Gesa Marken, Vivian Frick, Frieder Schmelzle & Andreas Meyer

The (Un-)Sustainability of Artificial Intelligence in Online Marketing

A Case Study on the Environmental, Social and Economic Impacts of Personalized Advertising

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ECOLOGICAL ECONOMY RESEARCH

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Institut für ökologische Wirtschaftsforschung
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Potsdamer Straße 105
10785 Berlin
Germany
Phone: +49 – 30 – 884 594-0
Fax: +49 – 30 – 882 54 39
E-Mail: mailbox@ioew.de
www.ioew.de

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Technische Universität Berlin / DAI-Labor
Fakultät IV für Elektrotechnik und Informatik
Sekretariat TEL 14
Ernst-Reuter-Platz 7
D-10587 Berlin
E-Mail: sekretariat@dai-labor.de

DAI-Labor
Distributed Artificial Intelligence Laboratory

Abstract

Artificial intelligence (AI) systems can be used in various sectors, including online marketing. The probably most influential case within that sector can be found in targeting techniques that enable personalized advertising. They rely on extensive data mining, segmentation and the creation of user profiles, whereby specific ads are matched to specific persons in real time with the help of automated ad auctions. AI systems help a business to effectively approach potential consumers by allowing it to know them well thanks to detailed digital insights. The online marketing industry uses AI to gather information on online users, their devices, the software they use, the content they access and patterns of their online behavior. The structure and interplay of involved actors is deeply intertwined, opaque and strongly shaped by only a few market players who often take multiple roles (e.g., advertisers, publishers and intermediaries) at the same time. AI contributes to their immense revenues and market power. Simultaneously, fast-paced technological developments are deployed at the expense of individuals, the environment and society.

Our study contributes a holistic sustainability assessment perspective to the state of research by examining effects of AI in personalized online advertising in several dimensions: direct and indirect environmental effects, individual and societal effects and economic effects on a direct business level and a macroeconomic level. We use a mixed methods approach to investigate the role of AI in online marketing, identify different applications, their functioning and consequences for sustainability. As a complement to a literature review, we conducted several modellings and measurements on energy consumption. We also interviewed actors from the industry and used an online survey to gather data on online users' and businesses opinions. In the interviews and survey, we captured views on personalized online marketing, AI, personal awareness, conduct, measures and business strategies. Finally, we derive recommendations for (political) action to strengthen sustainability.

We identified nine harmful sustainability impacts and ten sub-effects. Risks associated with personalized online marketing are not limited to privacy protection issues in Web tracking – the backbone of personalization. The demand for data transmission, processing and storage causes substantial energy consumption and carbon emissions. Both online advertising and the collection of user data contribute significantly to these impacts. Material and energy intakes increase along 'data life cycles' and due to increasing consumption. From a social perspective, there are immense challenges concerning data protection and individual privacy of online users as well as autonomy loss, manipulation and the dissemination of disinformation. AI systems have an intensifying effect on those dangers as they make processes less controllable and comprehensible. Especially smaller companies are recognizing susceptibilities to errors and difficulties. Further issues arise because the few leading actors in online marketing own most of the required data, technology and infrastructure.

In conclusion, the application of AI in online marketing is more a barrier to sustainability than an opportunity. We argue that regulation in the form of a ban on data- and surveillance-based personalized advertisement is needed. Alternatives exist to address privacy, data protection and environmental risks. Moreover, there is a need for a public debate on what kind and how much advertising is desirable. As first steps towards sustainable digital infrastructures, we suggest using technology design principles to limit the flow and processing of data produced by online advertising. Furthermore, to address their environmental impact, businesses in digital marketing must provide more transparency about the 'intelligent' systems they use. This transparency includes disclosing methods, models and their training data, resulting energy consumption and greenhouse gas emissions.

Authors

Gesa Marken is an environmental scientist and heterodox economist working at the Institute for Ecological Economy Research (IÖW). She examines the role of businesses and digitalization in the social-ecological transformation.
Contact: gesa.marken@ioew.de

Dr. Vivian Frick is a social psychologist working at the Institute for Ecological Economy Research (IÖW). Her research includes topics such as the social-ecological and digital transformation, energy and mobility transition.
Contact: vivian.frick@ioew.de

Frieder Schmelzle is a sustainability researcher at the Institute for Ecological Economy Research (IÖW). With a background in engineering and social sciences, he investigates socio-technical systems and innovations.
Contact: frieder.schmelzle@ioew.de

Andreas Meyer is a research associate at the Distributed Artificial Intelligence Laboratory of TU Berlin. His research includes the sustainable design and deployment of AI systems and applications of machine-learning methods for load forecasting.
Contact: andreas.meyer@dai-labor.de

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List of Abbreviations

AI	Artificial Intelligence
GDPR	European General Data Protection Regulation
IMEI	International Mobile Station Equipment Identity
Int.	Interview
IÖW	Institut für ökologische Wirtschaftsforschung (Institute for Ecological Economy Research)
IP	Internet Protocol
ML	Machine Learning
NAS	Neural Architecture Search
NLP	Natural Language Processing
SDK	Software Development Kit

1 Introduction

The application of artificial intelligence (AI) systems in business and daily lives has rapidly expanded over the last years. In light of recent developments around technological advancements in fields such as automated driving or large language model-based systems (e.g., the chatbot ChatGPT), **debates on opportunities and risks of AI usage have reignited**. While AI models and their applications are on the rise in both numbers and complexity (McCandless et al., 2023), fundamental questions have emerged around their impacts on sustainability. Sustainability impacts can manifest in terms of environmental (Kongsbak et al., 2021), social (Perrigo, 2023) or economic benefits or harms (Chiang, 2023). Research is endeavoring to grasp and capture these various positive and negative effects of AI (Rohde et al., 2021).

