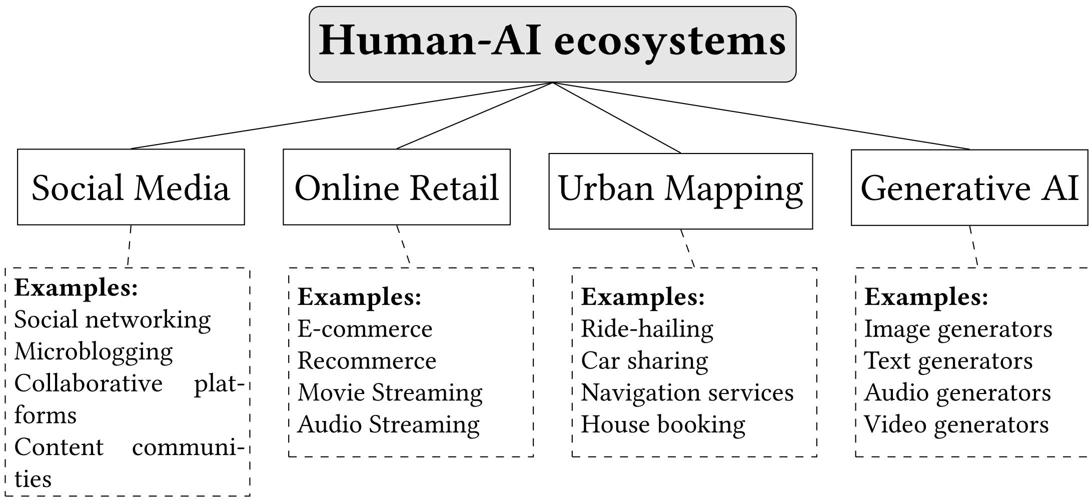


Fig. 1. Surveyed human-AI ecosystems: articles are categorized into social media, online retail, urban mapping, and generative AI. The schema illustrates real-world examples within each ecosystem.

offering a variety of solutions to users' requests. Examples include ride-hailing platforms like Uber and Lyft, navigation services like Google Maps and Waze, accommodation rental platforms like Airbnb and Booking.com, and point-of-interest search services like Tripadvisor and Yelp. The generative AI ecosystem encompasses research on tools that generate content (e.g., text, image, audio, video) based on users' prompts. Noteworthy examples include chatGPT, LLama, Mistral, and DALL-E.

The interdisciplinary team of authors – including computer scientists, complexity scientists, mathematicians, and sociologists – has been constructed to cover expertise on these four human-AI ecosystems and the different methodologies employed. This classification is mirrored in the paper's organisation. Each section corresponds to a human-AI ecosystem, enhancing readability and accessibility for readers interested in specific application contexts. This structure allows readers to focus on their areas of interest without the necessity of delving into ecosystems less relevant to their concerns.

Methodologies. We systematically categorise articles within each human-AI ecosystem into empirical and simulation studies. Within each category, we distinguish between controlled and observational studies. Empirical studies derive insights from data produced by user and recommenders' interactions. When datasets are large and diverse, these studies allow for broad generalisations. However, the ability to draw universal conclusions is constrained by specific geographic, temporal and contextual circumstances. Moreover, reproducing these studies is challenging because data are often owned by big tech companies that are generally reluctant to share them.

Simulation studies are anchored to model-generated data, whether mechanistic, AI-driven, or based on digital twins. They offer an alternative methodological pathway to deal with large-scale ecosystems or when data is not readily available. These studies allow reproducibility under the same initial conditions, facilitating result validation and verification. By manipulating parameters, scholars can scrutinise recommenders' impacts on the human-AI ecosystem, improving the understanding of intricate human-recommender interactions. However, as they are based on heavy assumptions, simulations do not necessarily reflect real-world dynamics and are limited in unveiling unexpected or unintended outcomes. Simulation studies can be realised as prototypes for a preliminary feasibility evaluation of subsequent empirical and controlled studies.

Both empirical and simulation methodologies can employ observational or controlled approaches. Controlled studies comprehend quasi-experiments, randomised controlled trials, and A/B tests [42, 71]. These studies divide user samples into control and treatment groups exposed to different recommendations. Sample randomisation may reduce selection biases, ensuring that participants in both groups have an equal chance of receiving the recommendation. Controlled studies enable researchers to control for various factors and conditions, allowing the isolation of the effect produced by a specific intervening variable. Their main advantage is establishing causal relationships and attributing observed effects to the recommendation. However, a limitation stems from the interaction among individuals [11]. In complex social systems, individuals within the control group can never be isolated from the indirect effects of recommendations, as they are also influenced by choices made by users in the treatment group. Therefore, controlled experiments may not satisfy the Stable Unit Treatment Value Assumption (SUTVA) for causal inference [39] and might not provide unbiased estimates of causal quantities of interest. Controlled studies also have other important shortcomings: the inclusion and exclusion criteria of the controlled settings might limit the generalisability of findings; and there is limited flexibility in adapting to changes intercurring during the experiments. Moreover, they are hard to design because they require direct access to platforms' users and recommenders [88]. While platforms routinely conduct internal controlled studies to validate different recommenders and maximise user engagement [6], access of external researchers to the studies' results is restricted.

Observational studies, whether grounded in empirical or synthetic data, operate without control, assuming a single recommendation principle for the entire population. These studies include the analysis of Facebook users' behaviour, Google Maps' driver suggestions, and data gleaned from browser loggers and platform APIs [5]. While offering broad insights when data is large and representative, observational studies struggle to establish causal relationships firmly, often necessitating supplementary evidence. Additionally, they are susceptible to biases, measurement errors, and issues related to confounding variables, which may compromise their accuracy and reliability.

To clarify the differences between these methodologies, we propose some prototypical examples. If we have access to data reflecting users' behaviour on a platform and solely analyse this data, we conduct an empirical observational study. However, if only a subset of platform users is exposed to a recommender, and we compare the behaviours of those exposed to those who are not, this is an empirical controlled study. On the other hand, when actual platform data are inaccessible, and we generate synthetic data through simulation tools (such as a digital twin), we conduct a simulation study, which can be observational or controlled, as discussed above. It is essential to acknowledge that quasi-experiments [60], in which an exogenous element splits the population into two or more groups, according to our definition, must be considered controlled studies. Differently, when an exogenous element does not segment the population into different groups, studies have to be considered observational in their methodological approach. A paper may be classified under different methodologies if it employs two or more of them.

Outcomes. We define an outcome as the result of a recommender's influence on a human-AI ecosystem. We initially defined outcomes inductively and then refined them deductively. First, we let the team classify the outcomes using the keywords in the articles. Then, in subsequent meetings, we uniformed the categories using terms that could broadly cover these keywords. For example, popularity bias and concentration refer to a similar kind of outcome. We opt for concentration because it fits different ecosystems. We also extend the term concentration to describe situations with consensus around an attribute (e.g., opinions in social media ecosystems). This parsimonious classification is a crucial contribution of this paper because it allows for the standardisation of outcomes terminology across different fields of study.

In the literature, outcomes are measured at different levels: individual, item, model, and systemic. Individual outcomes refer to the effects of recommenders on users. Users may be drivers and passengers in the urban mapping ecosystem and sellers and buyers in the online retail ecosystem. Item outcomes refer to the effects of

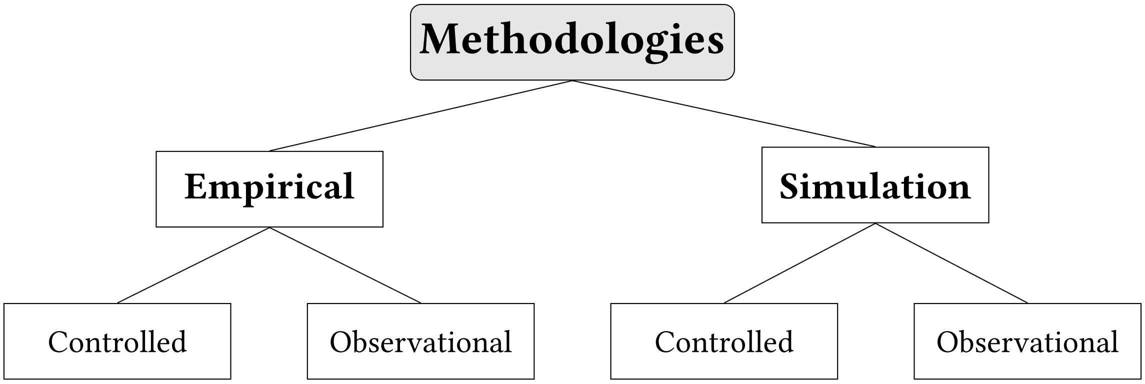


Fig. 2. Two-level categorization of methodologies of the surveyed articles. At a first level, we categorize articles into empirical or simulation; at the second level we classify them as controlled or observational

recommenders on specific objects. Items may include posts on social media, products on online retail platforms, rides in urban mapping platforms, or generated content on generative AI platforms. Systemic outcomes refer to collective effects of recommeders.

Table 1 provides the definition and analytical level of the recommenders' outcomes investigated in the literature (see Figure 3 for the frequency of outcomes encountered in these studies). In our taxonomy, each outcome is associated with a single analytical level, except for *diversity* and *volume*, which can be individual, item, and systemic. To illustrate this point, we showcase examples from the online retail ecosystem. Various studies examine changes in revenue and purchased products, measuring whether users spend more (individual level), specific items are purchased more (item), and aggregate consumption increases or decreases (systemic). Similarly, they explore whether users engage with a more diverse range of products (individual), items are purchased by a more diverse set of users (item), and aggregate consumption diversity increases or decreases (systemic). The other recommenders' outcomes are: *radicalisation* in the social media ecosystem (individual), *filter bubbles* in social media and online retail ecosystems (individual); *model collapse* in the generative AI ecosystem (model); *concentration*, *echo chamber*, *inequality*, and *polarisation* in social media, online retail, and urban mapping ecosystems (systemic). The distinction between different analytical levels allows us to disambiguate some outcomes that are often confused in the literature. For example, the terms filter bubble and echo chambers are often used interchangeably in the social media ecosystem.

Some recommenders' outcomes appear in the literature with a different nomenclature. This happens both within the same ecosystem and across different ecosystems; some examples help clarify this point. The terms polarisation and fragmentation are slightly different: polarisation has been developed to capture different opinions, mainly in contexts with a clear division into two groups; fragmentation instead indicates the presence of more poles of polarisation. This distinction mainly comes from historical reasons, as seminal studies on polarisation originated in the US bipartite system. The term polarisation has been extended to cover the study of political attitudes in multi-party systems. Consequently, the term polarisation has been stretched to describe a wide array of scenarios (at present, there are at least twelve definitions of polarisation in the literature [23]). For the sake of parsimony, we merge studies on fragmentation and polarisation into one category labelled polarisation. Within the urban ecosystem, we devised another simplification of the terms concentration and congestion. We consider the latter to be an extreme case of the former.

It is important to acknowledge that some outcomes in the classification may partially overlap. For example, the concentration of user purchases can also be associated with a reduction of diversity at the systemic level. However, the opposite is not always true: diversity reduction does not imply an increase in concentration. Therefore, to provide a detailed picture of the surveyed studies, we consider all pertinent outcomes.

Level	Outcome	Description	Ecosystems
Individual	Diversity	Variety of users' behaviour, items consumed and users followed	SM, OR, UM
	Filter Bubble	Conformation of items or contents with own preferences or beliefs	SM, OR
	Radicalization	Items or individual attributes going towards an extreme	SM
	Volume	Quantity value of some users' attribute	SM, OR, UM
Item	Diversity	Variety of users that consume the item	SM, OR, GAI
	Volume	Quantity value of some items' attribute	SM, OR, UM
Model	Collapse	AI model degradation over time	GAI
Systemic	Concentration	Close gathering of people or things	SM, OR, UM
	Diversity	Aggregate diversity of users or items	SM, OR, UM
	Echo Chamber	Environment reinforcing opinions or item choices within a group	SM, OR, UM
	Inequality	Uneven distribution of resources/opportunities among group members	SM, OR, UM
	Polarization	Sharp separation of users/items into groups based on some attributes	SM
	Volume	Aggregate volume of users' or items' attributes	SM, OR, UM

Table 1. The table details: the definition of each outcome, its level of analysis, and the ecosystems where it can be found. We use the following acronyms for each ecosystem: social media (SM), online retail (OR), urban mapping (UM), and generative AI (GAI).

