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# WELFARE EFFECTS OF ALGORITHMIC SEARCH AND RECOMMENDATION SYSTEMS[1]

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## 1. What Are Algorithmic Search and Recommendation Systems?

When consumers consider buying a good (i.e. a commodity or a service), they need to be willing to pay the price of the good (depending on the marginal utility, they expect to derive from the consumption; [18; 19; 22; 27]). However, additional costs occur in the course of the actual transaction [9]. Such transaction costs consist of all costs that are attached to initiating and concluding the transaction. Part of the initiation process are search and decision costs. Search costs cover all costs related to the collection of relevant information about the good such as time to find information or cognitive capacities spent on searching. Usually, consumers do not attempt to collect all available information. Instead, they stop the searching process when they think they acquired sufficient information to make an informed decision. How much cost consumers are willing to bear depends on individual preferences but also on the importance of the transaction: routine shopping (e.g. daily products) will usually be associated with low spending willingness, non-routine shopping (e.g. a new car, an expensive holiday trip, a house, etc.) with considerable higher efforts to find information [25; 26; 5]. Notwithstanding, virtually all purchasing decisions will be made under imperfect information, implying that there is scope for decision costs, i.e. the costs of weighing the pros and cons, risks and chances of each offer in order to decide for the one that best fits the consumer's preferences.

[1] This paper draws on insights from the research project Data (R)Evolution - The Economics of Algorithmic Search & Recommender Services conducted in cooperation with Sophia Gaenssle, M.Sc. (Ilmenau University of Technology) and Prof. Dr. Nadine Lindstädt-Dreusicke (Pforzheim University of Applied Sciences, Germany) and to be published as *Budzinski* et al. (2021).

Companies may seek to help consumers' searching and decision process by offering services providing information about existing offers (search services) and helping hands for the decision (recommendation services). Retailers have always done so by presenting different products of one (heterogeneous) good and by providing information by salespersons. While already the way the information is ordered and presented may entail – voluntary or involuntary – recommendation elements, explicit recommendations may also be part of a salesperson's job. Retailers provide search and recommendation services with the goal to increase the number and the value of transactions, i.e. matching the consumer's preferences and building up a positive reputation are usually helpful for salespersons as word-of-mouth may attract or deter new consumers and recurrent transactions make consumers come back or not. While salespersons as search and recommendation service providers may or may not be neutral regarding the choice among the competing products (see also section 3 on biases), there usually exist specialized services who only provide search and recommendation but do not do the transactions themselves. In the analogue world, they often were non-commercial like non-for-profit product testing services.

The digital economy has considerably changed the nature and the economics of search and recommendation services by applying algorithms utilizing personalized consumer data. This personalized data consists of

(i) standard data about consumer identity, i.e. email-addresses, names, IP-addresses, account information, etc.,

(ii) advanced data revealing either (a) stated preferences by the consumer, e.g. comments, ratings and reviews, "likes" and similar automatized statements, "follows" of persons, goods, and companies, etc., or (b) revealed preferences, e.g. tracking consumers actual browsing, searching, and shopping behavior, and

(iii) derived data, i.e. data created by combining (i) and (ii) with each other as well as with data from similar individuals who most closely match the consumer in question in several dimensions.

Depending on the amount and the quality of the data as well as on the analytical competencies, consumption patterns of individual consumers may be derived from the data allowing for more or less accurate estimations of their preferences. In combination with the digital internet technology, this allows for individualizing and personalizing search rankings and recommendation according to the estimated preferences of the individual consumer. This is achieved by training complex algorithms with the available data from the three types categorized above, so that the algorithm automatically produces rankings of search results and recommendations that seek to match the estimated preferences of the consumer. The knowledge that in particular large online services like Google and YouTube (both subsidiaries of Alphabet), Facebook, WhatsApp and Instagram (all subsidiaries of Facebook), Amazon, Apple, Spotify, WeChat, Yandex, and others may accumulate about their consumers will – on average – considerably exceed what salespersons knew about their consumers in the "old" world.2[1]

**2. What Are the Welfare Benefits?**

Algorithmic search and recommendation systems entail a number of advantages for consumer welfare:

(1) They reduce search costs, i.e. consumers find more quickly what they are searching for and, due to the preference-oriented ranking of search results, benefit from a better overview on relevant offers (increasing market transparency). This is particularly relevant in online markets since the number of available goods is usually much higher from online retailers/services. First, storage costs are often significantly lower for online stores/services compared to offline competitors, especially if goods can be stored digitally (e.g. in the case of streaming services). Second, the cost of geography decreases in the online world, so that dispersed demand for niche products, which is too dispersed for local stores to store the good, sufficiently accumulates to make selling these goods profitable (the so-called long tail-effect). The high number of items, in turn, aggravates information overload problems by consumers who need an external pre-structuring by search services in order to receive a cognitively manageable range of offers. At the same time, the sheer amount of information is likely to overstrain even experts, whereas algorithms can (better) handle them.

