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Working Paper

The invisible algorithm: The impact of search and recommender systems on the digital creative industries

Ilmenau Economics Discussion Papers, No. 199

Provided in Cooperation with:

Ilmenau University of Technology, Institute of Economics

Suggested Citation: Schlott, Fabian; Gänßle, Sophia (2025) : The invisible algorithm: The impact of search and recommender systems on the digital creative industries, Ilmenau Economics Discussion Papers, No. 199, Technische Universität Ilmenau, Institut für Volkswirtschaftslehre, Ilmenau

This Version is available at:

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Ilmenau Economics Discussion Papers, Vol. 30, No. 199

**The Invisible Algorithm: The Impact of Search and
Recommender Systems on the Digital Creative Industries**

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März 2025

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ISSN 0949-3859

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1.	Necessity of Pre-Selection and Automatised Recommendations in the Digital Realm	3
2.	Literature Review	5
2.1	Trends in Recommender Services Research	5
2.2	The Cultural Economics Gap	11
3.	Impact of Search and Recommender Systems in CCIs	16
3.1	Platforms and Content Services	16
3.2	Creators and Artists	19
3.2.1	Traditional Media Supply	19
3.2.2	Social Media Creators	22
3.3	Content Consumer (Bubbles)	24
4.	Meta-View on a Societal Level and Discourse	25
4.1	Feedback-Loops and Path-Dependency	25
4.2	Long-Term Effects and Societal Costs	27
5.	Conclusion	28
6.	Bibliography	30

1. Necessity of Pre-Selection and Automatised Recommendations in the Digital Realm

Digital markets are typically characterised by a vast amount of available information. Consumers find a horizontally wide and vertically deep range of content and comparison options. Even in pre-digital times, there were scientific discourses about the scarcity of attention and cognitive resources for processing the amount of information. “Information consumes the attention of its recipients” (Simon, 1971, p. 40). Thus, the concept of limited attention is not new, but it has gained rapid significance in the digital age. Access to information is typically no longer limited; rather, its processing is (Shapiro & Varian, 1999). The increase in available information shifts the focus; information overload becomes a prevalent problem in modern society. Just on YouTube alone, worldwide, 500 hours of video material are uploaded per minute (as of 2019)¹. The limited attention of recipients must be distributed efficiently and dynamically across various sources and platforms. The diversity of offerings on the internet as a whole and on online marketplaces such as Amazon or Zalando, audio and video streaming services like Spotify or Netflix, and in app stores like Google Play or the Apple App Store regularly exceeds consumers’ processing capacities (Budzinski & Karg, 2022). As capturing the entire offering is not possible, a preselection of content is essential. Typically, content preselection is done by so-called search and recommendation systems to enable rational selection. These systems operate algorithmically and mostly data-driven, often using personalised data. The selection of which content is presented and displayed online is thus not made by human preselection (e.g., by editors or curators) but automated by algorithms.

By systematic preselection, so-called transaction costs (which also include search and decision costs) are reduced for consumers, thereby relieving the limited available attention that plays a role in the selection of a good. Consumers do not use unlimited cognitive resources in searching for and selecting suitable content and goods. Depending on the strength of individual preferences, consumers are willing to invest more (or less) energy in the respective selection. For extraordinary consumption intentions, for example, sorting and comparison could be done much more carefully than for routine actions. If the selection process is not maximised to an optimum but already completed at the level of a satisfactory good or content, this is referred to as “satisficing” (Güth, 2010). The consumer is satisfied with a satisfactory product and does not further invest proportionally valuable cognitive resources in the process.

Recommender services (RSs) are ubiquitous in today’s digital ecosystem. It would be difficult to find an e-commerce business, social media platform or user-generated content distributor that does not provide a system which enables consumers to navigate the vast assortment of options quickly, particularly when

¹ <https://www.tubefilter.com/2019/05/07/number-hours-video-uploaded-to-youtube-per-minute/>

compared against manual searching approaches. Digitalisation of goods and services, and the platformisation of the cultural and creative industries (CCIs), has positioned RSs as an integral tool for platform strategy to attract and retain consumers, as well as advertisers, a primary source of revenue for many platforms (Maslowska et al., 2022; Cutolo and Kenney, 2021). In the past, physical book and music offerings were limited by the spatial properties of a store. Businesses had to strategically pre-filter products based on their likelihood to be purchased, resulting in an assortment of products that could be navigated by consumers without external aids. Similarly, RSs are unilaterally developed, implemented, and maintained by the platform operator. Developed using complex algorithms to predict, or perhaps even, change consumer taste and demand, the mechanisms and decisions underlying RSs are unknown to stakeholders. Platform operators have no incentive nor legal obligation to share the inner workings of their RSs, however, in the span of a few years, the EU has developed numerous regulatory measures for the platform economy and their use of AI and algorithms, such as the AI and Digital Services Acts (Gössl, 2023). The DSA was developed to address issues related to platform market concentration, big (user) data, and consumers' fundamental rights and thereby, regulate large platforms at the core of the digital ecosystem (Eifert et al., 2021). According to the act, some platforms must comply with RS-specific regulations, such as allowing consumers to learn about what information is used and to have access to an RS that does not use personal information (European Commission, n.d.).

Research on RS and regulations has considerably increased over the last years. However, an economic perspective with specific focus on CCIs is (to the best of our knowledge) not available. This paper provides an in-depth reflection on recommender systems and their impact on different stakeholders in cultural industries and raises the following research question: *What is the (long-term) impact of search and recommendation services on cultural and creative industries (CCIs)?* It is a conceptual review tailored to CCIs, considering the special characteristics of those markets. The structure is as follows: Section 2 gives an overview and insights in research on RS overall and in particular the gap in the cultural economic research stream. Section 3 provides a systematic discussion on the effects of RS on different stakeholders in CCIs while Section 4 sheds light on the meta-level including potential societal (long-term) effects. Section 5 concludes and summarises the main findings.

2. Literature Review

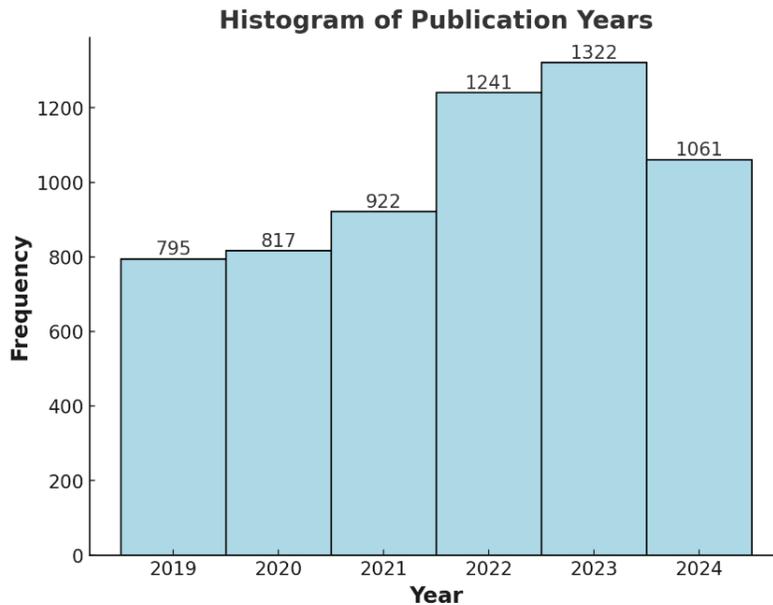
2.1 Trends in Recommender Services Research

Research on RSs has surged in the past years, including studies on their implications and the expected efficacy of regulations, mirroring the mainstream attention paid to commercial and consumer applications of artificial intelligence. For this paper, we analyse a significant corpus of research using a computational bibliometric approach. To begin scoping the literature, we cast a wide net by setting our starting point on Scopus, one of the most comprehensive academic catalogues with favourable researcher API access. Among the long-standing research databases, such as Web of Science and SemanticScholar, Scopus stands out due to having the largest number of indexed journals and publications, as well as favourable API access for researchers, allowing the utilisation of all *Litstudy* features. *Litstudy*, an actively developed and versatile Python programming package, was selected as the basis for this study's bibliometric literature review due to its ease-of-use, as well as synergy with Scopus metadata (Heldens et al., 2022).

To initiate the search, we used the query ““recommender s*“ OR "personalized recommend*“ OR "hybrid recommend*“”, a combination of relevant keywords that would gather most research that deals with RS in some form. To increase the relevance of results, we restricted the catalogue search to published English-language academic articles in their final stage of publication, thereby excluding journal pre-proofs and uncorrected proofs, conference papers and proceedings, and book chapters. Furthermore, only articles with “recommender system”, “recommender systems”, “recommendation system” or “recommendation systems”. As of the time of data collection, the search using the above query returned 9178 published articles that fit the inclusion criteria for this research. 67% (6603) of these articles have been published in the last 5 years (see Figure 1).