3 SOCIAL MEDIA ECOSYSTEM

What the ecosystem is about. The social media ecosystem includes social networking platforms, community and non-community content systems that promote content creation and sharing, and interaction among users. Social networking platforms include Facebook, Instagram, TikTok, and X (previously, Twitter). Community content platforms encourage users to join interest-based communities (e.g., Reddit and Gab) or engage in video consumption (e.g., YouTube). Non-community content platforms, like Google News or Apple News, diffuse their own content.

Main methodologies employed. There is a marked preference for observational studies (see Figure 4). This is because empirical research can also be conducted by researchers external to the platform via data sharing or APIs. Moreover, synthetic data may be easily gathered from agent-based and opinion dynamics models, allowing a successive analysis. Typically, empirical observational studies in this ecosystem exploit bots to simulate user behaviours (sock-puppet studies), collect information about the provided recommendations, or perform user surveys. Simulation observational studies are primarily based on agent-based modelling, with a minority of works focusing on a single user. Only a few empirical studies are controlled (see Figure 4), and this is because they require direct access to users' data to build control and treatment groups and to enable/disable recommenders'

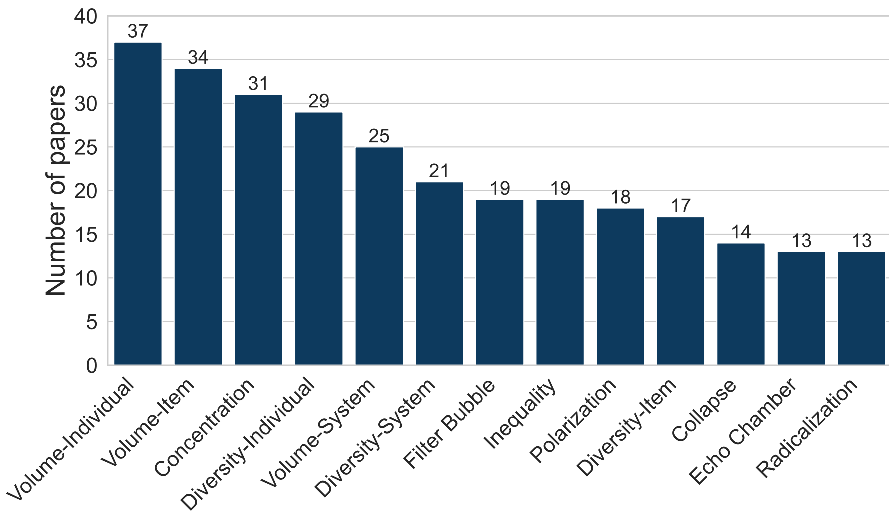
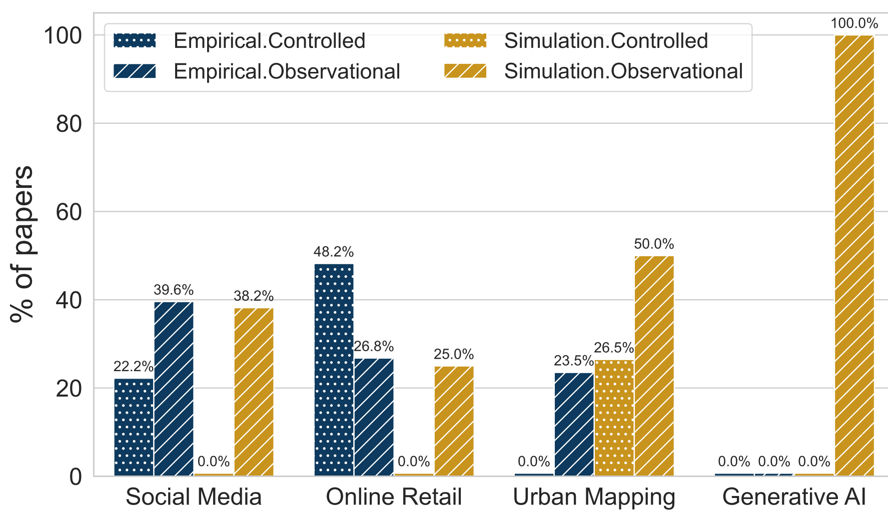


Fig. 3. Frequency of outcomes in the selected studies.



(a)

Fig. 4. Percentage of employed methodologies for each human-AI ecosystem.

features to assess effects on users. We do not find simulation-controlled studies as open digital twins are not available to replicate the main characteristics of real social media platforms. There is, instead, a preference for abstract simulations. In these studies different recommenders are tested across various independent experiments.
Main outcomes. Research within this ecosystem examines nearly all outcomes contained in our taxonomy, except model collapse (see Table 2 for a comprehensive outlook). As the role of recommenders is highly pervasive

Social Media		Empirical		Simulation	
		Observational	**Controlled**	**Observational**	**Controlled**
Individual	**Filter Bubble**	[14, 22, 25, 30, 33, 65, 72, 76, 80, 92, 93, 162]	[17]	[140, 142]	
	Radicalization	[13, 25, 72, 79, 80, 83, 94, 139, 160]	[113]	[85, 140, 142, 157]	
Model	**Collapse**				
Systemic	**Concentration**	[76, 87, 94, 153]	[16, 113]	[41, 51, 52, 56, 134, 135, 137]	
	Echo Chamber	[14, 25]	[126]	[32, 34, 128, 129, 135, 137, 157, 159]	
	Inequality	[76, 87, 94, 145, 153]	[16, 82, 113]	[51, 52, 56, 135, 137]	
	Polarization	[33, 65, 162]	[67, 68, 102, 106, 126]	[32, 41, 128, 129, 134, 135, 137, 138, 150, 159]	
Individual Item Systemic	**Diversity**	individual: [14, 22, 25, 30, 33, 65, 72, 92, 162], item: [14, 19, 122, 169]	individual: [17], item: [102, 113, 126],	individual: [41, 62, 138, 140, 157], systemic: [51, 52, 56, 85, 135, 137, 142]	
	Volume	individual: [83], item: [13, 19, 22, 25, 72, 76, 87, 94, 145, 153, 160, 169]	individual: [16, 17, 67, 68, 102], item: [16, 67, 68, 82, 126], systemic: [163]	individual: [51, 52, 56, 135, 137, 139], systemic: [62]	

Table 2. Social Media Ecosystem. Classification of selected papers based on their methodology, outcomes and level of analysis.

in social media platforms, the literature is more extensive than in the other ecosystems under investigation: 53 out of 144 papers reviewed belong to this ecosystem.

3.1 Empirical studies

Observational studies. Ribeiro et al. [139] audit radicalisation pathways on YouTube's video and channel recommendations. By analysing users' migration patterns across 330k videos from 349 politically related channels, the study finds a recommendation flow from milder to more extreme (alt-right) content. Radicalization

Brown et al. [25] likewise explore whether YouTube's algorithm pushes users into filter bubbles and echo chambers or displays biases towards some political content. Through analysing videos' political orientation and surveying 527 users who navigate the platform according to randomly assigned rules, the study finds minimal evidence of filter bubbles and echo chambers. However, it identifies a platform bias leading to a stronger amplification of moderately conservative content. Radicalization Filter Bubble Echo Chamber Diversity.Individual Volume.Item

Similarly, Santini et al. [145] focus on Brazilian elections to examine YouTube's promotion of hyperpartisan content. They use a non-probabilistic sampling technique and analyse the news sources recommended on the platform by simulating the browsing behaviour of new users. The findings highlight an increase in inequality with preferential treatment for right-wing media outlets over similar content from left-wing media outlets. Inequality Volume.Item

Haroon et al. [72] investigate YouTube's recommender tendency to generate filter bubbles, radicalisation pathways, and extremist or problematic content recommendations. They rely on a sock-puppet audit using 100k accounts designed to represent various political leanings. The study discovers a filter bubble effect, particularly pronounced for right-leaning users. It also finds an increase in recommendations from channels linked to extremist or conspiratorial content, particularly for users characterised by views of extreme right-wing content. Filter Bubble Diversity.Individual Volume.Item Radicalization

Hosseinmardi et al. [79] investigate the role of users' preferences on received recommendations. They retrieve browsing histories of 310k users and profile these users based on viewing habits. The researchers then analyse on- vs. off-platform consumption habits of users, pathways to radical political content, and the effect of session length on content type exposure. In contrast with previous research, this study finds little evidence of the amplification of political content and radicalisation pathways. Radicalization

Ledwich and Zaitsev [94] examine the role that YouTube's recommender plays in encouraging online radicalisation. By examining the recommendation patterns among 800 political channels, the research finds that rather than promoting radical or extremist content, the algorithm amplifies views for mainstream media and politically neutral content. Radicalization Inequality Concentration Volume.Item

Heuer et al. [76] investigate the biases behind YouTube's video recommender. The study selects nine relevant political topics in Germany and performs a sock-puppet audit based on random walks to select video recommendations. The findings support the disparities highlighted by Ledwich and Zaitsev [94], showing that YouTube increases recommendations for popular and mainstream content rather than radical and extreme ones, but these recommendations do not focus on a particular topic. The study also finds an emotional shift effect in recommendation trails: videos perceived by users as sad and negative are increasingly replaced by videos conveying happier content. Filter Bubble Inequality Concentration Volume.Item

Ibrahim et al. [83] focus on YouTube's recommender propensity to create political filter bubbles. The study collects video recommendations via a sock-puppet audit with 360 bots that represent six personas across the US political spectrum. The findings show that the recommender steers users away from political extremes toward more moderate content. This effect is more pronounced for far-right than for far-left content. Radicalization Volume.Individual

Cho et al. [33] investigate the impact of YouTube's personalised recommender on political polarisation. The researchers conduct a laboratory experiment with 108 undergraduate students, where they manipulate the participants' search and watch histories related to the 2016 US presidential election. The findings indicate that algorithmic recommendations contribute to the creation of a filter bubble, reinforcing individuals' existing political beliefs. Filter Bubble Polarization Diversity.Individual

Hosseinmardi et al. [80] estimate the causal impact of YouTube recommendations on the consumption of highly partisan and radical content. The study compares the behaviours of bots designed to mimic real users' viewing patterns with those of bots following predefined rule-based trajectories. The findings show that the recommender does not steer users towards radical content. On the contrary, when users with strong political views start watching moderate content, the recommender shifts their recommendations after approximately 30 videos, assisting users in breaking out of their filter bubbles. Radicalization Filter Bubble

Le Merrer et al. [93] examine the impact of YouTube's personalised recommendations on generating filter bubbles and rabbit holes. The researchers conduct a sock-puppet audit to gather video recommendations and propose a straightforward theoretical model explaining why and how rabbit holes form on YouTube. The results indicate that user interactions could influence recommendations, but users are not consistently led further into specialised content. In fact, after a certain number of interactions, YouTube's recommender may forget previous user preferences, breaking down users' filter bubbles. Filter Bubble

Zhou et al. [169] investigate the impact of various YouTube features on video views, with a focus on the recommender's effectiveness in driving video popularity. By analysing metadata, related video lists, and view statistics for hundreds of thousands of videos, the study finds that recommendations increase video views and promote a wider variety of videos rather than just promoting the most popular ones. Volume.Item Diversity.Item

Kirdemir et al. [87] inspects YouTube's recommendation biases across different topics, languages, and entry points. The study analyses the structure of video recommendation networks through PageRank distributions, covering 257k videos and 803k recommendations. Despite variations based on factors like video language, content topic, and the source of seed videos, all experiments reveal an increase in recommendations for a small fraction of videos, fostering inequalities and a "richer get richer" effect. Volume.Item Concentration Inequality

Yang et al. [162] explore the dynamics of personalised search on Twitter using a sock-puppet audit. The findings indicate that factors such as following behaviour, cookies, and previous searches have a limited impact on personalisation. However, when it comes to polarised searches, the results reveal a noticeable bias toward one-sided views, raising concerns about filter bubbles. Filter Bubble Polarization Diversity.Individual