According to McKinsey (2022), marketing and sales belong to the sectors that profit most from AI. Advertising is omnipresent online, be it on search engines, media websites, social media or other platforms. It comes in many forms, such as paid hits in search result listings, on websites or in apps, for example, as banners or videos. It is so ubiquitous that no internet user can avoid being exposed to such advertising: Almost 93 % of all Web users in Europe search the internet with the Google search engine (Statista, 2023b), more than 3 billion people use the social network Facebook in Germany, more than 60 % of the population use Instagram and even more have a Facebook account (Statista, 2023c). Even though using these platforms is free of charge, their operators have grown to be some of the largest companies in the world and make enormous financial profits (Comvergence, 2021). These profits are possible because their **business models are based on using personal data for user-specific advertising**. In this way, ‘free’ content or services can be provided to users without the providers receiving direct payment. Google, for example, provides its services for users for free and generates 78 % of its revenue through advertising (SEC, 2023). Hence, the content and services are funded by advertisement, and users ‘pay’ for using these services by providing personal data and being exposed to the advertising. Over the years, digital targeting mechanisms have inflated the online advertising market to an unprecedented scale. In Germany, its size has doubled just over the last six years (Statista, 2023a). In this business, AI plays a central role.

One of the most widespread applications of AI lies in the personalization of online marketing. Personalization in digital marketing has been continuously increasing over the last 15 years (Ma & Sun, 2020, p. 490). The rationale that drives this continuing trend is that **AI can be used to predict behaviors of online users** in order to “make the right offers to the right customers” (Kaponis & Maragoudakis, 2022, p. 1). This ability requires data that are relatable to individual online users. The analysis of such personal data is generally enabled by machine learning (ML), a set of techniques that is at the heart of most current AI systems.[1] To match offers with customers, the capabilities of AI are used in marketing not only in analyzing the personal data but also in obtaining it and in placing the advertising. Haleem et al. (2022), for instance, speak of “Mechanical AI” for the collection and structuring of user data, “Feeling AI” for deep understanding of customers and markets and “Thinking AI” for personalization and targeting. The latter is a particularly interesting object of research because this marketing approach holds significant implications for economic and social realities – next to the largely application-independent environmental effects of AI use. It seems

[1] ML techniques are the most widespread instrumental basis for many kinds of AI applications. Throughout this study, we occasionally use both terms – ML and AI – synonymously.

plausible that marketers embrace AI to address online users in highly specific groups (segments) and increase sales: “While determining targeting strategies for several segments is humanly possible, for hundreds of precisely defined microsegments, automation is a must-have.” (Ma & Sun, 2020, p. 490). AI systems can put this automation into practice, although their inner mechanisms are barely comprehensible to humans. Even research still struggles to embed ML methods into marketing theories (ibid., p. 501). This struggle is remarkable given the fact that enormously profitable companies such as Alphabet, Amazon, Meta have benefitted from using just those advertising methods for many years.

Despite the meteoric rise of personalized marketing, it is controversially debated. On the one hand, **expectations in the advertising industry are high** that AI adoption will steadily increase. Zulaikha et al. (2020, p. 7), for example, state that “AI revolutionizes marketing by presenting quality data through the use of machine learning”. Shah et al. (2020, p. 18) believe that “[t]he future of Advertising is going to be even better than before as Artificial Intelligence and Machine Learning will bring more control of Advertising to companies”, heralding nothing less than a “New Age of Advertising” (ibid., p. 19). In light of the recent research literature on AI in marketing, Verma et al. (2021, p. 6) are convinced that “[artificial] intelligence will reign supreme”. On the other hand, the inherently required collection of personal data for personalized marketing is under the close observation of many public regulators and advocates of civil liberties. The Norwegian data protection agency, for example, recently prohibited behavioral advertising on Meta’s social media platforms Facebook and Instagram due to excessive user profiling practices (Datatilsynet, 2023).

ML-based **AI systems have long been known to be anything but unproblematic** for at least three reasons. First, the massive amount of personal data needed for AI analyses is deemed problematic: “Large-scale models are impossible to build, at least in the current paradigm of supervised machine learning, without access to correspondingly large-scale datasets” (Gupta, 2021). This structural dependence on digital extraction comes with consequences. Every piece of data captured, transmitted, processed or stored consumes energy and is dependent on a large and resource-intensive digital infrastructure. Second, depending on data content, inferences on sensitive social or personal attributes (even if only implicit) are possible. And third, centralization of economic and political power is structurally favored in AI products (ibid.). Digital markets are already highly concentrated, i.e. dominated by only a few competitors. In some cases, those big players are also exploiting their market power; in June, for instance, EU regulators officially stated that Google has been abusing its powerful position on the online advertising market “by favouring its own ad exchange, AdX, in the auctions held by its own ad server, DFP, and in the way its ad-buying tools, branded as Google Ads and DV360, place bids on such exchanges” (Hern & O’Carroll, 2023, np). As a consequence, Google has now been forced to sell parts of its business. Yet, with AI applications becoming more and more indispensable in the online marketing sector and these technologies depending heavily on enormous data sets and computational power, large companies have even more of a competitive advantage.

This introduction only represents a short summary of the potential ecological, social and economic effects that can be expected of AI application in the personalization of online advertising. Its impacts on sustainability have not been investigated systematically yet. Various researchers and policy actors have identified a prevailing lack of knowledge among actors of research, civil society, companies and policy about the functioning and effects of the online marketing industry (Armitage et al., 2023; McCann et al., 2021). Christl (2017, p. 5) states that “the inner workings of today’s advertising technology are barely understood outside of this business, and even fewer people grasp its social, economic and ethical consequences”. Previous studies have mainly focused on the social and societal impacts of using data in the marketing industry (Galli, 2022; Nurm, 2019; Roetzer

& Kaput, 2022). However, the role of AI within (personalized) online marketing and its ecological consequences have not yet been thoroughly investigated.

Therefore, this study follows a mixed-methods approach to shed some light on the use and role of AI in online marketing and the relations of ecological, social and economic consequences for sustainability. The report gives an overview of these impacts based on sustainability assessment indicators for AI systems (Rohde et al., 2021). We do not claim to provide an exhaustive assessment but rather approach the role of AI in personalized online marketing with a focus on sustainability effects. To do so, we first describe how AI functions in personalized marketing and map central market actors. This introductory overview is complemented and elaborated on by a set of interviews with industry experts and an online survey among end consumers. Quantitative estimations of environmental effects are then calculated to make the energy consumption of online advertising tangible. Finally, we take a look at possible strategies to support sustainability in online advertising.