A comprehensive review of the vast published research focusing on RSs is not within the scope of this conceptual paper. However, the computational bibliometric approach allowed us to establish an overview of the key focus areas of our unique dataset of publications on RSs. A bibliometric approach was chosen as a suitable method of addressing the size of the RS research field. The proliferation of bibliometrics in the last decades can be accredited to the similarly burgeoning amount of research published across academia, a rise that diminishes the feasibility of conventional literature review approaches (Donthu et al., 2021). *Litstudy*, an actively developed and versatile Python programming package, was selected as the basis for this study's bibliometric literature review (Heldens et al., 2022). The dataset used in this research was sourced from Scopus accessed using an approved researcher API, thus allowing for large-scale and frequent access to the catalogue's repository.

Figure 1 Distribution of articles published since 2019.

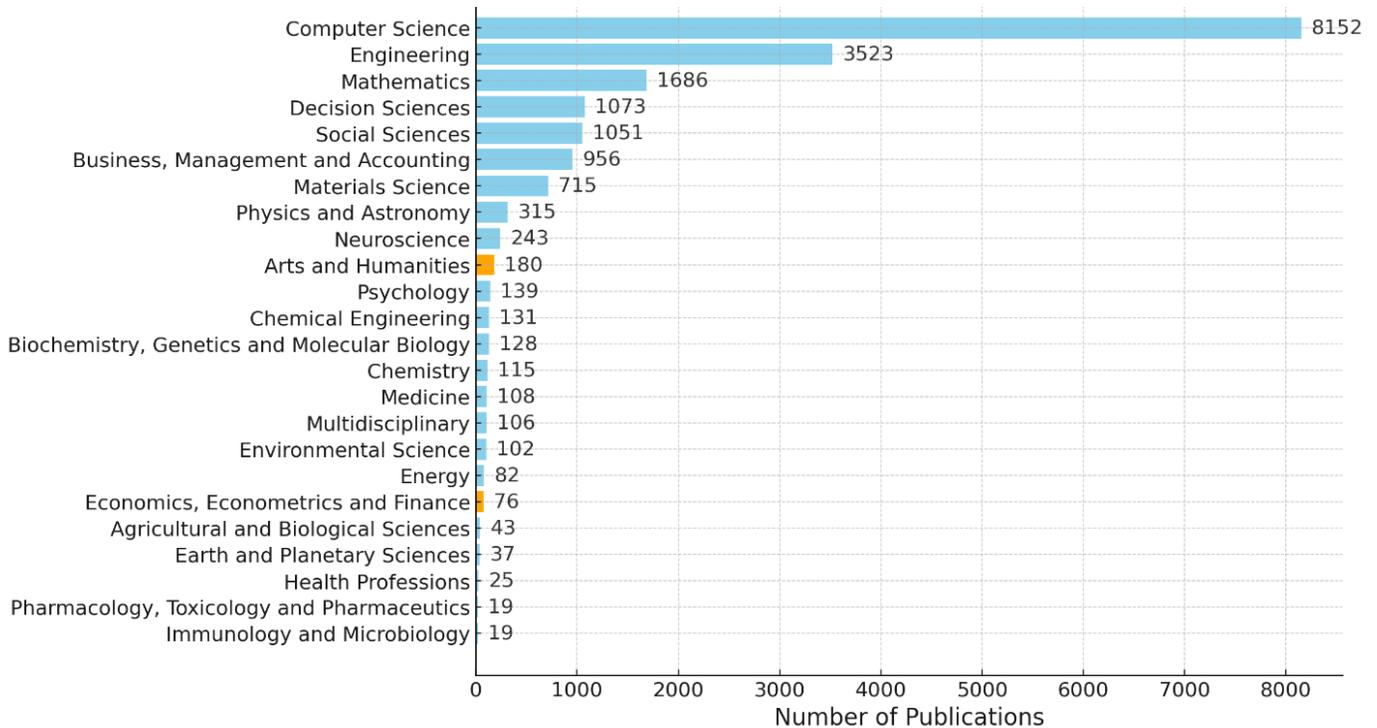


To identify topics in the research corpus, we modified *Litstudy*'s natural language processing capabilities to suit the dataset size and diversity by limiting it to 10 topics as well as restricting certain filler words (such as "data", "items", and "model"). A resulting assortment of topic groups based on the publications' titles and, particularly, abstracts are used to roughly identify key focus areas of the publications. We were able to estimate the academic disciplines each publication originates from by referring to the publishing journal's Subject Area, a characteristic developed by Scopus. Based on a journal's aims, scope and published content, in-house experts assign at least one subject area when the source enters the catalogue. The process of how these individuals reach a final decision, however, is unclear and open to criticism. The *Journal of Cultural Economics* (JCE) has the assigned subject area of "Economics, Econometrics, and Finance", meaning that all JCE articles, regardless of content, are categorised under this subject area in the catalogue. *Cultural Trends*, on the other hand, is categorised as both "Social Sciences" and "Arts and Humanities", while *Journal of Cultural Heritage* is "Arts and Humanities", "Economics, Econometrics, and Finance", "Chemistry", "Computer Science", and "Materials Science". Although a journal's corpus may differ from their initially assigned subject areas, particularly as they evolve and adapt to trends over time, these subject area designations will be used for this analysis to provide a rough understanding of what types of journals are active in publishing RS research.

A total of 19,024 subject areas are identified for the 9178 publications. Figure 1 depicts the distribution of academic fields (as per the publishing journal) across the RS research corpus. Computer Science journals

stand out by accounting for 42.9% of all subject areas. Although there are journals that have both computer science and another subject area assigned to them, it can be presumed that these papers are primarily of a computational nature. Notably, Arts and Humanities, and Economics, Econometrics, and Finance subject areas account for only 1.4% of subject areas, highlight a significant lack of representation from journals that have *some* research focus in these two areas in regard to RS research.

Figure 2 Distribution of publications across Journal Subject Areas.



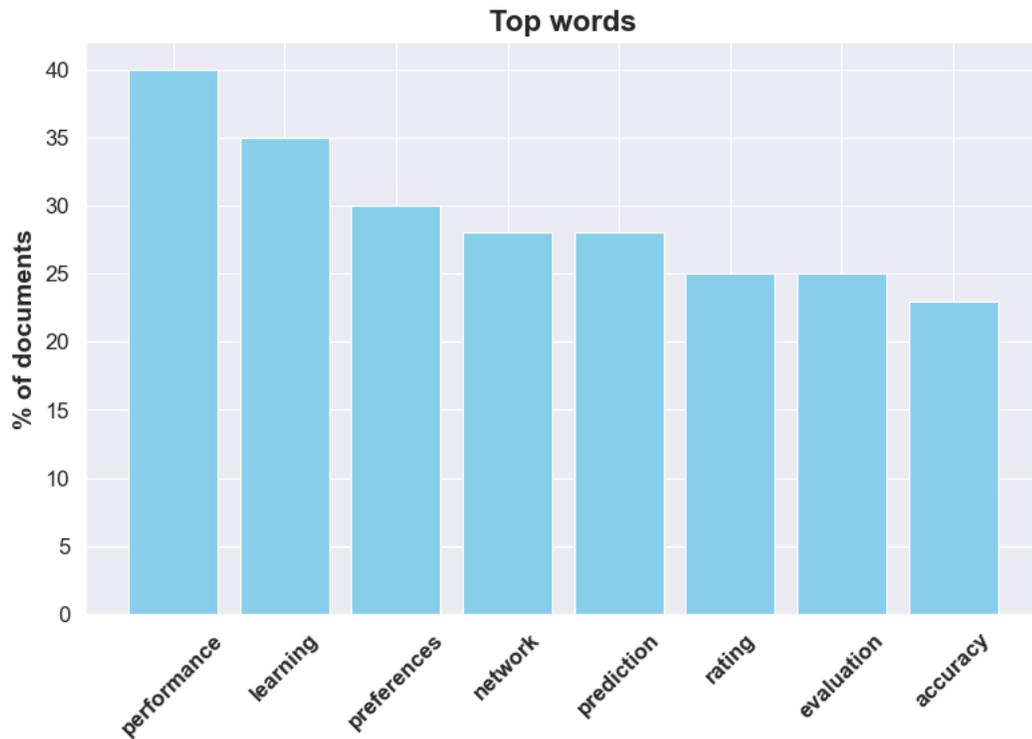
Considering that RSs are developed by computer and data scientists, it is unsurprising that 13361 of these subject areas are Computer Science (CS), Mathematics, and Engineering, accounting for 70.2% of the total. In contrast, Social Sciences (1051 occurrences), Arts and Humanities (180), and Economics, Econometrics and Finance (76) form just a sliver of the published research on RSs. Publications from the JCE fall into this latter category; however, the RS-related search query returns zero articles from this journal.