Using a similar sock-puppet audit methodology, Chen et al. [30] evaluate the impact of Twitter's content curation mechanism on the creation of political filter bubbles. The study finds that although the political alignment of a bot's initial connections influences its exposure to political content, there is weak evidence to support the presence of inherent political bias in the recommender. Filter Bubble Diversity.Individual

Su et al. [153] examine the impact of Twitter's "Who-To-Follow" recommender, comparing the social networks collected before and after the recommender was implemented. The findings reveal that there is a concentration of "follow" recommendations for the most influential users, leading to a rich-get-richer phenomenon. The study also identifies a feedback loop where recommendations for popular users often result in more followers, exacerbating existing network inequalities. Inequality Concentration Volume.Item

Bouchaud [22] explore how Twitter's engagement-maximising recommender affects the visibility of tweets by Members of Parliament in users' timelines. The researchers use tunable engagement predictive models to simulate users' timelines and a Twitter dataset collected via a browser add-on installed by volunteers. The findings show that engagement-based timelines display lower ideological diversity, leading to the creation of a political filter bubble. Additionally, the study uncovers inequalities in reach among political groups, with right-wing parties being prioritised over left-wing ones. Filter Bubble Diversity.Individual Volume.Item

Bakshy et al. [14] explores the impact of Facebook's recommender on the formation of filter bubbles and echo chambers. The researchers examine the news consumption patterns of 10 million users in the US, focusing on how their political beliefs align with the content they encountered in their news feeds and through their connections with friends. The study finds that individual choices have a more significant impact than Facebook's recommender in limiting exposure to diverse political news. Additionally, the researchers emphasise that users' friend networks can serve as a potential source of diverse perspectives. Echo Chamber Filter Bubble Diversity.Individual Diversity.Item

In a collaborative effort between Meta and a team of external researchers, González-Bailón et al. [65] investigate the presence of filter bubbles in political news on Facebook during the US 2020 election. The researchers analyse news content and assess its ideological alignment with the content 208 million users visualise and interact with. In contrast to Bakshy et al. [14], this study reveals that algorithmic curation worsens filter bubbles, with conservative users exhibiting less diverse consumption patterns than liberals. Additionally, conservatives engage more with news ecosystems that feature misinformation. Filter Bubble Polarization Diversity.Individual

Boeker and Urman [19] investigate how user actions and their attributes impact recommendations displayed on TikTok's "For You" page, using a sock-puppet audit. The research reveals that likes, follows, watch duration, as well as user language and location settings all play a role in shaping the volume and nature of content recommended to users. Among these factors, follows, video view rate, and likes are the most influential in determining the content presented to users. Volume.Item Diversity.Item

Baker et al. [13] investigate whether the recommenders on YouTube Shorts and TikTok contribute to the radicalisation of young males. The study creates fake accounts posting as 16 and 18-year-old boys with different content interests and analyses 29 hours of recommended videos. The findings reveal that on both platforms, the prevalence of toxic content such as reactionary right-wing, conspiracy, and manosphere content significantly increases once users engage with it, eventually constituting over 75% of recommendations. Furthermore, YouTube Shorts recommends more toxic content compared to TikTok. Volume.Item Radicalization

Using sock-puppet audit, Le et al. [92] examine whether Google News personalises search results based on a user's political browsing history. Sock-puppets, representing distinct political views (pro- and anti-immigration), browse related content and conduct identical searches on Google News. The findings show significant personalisation in Google News search results, indicating the presence of a filter bubble that reinforces the assumed political bias of sock-puppets. Filter Bubble Diversity.Individual

Möller et al. [122] explore how various news recommenders affect content and topic diversity. The researchers analyse data from a Dutch newspaper and assess recommenders based on editor choices, popularity, collaborative filtering, and semantic filtering. The evaluation includes topic, category, tag, and tone diversity. The findings show that while standard recommenders maintain topic and sentiment diversity, personalised collaborative filtering achieves the highest topic diversity. Diversity.Item

Whittaker et al. [160] investigate whether recommenders on YouTube, Reddit, and Gab promote radicalisation pathways. The researchers use a sock-puppet audit, exposing bots to varying levels of extreme content. The findings indicate a clear trend towards the promotion of more radical content on YouTube, especially after interacting with far-right material. Reddit and Gab do not show a significant algorithmic promotion of extremist content. Radicalization Volume.Item

Controlled studies. Liu et al. [102] investigate the impact of algorithmic recommendations on political polarisation using a custom video platform akin to YouTube, involving 7,851 participants. The researchers collect videos on gun control and minimum wage, then manipulate YouTube's recommender, submitting a balanced version to one group of users and a slanted version to another group. The findings indicate that while the altered recommendations affect the diversity of videos selected and the volume of user engagement, they do not significantly influence users' political attitudes. Polarization Diversity.Item Volume.Individual

Markmann and Grimme [113] investigate whether YouTube's autoplay recommender leads users to more radical and extreme content. By using remote control of the browser, the researchers gather data from two groups of accounts: one with personalised recommendations and one without. The findings suggest that autoplay fosters engagement-boosting content, which may be sensational or extreme. Overall, the diversity of recommended content is not significantly affected by personalisation. Radicalization Inequality Concentration Diversity.Item

Bartley et al. [16] examine how Twitter's recommender impacts users' information consumption habits. The researchers conduct a sock-puppet audit, dividing users into a treatment group that receives personalised tweet recommendations and a control group where recommendations are provided in inverse-chronological order. The study finds that personalised recommendations tend to prioritise popular content, leading to a "rich get richer" effect and increased visibility for a minority of accounts. As a result, there is a strong inequality in the visibility of content and users on the platform. Inequality Concentration Volume.Individual Volume.Item

Huszár et al. [82] analyse how Twitter's timeline algorithm affects the amplification of political content employing proprietary data and a multi-year experiment with nearly two million users. They compare a control group with a reverse-chronological feed against a treatment group with personalised feeds. Their findings reveal that mainstream right-leaning political content is consistently more amplified than left-leaning content. Additionally, the study indicates that algorithmic amplification generally increases the visibility of mainstream news sources in the US, while it does not disproportionately boost far-left or far-right groups compared to moderates. Inequality Volume.Item

In a collaborative effort initiated in early 2020, Meta and a team of external researchers launched the US 2020 Facebook and Instagram Election Study[1] that resulted in the publication of four articles [65, 67, 68, 126], three of which are empirical controlled studies. Guess et al. [67] compare the behaviour of Instagram and Facebook users in a control group receiving chronologically ordered feeds to a treatment group of users with personalised recommendations. Chronologically ordered feeds show a decrease in platform engagement and exposure to uncivil content yet an increase in access to political and untrustworthy information. Over three months, these changes did not significantly influence polarisation levels, political knowledge, or other major attitudes. Guess et al. [68] extend this study by exploring the effects of reshared Facebook content on political news exposure and its impact on political polarisation and knowledge. By comparing a control group with a standard feed to a treatment group with reshared content removed, the researchers observe a significant reduction in exposure to political news, particularly from unreliable sources. Also, this reduction does not affect political polarisation or attitudes but leads to a noticeable decrease in users' political knowledge. Polarization Volume.Item Volume.Individual Nyhan et al. [126] examine the impact of reducing Facebook users' exposure to like-minded political content during the 2020 US election. The researchers compare a treatment group of more than 20,000 users subjected to an algorithm that considerably reduces their exposure to like-minded content to the rest of the population. The findings reveal that the treatment leads to increased exposure to more diverse content and a decrease in the use of uncivil language. The study does not find any evidence of shifts in the polarisation of beliefs, nor does it observe the formation of echo chambers. Echo Chamber Polarization Volume.Item Diversity.Item

Ludwig et al. [106] investigate the impact of news recommenders on political polarisation. The researchers conduct an online experiment involving 750 participants and divide them into four groups. Each group is exposed to a different type of news recommender: content-based, content-based with positive sentiment, content-based with negative sentiment, or no recommendations. Their findings indicate that recommenders do not significantly modify polarisation levels. However, prolonged use of content-based recommenders with negative sentiment increases affective polarisation, while a content-based recommender with balanced sentiment leads to ideological depolarisation over time. Polarization

Yang [163] explores the impact of "most-viewed" news recommendations on user engagement with news stories, recruiting 107 participants who use a website mimicking real news platforms. The participants are divided into a treatment group that receives popularity-based recommendations and a control group that does not. The

[1]https://research.facebook.com/2020-election-research/

study collects several variables, such as recommended content features and exposure duration. The findings show that participants in the treatment group view more recommended news stories, engage with such content for longer periods, and spend less time independently browsing for news stories. Volume.System

Beam [17] investigates the impact of personalised news recommenders on political news exposure, user engagement, and political knowledge. The researchers assign 490 adult Internet users to either a generic news page or one of four personalised conditions, differing by recommendation source (computer-generated vs. user-customised) and content display (recommended stories only vs. all stories). The study reveals that personalisation increases filter bubbles and reduces viewpoint diversity. However, certain design choices, such as user customisation or displaying only recommended stories, can partially offset these effects by fostering deeper engagement and indirectly boosting political knowledge. Filter Bubble Diversity.Individual Volume.Individual

3.2 Simulation studies

Observational studies. Sîrbu et al. [150] examine the impact of biasing interactions towards like-minded individuals in synthetic social networks. The researchers introduce a recommender parameter that influences the probability of interacting with users who hold similar opinions. By simulating opinion evolution on a fully connected network under bounded confidence, the study reveals that stronger semantic bias in the recommender leads to increased opinion polarisation. Polarization

Pansanella et al. [128] builds upon Sîrbu et al.'s research by exploring various network topologies, including random, scale-free, and clustered networks. The study reveals that opinion polarisation persists across different network topologies. Additionally, introducing a certain degree of sparsity in the network amplifies the divisive impact of recommenders on the distribution of opinions within the population. Furthermore, the researchers indicate that the presence of homophilic communities, combined with cognitive biases, leads to the formation of echo chambers. In an expanded version of this model, Pansanella et al. [129] explore the impact of adaptive topologies, which allow connections to be changed from conflicting agents to those with similar views. The study finds that recommenders may intensify polarisation and hinder the formation of echo chambers. This is due to the homophilic rewiring process and the evolution of opinions. Polarization Echo Chamber

Building on a different opinion evolution model, Valensise et al. [159] simulate social network sessions exposed to a feed algorithm that adjusts the range of opinions viewed by users. The simulation accounts for bounded confidence and adaptive topologies. The study finds that a strong filtering algorithm increases polarisation, while milder personalisation is necessary for echo chamber formation. Polarization Echo Chamber

Chitra and Musco [32] explore the impact of recommenders on social network polarisation using an opinion dynamics model. A recommender encourages connections among users with similar viewpoints, thus creating a similarity bias. The findings show that a greater bias results in increased polarisation and the creation of echo chambers within clustered networks. Polarization Echo Chamber

Perra and Rocha [137] examine the impact of different network topologies and timeline filtering strategies, such as random, chronological, reverse chronological, semantic ordering, and nudging. The researchers represent users' opinions as binary variables, simulating a two-party system, and find that algorithmic filtering exacerbates initial inequalities and reduces the visibility of minority opinions. The study also highlights that semantic or temporal biases in highly clustered networks lead to opinion polarisation and the formation of echo chambers. Additionally, combining semantic filtering and nudging in networks with spatial correlations impedes convergence, reinforcing echo chambers that resist nudged opinions. Polarization Echo Chamber Inequality Concentration Diversity.System Volume.Individual

Peralta et al. [135] investigate the interactions between semantic filtering and network topology. Semantic filtering is adjusted using a bias parameter that hides a portion of the population from the agent. The stronger the bias, the more contrasting opinions are hidden. The study employs mathematical analyses and simulations of extended binary opinion models considering pairwise and group interactions. The findings show that semantic bias drives opinion polarisation and echo chamber formation in modular networks, while it fosters only polarisation in non-modular networks. When the bias is below a certain level, it encourages consensus around a single opinion after pairwise or small-group interactions, whereas interacting in larger groups encourages polarisation. In subsequent work, Peralta et al. [134] expand their model to include algorithmic nudging, where the algorithm exhibits a bias towards one of two opinions. The simulations reveal that if the social platform favours the opinion of the minority group, it promotes polarisation. Conversely, if the visibility of the minority opinion is hindered, it leads the population towards consensus. Concentration Echo Chamber Inequality Polarization Diversity.System Volume.Individual