The following superordinate research questions guided our analyses:

1. How is AI used in personalized online advertising and which actors are involved?
2. Which ecological, social and economic benefits and harms result from using AI in personalized online advertising?
3. How do companies and civil society perceive these benefits and harms?
4. What political and organizational strategies are suitable for coping with the social, ecological and economic harms?

The study is structured as follows: Applied methods are described in Section 2 along with their strengths and limitations. Section 3 presents AI applications in the online marketing industry, enlarges on their role in personalized advertising and gives an overview of central actors in the field. Section 4 examines risks and opportunities of AI-driven online advertising in three sustainability dimensions. Strategies for promoting good advertising practices and mitigating the harmful effects of present patterns are developed in Section 5. Finally, we draw conclusions related to enhancing sustainability in Section 6.

2 Methods

This research is based on a case study approach. As case studies are often applied for understanding “complex social phenomena” (Yin, 2009, p. 4), they are suitable for investigating the application of AI technologies in the field of online marketing. The case study at hand includes various empirical methods with a four-step-approach: a literature analysis, a modelling of direct environmental impacts, qualitative interviews and two quantitative surveys. This approach allows a broad exploration of this complex field as well as the investigation of the perception of different actors within or affected by online marketing. In line with (Yin, 2009) the case study design was not linear but followed an iterative process in which methods and implementation were continuously adapted to newly gained research insights. For example, the research focus was narrowed down within the process from ‘AI within Online Marketing’ to ‘AI within Personalized Online Advertising’.

2.1 Literature Analysis

To approach the role of AI personalized online advertising and its effects on sustainability, a semi-structured literature analysis was conducted as a first step in providing an overview on the state of practice and research. The process is outlined below together with main strengths and limitations.

Data collection and analysis

An initial literature research was done with the help of different scientific and gray literature databases (e.g., ACM Digital Library, Google Scholar and ScienceDirect) as well as general Web search engines (e.g., DuckDuckGo and Google Search). This procedure was repeated for each research question with respective search queries (keywords) to capture the state of research on each subject. The process also enabled key authors to be identified, who were also considered as partners for the interviews to deepen relevant insights found in the literature (see Section 2.3). To achieve an adequate balance between search sensitivity and specificity (Petticrew & Robert, 2006), relatively broad search terms were initially used (e.g., artificial intelligence, machine learning, advertising, online marketing) and then supplemented with refined queries in following searches to obtain more targeted results (e.g., segmentation, real-time bidding, antitrust, carbon footprint). This approach allowed for deeper analyses of, for instance, certain sustainability aspects, market structures and political implications. Gray literature such as conference contributions and reports as well as newspaper articles and documented public debates were deliberately included to obtain a more comprehensive and differentiated image. Finally, to extend our pool of documents, we also scanned references in central pieces of literature and checked for citations of the identified literature.

In an iterative process, we approached the formulation of our research questions with initial scanning and classification of relevant literature, followed by excerpting and interpreting most relevant results, supplementary specific searches and finally conclusive analyses. To systematically analyze the obtained literature effectively, documents or abstracts were first scanned briefly to classify their relevance for our case study. Criteria were not explicitly stated and no formal ranking was applied. Our analyses fulfill the standards of a scoping review rather than a systematic literature review (Arksey & O’Malley, 2005), similar to the approach described by (Sucharew & Macaluso, 2019). This method is particularly suited for diverse and complex fields of study that have been investigated relatively sparsely (Peters et al., 2015). The approach showed itself as suitable for our

purpose. As described below, the explorative character of our case study also helped to inform the design of the quantitative surveys and qualitative interviews.

Limitations

The field of online marketing is broad and complex, which led to several decisions on thematic focuses and simplifications in our study. The same holds true for the body of literature on AI, which is largely put on a level with ML systems in this study. We chose simplifications in cases that significantly help comprehension of a certain subject or mechanism and make these simplifications transparent throughout the report. As our literature analysis followed a flexible procedure rather than a formalized systematic approach, some relevant documents may have not been identified through this method. Moreover, some findings can be particularly difficult to interpret because our object of research – AI and sustainability in online marketing – is a highly diverse and cross-disciplinary field. We addressed this challenge with triangulation through qualitative expert interviews. A further limitation lies in the speed of changing AI development, regulation, debates, etc., with which technology assessment and research barely manage to keep pace. This issue is overcome by including conference papers in the analyses, which are often closer to the latest developments and novel issues.

2.2 Modelling

A simulation study was performed to assess the energy consumption associated with deploying personalized online advertising. The study was limited to measurements that can be obtained from end devices. For this purpose, data on the power consumption of advertisements and data transmission were collected. Estimating the power consumption of the AI systems and data analysis methodologies employed for personalization as well as of the requisite data storage procedures in remote data centers remains a complex challenge due to the often-guarded nature of information provided by advertising entities. Due to these limitations, this modelling approach only estimates a share of the energy usage for online advertising.

The simulations estimated the impact of online ads on the energy consumption of an end user's device and measure how much data is transferred between the advertiser and the browser. They used the Web privacy measurement framework OpenWPM,[2] which provides comprehensive browser instrumentation for automation while collecting information on tracking and personalization. The simulation involved repeatedly crawling the 200 most visited German websites according to the Tranco list, which combines rankings from multiple sources to make it more reliable and resilient to manipulation (Tranco, 2023). The sources it combines include the Alexa Internet Top 1 million (data collected from Amazon's Alexa browser extension), the Cisco Umbrella Popularity List (data collected from Cisco's DNS services) and the Majestic Million (a ranking based on how many other websites link to a site). For each visit, we measured the loading time to access the website and the energy consumption of the device for that visit. To assess the impact of online advertisements, we ran these simulations with and without the use of an adblocker. Furthermore, we collected data on the number of third-party cookies that were stored during the visit and the amount of traffic that was caused by cookies.

