Factsheet Nr. 5 – July 2022

Algorithmic recommendation systems

What does the German public think about the use and design of algorithmic recommendation systems?

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Algorithmic recommendation systems are regularly used by a majority of the population. The recommendations given are usually based on large amounts of data collected about users. The evaluation of the data takes place both on a supervised basis and as part of a self-learning process. Research on the so-called automation bias assumes that people tend to follow recommendations made by algorithms. Even if, for example, they merely prepare people's consumption decisions, they come quite close to being an automated decision-making system in this respect. However, it is unclear how the German population think about such systems: What are the opinions on the consequences of algorithmic recommendations? And based on which data are respondents more likely to opt for the best possible outcome? Our data from the Opinion Monitor Artificial Intelligence (Meinungsmonitor KI [MeMo:KI]) show, that in many application areas (e.g., on music platforms or in media libraries), algorithmic recommendation systems are perceived as useful. However, a closer look paradoxically reveals that many respondents expect only limited time savings, orientation or the best possible result from the use of such systems. Furthermore, 67 percent of respondents consider algorithmic recommendation systems to be not at all or only slightly trustworthy. Unsurprisingly, the respondents are very critical of the use of personal data by such systems, especially when it comes to information about personal contacts or consumer behavior.

Background

Algorithms are playing an increasingly important role in everyday life. In various consumer contexts, such as online shopping or in music and movie databases, algorithms are at work. Even suggestions for expanding one's personal or professional network are now being automated by algorithmic recommendation systems. From a technical point of view, they are usually based on the collection of large volumes of data, known as big data. With the assistance of artificial intelligence (AI) methods, in particular machine learning procedures, algorithmic recommendation systems evaluate these huge amount of data and create (personalized) recommendations based on the information from users. The more data such a system uses, the more precisely recommendations can be tailored. Thus, music lists are created based on the preferences of listeners, or certain products are presented in online stores with the note "other customers also bought".

Under the keywords *algorithmic appreciation* (Logg, Minson, & Moore, 2019) and *algorithmic aversion* (Dietvorst, Simmons, & Massey, 2015) scholars discuss how people deal with algorithmic recommendations. While the *algorithmic appreciation* literature shows that laypeople in particular value algorithmic advice more than the advice of fellow humans (Logg et al., 2019), the *algorithmic aversion* literature paints a very different picture. The use of algorithms is viewed skeptically, especially in the case of recommendations that are associated with a certain degree of uncertainty (Dietvorst & Bharti, 2020). Research on the *automation bias* shows that people rarely question recommendations or decisions made by computers (Cummings,

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2004). Supposedly "wrong" or worse recommendations of such systems are then incorporated into human decisions (Abdollahi & Nasraoui, 2018). While this literature mainly focuses on the psychological components of the evaluation and works with experimental designs, we address the general attitude of the population towards algorithmic recommendation systems in our questionnaire.

Four questions are at the core of our study: How widespread is the use of algorithmic recommendation systems? How useful is their content considered to be? What are the perceived circumstances and consequences of such systems? What ethical challenges are seen in association with AI? Finally, we break down which (personal) information should be used and which should not be used in the eyes of the German public.

Methodology

Method	Online Survey
Executing Institute:	forsa Politik & Sozialforschung GmbH
Population:	German population over 18 years of age who use the Internet at least occasionally
Sample:	Weighted random sample (N=1.006)
Weighting criteria:	Age, gender and region (federal state)
Survey Period:	2020, September, 21-25
Further information:	Detailed Methodology Overview for the MeMo:KI project [in German language]

Primarily use for consumer decisions

Contact with algorithmic recommendation systems can hardly be avoided because of their widespread use. We wanted to know from the respondents where they encounter recommender systems and how often they actually use them. For this purpose, the respondents were asked to indicate whether and, if so, how often they use six different applications. Figure 1 shows how often algorithmic recommendation systems are utilized.

According to the survey, suggestions from algorithms are used consciously, especially for consumer decisions. For example, respondents often follow recommendations from algorithms when consuming video material on streaming platforms such as Netflix or when selecting news. Around 84 percent of online shoppers have at least occasionally followed algorithmic suggestions. Machine recommendations are used less when it comes to personal networks. Still, two-thirds of users have already accepted a friend suggestion in social media such as Facebook. The reluctance is even more pronounced in the case of professional networks.