Gausen et al. [62] investigate the impact of different recommenders on the spread of information in news feeds. Using an agent-based model to simulate information diffusion and opinion evolution, the researchers compare a random recommender with three filtering strategies: chronological, belief-based, and popularity-based. The findings reveal that belief-based and popularity-based recommenders increase the spread of information, while the random recommender decreases the amount of content shared. Additionally, belief-based recommenders lead to a higher belief purity of agents' feeds, decreasing content diversity. Volume.System Diversity.Individual

Törnberg et al. [157] investigate echo chambers and toxicity using Large Language Models (LLM) to simulate social media interactions. The study evaluates three feed algorithms: one that shows posts from followed users, one that shows posts from all users, and one that ranks posts by likes from the opposite party to bridge the gap between different viewpoints. In the simulation, LLM agents select and interact with news stories to simulate a day of activity. The results indicate that the first algorithm reduces toxicity but creates echo chambers; the second produces the opposite effect, while the bridging algorithm mitigates echo chambers and reduces toxicity. Radicalization Echo Chamber Diversity.Individual

De Marzo et al. [41] investigate how collaborative filtering affects opinion polarisation, specifically focusing on the impact of recommendations on content exploration. The study examines a non-networked population in which users are exposed to either user-user collaborative filtering or a matrix factorisation algorithm. The findings indicate that over time, the population tends to converge towards a state of consensus, where all users become highly similar. User-user collaborative filtering does not lead to polarisation but increases diversity in clicked items compared to scenarios without algorithmic assistance. Conversely, the matrix factorisation algorithm contributes to opinion polarisation within the population. Concentration Polarization Diversity.Individual

Cinus et al. [34] look into the long-term evolution of opinions when people recommenders are used on synthetic networks with tunable levels of homophily and segregation. The findings reveal that when initial network conditions are homophilic and non-modular, following link recommendations leads to the formation of echo chambers. This effect becomes absent or reversed if networks are already segregated or heterophilic. Additionally, the more personalised the recommendations, such as those based on the algorithmic bias proposed by Sîrbu et al. [150], the more they contribute to the rise of echo chambers. Echo Chamber

Similarly, Ramaciotti Morales and Cointet [138] explore how the evolution of links, combined with an opinion evolution model, impacts polarisation. The study shows that when there is no biased assimilation, i.e., the tendency to be more influenced by similar opinions, some recommenders reduce polarisation, while others slightly increase it. However, with high levels of biased assimilation, all recommenders lead to smaller increases in polarisation compared to what is caused by sole cognitive biases on a fixed population. This indicates that recommenders often expose users to more diverse connections, mitigating polarisation compared to what would be achieved through user choice alone. Polarization Diversity.Individual

Fabbri et al. [51] investigate how homophily and different types of recommenders affect minority groups in social networks. The researchers compare random link prediction with link prediction algorithms based on network topology, random walk, and collaborative filtering. They then create recommendations in a social network divided into a majority cluster and a minority cluster. The findings indicate that recommendations increase the visibility of the minority group if they are homophilic. If this is not the case, the majority class receives increased visibility. Additionally, hubs within the minority group receive even greater visibility, exacerbating existing inequalities. In a follow-up of this study, Fabbri et al. [52] examine the long-term impacts of user-recommendations feedback loops. The findings indicate that recommenders increase the visibility of the minority groups with homophilic initial conditions and exacerbate concentration (rich-get-right effect) in the long term. Inequality Concentration Diversity.System Volume.Individual

Ferrara et al. [56] investigate the impact of user recommenders on networks with two distinct groups, one being the minority category. The researchers consider various recommenders suggesting new connections while removing existing random links. These include personalised page rank (PPR), egocentric random walks (WTF), friends-of-friends recommender (2H), common-following (CF) users recommenders, and Node2Vec (N2V). The findings indicate that networks become more closely connected with repeated recommendations, regardless of the algorithm used. However, not all tested algorithms exhibit a concentration (rich get richer) effect: Node2Vec prevents the network from increasing inequalities. Overall, CF can increase or decrease the visibility of the minority, N2V maintains a balanced impact, and PPR, WTF, and 2H generally maintain the status quo but may decrease minority visibility. Volume.System Inequality Concentration Diversity.System Volume.Individual

Jiang et al. [85] present a framework to study feedback loops between user's choices and recommendations. In this framework, individual users engage with content recommenders using various strategies such as random selection, oracle-based methods, and reinforcement learning algorithms. The study finds that, compared to a random recommender, both oracle and reinforcement-learning recommenders lead to a fast model degeneration. This degeneration is characterised by a decrease in item diversity and user interests. Radicalization Diversity.Individual

Rossi et al. [142] examine the influence of recommenders on news platforms on user opinions and engagement. In the simulations, users interact with a popularity-based recommender with random exploration, which suggests articles supporting or opposing a topic. The findings show that the recommender prioritises articles that align with the user's existing opinions and tends to radicalise initially extreme users. Filter Bubble Diversity.Individual Radicalization

Ribeiro et al. [140] examine YouTube's amplification paradox. This refers to the discovery that sock-puppet audits reveal amplification of problematic content due to recommenders, while user data suggest recommenders are not the primary driver of attention towards this content. The researchers build a recommender based on collaborative filtering to simulate recommendations. Moreover, they develop an agent-based model where users consume content based on their preferences. The results help explain the paradox: users who blindly follow recommendations are exposed to more extreme content, while user choices tend to attenuate such content. Radicalization Volume.Individual Filter bubble Diversity.Individual

4 ONLINE RETAIL ECOSYSTEM

What the ecosystem is about. The online retail ecosystem includes platforms that allow customers to buy products or services, e.g., Amazon, eBay or Alibaba for products, Netflix or Spotify for movie and music streaming, respectively. This ecosystem appears more heterogeneous than the others and includes studies from various disciplines (e.g., computer science, marketing, management and economics).

Main methodologies employed. Overall, empirical studies outweigh the simulations. This is mainly because platforms have a strong interest in maximising revenues, and therefore, understanding the impact of recommenders in real situations is crucial. Most empirical studies analyse users' activity on e-commerce platforms, while simulation studies tend to build models of user tastes based on ad-hoc assumptions or data gathered from platforms. Typically, they also compare content-based recommenders and collaborative filtering. Among empirical studies, there is a prevalence of controlled over observational studies (see Figure 4), as it is easier than in other

Online Retail		Empirical		Simulation	
		Observational	**Controlled**	**Observational**	**Controlled**
Individual	**Filter Bubble**	[124]	[29]	[125]	
	Radicalization				
Model	**Collapse**				
Systemic	**Concentration**	[58, 78]	[96, 97, 164]	[57, 59, 111, 161]	
	Echo Chamber	[63]			
	Inequality				
	Polarization				
Individual Item Systemic	**Diversity**	individual: [9, 63, 124], systemic: [28, 130]	individual: [8, 77, 96–98, 100, 164], item: [118], systemic: [47, 77, 95, 117, 118, 164]	individual: [10, 57, 59, 125], item: [74], systemic: [10, 26, 74, 111]	
	Volume	individual: [58, 78, 124], item: [28, 44, 130]	individual: [29, 47, 77, 96, 98, 103], item: [95, 97], systemic: [9]		

Table 3. Online Retail Ecosystem. Classification of selected papers based on their methodology, outcomes and level of analysis.

ecosystems to divide users into control and treatment groups. Moreover, interactions between the two groups are often weak and manageable. We do not find simulation-controlled studies. See Table 3 for a comprehensive outlook of the outcomes studied in this ecosystem.

Main outcomes. Overarching concerns relate to volumes and diversity of sales, views, and clicks, as well as implications of customers' engagement on their decision quality, retention, and product ratings. Concentration is also investigated, while filter bubbles and echo chambers are considered in the analysis.

4.1 Empirical studies

Observational studies. Dias et al. [44] examine the impact of LeShop's recommender on sales over 21 months. The study finds that the amount of money shoppers spend on recommended items increases over time. This leads to accrued sales at the item level and the growth of direct revenues. Additionally, the study finds an increase in indirect revenues, i.e., those related to purchases of items recommended in previous sessions and purchases of non-recommended items from previously recommender categories. Volume.Item

Nguyen et al. [124] explore the impact of item-item collaborative filtering on MovieLens users. The findings reveal an overall diversity decrease in the movies viewed and purchased. However, this effect is less pronounced for users who follow recommendations, as they tend to consume a wider variety of movies compared to those who ignore recommendations. Additionally, the recommendation-following users actively seek out diverse movies, which helps reduce the risk of creating filter bubbles. These users also tend to give more positive ratings to the recommended items. Diversity.Individual Filter Bubble Volume.Individual

Ge et al. [63] analyse clicking and purchasing behaviours using real-world data consisting of user clicks, purchases and browse logs from Alibaba Taobao. To measure the impact of recommenders on users, the researchers follow the strategy proposed by Nguyen et al. [124] and separate all users into "following" and "ignoring" groups. The study shows that personalised recommendations reinforce cluster formation in click-behaviors (echo chambers), i.e., there is a strengthening trend over time for the "following" group of users. Moreover, the set of suggested products is less diverse for the "following" group in comparison to the "ignoring" group. This is because personalised recommendations shrink the scope of the offered content, and therefore, the gap further enlarges over time. Echo Chamber Diversity.Individual

Anderson et al. [9] investigate how Spotify's recommender impacts the diversity of streaming content users listen to. The researchers split user streaming behaviour into two categories: user-driven listening, where users actively seek out specific music or listen to playlists created by other users, and algorithm-driven listening, where users listen to algorithmically personalised playlists (e.g., Discover Weekly) or radio stations generated by Spotify's algorithm. The study finds that personalised recommendations lead to greater diversity in streaming at the individual level, with user-driven listening showing more diversity than algorithm-driven listening. Furthermore, users who listen to a diverse range of songs are significantly less likely to leave the platform and more likely to become paying subscribers. Diversity.Individual

Chen et al. [28] analyse a dataset sourced from Amazon to examine the effects of recommendations and consumer feedback on sales. The findings indicate that more recommendations are associated with high sales volume, but consumer ratings do not have a significant impact on sales. However, the number of consumer reviews positively correlates with sales volume. The study also finds that recommendations lead to increased diversity at the systemic level, indicating that they are more effective for less-popular books than for popular ones. Diversity.Systemic Volume.Item

Pathak et al. [130] analyse a dataset from Amazon and Barnes & Noble to explore how the strength of recommendations (i.e., the number of books pointing to a particular book and their popularity) impacts book sales and prices. The study finds that stronger recommendations lead to increased sales volume and higher prices. Additionally, the recommender may contribute to increased diversity in book sales, a phenomenon referred to in the paper as a long-tail effect. Diversity.Systemic Volume.Item

Fleder et al. [58] analyse consumer behaviour in time in an online music store. The store uses a free software add-on to Apple's iTunes to provide personalised recommendations to registered users through a combination of content- and user-based collaborative filtering. To account for potential confounding factors, the researchers employ propensity score matching to match registered and registered users. The findings show that recommendations lead to an increase in commonality among consumers. This occurs because individual consumers purchase a greater volume of songs and a more similar mix of products after receiving the recommendations. Concentration Volume.Individual

Hosanagar et al. [78] employ the same research design and reveal that personalised recommendations have two main effects. On an individual level, personalised recommendations increase sales volume, making it more likely for users to purchase the same songs. At a systemic level, there is a concentration of purchases as consumers tend to buy a more similar mix of products after receiving the recommendations. Concentration Volume.Individual

Controlled studies. Anderson et al. [9] investigate the impact of Spotify's recommender on the diversity of content that users listen to. The researchers randomly split users into three test groups exposed to different recommenders: a popularity ranker (sorting songs based on their popularity), a relevance ranker (sorting songs based on their relevance to the user's tastes), and a learned ranker (a neural network trained on user preferences). The study finds that the relevance ranker is more effective than the popularity ranker for generalist users (those who listen to a wide variety of songs) and specialist users (those who prefer specific genres), resulting in an overall increase in the number of songs streamed. Although the learned ranker employs a broader set of features, it performs similarly to the relevance ranker. Volume.Systemic