(2) Furthermore, preference-matching recommendations reduce decision costs. The so-called abundance-of-choice problem resulting from the availability of vastly more goods online (compared to offline) increases the relevance of external recommendation in the digital world – and emphasize the superiority of algorithmic recommendations in dealing with

[1] Of course, a specific salesperson may know more about a specific (often returning) consumer than any algorithmic system may ever do. However, looking at the mass of the cases, algorithms are likely to be superior.

the many information. Empirical studies confirm that most consumers choose among the top ranked recommendations and search results and do not look towards the lower ranked offers [21; 24; 15], i.e. the algorithmic recommendations are effective.

(3) The improved market overview also facilitates one-stop shopping.

(4) The benefits are particularly high for consumers who have a high adversity against search and decision costs and least relevant for consumers who love the search and decision process.

(5) Transferring the insights from *Vanberg* [25] to the digital age, consumers should follow algorithmic search and recommendation services more in the case of low-key and routine consumption decisions than in the case of exceptional and outstanding important transactions.

The better the fit of the data-based preference estimation is, the higher is the positive welfare effect from these transmission channels. Individualized recommendations are well used by consumers. In the case of the music streaming service Spotify roughly 40 per cent consume recommended content, whereas Netflix estimates that about 75 per cent of its viewing consumption is driven by its algorithmic recommendations [4].

Furthermore, employing algorithmic search and recommendation systems is beneficial and profitable for the companies as well [8]:

(a) The individualization of search rankings and recommendations leads to an increase in transactions and a longer and more intensive use of the respective service, thus, increasing demand and turnover.

(b) A longer and extended consumption from the company, in turn, increases the amount of personalized data that the company can collect, including learning from the actual choices of the consumers facing the suggestions from the algorithmic search and recommendation system. This data may be profitably used in a number of ways:

a. It may further improve the individualized search rankings and the personalized recommendations, fueling a self-reinforcing mechanism.

b. The analyses based upon the data collected from the consumers are valuable for vertical or horizontal integrated services of the company. For instance, employing user data from its streaming services increases the competitiveness of Netflix or Amazon self-productions of audiovisual content because they can better estimate what viewers probably like [13]. A horizontal example would be Facebook using personalized data from WhatsApp in order to optimize their Instagram service. Profitability then originates from improving related goods and increasing their sales or usage.

c. These data analyses are also interesting for third-parties who are willing to pay for it. For instance, Spotify makes money by selling data analyses (the analysis result, not the data itself) upstream to the music industry. Targeted advertising is another example of this profit channel. Here, online services sell the result of their data analysis to advertisers through placing their ads so that they reach their data-based target group, i.e. the consumers who are according to the data-based estimations most likely to buy the advertised good.

d. Data-based price discrimination refers to cases where a company employs its user data to estimate the willingness-to-pay of individual consumers and adjust its prices accordingly. Reaping consumers' rents by individualized pricing is obviously highly profitable.

(c) Algorithmic search and recommendation services may be used as a promotional tool for other goods offered by the same company. For instance, Google Search may be inclined to rank search results to other Google subsidiaries like Google Shopping, Google Maps, Google Travel, etc. higher than to their competitors. Another example refers to Amazon offering a marketplace and running a shop on this marketplace. Thus, Amazon may benefit from biasing its search and recommendations services towards his own shop. Similarly, Netflix and AmazonPrime may be incentivized to direct viewers to their own productions instead of to content from their upstream competitors. Profits are then derived from higher sales and uses of the upstream or downstream goods offered by the respective company.