An analysis of the top keywords and topics in the dataset depict a tendency for research to focus on more technical aspects of algorithms, with the most frequently occurring keyword “performance” being relevant to 40% of publications. Although the exact context in which these keywords appear in publications have not been investigated, a significant amount of research on RS focuses on different ways to improve algorithms using intrinsically quantitatively measurable metrics, such as efficiency, recall, and accuracy. Considering that, Schedl et al. (2018) argue that computer science research places undue emphasis on quantitative metrics and user behaviour proxies to evaluate RSs. Similarly, Jannach and Jugovac (2019), in

their survey of RS business applications, find that the most common metrics are quantitative measures, such as user click-through rates (how often a user clicks on a recommended item), page views, and revenue and profit. The dominance of technical and business-oriented quantitative evaluation metrics by for-profit and commercial digital platforms is therefore unsurprising. Nevertheless, the exclusive use of such metrics when developing, maintaining, and evaluating RSs are at the cost of the nuanced subjectivities of user experience, preferences and the (long-term) impacts beyond the platform, such as cultural capital externalities (Bille, 2024), that are not understood.

Figure 3 shows the most common keywords found across the dataset which primarily consists of CS papers. The influence of the abundant CS-oriented publications in the last five years of RS research is noticeable in the top five keywords. At least two of the most common keywords refer to technical dimensions of RS algorithms, such as performance and learning (as in, a model is learning). The remaining keywords – information, improve, and effectiveness – can reasonable also stem from the CS literature in the analysed corpus, but is not limited to it. Serendipity, novelty, and diversity of recommendations are common ‘beyond accuracy’ metrics used to evaluate RSs, and commonly appear in CS research on algorithmic fairness, however, these are difficult, if not impossible, to capture purely quantitatively. Additionally, the lack of any of these metrics in the top keywords may be indicative of the overall smaller proportion of fairness-focused literature on RS. Here, fairness refers to the notion that RSs treat stakeholders equally, regardless of their sex, race, gender, geographic location, and other attributes beyond their implicit and explicit preferences (Jin et al., 2023). Fairness as a goal for RSs is difficult to achieve, particularly due its numerous definitions and conceptions spanning different stakeholders and areas of (dis)advantage and discrimination.

Figure 3 Prevalence of keywords across corpus.



In establishing stakeholders who derive utility from recommender services, Milano et al. (2020) present four groups: providers, system operators, users, and society at large. Missing from this line-up are advertisers who derive utility from RSs which lead to more engagement with the platform and therefore, more visibility for ads. Society as a stakeholder is of particular interest to this paper, as the authors rightly point out: RSs have had notable negative implications for society. Some consequences have been discussed by other publications, such as the spread of anti-vaccine misinformation (Burki, 2019) and the promotion of extremist views (Whittaker et al., 2021). On the other hand, literature on the impact of RSs in the CCIs regarding social and cultural topics, such as the impact on taste and creative production processes, is scarce, particularly empirical work. Celma's (2010) book on music discovery and the long tail presents an early shift in research that lends attention to user experience and an RS' "perceived quality", rather than purely focusing on algorithmic performance and efficiency from a technical perspective. In recent times, research has shifted away from only incorporating conventional RS metrics, such as the purely computational performance of an algorithm, its accuracy in matching user to option, and its efficiency in doing so, to an increasing focus on "beyond-accuracy" metrics (Kaminskas & Bridge, 2017). These metrics, as their name implies, refer to RS evaluation metrics such as how serendipitous, diverse or novel recommendations are. "Serendipitous", for example, in the context of RS, refers to the rate of users being pleasantly surprised by recommended content that they were not initially looking for. Although these types of metrics refer to

important aspects of a user's experience with RS, they are typically evaluated with offline experiments using historic data and no human participants, thus not accounting for critical nuances in user experience not captured by data (Ziarani & Ravanmehr, 2021). On the other hand, qualitative studies on RS user satisfaction, involving human participation, find that personal demographic attributes influence how diverse or serendipitous recommendations are perceived, independently from how serendipitous a model is quantifiably measured a priori (Alslaity & Tran, 2021; Fazeli et al., 2018; Vargas et al., 2014). Findings on subjective and varied user experiences, such as this, are at risk of being overshadowed due to the potentially overestimated explanatory power of quantitative methods, particularly of beyond-accuracy aspects. A focus on algorithmic accuracy and error measures in RS research, instead of, for example, their social, creative and cultural implications, has long been the standard evaluation approach with beyond-accuracy metrics only being introduced recently (Silveira et al., 2019). Conventional approaches, such as improving RSs' root-mean-square-error, for example, has approach in RS evaluations as a result of Netflix' open competition to improve their algorithms in 2006 (Bennett & Lanning, 2007; Hernández del Olmo & Gaudioso, 2008; Steck, 2013).

Although beyond-accuracy metrics are more commonly applied in current evaluations of RSs, their limitations as quantitative measures of qualitative difference require further steps to be taken. Additionally, their application by a computer science field lacking the expertise of social sciences and humanities necessitates a new evaluation strategy that can address subjectivities beyond the beyond-accuracy metrics. (Hesmondhalgh et al., 2023) argue for increased interdisciplinary research on RS, particularly between computer science (and related fields), and the humanities and social sciences to address the limitations that each field encounters when operating independently. This call for increased collaboration between academics with relevant technical backgrounds and critical social scientists has been echoed by many researchers who aim to investigate the socio-cultural influence and fairness of RSs (Draude et al., 2019; Fazelpour & Danks, 2021; Garcia-Gathright et al., 2018; Kordzadeh & Ghasemaghahi, 2022). Relevant to this paper, the authors mention that research that places cultural intermediation in a historically informed context stems from the humanities and social sciences, such as sociology and anthropology, with most research stemming from the media and communications discipline. They explicitly highlight how these differ from CS research. Although the lack of extant cultural economics research on RSs can explain why the field is not mentioned alongside the other non-CS fields, it seems to be an oversight that no publication highlights the value of future collaboration and research from cultural economics. An interdisciplinary approach incorporating cultural economic theory would provide valuable insights that are lacking from the existing research, including those of non-technical fields, particularly regarding the digital creative industries.

2.2 The Cultural Economics Gap

Cultural economics as a field has typically concerned itself with the study of traditional CCIs, with highly cited papers focusing on the economics of the film industry (De Vany & Walls, 1999; Prag & Casavant, 1994; Wallace et al., 1993), museums (Frey, 1998; Frey & Meier, 2006), theatres (Hansen, 1997), and cultural participation (Falk & Katz-Gerro, 2016). The Handbook of Cultural Economics (Towse & Navarrete Hernández, 2020) is compilation of chapters written by experts in the field and is updated every decade to reflect changes in the field. While the newest edition sets the tone for cultural economics in the age of digitalisation, with chapters on AI and cultural diversity in the digital CCIs which touch upon the influence of RSs, there remains a notable lack of published research on RSs in the Journal of Cultural Economics, the primary journal in the field. Concepts further developed by and commonly applied in cultural economic research on CCIs can produce value for research on RSs.

As substantial cultural consumption takes place in the digital economy, employing the concept of cultural capital in relation to RSs mediating role can provide insights for cultural policy, an instrumental application of cultural economics. Since Bourdieu (1986) developed the concept of cultural capital four decades ago, much research has been published on its connection to social status, education, behaviour and cultural consumption and taste. Some researchers have suggested that cultural capital accumulation depends on various factors, including the quality and quantity of cultural consumption and participation. There are a few difficulties with this suggestion. For one, it is difficult, if not impossible, to assign an undisputed quality judgement to cultural goods. The division between high and low culture has commonly found its place between popular culture and elite mediums, such as theatre and classical music. While high culture is understood as requiring sufficient cultural capital to be decoded and enjoyed, such as from upbringing and socio-economic environment, the lower barriers to enjoyment associated with lowbrow, or popular, culture allow for easier interpretation by people with a wider range of accumulated capital (Suarez-Fernandez et al., 2020). In this case, it matters less whether a video game is perceived as low or high art, than whether the video game, as an artistic expression, with its narrative, creative and interactive features, can contribute to an individual's cultural capital. By extension, cultural economics can contribute to understanding whether a particular video game can amplify the player's capital to the benefit of themselves, their surroundings, and society. In terms of consumption influence on cultural capital, this undoubtedly depends on various content characteristics, such as type of video game, music, film, or play, as well as individual characteristics, like education level, socio-economic status, and accumulated cultural capital. An important question, then, is to what extent an RS as a ubiquitous discovery tool, can shape individuals' cultural capital and consumption patterns, and further, how the recommended and consumed content, whether video games or conventional art, has an impact beyond the consuming party.