Many respondents follow algorithmic recommendations - at least occasionally. In our sample, only around 4 percent of respondents reported that they had never used an algorithmic recommendation system. The vast majority of respondents have had experience with algorithmic recommendation systems in at least one area - most frequently with video-on-demand offerings and online shopping.

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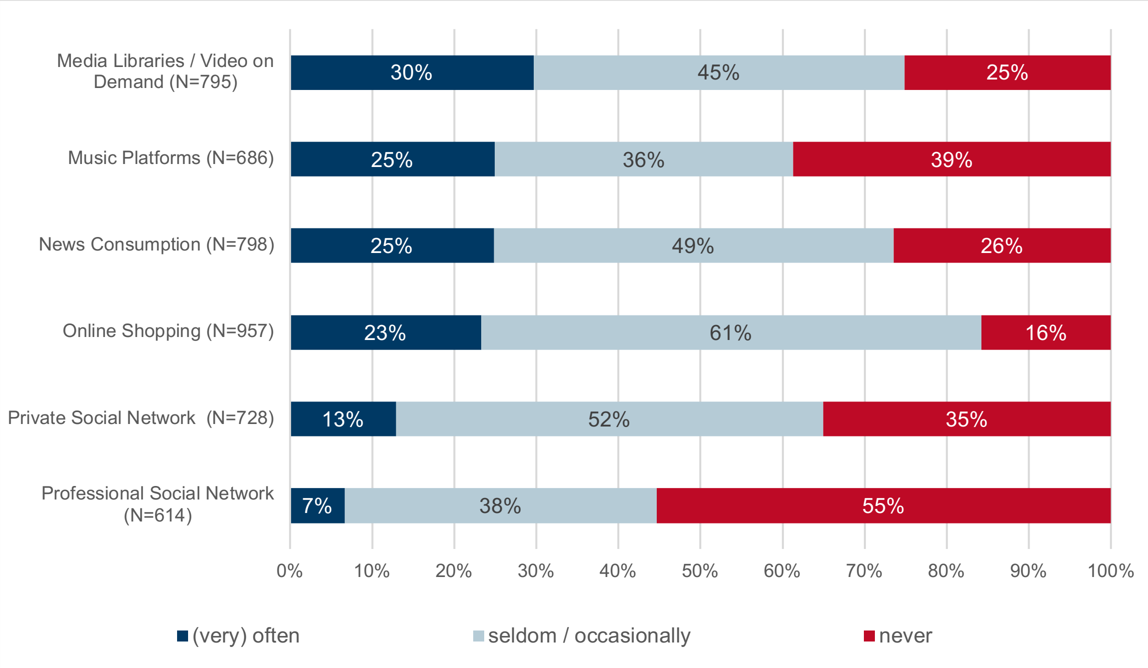
Figure 1: Use of algorithmic recommendation systems



Annotation: N=614-957, The reference value are the users of the respective application

Question text: Let us now turn to a topic from the field of digitization, specifically algorithmic recommendation systems. By algorithmic recommendation systems, we mean services that automatically provide individualized recommendations for specific products, services, or contacts by evaluating various data about users. They are used in a wide variety of digital applications and made available to users. What about you? How often do you buy a product, use a service or initiate a relationship when they are suggested to you by such an algorithmic recommendation system? How is that for..." (1=never; 2=seldom; 3=occasionally; 4=often; 5=almost always; 6=have never used such an application; 9=do not know)