## 3. How Can Algorithmic Search and Recommendation Systems Be Employed to Mislead Consumers and Abuse Market Power?

Profit channel (b)d. (databased price discrimination) is at the detriment of consumer welfare since any quantity-enhancing textbook effect is quickly overcompensated by cross-market effects (i.e. the reaped consumer rent is not available for purchases of other goods on other markets anymore) and eroded by the presence of naïve consumers [17]. The other profit channels (a) and (b) should mostly not affect consumer welfare in any negative way as long as data analyses' results are traded (and not the personalized data itself) and as long as the less annoying character of targeted advertising (compared to untargeted advertising – because one receives advertising for goods that at least match one's own preferences) is not outdone by an increase in the volume of advertising [8]. With respect to some specific goods, algorithmic search and recommendation systems may fuel binging phenomena, i.e. over-consumption of goods [14].

Profit channel (c) from section 2, however, raises concerns. If the providers of search and recommendation systems experience incentives to bias the ranking of search results and recommendations, consumer welfare may be jeopardized in favor of company profits. A priori, they should not experience such incentives because maximizing the fit with individual consumer preferences is profitable (see section 2). However, biases can also be profitable if the provider of the search and recommendation system benefits from consumers choosing *specific* candidates from search results and recommendations. If for instance the profit margins for an online marketplace service differ among sellers on this marketplace, the marketplace service experiences incentives to recommend preferably goods from those sellers where the marketplace service's profit margin is highest. Similarly, the incentive to rank these items systematically higher in search results, independent of the consumer's preference, is given.

A particularly relevant case in question is nowadays discussed as the "dual role"-phenomenon. It describes the case where the provider of search and recommendation services also offers its own goods that are part of the search and recommendation items (see the examples of Google, Amazon, and Netflix in section 2). In such cases, algorithms providing search results or recommendations may be tweaked so that the own products (or in-house productions) are systematically upgraded and the goods from competitors of these products systematically downgraded.[1] In the Google Shopping case of the European Commission, for instance, a system was detected through which Google allegedly allocated penalty points to particularly close competitors to their own product (here: competing shopping comparison services), so that they tumbled down the rankings shown to consumers [12].

Recently, a new literature has emerged that is analyzing the conditions under which incentives to bias algorithmic search and recommendation systems are likely to occur and reduce social welfare. Most studies model a monopoly retail service (either a marketplace service or a streaming service) that includes an algorithmic search and recommendation system and two competing providers of goods (content, commodities, or services) through this service, one of them being integrated with the retail service,

[1] In particular recommendation biases took also place in the pre-digital world, when salespersons biased their recommendations to goods with a particular high profit margin or to goods for whose sales they received extra payments.

the other one independent [4; 11; 10]. *Padilla* et al. [23] also employs a monopoly service (in this case an app store) but allow for more than two providers (of apps), whereas *Hagiu* et al. [16] not only include more than two providers of goods but also a specific type of competition to the retail service (a marketplace service in their case) through direct sales by goods providers. The way and the extent of heterogeneity among consumers considerably differs between the studies. Notwithstanding, a number of insights can be extracted. According to this limited amount of theoretical analyses, incentives for algorithmic search and recommendation bias (self-preferencing) increase with the following characteristics:

- higher market power by the biasing retail service [4; 10; 16].
- larger insensitivity of consumers to biased recommendations [4; 10].
- larger differences in mark-ups across goods/contents from different providers [4;10]: if the retail service earns more from selling goods from provider A than from provider B, it experiences incentives to bias in favor of the more profitable sales. Note that this characteristic may lead to biased recommendations and search rankings even in the absence of vertical integration.
- higher search costs for consumers circumventing the search and recommendation service [4].
- higher market shares of the integrated firm on the upstream market (of goods/content providers) as it then becomes less necessary to deceive consumers [11] – especially if they are sensitive to bias.[1]
- more saturated or more mature markets [23], i.e. when growth dynamics in the primary markets of the biasing services start to slow down.
- the existence of essential "superstar" or "must-have" content/goods because consumers find it more difficult to avoid the biasing retail service [4].
- smaller quality or utility differences between the goods/contents from the integrated and the non-integrated providers [10; 23][2].
- more or more likely options to personalize subscription prices, which enhance profits of the monopoly streaming service but reduce consumer surplus [4].

[1] However, the studies do not analyze whether in such scenarios search and recommendation bias may be used to eliminate fringe competition and/or to deter market entry (i.e. securing market power).

[2] *Drugov* and *Jeon [11]* arrive at the opposite conclusion, though.

Interestingly, some of these studies also look into potential policy remedies against harmful search and recommendation biases, concluding:

- banning dual role phenomena including break-up/divestiture of the integrated firm decreases social welfare [16], except if price competition is more relevant to a monopoly retail service than quality/utility competition [10].