The JCE has published 807 research articles since its inception, with 167 of them containing “digit*” in their title or abstract (thus encapsulating “digital”, “digitisation”, “digitised”, etc.). On the other hand, a search for “museum* AND NOT digit*” alone returns 276 articles, while “book* AND NOT digit*” returns another 325 articles. Considering the age of the journal, the dominance of literature on the traditional CCIs is expected. A significant portion of research dedicated to digitalisation within and of the traditional industries, too, shows a trend of staying up to date. However, while research on RSs has drastically increased in the last five years, no articles are found in the JCE using the same queries as in Section 2.1. Some articles touch upon RSs (Jensen, 2024; Peukert, 2019), however, none focus on their role as intermediaries to culture specifically. Although there is growing research on the digitalisation of culture, we struggle to find any publication that investigates the influences of RSs from a cultural economics perspective from other journals. In the context of multisided platforms, the basis of research investigating the long-term impact of algorithmic mediation could study either consumer taste formation and consumption patterns or how the use of algorithmic tools may influence the creative production process and strategic decisions by producers regarding their output. The long-term ramifications of changing consumption and production patterns because of algorithmic mediation would be the vital step to take current literature to the next stage and up to date with the platform economy, the landscape accounting for most contemporary creative consumption and dissemination. Coming close to this, numerous publications briefly touch upon these concepts that are also of interest to cultural economics, such as RSs’ impact on the diversity of consumption, production, and the digital competitive field. For example, Nguyen et al. (2014) published one of the first articles on RS-mediated filter bubbles and the narrowing content diversity of recommended and consumed movies. The authors, who are researching from a CS perspective, find that RSs homogenise user consumption and provide potential solutions to this for platforms, however, stop short of discussion what the effects of such an outcome are on user, producer, and society. Similarly, Pajkovic (2022) posits that taste-formation on Netflix occurs iteratively between user and RS, passing agency of consumption and preference from one to the other. By understanding that consumers never have full agency over their taste, the author argues against literature that frames RSs as a threat to creativity and sees them as adding another layer to taste-formation. Pajkovic finally argues that RS research from this stance can offer opportunities to understand the new relational processes between culture and technology, despite being coopted by for-profit platform that mediate them. He touches on important points regarding scholarly concern potentially being misplaced as RS themselves are only a concern when “hijacked by corporate and commercial interests” (Pajkovic, 2022, pg. 231). However, RSs are commonly developed by profit-seeking commercial operations, therefore devaluing the distinction between RSs as a ‘natural’ digital factor of taste-formation and their co-option by corporations. Another relevant paper was published by the Spotify

Research division in which they find that users who use the platform's RS to discover music have less diverse content consumption patterns than users with organic music discovery habits. While the authors discuss short and long-term implications, they do so from the view of Spotify's goal of maximising user retention and argue that addressing content diversity concerns is necessary to satisfy users (Anderson et al., 2020). They do not discuss or mention the potential societal, cultural or artistic impact of automated music homogenisation on the scale of hundreds of millions of Spotify users (Spotify, n.d.). Arguably, this type of research focuses is typically out of the scope of computer and data science research that populates RS literature, for example, and are more appropriate for social sciences, critical internet studies, and for our case, cultural economics. Milano et al. (2020) reviewed the published research on the ethical challenges associated with the widespread use of recommender systems. They establish six areas of concern, including social effects and fairness. Their literature review initially began with over 500 publications which were filtered down to 37 relevant works. Of these, only 9 articles addressed concerns of RS' social effects, 7 of them from philosophy and social science publications. The remaining 2 articles were from computer science. Clearly the question of (long-term) social effects is relegated to fields that traditionally investigate societal changes and patterns, but which typically do not possess in-depth computational expertise to investigate RS. While Milano et al. research RS effects regarding normative outcomes, they do not touch upon concepts such as taste formation and creative homogenisation. This is not to say that any one field is appropriate for such a task, but to argue for multi-disciplinarity, akin to how cultural economics merges disparate disciplines to provide cohesive alternatives to mainstream economics to research and understand the CCIs. Taking account of economic, social, and cultural factors, the field can address how digital intermediaries differ from traditional gatekeeping agents, as well as their long-term influence as tastemakers of experience goods.

The body of literature on platform economics has grown since its inception over two decades ago and has come to address and adapt to the rapidly evolving digital field (Rochet & Tirole, 2003). Although studies investigate platform business models and their operators' incentives to bias recommendations (Bourreau & Gaudin, 2022; Calvano & Polo, 2021; Chen & Tsai, 2019; Drugov & Jeon, 2019), few synthesise these points beyond the theoretical or empirical conclusions of possible RS manipulation and bias. Much research addressing algorithmic bias stems from the CS field and takes the form of technical solutions, such as value-aware and fair recommender systems that mitigate the bias from the training data, and by extension, society (De Biasio et al., 2023). In light of more nuanced understandings of how bias is (re)produced in algorithms, the existence of bias in various tools, such as recommender systems, is no longer questioned (Gössl, 2023; Powles & Nissenbaum, 2018; Schwartz et al., 2022). Insight into the impact of algorithmic bias, such as on consumption, production, and other factors, heavily relies upon empirical data, particularly that belonging

to platform operators. This, in turn, limits the type of methods and auditing approaches available to researchers. As a result, much research on algorithmic bias and auditing makes use of the same publicly available datasets (Amini et al., 2019; Fabris et al., 2022), as is the case with music recommendation systems research (Hesmondhalgh et al., 2023; Melchiorre et al., 2021). Despite this, it is possible to produce theoretical and empirical works from a cultural economic perspective, such as on the relationship between platform incentives, network effects, and prosumer characteristics of livestreaming or the impact of RSs on digital arts and crafts marketplaces and producers' adapted creative processes (Bishop, 2019; Duffy & Meisner, 2023).

Livestreaming as a mode of content production and dissemination has drastically increased in popularity across the digital (creative) economy with millions of monthly users across Twitch.tv, YouTube Live, TikTok and other platforms globally. Content production and consumption occurs simultaneously and interaction between producer(s) and viewers is situated at the centre of the creative process (Chung et al., 2021; Lee et al., 2019). More recently, TikTok "NPC" (Non-Player Characters), have risen in popularity and represent an extreme end of how consumers can influence, and even control, the creative output they consume. Producers of NPC livestream exclusively behave (speech and movement) according to interactions by viewers, typically in the form of donations. Here, NPC refers to programmed characters in video games that have no agency and respond only to the player's actions (Fasnacht, 2024). A viewer's ability to instruct the producer, even if just for a moment, as well as the output that is shown to other viewers, is undoubtedly a motivating incentive to donate. This incentive is affected by network effects, as the enjoyment gained from instructing a producer is likely increased the more viewers the livestream has. Livestreaming as a content genre stands out due the possibility for a dialogue to be opened between consumers and producers, allowing creatives to shape their content and processes to explicit consumer preferences and feedback. This stands in stark contrast to the operations of the platform's RS that unilaterally steers consumers according to their implicit and explicit preferences. This approach cuts the producer out of the equation and with that, their ability to effectively adapt. Bond et al. (2021) discuss how prosumption takes shape on social (media) platforms and their inherent reliance on network effects. Interestingly, they posit that intermediaries can enjoy a strategic advantage to extract more value from prosumption than users. The authors do not expand on the specifics of how platforms can leverage their strategic advantage, nor what this advantage is specifically. This strategic advantage can be linked to the platform's access to all information and its agency in guiding consumers, such as through RSs and front-paging, towards producers with a community conducive to prosumption and who already exhibit direct and indirect network effects for users and advertisers (Katz & Shapiro, 1994; Leibenstein, 1950). In that sense, superstar producers are ideal candidates to garner preferential treatment from platform operators. In

platform economics, network effects can be applied to the platform industry and to the supply-side on individual platforms. While Bond et al. discuss the latter application, in the context of recommender systems and platform incentives, it is also useful to discuss network effects within the industry and its role in influencing managerial decisions to the end of increasing market power. Nevertheless, these distinct areas of network effects are two sides of the same coin and intertwined on digital platforms. Partin (2023) demonstrates the continuities between livestreaming and the traditional CIs, particularly how livestreamers balance creativity and commerce, a process that is explicitly shaped by viewers, and sponsors, and implicitly by an opaque RS. Cultural economics possesses the toolbox to research RSs in the digital CIs, such as UGC livestreaming's similarities to and departures from traditional CIs, and superstar creation due to automated gatekeeping and network effects. Although not specifically RS-focused, cultural economic research has been published on music streaming (Hracs & Webster, 2021; Jensen, 2024; G. D. Nguyen et al., 2014), social media influencers (Arriagada & Bishop, 2021; Gaenssle & Budzinski, 2021), and Netflix (Aguiar & Waldfogel, 2018; Hadida et al., 2021). RSs represent the common mediating force guiding millions of consumers through the digital CIs and for which there is an evident cultural economic gap.