[2] https://github.com/openwpm/OpenWPM

2.3 Interviews

A core part of the case study was eight qualitative interviews with online marketing experts. The interviews pursued two main objectives:

1. Substantiating the results of the literature review on the use and role of AI in online marketing and verifying the literature-based actor mapping by discussing drafts of the infographics (see **Figure 1** and Figure 2) with selected interview partners.
2. Identifying the perceived ecological, social and economic benefits and harms of AI use in (personalized) online advertising and discussing possible solution strategies.

Data collection and analysis

Eight online expert interviews were conducted from April to June 2023, each approximately one hour. To cover perspectives from various actors involved in the online marketing process, we interviewed experts from three different actor groups: organized civil society, companies that advertise their own products and services, marketing agencies. The final sample included the interview partners listed in Table 1.

Table 1: Interview partners

Nr.	Organization	Position of interviewee
Organized civil society		
1	Association for fundamental rights and digital data protection	Founder and activist
2	Network for human-rights-based advertising	Co-Chair and activist
3	Referendum against public advertising	Activist and lawyer
Companies		
4	German large retail and e-commerce company	Team Lead Online Marketing
5	German sustainability-oriented, medium-sized mail order company specialized in office supplies	Head of Marketing and E-Commerce
6	German sustainability-oriented, medium-sized manufacturer of outdoor and sports gear	Head of Marketing
7	German sustainability-oriented, small-sized online marketplace	Head of Marketing
Marketing agency		
8	Large European marketing consultancy agency	Data scientist

All interviews were recorded and transcribed. Based on Mayring (2000), deductive-inductive qualitative content analysis was conducted by three independent researchers using the program MAXQDA. The main categories for analysis were derived from the sustainability concept of Rohde et al. (2021) as well as a prior literature review on the benefits and harms of AI in online advertising. The analytic grid applied distinguished between social, ecological and economic opportunities and benefits as well as risks and harms. Social risks and harms were differentiated into direct individual and indirect societal harms. Ecological risks and harms were differentiated into direct and indirect ecological impacts. Economic risks and harms were differentiated into impacts on the direct

business level and indirect impacts of the macroeconomic level. Further subcategories were derived inductively during the coding process. Direct quotes from the interview material will be used in this report for illustrating the results. They are referenced with “Int.” for interview and the number of the interview according to Table 1.

Limitations

Qualitative interviews do not claim to be representative but rather to give an in-depth insight into specific cases. They provide a deeper understanding of the internal processes, views and paradigms of certain areas, e.g., the marketing department of a company, and therefore contribute to answering the research questions. However, it is important when interpreting the results to be aware that the answers of the interview partners do not stand for the views of, e.g., all civil society organizations or all marketing consultancy agencies. In this case study, two complementary surveys were conducted (see section 2.4) in order to gather more generalizable results.

Besides this overall limitation of qualitative interviews, there are two further limitations specific to this case study. First, there was a lack of interview partners of marketing agencies as the response rate to interview requests was low. Only one of 16 contacted marketing agencies agreed to an interview. Related to this limited response, a bias in the response rate of the company interview partners can also be assumed. Especially those companies that already claimed to have sustainable policies were willing to participate in an interview. This willingness influences the results because the interview partners might be more informed and more engaged in sustainable ways of personalized online advertising than an average company.

Second, within the interviews, it was difficult to obtain and establish a common understanding of benefits and risks of AI in personalized online advertising. Because not all interview partners had a common understanding of the term ‘artificial intelligence’ and were not equally aware of the specific application of AI in personalized advertising, it was not possible to clearly distinguish between the consequences of AI use and the general consequences of personalized advertising. However, this limitation was not considered to inhibit the answering of the research questions because the literature analysis has shown that AI is widely applied in all steps of personalized advertising (data mining, data analysis, targeting; see section 3.2). Therefore, it can be assumed that AI-based advertising and personalized advertising can be used almost synonymously, regardless of whether interview partners were aware of this connection. Further, all general consequences of personalized advertising are amplified through using AI and, thus, a clear distinction is not mandatory within the scope of this case study.

2.4 Representative online surveys

Two online surveys were conducted in June 2023 as part of omnibus surveys – a form of survey in which various topics are queried. The first survey was targeted at households. 2086 participants answered and the sample was recruited from the German adult population (18 years and older). Reported data were weighed and are, therefore, representative for the categories age, gender and region. For sociodemographic details, see Table 2.

Table 2: Representative sample of German households (N = 2086)

Gender	male	49 %
	female	51 %
Age	18 - 24 years	9 %
	25 - 34 years	15 %
	35 - 44 years	15 %
	45 - 54 years	20 %
	55 years and older	41 %
Highest level of education	No degree	4 %
	Still in education	3 %
	Still studying	5 %
	Apprenticeship or comparable degree	55 %
	University or technical college degree	28 %
Monthly household income	Less than EUR 500	3 %
	EUR 500 to under EUR 1000	7 %
	EUR 1000 to under EUR 2000	20 %
	EUR 2000 to under EUR 3000	19 %
	EUR 3000 to under EUR 4000	14 %
	EUR 4000 to under EUR 5000	10 %
	EUR 5000 and more	13 %
Household size	1 person	29 %
	2 persons	39 %
	3 persons	16 %
	4 persons	12 %
	5 persons or more	5 %

The second survey was targeted at companies. In total, 520 decision makers in German companies responded. Reported data were weighed and are therefore representative for the number of employees in Germany. Table 3 lists details of the assessed companies such as size, sector or generated revenue.