- preventing self-preferencing increases consumer welfare [16; 10], except if it softens competition between goods/content providers, e.g. because of a neutrality obligation requiring a randomized order of search and recommendation rankings [10], thus eroding the procompetitive effect of algorithmic search and recommendation systems.

- preventing the integrated retail service provider from imitating superior products by independent providers (e.g. through using exclusive marketplace or streaming data about this upstream competitor) increases total welfare but decreases consumer welfare because it erodes innovation incentives [16].

- banning both self-preferencing and imitation: increases consumer and total welfare [16].

- transparency policies improving consumers' knowledge about the bias (but not in the sense of revealing the properties of the algorithm) yield ambiguous results [10].

Altogether, the inclusion of self-preferencing biases in algorithmic search and recommendation systems clearly represents a welfare problem in the case of dominant market power. However, if consumers are not sufficiently sensitive towards such biases and/or incompetent to detect them, then also vertically integrated search and recommendation service providers below the threshold of market dominance are likely to cause harm to consumer welfare if they introduce self-preferencing biases. In the real world, with imperfect information and transparency as well as the presence of naïve consumers, and in the face of widespread information overload problems in the digital age, such a scenario seems to be very likely. In the most radical scenario, the combination of the just described phenomena with the existence of different mark-ups for sales of different provider's goods/contents may already suffice to incentivize harmful biases – without vertical integration or market power being a necessary ingredient.

**4. Conclusion – A New Concept of Market Power?**

Driven by the impression that traditional competition policy tools may not suffice to combat the anticompetitive challenges of the digital age, several jurisdictions are discussing reforms of their competition rules for digital business and have commissioned expert studies on this subject.

*Kerber* [20] provides an interesting comparison of several of these studies. One common feature is skepticism whether the traditional concept of market power – single-firm dominance of a distinct market – is still adequate to tackle powerful firms within digital ecosystems. In such digital ecosystems, it is notorious difficult to delineate single markets since the interrelations between markets and goods are complex. The interrelation between a retailing service (like a marketplace, a streaming service, or an app store) employing algorithmic search and recommendation services and upstream good and content producers represent a good example: phenomena of *economic dependence* [3] become widespread and power across supply chains but also across markets may be *systemic* rather than based on identifiable market shares or hypothetical monopoly tests [7]. Inspired by several expert studies, Germany [2] suggests an additional new market power concept that may be better suitable for anticompetitive problems in digital ecosystems: outstanding relevance across markets (ORAM). A non-exhaustive list of criteria for identifying such market power includes (i) dominant position in one or more markets within a digital ecosystem, (ii) financial strength and access to other resources, (iii) vertical and conglomerate integration or activity, (iv) access to competition-relevant data, and (v) significance for or influence on third-party business activities, in particular market access (also upstream and downstream) [2]. If such a market position is identified, special obligations would apply for companies enjoying such an ORAM-position. Interestingly, a prominent part of them is a general prohibition of self-preferencing as well as limitations to the use of third-party data, including such relating to upstream competitors of the ORAM-company. This new concept of market power may be implemented in Germany with the currently ongoing 10$^{th}$ amendment of the German competition law in the near future. *Budzinski* et al. [7] provide a critical discussion of this innovative concept, concluding that it entails more pros than cons and may also represent a suitable framework to address problems of strategic biases of algorithmic search and recommendation problems.

## References

1. Belleflamme, P. & Peitz, M. (2020), Ratings, Reviews, Recommendations and the Consumption of Cultural Goods, in: R. Towse & T. Navarrete Hernández (Hrsg.), Handbook of Cultural Economics, 3$^{rd}$ Edition, Cheltenham: Elgar, pp. 466–473.

2. BMWi (2020). Entwurf eines Zehnten Gesetzes zur Änderung des Gesetzes gegen Wettbewerbsbeschränkungen für ein fokussiertes, proaktives und digitales Wettbewerbsrecht 4.0 (GWB-Digitali-sierungsgesetz). Referentenentwurf (24.01.2020), Bonn.

3. Bougette, P., Budzinski, O. & Marty, F. (2019), Exploitive Abuse and Abuse of Economic Dependence: What Can We Learn from an Industrial Organization Approach? In: Revue d'Economie Politique, Vol. 129 (2), pp. 261–286.