The UGC and consumer-to-consumer platform supply side is characterised by a winner-takes-most landscape where popular producers will continue to disproportionately capture and attract consumers (Frank & Cook, 2013; White, 2019). Indeed, Foerderer et al. (2023) find that platforms engage in strategic poaching of superstar producers to integrate their reputation, reach, and network externalities into their platform. Although primarily media platforms have been discussed thus far, arts and crafts platforms such as Artsy and Etsy can exhibit similar behaviours and outcomes, such as superstars and homogenisation of consumption and tastes, because of their recommender system. While their revenue is derived from sales commissions and advertising, they retain the economic incentive to recommend popular goods and services at the cost of other potentially more suitable ones. Such products, especially after being explicitly recommended, have a higher likelihood of being bought due to their inherent characteristics, bandwagon effects, marketing, or a combination thereof. Akin to supply-sides within individual platform markets, the platform industry itself exhibits a winner-takes-most situation with established platforms leveraging user-centric network effects and superstar producers to increase their market share and valuations (Foerderer et al., 2023; Subramanian et al., 2021) Both indirect and direct network effects are vital for a platform's success in the attention economy and its subsequent valuations (Parker et al., 2016). On the one hand, direct network effects have the positive externality of improving utility for each consumer and producer as more participants on each side of the market join due to increased supply and demand. On the other hand, arguably more important for the platform operators, indirect network effects because of the increased user-

base, increases the value of the platform for advertisers, a primary source of platform revenue (P. Anderson & Gabszewicz, 2006; P. Anderson & Jullien, 2016).

Platforms reserve the right to unilaterally alter the competitive field by tweaking the RSs to their benefit as a profit-maximising firm, at the cost of producer visibility, and exploit the information asymmetry to enter profitable market segments (K. H. Lee & Musolff, 2023; Padilla et al., 2022). These practices, however, are obscured from all stakeholders that are potentially disadvantaged from such managerial decisions, such as competing producers, users with deprioritised tastes and demands, and in the long-term, society at large (see Section 4). Cutolo and Kenney (2021) in their study of platform power asymmetries and strategies, highlight the precarious situation that platform-dependent entrepreneurs find themselves in. Firms and entrepreneurs in the CCIs are no strangers to the precarity and instability of their occupations in offline settings, however, this risk is exacerbated on platforms. The body of qualitative RS research tends to investigate how users experience and trust algorithmic features, while their effect on producers is less sought out. Further, the highlighted studies do not pay much, if any, attention to the long-term implications of pervasive RS use to nudge and potentially form consumer tastes and producer output. With contemporary cultural and creative consumption overwhelmingly taking place on platforms, RS can have wide-ranging and long-lasting implications that need to be addressed from an interdisciplinary and cultural economic angle. Cultural economics as a field is no stranger to digitisation and its opportunities for the CCIs, thereby conveniently situating associated researchers to take the next steps by addressing the continuously growing creative platform economy. By explicitly drawing parallels to cultural economic theory, while simultaneously highlighting new divergences from it brought on by digitalisation and platform business models, we are aiming to set the starting point for future empirical cultural economics research on the use of RSs by profit-maximising platforms and their influence on arts, culture and creativity on a macro scale.

3. Impact of Search and Recommender Systems in CCIs

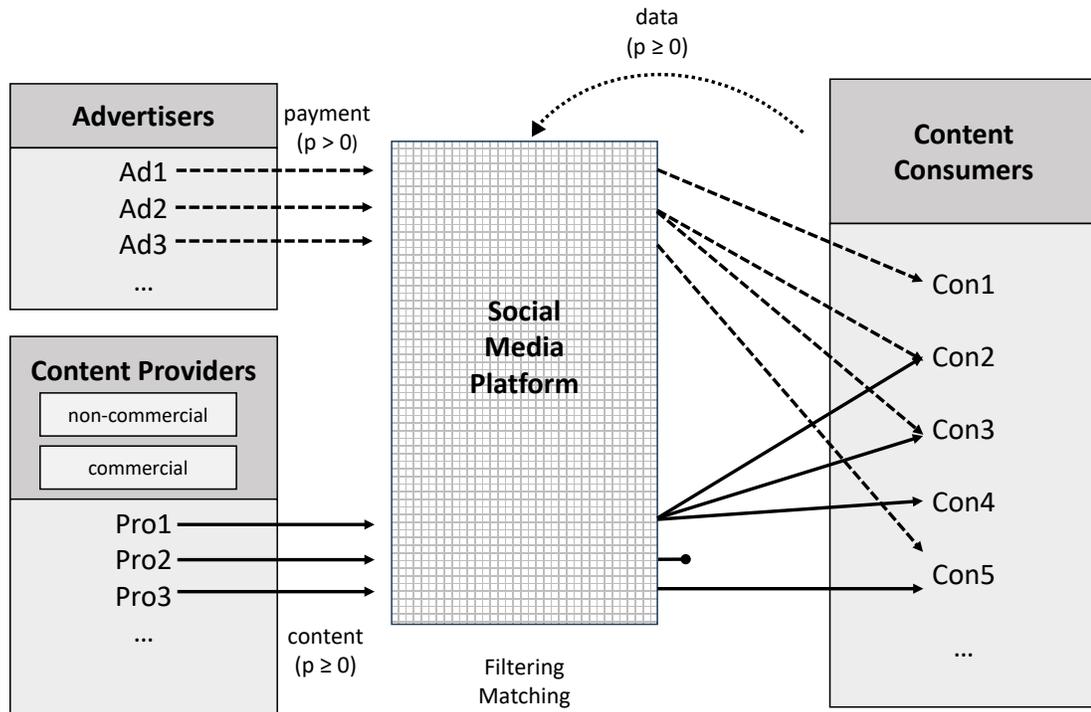
3.1 Platforms and Content Services

Platforms and digital (content/art) provision services are at the centre of RS. They program and train the algorithms and have influential power over algorithmic decision making. These services need to provide a pre-selection and filtering options. By now, functioning RS can be a decisive competitive advantage or even a necessity to compete at all (Gaenssle, et al., 2024). In this section, we differentiate between three revenue models (i) commission/subscription based, (ii) ad revenue based, (iii) hybrid.

- i. Commission/subscription based: Streaming services like Spotify Premium, Netflix, etc. but also marketplaces like Etsy, or Artsy are based on consumers subscription or commission on buying behaviour. The nature of RS on in these markets depends on the portfolio of content the distributor owns and the preferences of consumers. They own the rights to distribute the content or recommend goods within the marketplace. Streaming services like Netflix utilise algorithmic recommendations to enhance user experience and increase engagement on their platforms. These algorithms analyse vast amounts of user data, including viewing history, preferences, and interactions, to suggest personalised content tailored to individual tastes. By effectively curating content recommendations, streaming services aim to keep users engaged for longer periods including so-called binge watching (Gaenssle & Kunz-Kaltenhäuser, 2020). Moreover, algorithmic recommendations play a crucial role in maximising profits. E-commerce and streaming services operate under varying marginal revenue models per license or good. Some goods may attract higher sales and generate more revenue, while others earn a higher profits per piece/license. The margin per sale/view is decisive. Therefore, the algorithms prioritize recommending products with higher profit potential, balancing user preferences with profit-maximizing incentives. This strategic approach not only enhances user satisfaction but also ensures the financial sustainability and growth of services in highly competitive market landscapes.
- ii. Ad revenue based: Platforms like YouTube (traditional model) or Instagram do not charge consumers a subscription fee or per click; rather, they are financed by attention paid to advertisement on the respective service. They utilise algorithms to gather and analyse user data, providing personalized experiences. This data serves two main purposes: targeted advertising and tailored content recommendations. Firstly, targeted advertising means that consumers “pay” with the provision of their personal information to subsequently receive individually customised advertising. Consequently, advertisers receive more effective advertising to reach their specific target group. Secondly, the provided data is used for tailor-made recommendations of contents as well as search results within the platform. Based upon the consumers’ individual historic behaviour and preferences, RS create an individual compilation of contents (Belleflamme & Peitz, 2018; Budzinski et al., 2021). While the specifics of these algorithms are closely guarded and changed/adjusted frequently (Budzinski & Kuchinke, 2020), factors like content popularity, content “age” since up-load, and uploader audience size have always mattered for social media

recommendations (Borghol et al., 2012). Figure 3 shows the RS and illustrates the matching and filtering of (a) advertising content, (b) user generated content. We differentiate between *content consumers* (solely the receiving role) and *content providers* (producing role of uploading content). There are commercial and non-commercial providers of contents, indicating that social media influencers generate income with the provision or not. However, consumers take a much more active role in production cycles; they get into a dialogue with creators and, thus, influence production processes and contents much more directly. Consumers gain a vital role, and creators respond in their videos, creating tailor-made content. This is the active consumer part referred to as prosumption (see Section 2.2). The process of RS filtering is illustrated in Figure 3. The social media RS match targeted advertisements to consumers (dashed arrows), e.g., Ad2 is suitable for consumers 2 and 3 in this example and according to the platform’s algorithms. Moreover, the social media content (solid arrows) is delivered in an individual compilation to consumers. In this example, provider number 1 (Pro1) is particularly successful, and the RS pushes her content to consumers 2, 3 and 4, while Pro2 is not pushed but cancelled by the algorithmic system. This fictional example aims to illustrate the gatekeeping power of filtering, selecting, and pushing specific contents.