Table 3: Representative sample of German companies (N = 520)

Industry	Mining, Construction, Real Estate	8 %
	Production: automotive, machinery, technology, other	10 %
	Wholesale, Retail	8 %
	Service industry: Media, research, IT, engineering, maintenance	16 %
	Business services	5 %
	Finance: Financial accounting/accounting & financial services	7 %
	Legal	3 %
	Education	6 %
	Health care, nursing	7 %
	Arts, Entertainment, Leisure	3 %
	Restaurants, Hotels, Airline, Tourism, Transportation	13 %
	Other	10 %
Revenues	Company in formation, no sales available yet	1 %
	Less than 1 Mio €	23 %
	1 Mio € to under 10 Mio €	23 %
	10 Mio to under 100 Mio €	14 %
	100 Mio € or more	15 %

Company size (number of employees)	1 (only myself)	8 %
	2 -19	18 %
	20 - 49	14 %
	50 - 99	12 %
	100 - 249	16 %
	250 - 499	11 %
	500 - 999	8 %
	1000 and more	15 %
Field of activity of the organization	Private sector (for-profit company)	75 %
	Public sector (salaried, civil servant)	15 %
	Non-profit sector (non-profit organizations, such as charities)	7 %
Department / area of the interviewee	Management/Administration	28 %
	Sales	8 %
	Marketing	3 %
	Finance/Controlling/Financial Accounting	5 %
	Human resources	7 %
	Purchasing/Procurement	4 %
	Production/provision of services (e.g., consulting, customer support, programming, etc.)	8 %
	Manufacturing (of goods and commodities, e.g., assembly, production)	4 %
	Shipping and logistics	2 %
	Research and development	3 %
	IT	14 %
	Other area	11 %

3 Advertising with AI

The processes of online marketing that use AI are often not transparent. Moreover, they are subject to rapid development. Notwithstanding these challenges, a status quo analysis is essential to make the effect of AI in marketing assessable. In the following, we outline the areas of online marketing in which AI systems are used and how AI-driven placement of personalized advertising works. This use includes processes of data mining and tracking; the development, application and optimization of algorithmic systems; the final playout of online ads based on highly automated auction mechanisms and the actors and players involved in personalized advertising businesses and markets.

3.1 The Role of AI in Online Marketing

AI has not been developed for one specific application context or to solve a certain problem. It is more considered an **'enabling' technology** (Ramahandry et al., 2021) that can be applied in enormously diverse contexts and for various objectives – including sustainability targets. Online marketing can leverage the properties of AI as self-learning systems in numerous ways (Rohde et al., 2021, p. 14). Dauvergne (2022), for example, mentions not only the general promise of increased efficiency but also the use specifically for marketing campaigns and automation of customer contact and service and for the precise classification of customers into segments, the corresponding targeted allocation of advertisements (microtargeting) and the adjustment of sales prices depending on the consumption profile. The possible and already widely used applications of AI in online marketing are distributed across different sub-areas, which are not always clearly separable.

Kingaby (2020) takes a perspective on AI in online marketing that mainly addresses three broad value propositions: **personalization, interactivity and efficiency**. These three functions of AI systems in marketing are related to each other rather than isolated. The aim of tailoring content to recipients as finely as possible (personalization) is to make marketing more effective. Potential buyers are meant to become actual buyers, who purchase products or services. Data capturing elements on the Web can generate further data from AI-enabled features such as voice or image recognition or text and speech creation (interactivity). Finally, overall marketing effectiveness profits from both interactivity and personalization if it is widely automated (efficiency). In digital marketing ecosystems, information on consumers is drawn from online behavior and interactions in a way that is not directly visible to online users and takes place in the background. Clicking, watching, reading or purchasing decisions are thus maximized with different forms of AI systems, making online marketing more effective. However, measuring the effectiveness is difficult and reported results are accordingly inconsistent (Marotta et al., 2019). After all, a glance at empirical online marketing industry data (volume and growth) strongly suggests that personalization must be either very effective or overloaded with excessive expectations.

The basic capability of an ML-based AI system is that it can **infer the most likely useful output** not based on explicitly programmed rules (as would be the case for classic software solutions) but through using a model that autonomously processes input data based on very large sets of previous examples. This learning of previous examples is called model training, and the input examples are called training data. Training processes exist as supervised learning, where human feedback to training inferences increase model performance, and unsupervised learning, where a system learns completely on its own. The ‚usefulness' of an output is usually defined by AI developers/operators. For instance, a useful output of an automated recommendation system could be

recommendations that are particularly close to a user's momentary preference, but it could also be something particularly cheap, healthy, profitable for a third party, and so on.

For the fully online digital advertising business, **AI applications are basically omnipresent** in marketing companies and departments. Common systems facilitate, for instance, market research, consumer and market intelligence, ad performance management, marketing strategy and planning, predictive analytics and process automation in the workplace, as well as chatbots, translators and other tools based on text, speech or image recognition, etc. (Bünte, 2018; Galli, 2022; Seifert et al., 2018; Terstiege, 2021). Even in physical stores, AI systems can serve ads based on real-time customer analysis or provide augmented realities to "make the shopping experience efficient and enjoyable" (Ma & Sun, 2020, p. 491). The concrete AI use cases in marketing thus reach from automated customer services to dynamic pricing. In advertising companies, digital assistance systems help optimize processes and implement and efficiently use data-driven analyses. If training data sets are available internally, a company can also develop and possibly distribute its own AI products. However, these data sets are rare and, as a rule, such cases involve very large and thus structurally favored players (Galli, 2022, p. 39). The most common approach in digital marketing is either to use tools provided by Big Tech companies or to involve specialized ad tech service providers.

A central case of ML-based marketing applications is the prioritized display of **personalized online content**. Tangible examples exist in the results of online search requests. On the internet, these results are almost never sorted randomly: The displayed order of items is instructed by AI systems that optimize it towards predefined parameters, search results that are not sorted by criteria a user has consciously chosen (e.g., by novelty, product characteristics, price, brand, etc.). Throughout the Web, algorithmically matched (personalized) displays often appear as content that is labelled as particularly 'relevant' or 'recommended'. About one third of the sales of the online retail marketplace Amazon, for example, can be traced back to such recommendation systems (Dauvergne, 2022). Although such systems do not deliver advertisements in a narrow sense, the technical mechanisms are similar to those in the focus of this study (see Section 3.2). They are used widely in general online search engines, social media interfaces and on media platforms delivering videos, music, news, or research articles, etc., and the relevance and intensity of use of AI for marketing in companies of all sizes is expected to increase (Lichtenthaler, 2021).

Due to the above-mentioned enabling (general purpose) character of AI and an advertising market structure that is remarkably complex, the different actors, cases and domains of AI use are often intertwined and almost inseparable. For our study, we chose **the case of personalized advertising**, which touches on a range of different actor types and systems. It can be seen as a particularly defining characteristic of AI-supported online marketing as it combines the main value propositions pointed out by Kingaby (2020) and relies particularly heavily on ML methods, i.e. the most dominant technical foundation of today's AI applications. Moreover, isolated AI applications such as chatbots seem less disruptive with regard to the advertising system as a whole. We argue that AI systems are a key factor in some substantial changes that the online marketing business – and the largest part of the digital economy – has undergone over the last years.