Yi et al. [164] conduct a laboratory experiment to explore the impact of product recommendations on search (e.g., computers) and experience goods (e.g., music). The participants are divided into a treatment group that receives recommendations and a control group that does not. The findings show that users in the treatment group visualise a wider range of products. However, they end up purchasing fewer products and concentrating their purchases on the most popular items. This effect is more pronounced for search goods. Concentration Diversity.Individual Diversity.Systemic

Matt et al. [117] split users on an online music store into four randomised treatment groups exposed to different recommenders: content-based filtering, collaborative filtering, bestseller recommender, and random recommender. A control group receives no recommendations. The results indicate that, compared to the baseline, all recommenders (except content-based filtering) lead to an increase in sales diversity. In a subsequent study, Matt et al. [118] introduce two additional randomised treatment groups. These groups are exposed to variants of collaborative filtering and bestseller recommender, which are trained on data describing other users' ratings and purchases. Recommending niche products and blockbusters with the same probability, content-based filtering increases diversity at the item level. At the systemic level, the study finds that recommenders have varying effects on sales diversity: the random recommender increases it, collaborative filtering decreases it, and other recommenders (including the collaborative filtering variant) have no effect. Neither of the bestseller recommender variants differs from the baseline. The other recommenders have no noticeable effect on sales diversity. Diversity.Item Diversity.Systemic

Alves et al. [8] examine the effects of nudging customers of a book recommendation app towards genres they do not normally prefer. All participants in the experiment receive book recommendations from their preferred genres as well as from other genres. Users in the treatment group receive enhanced recommendations with various types of nudges, such as the popularity or appreciation of the suggestions by other users or experts. Users in the control group are not provided with any nudging. While these enhanced recommendations diversify the selection of books, the nudging also decreases the time spent on the app. Diversity.Individual

Lee and Hosanagar [96] investigate the impact of different recommenders on movie sales at a top retailer in North America. Customers are randomly assigned to one of four groups: a control group with no recommendations, three treatment groups exposed to purchase-based collaborative filtering (who bought this also bought that), view-based collaborative filtering (who viewed this also viewed that), and recently-viewed recommender (recently viewed items). The study finds that purchase-based collaborative filtering significantly increases the average number of views per individual and the average number of purchases compared to the control group. In contrast, the effects of view-based collaborative filtering and recent-views-based recommenders are not statistically significant. Both collaborative filtering algorithms increase sales diversity at the individual level but decrease aggregate sales diversity. This indicates that both algorithms encourage users to purchase the same products, leading to a concentration effect at the systemic level. The recently-viewed recommender decreases sales diversity at the systemic level but has no effect at the individual level. Diversity.Individual Volume.Individual Concentration

Liang and Willemsen [100] examine the behaviour of four random groups of Spotify users over six weeks. These groups are composed on the basis of algorithm personalisation and the visual presentation of recommendations. In their first session, users are randomly assigned to either a representative or a personalised initial playlist. Then, they are further assigned to one of two visual presentations. The study reveals an initial increase in the diversity of music exploration within the playlist, driven by nudging techniques such as default initial playlists and visual anchors. However, this heightened exploration gradually diminishes over time. The residual effect on the change in users' profiles indicates the potential (long-term) benefits of combining nudging with personalisation in exploration tools. Diversity.Individual

Long et al. [103] employ data from 1.6 million Alibaba customers to examine how the quantity of recommended products impacts on consumers' search and purchase behaviours. The researchers leverage Alibaba's recommendation technology and randomly assign consumers to one of four treatment groups, each receiving a different number of recommended products. The findings reveal that increasing the number of recommended products boosts the probability of purchasing those items. However, this probability decreases as the number of recommended products continues to rise. Purchase probability declines mainly because consumers reduce the number of searches as a consequence of choice overload. Volume.Individual

Lee et al. [95] investigate the impact of recommendations on views and sales of cosmetics and clothes on mobile and PC channels. The researchers split customers into a treatment group exposed to collaborative filtering trained on users' recent views and a control group exposed to best-selling items. The study finds that collaborative filtering increases views and sales volume when users access the platform through mobile devices. When users access the platform through PCs, the recommender only increases the volume of views. These outcomes are particularly pronounced for the most expensive items. Moreover, collaborative filtering increases view diversity on both mobile and PC platforms, but it has no significant impact on sales diversity. Diversity.Systemic Volume.Item

Donnelly et al. [47] investigate the impact of personalised recommendations generated by Wayfair's collaborative filtering on consumption patterns in the context of online furniture shopping. In the experiment, a treatment group of 95% of customers exposed to Wayfair's recommender is compared to a control group of 5% of the customers exposed to popularity-based recommendations. The study finds that the recommender encourages users to engage in more searches, increasing the number of clicks and positively influencing purchase probability at the individual level. Furthermore, the findings indicate that Wayfair's recommendations increase diversity in searches and sales at the systemic level. Diversity.Systemic Volume.Individual

Holtz et al. [77] examine the impact of personalised recommendations on podcast consumption among approximately 900,000 Spotify premium users across seventeen countries. Users in the treatment group are exposed to personalised recommendations based on their historical listening behaviour, while those in the control group are exposed to the most popular podcasts. The study finds that at the individual level, personalised recommendations lead to an increased volume of podcasts listened to, but a decrease in podcast streaming diversity. However, at the systemic level, personalised recommendations increase podcast streaming diversity. Diversity.Individual Diversity.Systemic Volume.Individual

Chen et al. [29] examine how recommendations affect the relationship between filter bubbles and consumers' preferences and decision quality on the e-commerce platforms Jingdong and Taobao. The researchers define decision quality as the ability of users to select the best products according to domain experts. The study distinguishes between personalised recommendations for users with personal accounts and non-personalised recommendations for users without them. The findings show that recommendations reinforce individual consumer preferences, creating a filter bubble effect and reducing decision quality. Filter bubbles limit the variety of products available to consumers, potentially leading to a decline in decision quality. Filter Bubble Volume.Individual

Lee and Hosanagar [97] explore the impact of collaborative filtering on sales diversity using data from a randomised field experiment conducted on top online retailers. The researchers split users into a control group with no recommendations and two treatment groups exposed to view-based collaborative filtering (who viewed this also viewed that) and purchase-based collaborative filtering (who purchased this also purchased that). The study finds that the two recommenders increase sales diversity at the individual level, leading to a decrease in views and sales diversity at the systemic level. As similar users explore the same products, this results in a concentration effect. At the item level, both recommenders generate an increase in views and sales. Diversity.Individual Concentration Volume.Item

Li et al. [98] conduct three experiments in a laboratory and a real-life online bookstore. Each experiment involves a control group of users receiving no recommendations and treatment groups exposed to recommendations based on a basket value. In the first laboratory experiment, three treatment groups are exposed to item-based collaborative filtering, best-selling, and random recommendations. The researchers find that collaborative filtering provides the highest basket value. In a subsequent laboratory experiment based on collaborative filtering only, the study finds that recommending three products of the same type is the most effective way to increase basket value.

In the real-life experiment, the treatment group receives recommendations about three different products from memory-based collaborative filtering. The findings show that this recommender leads to an increase in diversity in consumers' consideration sets, as well as an increase in views and sales. Diversity.Individual Volume.Individual

4.2 Simulation studies

Observational studies. Noordeh et al. [125] measure the impact of collaborative filtering on content consumption on MovieLens. The study reveals that prolonged exposure to recommendations decreases content diversity and fosters the emergence of filter bubbles. Furthermore, once a filter bubble is established, it becomes challenging for users to break out of it. Diversity.Individual Filter Bubble

Hazrati and Ricci [74] employ log data from three Amazon services (Kindle, Games, and Apps) to analyse the effects of recommendations on the evolution of users' choices over time. The simulation combines a choice model with five recommenders. Three recommenders offer personalised recommendations: popularity-based collaborative filtering, low popularity-based collaborative filtering (penalising the score with the inverse popularity), and factor model (mapping users and items into a common latent factor space). Additionally, the study includes two non-personalised recommenders, namely popularity-based and average rating, as well as a baseline case with no recommendations. The study finds that personalised recommendations lead to a greater increase in sales diversity compared to non-personalised recommendations, both at the item and systemic levels. Furthermore, at the systemic level, the low popularity-based collaborative filtering and the factor model increase sales diversity for the Kindle dataset. However, for the Games dataset, only the low popularity-based collaborative filtering increased sales diversity compared to the baseline case. Diversity.Item Diversity.Systemic

Mansoury et al. [111] design a method for simulating the feedback loop of user-recommender interactions by analysing the progressive effects of three different recommenders: user-based collaborative filtering, Bayesian personalised ranking, and a recommender suggesting the most popular items. The findings reveal that all recommenders lead to a progressive reduction in diversity and increased concentration. This effect is particularly pronounced for users who are underrepresented in the training dataset (e.g., female users). Concentration Diversity.Systemic

Wu et al. [161] compare various recommenders trained on MovieLens data, specifically a user-based collaborative filtering, a content-based recommender and a baseline condition with no recommendations. The findings reveal that the content-based recommender decreases sales concentration, whereas user-based collaborative filtering increases it. Moreover, the impact of these effects depends on how well the recommendations align with consumer awareness. For instance, suggesting popular products to consumers already aware of them has little impact. Recommending niche products could significantly influence consumer behaviour. Concentration

Aridor et al. [10] design a model in which products have both intrinsic and user-specific values. In this model, users (unaware of item values) make choices on the basis of their beliefs and risk aversion. This baseline condition is compared to one where users are exposed to recommendations that allow them to combine their value with the intrinsic value of items. The study shows that the more users become risk-averse, the more they consume items similar to those they previously considered valuable. This leads to filter bubbles that narrow their consumption patterns. Recommendations help reduce these filter bubbles, but at the cost of diminishing the diversity of items consumed at the systemic level. Diversity.Individual Diversity.Systemic

Chaney et al. [26] explore how training recommenders using data from users influenced by automatic recommendations can lead to algorithmic confounding. The researchers compare the effects of six recommenders (popularity-based, content filtering, matrix factorisation, social filtering, and random) with an ideal benchmark, which recommends items based on the true utility of users. The study finds that a single training session leads to a small homogenisation in user behaviour, which then reverts to the ideal case. However, repeated training causes a greater homogenisation of user behaviour, with the effect becoming more pronounced with each cycle through the loop. This homogenisation occurs both at the local level (users behave more like their nearest neighbours) and population level (users become more similar on average) for all recommenders (except for the random recommender). Diversity.Systemic

Fleder and Hosanagar [59] perform a simulation where users are exposed to collaborative filtering and have a certain probability of accepting the recommender's suggestion. The outcome is compared to that resulting from the same process, except for that when recommendations are not enabled. The study reveals a concentration effect towards a few items. A subsequent study [57] employs the same simulation settings to demonstrate that recommendations can increase sales diversity at the individual level, but decrease it at the systemic level. Concentration Diversity.Individual

5 URBAN MAPPING ECOSYSTEM

What the ecosystem is about. The urban mapping ecosystem encompasses a variety of recommenders designed to satisfy the needs of city dwellers. It includes navigation platforms suggesting travel routes (e.g. Google Maps or TomTom); house-renting services helping users find accommodation (e.g., Airbnb, Booking.com); e-mobility platforms providing users with taxi, ride-hailing or car-pooling services (e.g., Uber and Lyft); and platforms suggesting point-of-interest to users (e.g., Tripadvisor and Yelp).
Main employed methodologies. There is a predominance of simulation over empirical studies (see Figure 4), mainly because data are typically owned by big-tech companies that are reluctant to share them. For what concerns navigation and e-mobility platforms, empirical controlled studies are difficult to perform. This is because it is unlikely to avoid interactions between users in the control and treatment groups and other vehicles travelling on the streets. This would mean a violation of the Stable Unit Treatment Value Assumption for causal inference [39]. Moreover, several exogenous factors (e.g., sudden storms, strikes, accidents) may potentially bias the effect of the recommender at any time. These factors complicate the attribution of the observed outcomes to the recommender. Scholars tend to choose simulation-controlled studies to mitigate these issues.
Main outcomes. Most studies focus on the systemic level, investigating inequality, diversity, and traffic congestion (extreme urban concentration). Most studies are concerned with volume at all levels of analysis, assessing the impact of recommenders on various quantities (e.g., CO_2 emissions, travel time, and cost for users in ride-hailing and car-sharing platforms). See Table 4 for a comprehensive outlook.