Figure 1 Social media filtering and matching services



- iii. Hybrid revenue model: Platforms like TikTok, Amazon Prime including ads², or Twitch, utilise targeted advertising as well as platform internal payment systems (Gaenssle, 2024). Business model and revenue model innovations can be observed in these highly dynamic digital markets.

However, profit-driven platforms and services have incentives to strategically manage their algorithms, promoting certain content to specific target groups, particularly if they hold dominant market positions. By using algorithm-based recommendation services, they aim to reduce search costs and information overload for consumers, ultimately increasing overall consumption on the platform. By optimizing their algorithms, digital services maximise their revenue and profits (Budzinski, Ganessle & Lindstädt-Dreusicke 2021). The goal is to provide consumers with content that aligns with their preferences, achieved through personalised user data and the promotion of successful content that is likely to be well-received. While the effects of these practices are well-documented, platforms also have an incentive to further refine their selection processes, giving them decisive gatekeeping power. In the abundance of available products and users' reliance on algorithmic selection for content discovery, services can prioritise their profit interests over strictly catering to user preferences. This can lead to biases in recommendations and search results, particularly in cases where platforms hold significant market and gatekeeping power.

3.2 Creators and Artists

3.2.1 Traditional Media Supply

Prior to the internet and digital platforms, production and film studios, and record labels were the driving force behind superstars that occupied spotlights of varied reach. World-renown figures such as James Dean, Celia Cruz, and Akira Kurosawa are undoubtedly talented creatives, however, without the support structure and reach of key gatekeepers in their respective industries, they are far less likely to have reached superstardom. Talent alone does not guarantee visibility, a caveat that highlights the essential nature of humdrum professions, such as accountants, PR specialists, make-up artists, and so on, (Caves, 2003) that strongly influence creatives' chance at success in the traditional CCIs. Few artists become successful, let alone superstars, by the virtue of their talent alone. Gatekeepers, such as agents, recruiters, and talent scouts are powerful intermediaries that often determine success and visibility of aspiring creatives seeking to make a name for themselves.

² Amazon Prime introduced an advertised (hybrid) model in some countries in 2024. (<https://www.primevideo.com/help?nodeId=TMwh2aig8aCv0WgwDL>)

In the film industry, despite the limited influence superstar actors may have on a film's success, risk-averse film executives commonly only approve proposals if a known actor is involved (De Vany & Walls, 1999), thus filtering out prospective lesser-known actors in the tail of supply. To this day, being represented by renowned talent agencies, as opposed to "non-core" agencies, legitimises a creative's talents and value to production studios and improves their chances of success (Zafirau, 2008). In the US, centuries old societal biases about talent and competence are still being reproduced by gatekeepers in agencies and in production studios leading to the underrepresentation of historically marginalised groups (Erigha, 2018; Quinn, 2011). In the context of RSs, such societal biases can affect and skew data collection processes on which recommendation models are trained on. Indeed, this can be further exacerbated by the RS' engineers whose cultural, societal, and political values are (un)intentionally conferred upon the system (Gillespie, 2016). In the music sector, a prospective talent's commercial potential is the penultimate criteria determining whether they are selected and supported by labels. As per the nobody knows principle, producers and labels have no guarantee of consumer and critical reception of an artist when signing them and investing resources (Negus, 2011). While the future success of already established artists can be predicted using their number of released albums, awards won, and gender, newer artists must be gauged using different metrics (Lee et al., 2003). The influence of these factors on commercial success likely introduces, if not perpetuates, bias and disadvantages in and through the gatekeeping process (Tatli & Özbilgin, 2012). For example, in the Hollywood film industry, racial inequality among actors and directors is further driven by gatekeepers who link a creative's commercial prospects to their ethnicity, with white actors being seen as a less risky investment with higher chances of turning a profit (Erigha, 2021). Attracting as many viewers to cinemas as possible was and is a central objective for movie productions that are presented in cinemas, and which heavily rely on box-office revenue. This likely lead to attempts to reduce demand uncertainty by making conventional choices regarding casting, staff and narrative that toe the line of what is and is not desirable in each period (Scott, 2007), a process that inevitably favours certain types of creatives and content over others due to reasons beyond creative ability.

How has this changed in the digital CCIs? The end goal of platforms in the digital CCIs is identical to that of film studios and music labels in the 20th century – to make as much profit as possible. A significant difference, however, is found in the shift towards UGC-focused platform strategies and essentially passing on the responsibility and risk associated with creative production to content producers. Platform intermediaries assume little-to-no risk and invest no resources into the content that is produced and provided by third parties who may or may not be successful. That is not to say that platforms are operating completely hands-free. As with the 20th century film industry, attracting as many viewers as possible is of paramount

importance, however, in the case of platforms, these viewers must be recurring and as active as possible on the platform to maximise advertiser revenue, most platforms' main income. The transnational reach of the internet, as well as low barriers to entry to platforms, has led to millions of producers and prospective superstars. While this may have led to an overall more diverse array of productions and contracted creatives, the use of RSs and marketing to push certain content over others may lead to a feedback loop. As Arielli (2018) convincingly posits, a large profit-maximising service's RS is not intended to match content that most align with a user's preferences but is instead aimed at maximising user engagement with the platform, a key driver of a user retention according to the vice president in charge of personalised algorithms at Netflix. While seemingly counter-intuitive at first, the argument is that RSs, such as that by Netflix, intend to cultivate and shape personal preferences in a way to increase engagement with a platform's offerings. For highly vertically integrated services, such as Netflix, HBO Max, and Disney+, who produce, market, and distribute content, it appears plausible that RSs can be used to drive consumption of and taste for their own productions. A path dependency can ensue in cases where the success of a service's own productions, aided by their RS and marketing, are interpreted as a success of the production's characteristics, such as the lead actors, director, narrative, and location. A similar process may take place on UGC platforms where certain producers are prioritised over others by the RS. In this case, the RS discriminates against other producers who may offer content that matches a consumer's preference to the same degree or more but is not advertiser-friendly or whose commission structure is not as favourable for example (Kingsley et al., 2022). The economic incentives of the platform, therefore, permeates through the entire value chain, arguably spearheaded by their automated gatekeeping processes.

In the past, gatekeepers had to guide the artist to achieve commercial success for the parent company, which led to a creative output different from one the artist may have produced in isolation from the financial pressures of the other stakeholders (De Roeper, 2008). Here, creatives that were allowed through the industry's gates enjoy some employment stability as organisations further invest in their development and provide them with contracts to secure their talents. Creatives who reach this point in their careers are at the head of the supply curve and despite forming a fraction of total number of artists, will also capture a disproportionate amount of fame, compensation, and success. In the digital CCIs, the creative is kept in the dark regarding the RS and how it operates, thereby increasing the precarity of their employment which in the case of non-superstars is not guaranteed by any contract. The automated gatekeeping process now handles an influx of the producers who are reduced to quantifiable metrics to maximise user retention and attention. As we have shown, gatekeeping in past has been affected by human biases and RSs, although automated and computational, are designed along platform incentives and trained on quantified human behaviour and are therefore not free of bias.