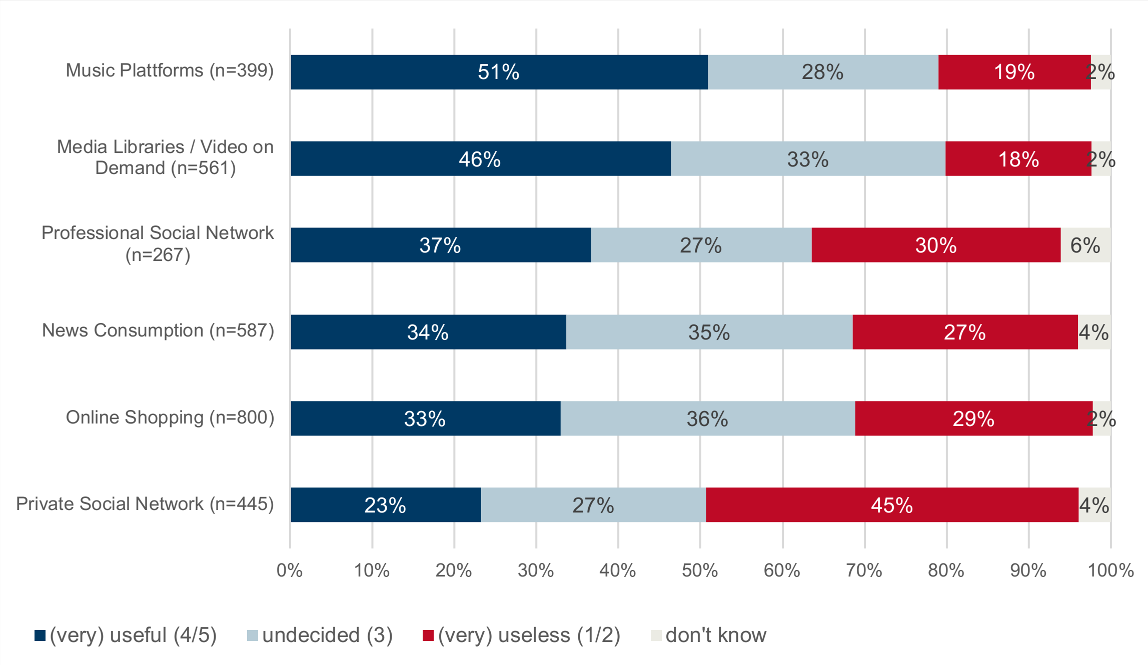
Recommendations particularly useful for entertainment purposes; quality assessment, however, generally rather reserved

The next step was to investigate how useful the algorithmic recommendation systems are judged to be in the various application areas.

The results show that the use of algorithms is perceived as particularly useful for entertainment consumption. Around half of the respondents find the machine support on music platforms (46%) and media libraries / video on demand platforms (37%) helpful. However, recommendations in professional social networks such as LinkedIn or Xing (34%) are also appreciated by the few respondents who use such recommendations at all. Interestingly, the assessment of the benefits of shopping - the application in which algorithmic recommendations are most frequently followed - is comparatively reserved. Only 27 percent felt that machine recommendations were helpful when shopping online; just under 24 percent of respondents did not even find them useful at all. The greatest skepticism about the usefulness of algorithmic recommendations is found in applications that relate to the area of private contacts. In private social media networks such as Facebook, the subjectively perceived usefulness is only 23 percent; usefulness ratings of algorithmic recommendation systems are therefore highly context-dependent.

Overall, however, it is also evident that those who follow algorithmic recommendations at least occasionally also attribute a certain usefulness to them in most cases. Especially in the consumption of entertainment media, algorithms are seen as a useful tool for providing advice.

Figure 2: Usefulness evaluation of algorithmic recommendation systems



Annotation: N=267-800; Respondents who at least rarely follow algorithmic recommendations in the corresponding applications

Question text: And how would you rate these recommendation systems, all in all? How useful do you find algorithmic recommendation systems...? ((1) I find them very useless; (5) I find them very useful; (9) I don't know)