5.1 Empirical studies

Observational studies. Falek et al. [55] perform a comparative analysis of various routing algorithms, finding that a strategy without re-routing (the route is established before vehicle departure based on actual travel times) consistently yields travel times that closely approach the best possible solution. In contrast, a strategy based on continuous re-routing (the route is adjusted while the vehicle is travelling based on actual travel times) is the best algorithm for congested areas. Concentration

Urban Mapping		Empirical		Simulation	
		Observational	**Controlled**	**Observational**	**Controlled**
Individual	**Filter Bubble**				
	Radicalisation				
Model	**Collapse**				
Systemic	**Concentration**	[55, 70, 115]		[35, 50, 86]	[36, 136, 156]
	Echo Chamber	[89]			
	Inequality	[48, 165]		[1, 21, 86]	[31]
	Polarization				
Individual Item Systemic	**Diversity**			systemic [37]	systemic [38]
	Volume	individual: [84, 104, 144, 146, 165], item: [70, 84, 104], systemic: [84, 115]		individual: [90, 107–110, 123], item: [2, 7, 37, 61, 108–110, 123, 170], systemic: [2, 7, 15, 35–37, 50, 53, 54, 90, 121, 152]	individual: [3, 12, 31, 136, 158], systemic: [3, 12, 36, 38, 136, 156, 158, 170]

Table 4. Urban Mapping Ecosystem. Classification of selected papers based on their methodology, outcomes and level of analysis.

Schwieterman [146] observes that transportation network companies (e.g., Uber and Lyft) in Chicago contribute to reducing travel times compared to public transit, but are also slightly more costly on average for users. Moreover, during peak weekday hours, the prices are marginally higher than at other times, suggesting that transportation network companies may use surge pricing to respond to mobility demand. Volume.Individual

Santi et al. [144] employ a large dataset of taxi trips in New York City to model the collective benefits of ride-sharing as a function of prolonged travel time. They find that ride-sharing reduces users' travel time, cumulative trip length, and service cost. However, it entails an increase in the number of taxi passengers. Volume.Individual

Jalali et al. [84] use GPS trajectories from private vehicles to investigate the potential impact of ride-sharing in a Chinese city. They discover that ride-sharing reduces: the number of trips, drivers' total travelled distance, and emissions. This is especially true if users are willing to walk to drivers within 3 km. Volume.Individual Volume.Item Volume.Systemic

Martinez and Viegas [115] develop an agent-based model to examine the impact of moving from private transportation to a shared and self-driving vehicle fleet (taxis and mini-buses) in Lisbon. Their study reveals that implementing the full-sharing scenario could substantially reduce CO2 emissions, congestion levels, and travel distances. Sharing vehicles leads to more intensive vehicle utilisation, significantly increasing vehicles' daily usage and travel distances. Concentration Volume.Systemic

Lotze et al. [104] propose a strategy in which bus routes and user stops' positions change adaptively with traffic demand. They observe a decrease in buses' route length and travel times, albeit at the expense of users being required to walk significant distances during their trips to reach dynamically adjusted stops. Volume.Individual Volume.Item

Hanna et al. [70] analyse the impact of lifting Jakarta's "three-in-one" high-occupancy vehicle policy (HOV), which restricted certain roads at specific hours to vehicles with a minimum of three occupants. By gathering data on road travel times from Google Maps before and after the policy lifting, the researchers uncover noticeable effects of HOV on traffic congestion: lifting the policy increased travel times both on high-occupancy roads and alternative routes, and both during and outside HOV periods. Concentration Volume.Item

A few works [48, 89, 165] focus on the empirical analysis of data from Airbnb. Koh et al. [89] analyse the diversity of the user base on the Airbnb platform across five cities in three continents. The study observes a predominantly young, female, and white user base, even in cities with a diverse racial composition. This creates an echo chamber effect where similar demographics tend to cluster. The authors also observe a similar homophily tendency between female hosts and guests and a relevant homophily tendency regarding race, while no tendency is highlighted in age. EchoChamber

Similarly, Edelman and Luca [48] analyse pictures of New York City landlords on Airbnb and observe revenue inequalities: non-black hosts' houses are about 12% more expensive than those of black hosts, even when the houses have similar attributes like the number of bedrooms, type of room, and user ratings. Inequality

Zhang et al. [165] investigate the impact of Airbnb's smart-pricing algorithm on racial disparities in daily host revenue. The researchers collect data on venue prices, host race (inferred from profile pictures), host revenues, and venue occupancy rates before and after hosts adopt the smart-pricing algorithm. They find that the algorithm reduces venue prices, increases host revenues, and decreases the revenue gap between white and black hosts. Inequality Volume.Individual

5.2 Simulation studies

Observational studies. Johnson et al. [86] investigate the impact on urban traffic of three routing criteria: scenic routing optimises routes for aesthetic enjoyment; safety routing avoids areas with higher rates of accidents or crime; and simplicity routing, where route complexity is reduced on the basis of the number of intersections and actions needed to traverse it (i.e., going straight or turning). Simulations in San Francisco, New York City, London, and Manila show that scenic routing leads to more complex routes, potentially increasing the risk of accidents and negatively affecting driver safety. Additionally, it diverts traffic from highways to parks, popular areas, tourist destinations, and slower roads. Safety routing, though to a lesser degree than scenic routing, also generates more complex routes and redirects traffic away from identified unsafe zones. Simplicity routing amplifies traffic on highways but does not explicitly favour or avoid any particular region. Concentration Inequality

Mehrvarz et al. [121] compare the impact of vehicle routing incorporating sustainability variables (e.g., fuel consumption, engine load, acceleration rate, speed, road slope) with traditional routing that prioritises travel time or distance. The study finds that fastest routes are not necessarily the most sustainable and that sustainable routing might reduce fuel consumption by about 5%. Volume.Systemic

Barth et al. [15] introduce a method for reducing energy consumption and emissions in navigation services. The method combines mobile-source energy and emission models with advanced route optimisation algorithms. The study applies this method in several case studies across Southern California, showing substantial energy savings and reduced emissions compared to navigation services that minimise distance or travel time. Volume.Systemic

Colak et al. [35] introduce a centralised strategy that optimises route choices to alleviate urban congestion while considering varying levels of social good awareness. The study shows that routing solutions mimicking socially optimal configurations decrease time lost in congestion by up to 30%, with individual travel time reduction ranging between one and three minutes. Concentration Volume.Systemic

Cornacchia et al. [37] introduce METIS, a traffic assignment algorithm designed to optimise vehicle routing by offering diverse alternatives. The study employs a traffic simulator (SUMO) to conduct a simulation across Florence, Rome, and Milan, evaluating the impact of METIS on various urban metrics, including CO2 emissions and road coverage. The study reveals that METIS produces a more equitable distribution of traffic on the road network than other state-of-the-art routing algorithms, increases road coverage and mitigates CO2 emissions considerably. Diversity.Systemic Volume.Item Volume.Systemic

Maciejewski et al. [108–110] employ floating car data and a traffic simulator (MATSim) to investigate the impact of taxi fleets on traffic in Berlin and Barcelona. The study evaluates two dispatching strategies: the "nearest-idle-taxi" approach, where the closest available taxi is dispatched to the first available request; and the "demand-supply balancing strategy," which classifies system states into oversupply and undersupply conditions. The demand-supply balancing strategy outperforms the nearest-idle-taxi approach, considerably reducing waiting time for both drivers and passengers. Volume.Individual Volume.Item

In another work, Maciejewski [107] evaluates three taxi dispatching strategies: a "no-scheduling strategy" (NOS) that assigns the nearest empty taxi to each request; a "one-time schedule strategy" (OTS) that assigns new customers to the taxi soonest available after current trips; and a "re-scheduling strategy" (RES) that recalculates assignments after each drop-off. Although NOS performs well under light system loads, slightly outperforming the other strategies in reducing passenger waiting times, RES is more effective as demand increases. Volume.Individual

Erhardt et al. [50] examine the effects of ride-hailing on San Francisco's traffic congestion using simulation software (SF-CHAMP). They compare traffic volumes in 2010 – before significant ride-hailing activity – with those in 2016 when such services were available. Findings highlight that ride-hailing increases congestion, mainly because about 50% of vehicles' miles travelled are with no passengers. The study also finds a 62% increase in weekday vehicle hours of delay from 2010 to 2016 versus a 22% increase under a hypothetical scenario without ride-hailing. Concentration Volume.Systemic

Zhu and Prabhakar [170] introduce a combinatorial optimisation model for long-term taxi trip assignment to minimise the number of taxis required and idle time. Simulations in New York City demonstrate that the model effectively reduces by 28% the taxi fleet size needed to complete all trips and cuts by 32% per taxi average idle time. Volume.Individual

Kucharski et al. [90] show how ride-pooling services can significantly accelerate the spread of COVID-19 and similar diseases. The study finds that a small number of infected travellers can transmit the virus to hundreds of users. Therefore, they propose a mitigation strategy. This strategy contains the virus within smaller groups and breaks up the dense contact network by implementing fixed matches among co-travellers. Volume.Individual Volume.Systemic

Fagnant and Kockelman [53] use agent-based modelling to evaluate the environmental impact of shared autonomous vehicles (SAV) compared to conventional vehicle ownership and usage patterns. Their simulations indicate that a single SAV can replace eleven traditional vehicles. Despite a projected 10% increase in travel distances, the overall impact of SAVs remains favourable for reducing emissions compared to non-SAV trips. Additionally, the study suggests that centralised global strategies for SAV relocation are more effective in mitigating environmental impacts than localised approaches. In subsequent research, Fagnant and Kockelman [54] investigate the impact of SAV on travel costs and service times in Austin employing a Dynamic Ride-Sharing strategy (DRS). DRS brings together multiple users with similar origin and destination points at the same time. The findings show that DRS reduces average service times and travel costs for SAV users, presenting potential benefits for both autonomous taxis and travellers. Volume.Systemic

Afèche et al. [1] use a game-theoretic model to analyse ride-hailing services, focusing on passenger-driver matches in a spatial network. They assess the impact of admission control (accepting or rejecting ride requests based on destination) and positioning control (relocating drivers to high-demand areas). The study compares three approaches: centralised control with strict admission and repositioning; minimal control with open admission and decentralised repositioning; and optimal admission control – which combines centralised and decentralised repositioning. Results show that while decentralised repositioning can result in drivers idling in low-demand zones, admission control reduces such inefficiencies. However, this approach can also lead to rejecting requests from less busy areas. This may exacerbate inequality in service access and potentially decrease driver satisfaction. Inequality

Agarwal et al. [2] explore the effects of ride-hailing surge pricing on the demand for traditional taxi services in Singapore, focusing on the interaction between ride-hailing apps' dynamic pricing and taxi bookings. They find that a 10% increase in ride-hailing surge prices results in a 2.6% increase in taxi bookings within the same region and time interval. Furthermore, including surge pricing factors into demand prediction models enhances the accuracy by 12-15%, underscoring the practical utility of surge data beyond pricing adjustments. Volume.Item Volume.Systemic

Bokányi and Hannák [21] conduct an agent-based simulation to study the impact of ride-hailing matching algorithms. The study finds that the "nearest algorithm", which assigns passengers to the closest vehicle, exacerbates inequality among drivers' gains and is affected by the spatial location of pick-ups and drop-offs. Conversely, a "poorest algorithm", which prioritises drivers with lower earnings, reduces gain disparities. Moreover, with outward flows, it also boosts average driver gains. Inequality

Alonso-Mora et al. [7] present a ride-sharing algorithm for assigning passenger requests to a fleet of vehicles of varying capacity (i.e., number of passengers), validating its performance using New York City taxi data. The results show that 2000 vehicles (15% of the taxi fleet) of capacity ten or 3000 of capacity four can serve 98% of the demand within a mean waiting time of 2.8 min and a mean trip delay of 3.5 min. Moreover, the study finds that increasing vehicle capacity improves service rate and reduces the mean distance travelled by vehicles in the fleet. Volume.Item Volume.Systemic