3.2 Making use of AI in Personalized Advertising

In personalized advertising, targeting helps "choosing the right segments to focus the company's marketing activities on" (Kaponis & Maragoudakis, 2022, p. 7). If relatively small groups are targeted with a high degree of accuracy, this personalization method is referred to as microtargeting.

Enormous resources flow into the publishing of ads that appear exactly where the maximum of clicks, views or sales is generated. Digital targeting mechanisms have inflated online advertising markets over the last years. The German market size, for instance, has doubled over the last 6 years (Statista, 2023a). Today, **AI technologies are playing an essential role** in personalizing online advertising. Highly automated and thus efficient collection, processing, evaluation and organization of data is a fundamental characteristic of AI in general. Unsurprisingly, this automation also plays out in AI-supported online marketing processes. Using large volumes of personal data at relatively low cost marks the main driver of AI-based targeting in personalized advertising.

Countless human-computer interactions across the Web allow personal user data to be generated for the advertising industry, including, for example, movement and behavior patterns, geolocations, demographics and visual or audio data, which can, in turn, profitably extend databases for segmentation-based targeting (Patankar et al., 2021). The detailed analysis of potential customers forms a central field of application for AI in online marketing as it helps companies to address online users as precisely as possible. This capability is used to persuade individuals to purchase a product or service. Figure 1 outlines a typified 'lifecycle' of a personalized ad and shows key areas of the advertising industry in which AI is used. This lifecycle can be roughly divided into **data mining, profiling and targeting**. However, these steps are not strictly sequential processes but primarily circular and happening in parallel. For example, evaluations of ad campaigns feed back into the profiling processes to make use of learned predictions on consumer behavior and reactions to specific ads, thus making them more successful in the future. A wide range of AI and data analytics methods from domains such as natural language processing (NLP), computer vision and recommendation systems can provide insights on consumers, create tailored ads and automatically buy/deliver these ads (Qin & Jiang, 2019).

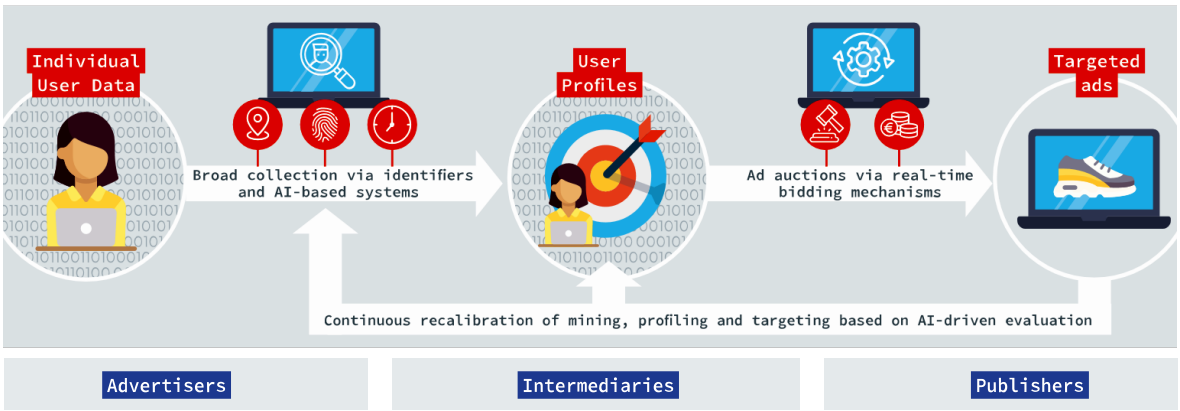

Figure 1: AI application in the circulation of data and ads in personalized advertising (own illustration, IÖW)

Currently, generating **user profiles and segments** is at the heart of predominant business models in the advertising industry. In the words of Ma & Sun (2020, p. 490), ML methods – the foundation of most AI applications – have recently been "propelling large-scale context-dependent personalization and targeting to a new level". This propulsion applies to both the expanse of AI's distribution (quantity) and the level of granularity (quality). Increased personalization is fed by a wide variety of data sources. The concept alone is as simple as it is plausible: With personal knowledge of an online user at hand, it is possible to place advertising that is specifically tailored to that person. Relevant characteristics do not have to be provided directly (for example, by asking a user to enter personal data into a form) but can be derived from proxies (for example, an automatically

transmitted device or advertising ID). AI enables such sophisticated targeting at scale and in an economically efficient and effective way (Haleem et al., 2022). Profiling and segmentation is powerful in driving estimations of customer resources and actions (Kasem et al., 2023) and in deriving information on customers' "needs" or "loyalty" (Das & Nayak, 2022, p. 492). This motivation can be driven by a desire to build strong customer relationships, or to maximize profit through finding and addressing, "silver, gold, [and] elite" customers (Singh et al., 2020, p. 103).

Online tracking is widely used to **collect data on a user's online activity with the purpose of creating a targetable user profile**, which can contain information on online purchases, social media interactions or online searches. Additionally, the profile can be enriched with information on offline activities, for example, geo locations and movement patterns, which is collected through tracking technologies such as cookies. A cookie is a small text file stored on a user's hard drive when a website is visited. It contains an ID generated by the server-side application of the website. This ID allows websites to re-identify a user browser later on. The server sends the cookie ID to the browser when visiting a website and the browser stores it for subsequent interactions. By reading the stored cookies, a server can recognize the user's browser and offer personalized functionality, like remembering shopping cart items or preferences. However, cookies are also extensively used in large-scale browser tracking schemes to create detailed user profiles.