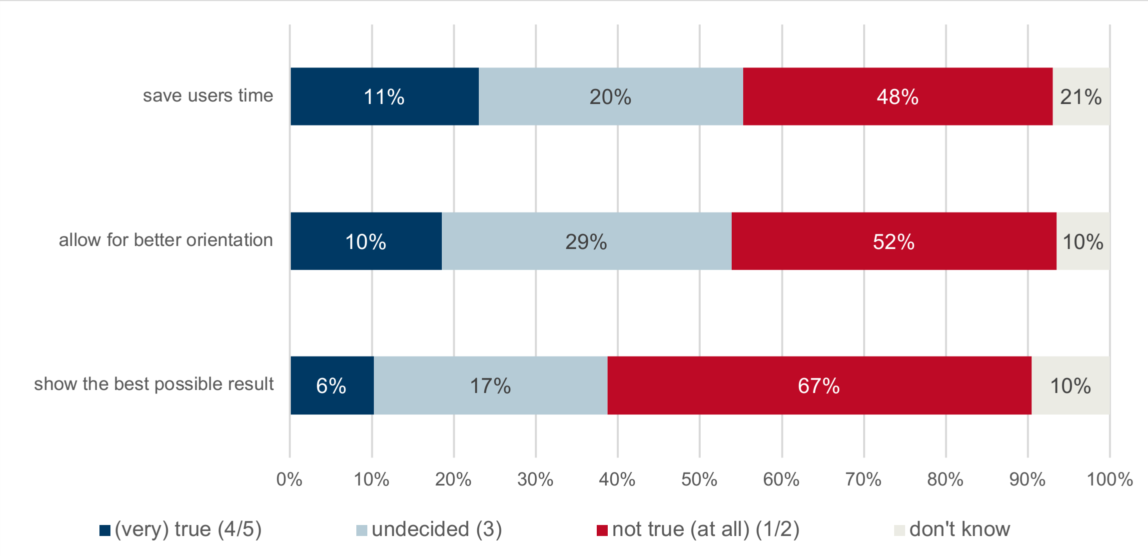
But what could this perceived benefit be based on? Although it was shown in Figure 2 that users of algorithmic recommendation systems also consider them useful in principle in most cases, these results are confirmed only to a limited extent when specific qualities of such systems are further investigated. For example, only 10 percent of respondents believe that algorithms generally provide the best results for users; more than half of respondents (52%), on the other hand, believe that this is not the case. Such systems also tend not to have an orientation and time-saving function. Only 23 percent of respondents believe that algorithmic recommendation systems can save time, and only 19 percent of respondents believe that machine recommendations generally provide good guidance.

The analysis of quality assessments of algorithmic recommendation systems shows a need for action: Many respondents do not think that these can indicate the best result for users. Similarly, algorithmic recommendation systems – in general – do not provide good orientation and hardly contribute to saving time. Regardless of whether this assessment is objectively correct, this represents a major challenge for companies that develop or deploy such systems. Companies can therefore try their hand at integrating a higher degree of usability into their applications.

From a scientific point of view, these findings can be linked to the aforementioned algorithmic aversion literature. As soon as algorithms have to include a certain degree of uncertainty in their decision – as is the case with recommendations based on user behavior and user data - uncertainty arises in the result. A song or movie recommendation cannot be a mathematically "correct" result. Rather, it is a probability estimate based on preference data. As Dietvorst and

Bathi (2020) show in experimental studies, people are more likely to reject algorithms in unpredictable situations. Further results from Dietvorst et al. (2015) show that people are more likely to reject algorithmic recommendations if they have had experience with errors in such systems. This could occur, for example, when people are recommended an item during online shopping that does not match – in their opinion – their personal preferences at all; thus, a certain skepticism towards algorithmic recommendations arises.

Figure 3: Opinions on the quality of algorithmic recommendation systems



Annotation: N=1006

Question text: In your opinion, to what extent do the following statements apply to algorithmic recommendation systems in general? Algorithmic recommendation systems … ((1) not at all true; (5) completely true; (9) don't know)

We thus see that although respondents regularly use algorithmic recommendation systems and attest a certain usefulness to them, this is hardly accompanied by a good quality assessment of the systems. Broad promises of such systems that they will save time or provide guidance are not perceived by the majority of respondents. Also, few believe that algorithms can actually show the best result for them. We therefore find a discrepancy between the usefulness rating and the quality rating of the systems. What is the source of the usefulness rating, if not the perceived increase in quality? And are the recommendations of the systems nevertheless followed or are they rejected?

One possible explanation could be that algorithmic recommendation systems are used habitually, and users see a general usefulness, but are unable to describe it or tie it to quality criteria. Another explanation could be that users want to check the accuracy of a hit in playful competition with the machine. The user compares the machine recommendation with the actual preferences and evaluates the result. Our results suggest – if this takes place – that the test should mostly be negative for the algorithm. These results raise questions that should be addressed in future research.