Mori et al. [123] explore the advantages of integrating ride-sharing taxis with traditional taxi services through traffic simulation and dynamic vehicle allocation. The findings indicate that increasing the number of vehicles decreases the average time from booking to arrival. This effect is especially pronounced for ride-sharing taxis, although it reduces vehicle occupancy rates. Volume.Individual Volume.Item

Storch et al. [152] employ a game-theoretic approach to investigate the incentives (financial discounts, expected detours and trip uncertainty, and the inconvenience of sharing a vehicle with strangers) affecting ride-sharing adoption. The study identifies two distinct adoption regimes: one characterised by decreased sharing as demand rises and another by consistent sharing regardless of demand levels. The simulation reveals a discontinuous transition between these regimes, suggesting that even modest increases in financial incentives could significantly boost ride-sharing adoption. This pattern is also observed in empirical data about ride-sharing adoption in New York City and Chicago. Volume.Systemic

Garcia-López et al. [61] investigate the influence of Airbnb on housing rents and prices in Barcelona. The study proposes a model that uses rent data, transaction prices, and posted prices in which Airbnb house owners decide between long-term or short-term rentals. The findings reveal that, on average, neighbourhoods experience a 1.9% increase in rents and a 5.3% rise in transaction prices after the introduction of the Airbnb service. This impact is the strongest in areas with high Airbnb activity, with estimated rent hikes of 7% and transaction price increases of 19%. Volume.Item Volume.Systemic

Controlled studies. Arora et al. [12] use Google Maps data and a traffic simulator (SUMO) to investigate the impact of Google Maps' real-time navigation on travel time and CO2 emissions in Salt Lake City, targeting the subset of vehicles that use Google Maps' suggestions. The study reveals that, on average, Google Maps users reduce CO2 emissions by 1.7% and travel time by 6.5%. For users whose routes differ from their original plans due to Google Maps' suggestions, there is a reduction of 3.4% in CO2 emissions and 12.5% in travel time. Volume.Individual Volume.Systemic

Valdes et al. [158] and Perez-Prada et al. [136] examine the impact of adopting eco-friendly routes on traffic and emissions under various traffic conditions in the region of Madrid. Valdes et al. [158] find that eco-routing significantly impacts CO2 emissions and fuel consumption in low and high traffic conditions, especially at low adoption rates. However, the benefits are less evident in medium-traffic conditions. Volume.Individual Volume.Systemic Perez-Prada et al. [136] discover that, in situations of congested traffic, a 90% adoption rate of eco-friendly routes leads to reductions of up to 10% in CO2 and 13% in NOx emissions. However, NOx exposure for the population increases by up to 20.2% and travel times by 28.7%. Additionally, while traffic volumes decrease by 13.5% for the entire region, downtown areas experience an increase in vehicle concentration of up to 16.4%. Concentration Volume.Individual Volume.Systemic

Cornacchia et al. [36] propose a simulation framework based on SUMO to assess the impact of navigation services on urban CO2 emissions. Using route suggestions collected through APIs provided by TomTom and OpenStreetMap, the authors set up scenarios with different service adoption rates in Milan. When the adoption rate is high or low, CO2 emissions are higher than the baseline scenario where vehicles do not follow recommendations. In contrast, when the adoption rate is around 50%, there is a reduction in the overall CO2 emissions over the road network. Furthermore, the higher the adoption rate, the fewer emissions are in the city centre and the more in the external ring road. In subsequent research, Cornacchia et al. [38] demonstrate that introducing randomness into recommended routes can reduce travel time and CO2 emissions. Concentration Volume.Systemic

Thai et al. [156] analyse the impact of navigation services on road usage from a theoretical perspective, modelling it as a heterogeneous routing game. The model distinguishes between routed users, who utilise real-time navigation data to follow the shortest routes, and non-routed users, who rely on highways due to limited knowledge of low-capacity roads. Simulations in Los Angeles reveal that navigation services can reduce average travel times and total vehicle miles travelled. However, they also transfer significant traffic from highways to city streets, exacerbating urban congestion. Concentration Volume.Systemic

Ahn and Rakha [3] investigate the impacts of dynamic eco-routing on the transportation network. The researchers consider various adoption rates and traffic conditions in downtown Cleveland and Columbus. The study finds that dynamic eco-routing may lead to considerable fuel savings and emissions reduction compared to traditional routing methods. Additionally, dynamic eco-routing reduces travel distance, but does not always result in shorter travel times. The findings also reveal that as the proportion of dynamic eco-routing increases, fuel consumption decreases at the systemic level. Volume.Individual Volume.Systemic

Cheng and Nguyen [31] develop a multi-agent simulation platform to analyse taxi interactions and evaluate fleet management policies. The simulation involves 2000 taxis, with an increasing proportion equipped with data and algorithmic tools to optimise service. The study reveals that although these advanced technologies initially promised enhanced efficiency, higher adoption rates led to lower average revenues, particularly when many taxis were equipped with these tools. Inequality Volume.Individual

6 GENERATIVE AI ECOSYSTEM

What the ecosystem is about. The generative AI ecosystem includes studies that analyse the impacts of the recent spread of conversational and generative AI models in society. In particular, research in this field focuses on

Generative AI		Empirical		Simulation	
		Observational	Controlled	Observational	Controlled
Individual	**Filter Bubble**				
	Radicalisation				
Model	**Collapse**			[4, 18, 20, 24, 45, 46, 64, 69, 73, 75, 114, 116, 147, 148]	
Systemic	**Concentration**				
	Echo Chamber				
	Inequality				
	Polarization				
Individual Item Systemic	**Diversity**			item: [40, 43, 81, 101, 127, 143, 151, 168]	
	Volume				

Table 5. Generative AI Ecosystem. Classification of selected papers based on their methodology, outcomes and level of analysis.

two major areas. The first analyses the effects of using generative AI to recommend items, products, or movies. The second investigates the self-consuming loop in generative AI, i.e., what happens when data generated by AI models are used to train or fine-tune the models themselves. Since research in generative AI is new and rapidly expanding compared to other ecosystems, we mostly include preprint papers.

Main methodologies employed. All studies are based on the simulation observational methodology (see Figure 4). This is because it is challenging to develop empirical studies where real users interact with generative AI platforms. Moreover, such studies would require the exploitation of longitudinal data; given the recent development of these platforms, these data are not yet available.

Main outcomes. Only two outcomes are investigated: diversity at the item level in studies using generative AI to recommend items, and model collapse in studies analysing the self-consuming loop. See Table 5 for a complete outlook.

6.1 Simulation studies

Observational studies. Palma et al. [127] evaluate ChatGPT's ability to provide helpful recommendations based on users' requests. They compare ChatGPT with other large language models (GPT3.5 and PaLM-2) and standard recommenders (collaborative filtering and content-based filtering recommenders) using three datasets (MovieLens Small, Last.FM, and Facebook Book). The study finds that ChatGPT provides more accurate music and book recommendations than other language models, while PaLM-2 performs better in movie recommendations. Overall, the research concludes that LLM's recommendations have a similar accuracy to standard recommenders.

Additionally, ChatGPT recommendations are less diverse than standard recommenders, but they offer a higher degree of novelty. ChatGPT shows a bias towards popular items that varies across the datasets. Diversity.Item

Liu et al. [101] assess how well ChatGPT performs in five recommendation scenarios: rating prediction, sequential and direct recommendation, explanation generation, and review summarisation. The researchers query ChatGPT with different prompts tailored to specific tasks, refining its output and providing results to the user. The study employs numerical and human evaluations, leveraging an Amazon dataset containing customer reviews of 29 categories of products. Results indicate that ChatGPT performs well in rating prediction and the generation of explanations, with a consensus among evaluators. However, it performs poorly in sequential and direct recommendation tasks, suggesting the need for further exploration and improvement. Diversity.Item

Dai et al. [40] test ChatGPT's ability to provide three types of rankings based on user preferences: point-wise ranking (rate an item), pair-wise ranking (provide a preference among options), and list-wise ranking (rank a list of items). The researchers conduct experiments on four datasets from different domains to analyse the distinctions among the three types of recommendations. The findings indicate that ChatGPT performs well in all three types of recommendations, with the lowest performance on point-wise ranking and the highest in list-wise ranking. Diversity.Item

Hou et al. [81] explore the capacity of LLMs (ChatGPT, LLama2, Vicuna, Alpaca) in ranking recommendation. The study shows that LLMs have promising ranking abilities, but struggle to understand the sequence of past interactions. Moreover, LLMs can be influenced by the popularity of items and their positions in the prompts. The researchers demonstrate that these issues can be addressed using specially designed prompting and bootstrapping strategies. Diversity.Item

Spurlock et al. [151] investigate the effectiveness of ChatGPT in providing movie rankings. The researchers compare ChatGPT's results with a dataset that describes movie characteristics, including their popularity. ChatGPT receives prompts based on three strategies (zero-shot, few-shot and chain-of-thought) and provides output accordingly. The suggested movies are compared against item-based recommenders, which suggest the most similar items to the user's history. The study reveals that ChatGPT tends to be biased towards recommending popular movies, as the most frequently recommended items coincide with the IMDB top 250 movies list. To address this bias, the study suggests prompt engineering techniques, such as requesting "non-popular" items and adjusting the values of temperatures and number of items to rank. Diversity.Item

Deldjoo [43] compare a GPT-based movie recommender with collaborative filtering. The study finds that the GPT-based recommender does not always outperform collaborative filtering, but it recommends newer and more diverse movies, especially if they were released after 2000. Additionally, the GPT-based model shows a preference for genres such as drama, comedy, and romance, whereas collaborative filtering favours genres like action and adventure. Diversity.Item

Sanner et al. [143] compare the movie recommendations generated by PaLM with those of item-based collaborative filtering. The researchers request movie recommendations from PaLM using completion, zero-shot and few-shot prompting strategies. The study reveals that the few-shot outperforms the zero-shot and completion strategies, displaying a performance similar to item-based collaborative filtering. Additionally, combining LLMs and collaborative filtering and including information about disliked movies and language preferences do not improve recommendation performance. Diversity.Item

Zhang et al. [168] test the effectiveness of BERT and GPT as movie recommenders. The researchers conduct experiments with zero-shot prompts describing each user's first five watched movies, asking the models to predict the next in line. The outputs from the models are compared to a random recommender, a popularity-based recommender and a recommender based on neural networks and item embeddings. The findings show that BERT and GPT outperform the random recommender by a large margin, but underperform the neural network recommender. The study also reveals a strong linguistic bias: the models provide content related to movie descriptions rather than movies' inner characteristics. The researchers demonstrate that fine-tuning the models could improve recommendations and reduce that bias. Diversity.Item

Shumailov et al. [148] investigate the effects of using model-generated content in fine-tuning generative AI models. The researchers find the emergence of model collapse, i.e., the overestimation of probable events and the underestimation of improbable ones over time. The study shows that this phenomenon can occur in Variational Autoencoders (VAEs), Gaussian Mixture Models (GMMs) and LLMs. The GMMs and VAEs are evaluated by training these models on synthetic data from scratch. As LLMs are expensive to retrain from scratch, the study initially fine-tunes an OPT-125M causal language model on the wikitext2 dataset and subsequently on the generated text. The study highlights the importance of using human-generated data during the recursive fine-tuning to avoid model collapse. Model.Collapse

Alemohammad et al. [4] investigate three families of autophagous loops that differ in how synthetic or real data is available through the generations of training: fully synthetic loop, synthetic augmentation and fresh data loop. They find that, without fresh real data in each generation, future models suffer from decreasing precision (defined as Model Autophagy Disorder or MAD). Fixed real training data may delay but not prevent this phenomenon. Model.Collapse

Guo et al. [69] focus on novel metrics for detecting lexical, syntactic, and semantic diversity across model generations. They employ three use cases – news summarisation, scientific abstract generations and story generation – finding that the decline of diversity is more pronounced in high entropy tasks (i.e., more creative ones). Model.Collapse

Martínez et al. [116] replicate Guo et al. [69]'s experiment in the context of image generation, using denoising diffusion implicit models. In this simulation, the original dataset is augmented with AI-generated images and used to train a new version of the model within an autophagous loop. The study finds that data augmentation leads to a decline in the quality of subsequent images generated. In another study, Martínez et al. [114] implement an autophagous loop where the generative model is trained using the same proportion of real and self-generated data. The researchers use precision and recall to measure the quality of the generated data as well as the similarity between generated images and the original dataset. The study finds the emergence of model collapse, with increasing similarity to real data and decreasing precision and recall. Model.Collapse