4. Bourreau, M. & Gaudin, G. (2018), Streaming Platform and Strategic Recommendation Bias, https://ssrn.com/abstract=3290617.

5. Budzinski, O. (2003), Cognitive Rules, Institutions, and Competition, in: Constitutional Political Economy, Vol. 14 (3), pp. 215-235.

6. Budzinski, O., Gaenssle, S. & Lindstädt-Dreusicke, N. (2021), Data (R)Evolution - The Economics of Algorithmic Search & Recommender Services, in: S. Baumann (Ed.), Handbook of Digital Business Ecosystems, Cheltenham: Elgar, forthcoming.

7. Budzinski, O., Gaenssle, S. & Stöhr, A. (2020), Outstanding Relevance Across Markets: A New Concept of Market Power? In: Concurrences, Vol. 17 (3), pp. 38-43.

8. Budzinski, O. & Kuchinke, B. A. (2020), Industrial Organization of Media Markets and Competition Policy, in: M. B. von Rimscha (ed.), Management and Economics of Communication, Berlin: DeGruyter, pp. 21-45.

9. Coase, R. H. (1937), The Nature of the Firm, in: Economica, Vol. 4 (16), pp. 386-405.

10. De Cornière, A. & Taylor, G. (2020), A Model of Biased Intermediation, in: Rand Journal of Economics, forthcoming.

11. Drugov, M. & Jeon, D.-S- (2018), Vertical Integration and Algorithm Bias, Mimeo.

12. European Commission (2017), Case AT.39740 – Google Search (Shopping), Brussels.

13. Gaenssle, S. (2020), Big Data Comes to Hollywood – Audiovisuelle Medienmärkte im Digitalen Zeitalter, in: O. Budzinski, J. Haucap, A. Stöhr & D. Wentzel (Hrsg.), Zur Ökonomik von Sport, Entertainment und Medien – Schnittstellen und Hintergründe, Berlin: DeGruyter, forthcoming

14. Gaenssle, S. & Kunz-Kaltenhäuser, P. (2020), What Drives Binge-Watching? – An Economic Theory and Analysis of Impact Factors, Ilmenau Economics Discussion Papers, Vol. 26 (138).

15. Ghose, A. & Yang, S. (2009), An Empirical Analysis of Search Engine Advertising: Sponsored Search in Electronic Markets, in: Management Science, Vol. 55 (10), pp. 1605-1622.

16. Hagiu, A., The, T.-H. & Wright, J. (2020), Should Platforms Be Allowed to Sell on their Own Marketplaces? Working Paper.

17. Heidhues, P. & Köszegi, B. (2017), Naivete-Based Discrimination, in: The Quarterly Journal of Economics, Vol. 132 (2), pp. 1019-1054.

18. Jevons, W. S. (1862), Brief Account of a General Mathematical Theory of Political Economy, in: Journal of the Royal Statistical Society, Vol. 24 (2), pp. 282−287.

19. Jevons, W. S. (1871), The Theory of Political Economy, London: Macmillan.

20. Kerber, W. (2019), Updating Competition Policy for the Digital Economy? An Analysis of Recent Reports in Germany, UK, EU, and Australia, http://dx.doi.org/10.2139/ssrn.3469624.

21. Lorigo, L., Pan, B., Hembrooke, H., Joachims, T., Granka, L. & Gay, G. (2006), The Influence of Task and Gender on Search and Evaluation Behavior Using Google, in: Information Processing and Management, Vol. 42 (4), pp. 1123-1131.

22. Menger, C. (1871), Grundsätze der Volkswirtschaftslehre, Wien: Braumüller.

23. Padilla, J., Perkins, J. & Piccolo, S., Self-Preferencing in Markets with Vertically-Integrated Gatekeeper Platforms, CSEF Working P. 582.

24. Pan, B., Hembrooke, H., Joachims, T., Lorigo, L., Gay, G. & Granka, L. (2007), In Google We Trust: Users' Decisions on Rank, Position and Relevancy, in: Journal of Computer-Mediated Communication, Vol. 12 (3), pp. 801–823.

25. Vanberg, V. J. (1994), Rules and Choice in Economics, London: Routledge.

26. Vanberg, V. (2002), Rational Choice vs. Program-based Behaviour – Alternative Theoretical Approaches and their Relevance for the Study of Institutions, in: Rationality and Society, Vol. 14 (1), pp. 7–53.

27. Walras, L. (1874), Éléments d'Économie Politique Pure, Lausanne: Corbaz.