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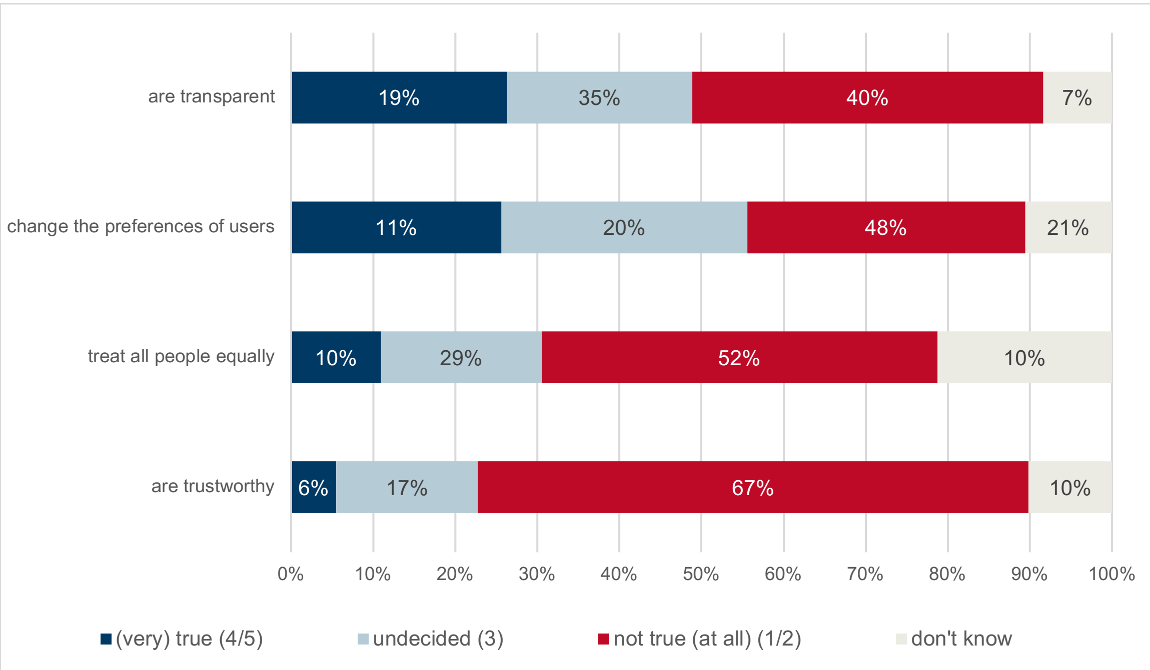
Skeptical attitude towards the ethical quality of algorithmic recommendation systems

While the analyses presented above provide information about the usefulness and quality ratings of the applications, in the following section we asked about the perceived riskiness of algorithmic recommendation systems.

Because algorithmic recommendation systems are often referred to as "learning systems", they fall under the umbrella term "artificial intelligence". According to EU guidelines, trustworthy artificial intelligence requires ethical design, which should focus on the principles of transparency, accountability and equal treatment (European Commission, 2020). In previous MeMo:KI studies, we have already surveyed the opinion of the German population on the ethical design of AI. There, it could be shown that the German population still has an underdeveloped risk awareness with regard to the ethical effects of AI (Kieslich, Starke, Došenović, Keller, & Marcinkowski, 2020). However, a roundtable discussion under the auspices of the German *Kommission zur Ermittlung der Konzentration im Medienbereich (KEK)*, a commission on concentration in the Media, revealed that transparency, equal opportunities and non-discrimination in algorithmic recommendation systems are definitely called for. But what does the German public think about the ethical design of algorithmic recommendation systems?

Figure 4: Opinions on the ethical design of algorithmic recommendation systems



Annotation: N=1006

Question text: In your opinion, to what extent do the following statements apply to algorithmic recommendation systems in general? Algorithmic recommendation systems … ((1) not at all true; (5) completely true; (9) don't know))

The results show that the respondents are rather skeptical about the ethical quality of such systems. Only 26 percent of respondents believe that algorithmic recommendation systems

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work in a comprehensible way, and only 11 percent believe that the systems treat all users equally. It is also worrying that only six percent of those surveyed consider algorithmic recommendation systems to be trustworthy; 67 percent, on the other hand, say that these systems are *not* trustworthy. In addition, 26 percent believe that algorithmic recommendation systems change the preferences of users, i.e., they not only recommend products and services to them, but rather suggest what one should want.