Traditional gatekeeping still exists and securing paid work heavily relies on connections made during work one secured in the past. Further, human gatekeepers enable creatives to better understand the reasoning for their rejection and perhaps even make a case for themselves. Therefore, creatives retain some agency over their own visibility and adaption to gatekeeping mechanisms that are not overly opaque and automated, leading to the possibility of accountability and flexibility on behalf of all stakeholders. Such gatekeeping is absent in the digital CIs, where platforms are no longer affected by the uncertainty and risk of whether any one creative good or service will be successful. The drastically increased supply and the platform's goal of retaining consumers leads to the introduction of a new type of gatekeeping to drive search costs to a minimum while concentrating consumption among a fraction of (superstar) options (Gomez-Uribe & Hunt, 2016; Maslowska et al., 2022). RSs, despite their ubiquity and effectiveness in reducing search costs, are not well understood by consumers, underlining the importance of RS transparency and understandability (Sinha & Swearingen, 2002; Tsai & Brusilovsky, 2021). Understanding the long-term effects are a necessary extension of this.

3.2.2 Social Media Creators

Social media platforms that exclusively distribute UGC depart from the gatekeeping and RS processes of the traditional media and streaming industries. RSs on platforms such as YouTube and TikTok have similar functions to those on Netflix, e.g., increasing user engagement. While SVOD services rely on subscriber numbers for revenue, UGC platforms primarily rely on ad revenue (see Section 3.1.2). This distinction informs the ways in which RSs can be leveraged by social media platforms who want to maximise user engagement in the form of attention given to the platform and advertisements. Characterised by winner-takes-most and superstars, UGC markets are easy to enter, but incredibly difficult to succeed in as a new creative, in terms of the risk borne and opportunity cost, as well as the RS-mediated visibility of one's content. While one can enter a platform's market using a phone and an internet connection, creatives are expected to invest more resources into themselves and their equipment to stand out from a sea of others who may have more funding and backing at their disposal (Partin, 2023). Prospective content creators who may want to reach a larger audience and earn an income heavily rely on the platform's content discovery features, of which the RS is but one. In the digital CCIs, automated RSs have entirely replaced the gatekeeping role performed by human agents and their accompanying flexibility and accountability. With digital platforms' inherent global reach and minimal barriers to entry for producers, consumers cannot navigate the virtually infinite range of supply without the support of discovery tools. RSs are primarily for the benefit of consumers to quickly find content that matches their preferences *enough* to remain on the platform. For social media creators, on the other hand, it's a tool that can either lead them to superstardom

or keep them in perpetual obscurity, with little to no chance of escaping using their own actions (Shin & Yoon, 2023).

In the case of the digital CCIs, qualitative studies involving entrepreneurs highlight mixed responses and ways of adapting to precarities introduced by RSs and their fundamental role in determining their success and visibility. Conventional strategies to alleviate uncertainty of demand and success in the CCIs, such as "hustling" (Langevang et al., 2022), cooperatives, and unions (Bain & McLean, 2013; McRobbie, 2011), may not be sufficient to combat the organised (in)visibility of particular producers by platform algorithms (Cotter, 2019; Duffy & Meisner, 2023). Being at the behest of platform intermediaries adds another layer of risk and, in the context of RSs, one that is not transparent nor easily understood by creatives and the general public (Pasquale, 2016). Duffy et al. (2021) conduct interviews to understand the "nested precarities" of the platformisation of the CCIs and in doing so, they can categorise the intermingled and compounding uncertainty of cultural and creative work across markets, industries, and platform algorithms. RSs undoubtedly can and have thrust individual producers into the spotlight, thereby significantly benefitting their careers, yet the platform market concentration characterised by a relative few superstars depict another angle of platform equity and competition.

Platforms reserve the right to "shadow ban" producers, effectively diverting users away from their goods and services without explicitly removing their business or account. In many cases, this is done without notice to producers whose chances at visibility and success have been hamstrung, hence it being called "shadow" ban (Goanta & Spanakis, 2020). With limited, if any, technical knowledge of the intricacies of RSs, Cotter (2019) finds that influencers on Instagram engage in a makeshift "visibility game" with platform algorithms. Being faced with information asymmetry vis-a-vis the RS, digitally-savvy and veteran influencers have found non-technical strategies to regain some agency over their visibility by "[instrumentalising] the rules in ways that seem to conflict with the interests of platforms owners" (Cotter, 2019, 908). The author claims that the recommender algorithms "parametrise rather than determine behaviour", a distinction that slightly lessens but not absolves the impact of RS on production processes and creative freedom (Cotter, 2019, 902). Other creators have echoed similar sentiments regarding the demonetisation, algorithmically or otherwise, of "controversial" content (creators) not deemed suitable for platform advertisers, particularly those of disadvantaged or marginalised groups (Kingsley et al., 2022; Rodriguez, 2023). While some "controversial" content creators are demonetised, others are rewarded as controversy breeds conflicts which inevitably leads to user engagement. In such cases, the line between acceptable and unacceptable controversial content is ambiguous and reliant on advertisers. In interviewing BreadTube creators, a leftist YouTube community with vested interest in for-profit platforms' algorithms,

Cotter (2024) finds that producers noticeably experienced the algorithm rewarding conflict and those who participate in it by driving user engagement, at the cost of fragmenting the community and movement. This raises the question of how production processes are altered according to algorithms' observed parameters and how this may differ per platform and content type, e.g. synchronous versus asynchronous content delivery. Additionally, (Cotter, 2019) underlines that primarily experienced and particularly resourceful influencers can and know how to engage and cope with the visibility game. It is theorised that for others, such as newcomers and less digitally savvy producers, the "game", i.e. the algorithm, operates as an unknown barrier to success and visibility for, thereby exacerbating digital and social inequalities (Cotter, 2019). To our knowledge, however, empirical investigation into this hypothesis has not been conducted yet.

3.3 Content Consumer (Bubbles)

Automated RS tailored to individual preferences can channel consumers in a particular direction, fostering path dependency. These recommendations determine the content displayed to users, potentially influencing its visibility/findability. Iterative feedback loops refine suggestions based on users' initial and subsequent interests, potentially leading to the formation of filter bubbles³ and echo chambers. Within such bubbles, consumers primarily receive recommendations aligned with their established interests, limiting exposure to new and diverse content. This reduction in diversity can invert the intended advantage of RS, transitioning from reducing transaction costs and information overload to limiting exposure to novel perspectives.

Budzinski et al. (2021) find four factors that contribute to the development of consumption bubbles:

- Homogeneous preferences for recommended goods: SRS cater to individual preferences, and when these preferences are highly homogeneous, the system tends to offer similar recommendations within the same category without significant variation.
- Presence of naïve consumers (Heidhues & Köszegi, 2017): Consumers who unquestioningly rely on recommendations without critical assessment increase the likelihood of being trapped in a consumption bubble, as they fail to explore alternative options.

³ On filter bubbles and echo chambers in news markets see inter alia: (Del Vicario et al., 2016; Flaxman et al., 2016; Sunstein, 2017; Zuiderveen Borgesius et al., 2016).

- Preference for one-stop shopping: Consumers who prefer relying on a single source for recommendations limit their exposure to diverse options.
- Accumulation of consumption capital (Adler, 1985; Stigler & Becker, 1977): Consumers accumulate knowledge about the system and the goods/services they consume, narrowing their focus and potentially missing out on opportunities for diversified taste and learning experiences.

From a normative standpoint, individuals may find comfort in a consumption bubble, avoiding irrelevant information and decision costs. However, this path-dependency may not always be beneficial, as it can hinder opportunities for growth and exploration of alternative tastes. Furthermore, at a societal level, consumption bubbles can lead to segregation, reducing social cohesion and hindering collective innovation (see Section 4).

4. Meta-View on a Societal Level and Discourse

Recommender systems have been in use for over a decade in the digital CCIs and other industries online. As more creative production and consumption is taking place on platforms than ever before, their influence on and beyond the digital sphere has become an increasingly important question for academic fields, regulators, and society. Clauses relating to RS transparency and standards in regulatory texts, such as the EU's DSA, and AI Act, highlight that their usage by the private sector is not flying under the radar of policymakers. Cultural economics is and should not be exempt from researching and addressing this.