Briesch et al. [24] investigate the autophagous loop comparing a full synthetic data cycle (at each generation, training data is fully replaced by the last data generation) with three data augmentation cycles and employing different proportions of real and synthetic data (balanced, incremental, expanding). The study finds that the full synthetic data cycle leads to model collapse. The incremental and balanced data cycles also decrease diversity, with the former showing a stronger effect. Only the expanding data cycle (new data is added to the previous dataset) shows no decrease up to 50 simulation steps. Model.Collapse

Hataya et al. [73] investigate text-to-image Stable Diffusion Model, considering different distributions of generated images. They find that generated images negatively affect task performance and that the level of model degradation depends on the level of contamination, suggesting that using synthetic images for data augmentation needs careful consideration. Furthermore, the researchers highlight the importance of developing methods for watermarking, i.e. the detection of AI-generated images. To this purpose, the study proposes a self-supervised learning method based on a masked autoencoder, showing how it may circumvent the negative effects of degeneration even if datasets are contaminated by synthetically generated images. Model.Collapse

Bohacek and Farid [20] also focus on the stable diffusion model, running five iterations of data generations, retraining the model at each simulation step with different proportions of real and synthetic data. The study finds that the model collapses and can be "healed" only by retraining it on real images. Model.Collapse

Dohmatob et al. [45, 46] perform experiments with Llama2 and propose a mathematical formalization of model collapse. They show that models trained on a mixture of real AI-generated data improve only at the beginning, and then they tend to collapse anyway. The researchers highlight the importance of early detection of model collapse. Model.Collapse

Bertrand et al. [18] develop a theoretical framework to study the iterative retraining of generative models on datasets that contain a mix of both real and self-generated data. The study demonstrates that iterative retraining is stable when the initial generative model is close enough to the real data distribution and the proportion of real data is sufficiently large. The researchers then validate theoretical results through iterative retraining on state-of-the-art diffusion models. Model.Collapse

Seddik et al. [147] consider various recursive training scenarios and show that model collapse cannot be avoided when performing model training only on synthetic data. This work theoretically and empirically estimates the maximal amount of synthetic data above which model collapse can be avoided. Model.Collapse

Herel and Mikolov [75] put a pre-trained GPT-2 model within an autophagous loop, stopping the simulation when model collapse is detected or after 1000 simulation steps. The study shows that model collapse is faster for high learning rates. Moreover, models with a large number of parameters exhibit quicker model collapse. Model.Collapse

Gerstgrasser et al. [64] investigate what happens in the autophagy loop when generated content is accumulated over generations. Through analytical framework and empirical experiments using both LLMs (GPT2, GPT3, LLama2) and diffusion models (GeoDiff), the study corroborates Briesch et al. [24]'s results showing that accumulating data may help avoid model collapse. Model.Collapse

7 DISCUSSION AND FUTURE RESEARCH AVENUES

This conclusive section has three objectives. The first is to summarise the key findings that emerged from our survey at the methodological and outcome levels. The second is to highlight what is missing and envisageable for future research on human-recommender interaction. The third goes beyond offering broader suggestions to rethinking the field of human-AI coevolution technically and methodologically.

7.1 What we learned

Methodologies. Our survey endeavour reveals two important differences across the human-AI ecosystems explored. First, the use of empirical data characterises most studies within the social media and online retail ecosystems. On the opposite, simulations prevail within the urban mapping and generative AI ecosystems. The main reason for this difference is the availability of data describing human choices. Indeed, social media platforms typically provide APIs that enable scholars to download relevant information regarding users' choices. This contributed to the construction of many datasets employed for empirical analysis. For the online retail ecosystem, studies are often conducted within companies or in collaboration with them, facilitating the usage of empirical data. In contrast, platforms in the urban mapping ecosystem are typically reluctant to share their data, and APIs do not provide enough information due to privacy reasons. In the generative AI ecosystem, there is a paucity of empirical studies because prompts and corresponding content generated are currently not made available to external researchers, and commercial platforms are too recent.

Second, observational studies prevail in all ecosystems. However, the online retail ecosystem displays the largest share of controlled studies. This is due to economic and technical reasons. On the one hand, there is a strong incentive to maximise revenues, which requires a causal understanding of recommenders' influence on users. On the other, it is easy to create control and treatment groups such that interactions among the two groups are weak and manageable. In the social media ecosystem, companies sometimes perform controlled studies but are reluctant to share the results. A notable example is the Facebook files, a leak of reports describing controlled studies made by Meta and reported in The Wall Street Journal[2]. The reports revealed that, based on internally commissioned controlled studies, Meta kept secret the negative impacts of Instagram on teenage users and of Facebook on fostering violence in developing countries. In the urban mapping ecosystem, interactions between users in the control and treatment groups and other vehicles in the streets cannot be easily prevented. Moreover, several exogenous factors (e.g., sudden storms, strikes, accidents) may bias the measurement of the effect of the recommender at any time. In the generative AI ecosystem, it is difficult to assess the influence of recommenders: a controlled experiment would require writing tasks with or without using the generative AI models, which is hard and time-consuming.

Outcomes. We classified thirteen outcomes at the individual, item, model, and systemic levels (see Table 1). Studies in the social media ecosystem investigated all types of outcomes except model collapse, which is characteristic of the generative AI ecosystem. A glance at the studies in the social media ecosystem reveals both consistent and contradictory results. While some outcomes, such as polarisation, emerge consistently in all studies and platforms, others do not. For example, studies on radicalisation are often contradictory due to variations in data used, platforms investigated, and methodologies employed. Studies in the online retail ecosystem focus mostly on outcomes related to revenues, such as concentration, diversity, and volume. A pattern emerging across many studies is that recommenders tend to increase diversity at the individual level and reduce it at the systemic one. In the urban mapping ecosystem, there is a predominant focus on congestion (extreme concentration), volume and inequality. Results are often contradictory, with research claiming that some routing strategies and mobility services may reduce traffic and emissions while others observing the opposite. Finally, studies within the generative AI ecosystem only investigate model collapse and diversity. The simulation frameworks employed are similar, leading to consensus on model collapse: all studies find that the self-consuming loop of generative AI leads to model degradation in the long run. At the same time, recommenders based on generative AI have strong biases, limiting the diversity of the content recommended.

7.2 What we do not know

Methodology. With the exception of the online retail ecosystem, there is a scarcity of empirical controlled studies. This is because there can be strong interactions between users (e.g., urban mapping); access to data and the possibility to manipulate recommendations on real platforms are limited (social media); and online platforms are too recent (generative AI). Despite often violating the Stable Unit Treatment Value Assumption for causal inference [39], controlled studies are considered the gold standard to test the effects of recommenders on users' choices as they intervene in platform users' experiences. A thorough understanding of the impact of recommenders requires the realisation of more controlled studies in social media, urban mapping, and generative AI ecosystems.

Outcomes. A comprehensive understanding of human-recommender interaction also requires additional research on under-investigated outcomes. For example, model collapse is only studied within the generative AI ecosystem. However, it is unclear how recommenders evolve in the other ecosystems. This evolution may be studied both structurally (e.g., how the set of model weights change in time) or behaviorally (e.g., how the model behaviour changes). Is continual re-training causing recommenders to systematically avoid certain items (e.g., users, roads)? At what rate do recommenders reduce the diversity of recommended content? In other words, while existing studies focus on the effect that recommenders have on users' choices, we need more research in the opposite direction – i.e., the effect that users' choices have on the structure and behaviour of recommenders.

More research on inequality is also needed in the online retail ecosystem. Many studies showed a decrease in systemic diversity, but this has not been linked to the inequality of visibility of brands, products, and product categories. To what extent do recommenders promote popular brands and products while making others even

[2]https://facebookpapers.com/

less popular? How does the specific type of recommender (e.g., collaborative filtering vs personalised) influence this phenomenon? Do recommenders push people to buy specific categories of products (e.g., junk vs. healthy food)? Research in this area is largely driven by the goal of increasing revenues for companies, while the broader impact of recommenders on the distribution of these revenues is not fully understood.

Studies within the urban mapping ecosystem often overlook the influence of recommenders on spatial polarisation and the formation of spatial filter bubbles. Spatial polarisation, also referred to as urban segregation [119], is the process by which citizens segregate on specific characteristics such as race and socio-economic status. It remains unclear how urban mapping recommenders might contribute to increasing or decreasing spatial polarisation. Do ride-hailing recommenders systematically avoid poorer neighbourhoods with less demand? Do route recommenders increase traffic in specific areas, leading to discomfort for residents and increased emissions? Moreover, there is a lack of research on the long-term effects of points-of-interest recommenders. Similarly to online retail, these recommenders may promote already popular points of interest, worsening inequalities and inadvertently directing more traffic towards specific areas. Additionally, similar to social media, these recommenders may confine users within spatial filter bubbles, restricting their exploration of new places.

Lastly, studies in the generative AI ecosystem are currently focused on a limited set of outcomes. However, recent research has begun exploring the use of generative AI in relation to social media. While this area of research is still in its infancy, it shows promise in simulating user interactions on social media by employing generative AI to write artificial online posts. This could help identify pathways of polarisation and radicalisation.

7.3 Going beyond: avenues for research from a holistic perspective

Our systematic review of recommenders' outcomes in four human-AI ecosystems unveils several technical and methodological gaps in the literature from the holistic point of view of human-AI coevolution [132].

Technical perspective. Since recommenders are based on AI, and machine learning in particular, their interactions with users always give rise to a feedback loop [132]: users' choices determine the datasets on which recommenders are trained; the trained recommenders then exert an influence on users' subsequent choices, which in turn affect the next round of training, initiating a potentially never-ending cycle. Understanding human-AI coevolution [132] requires a holistic approach, where the reciprocal impact of humans and recommenders is studied in both directions. Despite notable attempts [49, 85, 112, 124, 154], we lack a comprehensive understanding of feedback loop mechanisms, how they influence ecosystems in the long run, and how to manage them. We have to measure the feedback loop's impact continuously, tracking step-wise how the measured outcomes change every time the recommender is re-trained.

Another avenue of future research regards the standardisation of datasets and analytical and simulation frameworks. This is because results measuring outcomes of human-AI interactions are often contradictory due to different datasets and methodologies employed. Constructing standard datasets and making them public may be achieved only by solving critical legal challenges [88]. One way might be allowing vetted researchers to access online platforms, conduct controlled studies, and collect empirical data. Initiatives like the EU's Digital Services Act are going towards this direction; however, it remains unclear how vetted researchers will be allowed to access privately owned platforms.

Methodological perspective. We could develop new types of studies that combine observational and controlled approaches (quasi-controlled studies) as well as empirical and simulation ones (quasi-simulations). For example, quasi-simulations could use real data or real recommenders within a simulation framework. The recommenders may be trained on data from real platforms to capture the actual recommender's functioning. Then, simulations may be employed using these recommenders to mimic user behaviour on the platform.

Another crucial point regards the development of next-generation controlled studies. In human-AI ecosystems, preventing interactions between users in the control and treatment groups is difficult. This situation violates the Stable Unit Treatment Value Assumption for causal inference [39]. In the design of the controlled studies, researchers should limit interactions between the control and the treatment groups as much as possible. For example, in the social media ecosystem, the two groups may be composed of users from different social communities.

In conclusion, we observe that almost all outcomes studied are investigated at the systemic level. This implicitly indicates that scholars recognise the importance of studying collective phenomena despite following an epistemological approach imbued with methodological individualism. We suggest that epistemological approaches based on a more holistic view of reality might be suitable to unveil other outcomes of human-AI interactions.

Authors contribution

LP and EF directed the study, coordinated the pool of authors, and wrote the paper. All authors contributed to developing the taxonomy. VP, VM, SC, GR categorised articles in the social media ecosystem, wrote the related section and compiled the related table. EF, GG, ML categorised articles in the online retail ecosystem, wrote the related section and compiled the related table. LP, GM, GC, DG categorised articles in the urban mapping ecosystem, wrote the related section and compiled the related table. DG GG categorised articles in the generative AI ecosystem wrote the related section and compiled the related table. GM and LP made the plots and the figures. All authors read and approved the paper.

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