Many websites employ **third-party ad networks** that span multiple sites, enabling central data aggregators to track user activity across various domains. These third-party cookies are installed by websites different from the one the user is currently visiting. For example, when a user visits a news site displaying an ad from a different server, that server can store its own cookie on the user's device. By using referrer information or data from the news site's request, the ad server can identify a user's browser and build a user profile, particularly if the user later visits other websites that also contain ads from the same server (establishing a direct association with the third-party cookie) (Cucchietti et al., 2022). User profile information can contain personal and potentially sensitive data. These data can also be used for microtargeting in other contexts such as political campaigns (Christl, 2019), which is particularly controversial (Amnesty International, 2019; Tagesschau, 2021). Such activities even led the social network Twitter to announce a ban on the dissemination of political advertising on its platform in view of disproportionate social risks (Dorsey, 2019).

There are many ways of relating engagement with online content to the person who has, consciously or unconsciously, called it up. Besides behavior-related cookies, another evident foundation for re-identification lies in drawing upon **hardware-related identifiers**. For technical reasons, every device in a computer network identifies itself with a uniquely identifiable device address that contains information about the hardware used and is recognizable in different connection contexts (Verivox, 2023). Mobile-capable devices all have an International Mobile Station Equipment Identity (IMEI) – a sequence of digits that reveals information about technical specifications, such as brand, model, size, weight, memory capacity and processor (IMEI.info, 2023). In addition, the use of unique advertising IDs is implemented in the two most widely used operating systems for such devices (noyb, 2020, 2021). Furthermore, regardless of the access device, each connection is assigned an Internet Protocol (IP) address that allows to track users on the Web. Next to hardware-related identifiers, which make devices trackable by design, behavior-centric approaches have gained importance for the online advertising industry as well because such insights can contain much richer information on users, i.e. on potential customers. Such data mining can be supported by AI systems (Das & Nayak, 2022).

Furthermore, **software-related identification** allows advertising networks to approach potential customers online. Using these methods has, to a high degree, become institutionalized as its

foundation is laid already with the development of software applications. Mobile app development, for instance, is usually done with tools that are brought together in a so-called software development kit (SDK). For Android apps, for example, there is the Firebase SDK, which assigns an installation ID that makes subsequent users traceable in advertising networks. The use of such a development kit offers advantages for convenient app development. At the same time, SDKs enable the low-threshold placement of advertising on an app's user interface, including the definition of target groups "based on device data, custom events, or user properties" (Google Developers, 2023, np). The widespread service Google Analytics is "[a]t the heart of Firebase" (ibid., np). It is free of charge and offers app operators "unlimited reporting for up to 500 distinct events" (ibid., np) in order to "understand clearly how your users behave" (ibid., np). Personalized advertising is enabled by relevant information related to the individual ID being automatically transmitting, such as whether ads are on the screen and viewed or clicked on; whether a subscription is taken out, renewed or cancelled; whether another domain (e.g., a website) is accessed; whether and how long a video is viewed; whether a purchase is made within the app and much more (Google, 2023b). Such apps thus fuel data mining for user profiling by default. If different apps on a device have been developed with the help of the Firebase SDK, they can also identify each other via an app instance ID (Google, 2023a). Google's marketing ecosystem is one of several examples; however, it is particularly prominent and popular.

The precise allocation of personalized ads to exactly those for whom they appear most suitable (for advertisers) represents the end piece of the AI-driven 'ad lifecycle' in Figure 1. ML models that are specially optimized (trained) for this purpose estimate which advertising has **which effect on whom and with what statistical probability**. This estimation happens almost in real time, for example, as soon as a website is called up, a mobile app launched or a video played. While the desired content is loading, digital machinery in the background simultaneously calculates which accompanying ads (usually banners, videos or text) should be played. For those who want to place ads effectively on the Web, the clear advantage of this method is that an ad seems to be 'finding its target' autonomously. However, this method is only possible due to the availability of the target-specific information in the user profiles. The concept is not new: Identifying pregnant women by the mere knowledge of their buying behavior has been possible for more than a decade (Duhigg, 2012). At that time, what was particularly sensational was the drawing of conclusions from the purchase of certain lotions and food supplements that did not clearly indicate pregnancy (as opposed to, say, diapers). Today the paths to similar inferences have become far more convoluted and increasingly opaque. These convolutions are due to the sheer volume of digitally available personal data, coupled with more complex and refined algorithms as well as stronger and cheaper computing power. Moreover, it is a characteristic property of AI systems that transparency and traceability of their functioning are anything but easy to realize (Jobin et al., 2019).

The profiling and microtargeting techniques outlined above are a prerequisite for personalized advertising. The final delivery of ads on screens or speakers to accordingly well-known recipients is illustrated on the very right in Figure 1. It is commonly realized using a mechanism called **real-time bidding**, where various procedures combine the user-centric approach of profiling certain persons to derive the 'best-fitting' ads for them with a content-centric approach of playing out predefined advertising content to the 'best-fitting' online users (Choi & Lim, 2020). By deploying ML techniques, real-time bidding "allows instantaneous decisions to be made on whether to show a particular advertisement to a specific user based on insights gained from large data sets" (ibid., p. 177). From a marketing perspective, this real-time bidding helps in "not only matching the right offering to the right consumer, but also delivering it at the right moment in the right context" (Ma & Sun, 2020, p. 490). Prices for showing one's ad to a certain user (instead of ads from competing advertisers being shown) are set in automated auctions. Ad publishers such as media platforms or search

engine operators let advertisers bid against each other to determine the market price of a respective ad space in real time. Both initial profiling and final targeting are highly valuable for companies, driving profits with the particularly effective addressing of “high-value or niche customers.” (Zulaikha et al., 2020, p. 7).

Even though it might be perceived only fleetingly, the placement of an advertisement is often preceded by **long and winding paths along the most diverse data points**. How an AI system infers output from such input is, per se, not reproducible. What an ML expert expected seems to have become true in personalized advertising already, namely “that oceans of behavioral data […] will feed straight into artificial intelligence systems. And these will remain, to human eyes, black boxes […]. In the era of machine intelligence, most of the variables will remain a mystery” (O’Neil, 2016, p. 173). From a more techno-optimistic point of view, the analysis of this situation sounds fundamentally different: “The complexity of marketing environments has long surpassed the threshold of human analysts' intuitive understanding and […] make[s] it necessary to remove human agents from the critical path” (Ma & Sun, 2020, p. 490). However, it remains a well-justifiable normative question as to whether the marketing industry should develop towards the removal of human agents or towards the removal of – manifold – ‘critical paths’ (some of which are examined in Section 4).