4.1 Feedback-Loops and Path-Dependency

The relationship between RSs and the human interactions that inform its future decisions lead to the natural formation of feedback loops that, when unidentified and unaddressed, can cause undesirable outcomes. At the nexus of economic incentives and technological opportunities, RSs implemented by dominant platforms can cause two detrimental and contradictory results. From one perspective, the insulation from diverse voices and expressions by continuously only being exposed to similar content from similar producers, à la consumption bubbles, can lead to polarisation along cultural tastes and values. Conversely, research has examined RSs' homogenising tendencies, that, on a macro scale, can be detrimental to vulnerable and minority cultural expressions, values, and tastes who are pitted against Western hegemonic cultures (Asgary & Walle, 2002). Homogenisation is inherent in RSs as they recommend similar types of content to similar types of users based on their historical consumption patterns, thereby increasing their utility. However, utility derived from homogenisation decreases when the tastes and consumption patterns of the majority

are over-exploited, pushing those with different tastes to consume similar, i.e., mainstream, content (Chaney et al., 2018). Over-exploitation arises when a platform continuously trains its RS using data from content it had previously recommended, resulting in a feedback loop. As mentioned, filter bubbles and RSs that enforce them can provide some users with more utility due to consuming content they are accustomed to, however, on a national or global scale, this can be disadvantageous for social cohesion, and visibility of diverse cultural and creative expressions. Homogenisation of content as a result of algorithmic personalisation is empirically supported, however, the effect this has on polarisation, such as regarding political views, is more nuanced and requires more research (Keijzer & Mäs, 2022). Political and creative, i.e. taste, polarisation are two different phenomena, however, they are not entirely separate (Xu & Peterson, 2017). Thinking a step further, RSs can perpetuate a polarisation of taste found in society by extension of the social, digital, and demographic inequalities it can and has been shown to aggravate (Cotter, 2019; Noble, 2020). As Bourdieu (1984) argues, taste is inevitably determined, or at least, informed, by one's position in a social hierarchy, a distinction between classes that is continuously reinforced by the dominant hegemonic social groups. RSs, in this case, are a reinforcing measure by which tastes, content exposure, and consumption operate in a feedback-loop to the benefit of some stakeholders, at the cost of others. For an overview of potential benefits and disadvantages of RSs on different stakeholders, see Table I. A wide gulf of possibilities stands between these listed outcomes, and they are not fixed. Normative assessments of these outcomes are necessary for determining any regulatory action, particularly regarding society as a stakeholder.

Stakeholders	Potential Advantages	Potential Disadvantages
Content Creator	Chance at visibility and reach; Content recommended to appropriate audience	Algorithmic invisibility; not recommended by RS; reliant upon RS
Consumer	Minimised search costs; quick satisficing content; exposure to diverse content	Minority tastes not accounted for; narrow content exposure; mainstreaming of tastes; echo chambers
Platform	Strategic tool to attract and retain consumers; stand out from competition by use of RS; programmatically steer consumers towards specific (types of) content	Ineffective RS can turn away consumers; receive criticism for controversial recommended content; needing to balance freedom of expression and RS content moderation
Advertiser	Segment and micro-target consumers with advertising associated with recommended and relevant content	Risk of association with controversial recommended content; reliant upon RS and platform's own RS strategy

Society	Discoverability and global market access to and for diverse cultural content and forms; visibility and sustainability of niche cultural expressions	Amplification of mainstream and hegemonic cultural expressions; polarisation of societal values, and tastes; echo chambers
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Table I. Potential Impacts on Recommender System Stakeholders

Path-dependency is an outcome for both RSs and consumers. As with feedback loops, an RS can become path dependent by recommending content that is popular and sought after due to being systematically recommended in the past. The recommender could, therefore, remain on its path of recommending a fixed set of content despite better alternatives existing for certain consumers and preferences. On the consumer’s side, path-dependency can occur by becoming accustomed to certain (recommended) content producers, such as their content type, release schedule, or even locked into their social media ecosystem such as by monetarily subscribing or donating in return for benefits. Only possessing a finite amount of attention and time, consumers may not seek out more suitable alternative producers, let alone doing so manually without an RS. In such cases, the RS has accomplished its purpose of “satisficing” consumers enough to stick to some producers and discounting the rest (Pawlowski & Budzinski, 2014).

4.2 Long-Term Effects and Societal Costs

Opaque and biased algorithmic systems, self-preferencing, filter bubbles and echo chambers, inequitable platform markets, and increasing demographic inequalities, are some of the issues that can be caused by unregulated RSs implemented in accordance with a platform’s financial incentives. Studies have researched parts of these RS outcomes, but typically have not investigated what the implications of said outcomes are or could be in the long run. Researching RSs quantitatively requires a degree of computational research methods and knowledge that is often lacking in non-CS fields, such as the humanities, social sciences, and economics. Non-CS fields are better equipped at investigating topics such as long-term cultural implications and societal costs of RSs compared to CS fields yet can only do so using an interdisciplinary approach. Combining the computational knowledge of the CS field with the cultural and societal understanding of the humanities and social sciences would result in a study assessing RS outcomes and long-term consequences.

Lacking such research, particularly from the cultural economics perspective, necessitates coming to educated presumptions about the long-term effects of RSs. A few aspects of the current digital CCIs are evident: most creative production and consumption takes place in the global digital sphere and the stark increase in options necessitates some automated filtering for consumers. Following this, a sizeable amount

of literature exists on the inherent bias in RSs, their influence on widening demographic disparities, and a platform's economics incentives to self-preference and utilise an RS that fosters an inequitable competitive market for producers. For instance, new market entrants who create niche content or create goods of local or regional cultural significance may not provide the platform enough commercial value to be accorded any algorithmic attention or consideration. Etsy, Artsy, Bandcamp, etc. do not have the economic incentive to spotlight producers who's low(er) sales and engagement numbers may be mistakenly conflated with quality, talent or marketability. Very much a chicken-or-the-egg problem, new and smaller producers cannot become successful and create value, economic or otherwise, for themselves, the platform, and society, without first being systematically made visible by an RS and platform that favours the popular. Creators in such cases need to be creating art for art's sake, a motivation that privileges those that have the means to do so. Such a situation ultimately runs the risk of niche content, creative innovations, and culturally significant goods simply not being created to rival the homogenising trends of RS and the global reach of digital popular culture. While creativity still takes place in offline settings, the global platform infrastructure allows overlooked creative and cultural expressions to flourish instead of just surviving in the periphery.

5. Conclusion

At this point there are a few certainties regarding RSs and RS research. For one, despite the ubiquitous implementation and use of RSs across sectors, including the digital CIs, most research stems from CS, a discipline that is not suited for assessing the system's long-term societal, cultural, and economic implications. At risk of reproducing inherent and acquired biases when not sufficiently addressed by developers and platform operators, the diverse liabilities introduced by RSs necessitate interdisciplinary attention. Biases, such as popularity biases, can lead to outcomes that benefit some stakeholders, such as profit-maximising platforms, while disadvantaging others, such creators in the tail of supply.

The historic and current impact of RSs in the digital economy has been the subject of substantial research from different disciplines, including economics, law and regulation, strategic management, and to some degree, the wider humanities. Notably, cultural economics and its added value is not represented.

A sizeable body of literature touches upon or lies adjacent to researching the various long-term implications of RSs, however, to our knowledge, none sufficiently address or empirically test the extent of RS impact. Therefore, we answer this paper's guiding research question in two parts: for one, RSs and their bias for popular goods, have a compounding effect on producer superstardom, thus leading to further market concentration. Platforms' economic incentives to maximise profit through increased user engagement and purchases and the intrinsic nobody-knows quality of creative goods positions bias for popular producers as a risk reduction approach by increasing the chance of 'satisficing' consumers enough. This inevitably

occurs at the cost of lesser-known producers whose value to a platform is less than that of superstars and whose visibility is thereby reduced due to not being recommended.

We have shown that research on RSs has drastically increased and this without direct research or regulatory access to the systems. The unknowability of the intricate and minute details of a platform's RS leads producers to adapt to the algorithm on an ad-hoc basis. Discussed qualitative research indicates that some producers alter their creative processes, branding, and distribution methods to adapt or circumvent an RS that has shown to favour certain products and producer strategies over others. Producers who retroactively reverse engineer the RS can do so due to their digital acuity and knowledge. Others, such as amateur producers and those with less digital literacy are further disadvantaged, an outcome that is linked to research on RSs influence on worsening social inequalities, among others.

Finally, what can be said about the long-term effects of RS? Lacking focused research on this part problematises answering this question with definite certainty. However, following the research done for and discussed in this paper, we can make the educated prediction that the long-term application of RSs in the digital CCIs. The continued use of such systems while their cultural and creative homogenising and market concentrating effects go unaddressed by platforms or regulatory bodies will eventually lead to a CI further dominated by superstars. In such circumstances, under-exposed creative and cultural expressions are at risk of no longer being produced and/or seen, ensuring their relegation to the very edges of the creative industries that will increasingly be marked by homogenised popular products upsold by platforms with primarily economic incentives.

Future research can address questions such as:

1. What are the benefits and costs of recommender systems for the digital CIs? How are these distributed across implicated stakeholders?
2. To what extent do producers adapt their creative processes to increase algorithmic visibility?
3. What are the societal implications, e.g. cultural capital externalities (Bille, 2024), of RS on global and popular digital markets?
4. Should public policy regulate RS? If so, how?

Further interdisciplinary research informed by cultural economics is necessary in this domain to assess the long(er)-term outcomes associated with the increasing use of the RSs in the digital CIs.

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