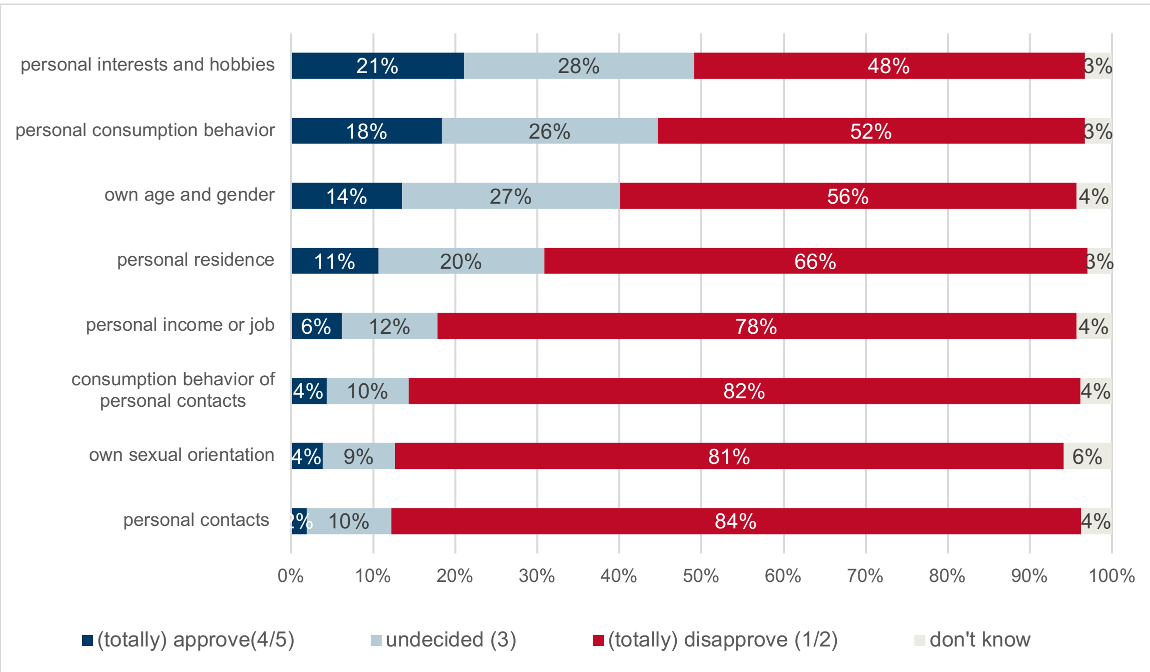
Overall, the data suggest a rather critical view of such systems among respondents. The majority of the German population does not believe that algorithmic recommendation systems meet ethical standards. In particular, the declared goal of the EU guidelines, the trustworthy design of AI, has not been met in the eyes of the citizens. These figures show that regulators and developing companies need to take action. In the sense of the EU objective, it should be ensured that a) algorithmic recommendation systems are designed transparently, fairly and trustworthy and b) the implementation of trustworthy system design is communicated to citizens.

Majority rejects use of personal data

Data is the key element to making algorithmic recommendation systems work. Without the inclusion of large amounts of data, machine recommendation systems cannot learn and cannot provide users with accurate recommendations.

But which data should algorithmic recommendation systems generally be allowed to include, and which should they not be allowed to include, according to the respondents? In the last block of questions, we examine the preferences of the German population on this question.

Figure 5: Attitudes toward the inclusion of personal data in algorithmic recommendation systems



Annotation: N=1.006

Question text: Usually, recommendations are based on information about the users. Different systems require different information. We are interested in how you evaluate the consideration of the following information in order to achieve the best possible result. How do you view the inclusion of the following information in algorithmic recommendation systems? (1= totally disapprove; 5=totally approve; 9=I don't know)

Our results show that there is a general tendency to disapprove the inclusion of personal data for all data types surveyed. The disapproval rate for almost all data types is over 50%. Above all, the inclusion of data on personal contacts (84% disapproval) and consumer behavior (82% disapproval) is perceived as particularly inappropriate. The respondents do, however, differentiate when it comes to the inclusion of their own data: Just over one-fifth (21%) of those surveyed approve of recommendation systems taking their own interests and hobbies into account. And 18 percent of respondents also approve of the inclusion of data on personal consumption. However, rejection increases when it comes to data such as one's place of residence (66% disapproval), income or profession (78% disapproval) or sexual orientation (81% disapproval).

Overall, the majority of the German population rejects the use of personal data for algorithmic recommendation systems. In this respect, the respondents are against a common practice, as the collection of user data by online platforms is commonplace. For example, suggestions from service providers such as Amazon, Spotify or Netflix are based on user data.

From a scientific perspective, there are follow-up questions to these results. First of all, the role of transparency or problem awareness in the face of the ubiquity of data collections needs to be explored. Do users even know that their data is being used for algorithmic recommendation systems? Research is needed to clarify when and why users know what data is being used, how it is being used, and by whom. Furthermore, the question arises as to the relevance of action when there is awareness of the use of one's own data. The literature on the privacy paradox can serve as a guide here, because it shows why online users are often quick to disclose personal information even though they claim to be concerned about the protection of their own data (e.g., Kokolakis, 2017).

Users are more positive about the inclusion of personal data

Are there differences in the assessment of the data basis of algorithmic recommendation systems between frequent and infrequent users of such systems? To answer this question, respondents were divided into two groups based on the usage question in Figure 1. People who use at least one algorithmic recommendation system frequently or very frequently were classified as "frequent users"; people who use algorithmic recommendation systems only sporadically (indicating a maximum of "sometimes" in the usage question for each application system) were defined as "infrequent users". The following table shows the mean values for agreement with the statements in Figure 5 in a group comparison. The values can range from 1 to 5, with a high value indicating agreement with the respective statement and a low value indicating disagreement with the statement. The asterisks indicate a significant difference between the two groups; this means that any differences found between the two groups are very likely to be found in the population (German population aged 18 and over who use the Internet at least occasionally).

The results show that frequent users are more positive about the use of personal data for algorithmic recommendation systems than are infrequent users. This applies without exception to all data sources surveyed. There are particularly strong differences between the two groups in the information sources, which generally receive the highest level of approval (see Fig. 4). In particular, frequent users rate the inclusion of data about their own interests and hobbies, their own consumption, and also their gender noticeably better than do infrequent users, while the difference in mean values (the difference between the mean values of infrequent users and frequent users) is quite small for assessments of sexual orientation or personal contacts.

Table 1: Attitude toward the inclusion of various data according to frequency of use

How do you feel about algorithmic recommendation systems include information…	Infrequent users	Frequent users
…about your interests and hobbies? *	2,18	2,81
…about your age and gender? *	1,97	2,48
…about your sexual orientation? *	1,33	1,59
…about your income or job? *	1,47	1,83
…about your current location or place of residence? *	1,79	2,20
…about your personal consumption behavior? *	2,12	2,62
…about your personal contacts? *	1,35	1,64
…about the consumption behavior of your personal contacts? *	1,45	1,68

Annotation: N=948-977, * indicate significant mean differences between the two according to design-based t-tests with significance level p<.05. The mean values for the respective groups are given; "don't know" data were not taken into account for the calculations.

Question text: Usually, recommendations are based on information about the users. Different systems require different information. We are interested in how you rate the consideration of the following information for achieving the best possible result. ((1) I totally disapprove; (5) I totally approve; (9) I don't know.)

In the future, it will be interesting to observe whether these trends can be further confirmed as the use of algorithmic recommendation systems increases. This could be a sign that skepticism towards data sharing is decreasing over time with increasing use. However, it should be noted at this point that the general openness to the use of personal data for algorithmic recommendation systems is quite low overall − even among frequent users. It is highly unlikely that people will simply approve the use of personal data in the future

Conclusion

Algorithmic recommendation systems are widely used in Germany. Only four percent of the German population, which is at least occasionally online, has had absolutely no experience with such systems. This makes it all the more urgent to understand and trace how citizens form their opinions about these systems.

Our results show that although online users generally consider algorithmic recommendations to be useful (Fig. 2), detailed inquiries leave it unclear exactly what this usefulness consists of (Fig. 3). The hope for accurate recommendations, orientation or more efficient decision-making is not fulfilled in the majority of the surveyed respondents. In this respect, it must be left open here what the perceived benefit is based on in the individual case. Although we did not ask for the assessment of orientation function and time savings for each individual system, it is surprising that the effectiveness and efficiency of algorithmic recommendation systems are on average rated rather low. Thus, the initially paradoxical finding of a widespread

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use of such systems remains, with a simultaneous skeptical perception of the performance and potential consequences for individual behavior. A more detailed scientific analysis of these phenomena is still pending.

The majority of respondents doubt the trustworthiness of algorithmic recommendation systems and complain about a lack of transparency. In addition, the use of private data to calculate individualized recommendations is strongly rejected by the vast majority of respondents. This indicates a widespread ignorance of the fundamentals of such systems, which could not function at all without mass data on consumer and search behavior.

For companies, consumer protection or political regulators, our results show that an empowered consumer alone is not enough. The consistent strengthening of the ethical design and quality improvement of algorithmic recommendation systems in the sense of the ethical guidelines, as formulated by the European Commission and the German government, must be implemented more strongly.

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