In a sense, AI-fueled microtargeting represents a refinement of practices that the advertising industry has been engaging in. Advertising banners and posters are hung in places where certain groups of people are expected to reside and be accessible. In television, different emphases in addressing target groups are played out depending on the time of broadcast and its content. Nevertheless, current microtargeting practices can hardly be classified as a mere further development of such marketing strategies. The now tremendously high degree of personalization (González-Cabañas et al., 2021) is accompanied by implications that are of **a significantly different quality than classic forms of advertising** with various implications (see also Section 4). It starts with the personal data-mining practices, the intrusion into deeply intimate personal areas, the analysis, recombination and evaluation of personal data and, finally, the resulting targeting. Addressing very small and deeply analyzed segments of a potential clientele exploits personality traits and individual attributes of material endowment, education, gender, place of residence, life stages, emotional states, etc., which are interpreted and targeted more or less explicitly.

Of extreme importance here is that the processes described above are not transparent but practically invisible to those being targeted. Moreover, repelling data mining, profiling or targeting is usually barely possible for average online users that participate in popular online offers and services. Without AI, today’s high degree of personalization would probably not be possible. AI systems involve both learning techniques and the that is data required to deploy them (Rohde et al., 2021). These are exactly the two enabling factors for microtargeting in the marketing industry.

3.3 Users, Actors and Players in Personalized Advertising

It has been shown that personalized advertising involves a multitude of ML applications from data mining and segment analysis to customer targeting. However, it is not clear yet which actors are involved in the process of personalized advertising. The following section sheds light on the intertwined and opaque ecosystem of actors. Identifying the companies involved is necessary for determining agency in the marketing sphere and is the basis for investigating beneficial and harmful impacts of AI use.

Other than on goods markets, the advertising industry usually does not trade commodities but ads, which, in turn, are expected to positively influence the selling of products (or services). However, advertisers often acquire **digital products and services from third parties** to better direct their spheres of influence. These products and services have become useful for advertisers since marketing activities are far more effective if channels are used that lead directly to the audience. For example, a company that sells sneakers can expect little benefit from advertising (only) on its own website. A company or its marketing department would tend to call in intermediary service providers that store and/or handle data on a myriad of potential customers. These intermediaries are, above all, ad tech companies. They mark a crucial link between advertisers (e.g., the sneaker company) and publishers (e.g., a social network). Figure 2 maps the groups of actors involved in personalized online marketing ecosystems.

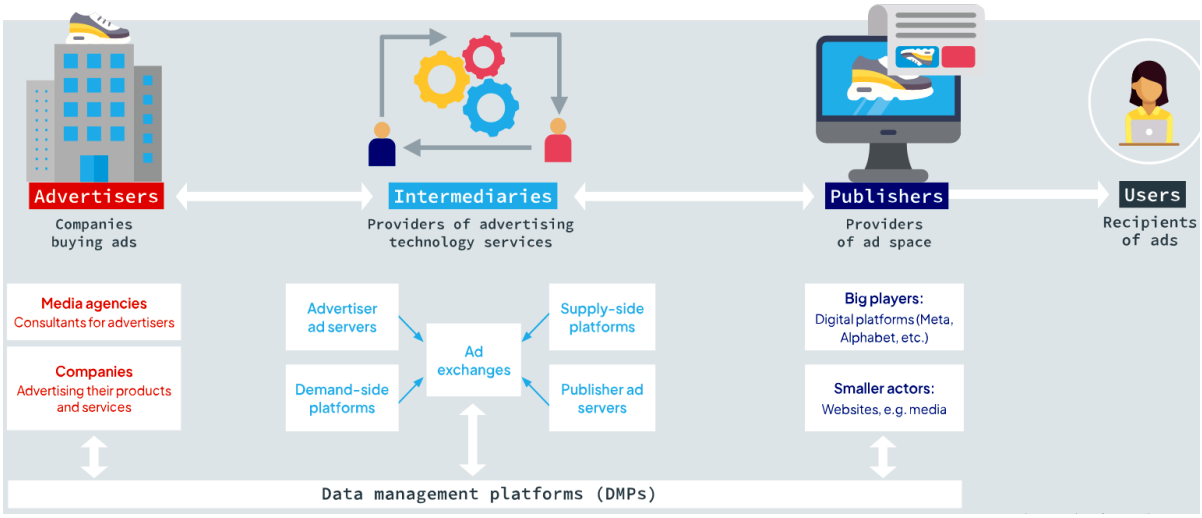

Figure 2: Actors in personalized online marketing (own illustration, IÖW, based on Armitage et al., 2023)

In practice, advertisers are often not just the companies advertising their own products but also purpose-built agencies that take on marketing services for them. Such agencies are **highly specialized in advertising and targeting technologies**. Between advertisers' demand-side platforms and publishers' supply-side platforms intermediary actors organize and manage actual advertising spaces. These are the spaces that ultimately deliver personalized ads to an end user, shaped as graphical or other interfaces in feeds, apps, search engines, websites, etc. under continuous monitoring by advertisers to maximize ad performance. Whether a specific ad is successful or not can be evaluated and controlled by, for example, varying its content, its size and shape or the frequency with which it is clicked on. Further services are provided by digital ad exchange platforms, which administer the buying and selling of ad space for personalized advertisements, backed by data management platforms that facilitate the storing, processing and enriching of datasets. Detailed and flexible targeting relies on continuous analyses and segmentation to obtain and maintain accurate user profiles.

Advertisers and especially media agencies measure and aim to predict the success of advertisements (Armitage et al., 2023), using various criteria: Engagement rates indicate how many users engage with (e.g., click or swipe) a specific ad; impressions represent absolute numbers of how often an advertisement is served; viewability tells whether it has actually been seen by users; reach is the total number of individual users that view or hear an advertisement; frequency indicates how many times a person sees an ad; and conversion describes the extent to which an ad leads people to take a particular action (e.g., buying an advertised product or service). Analyses that run with the

help of these indicators typically incorporate ML, not only to target users but also to evaluate performance and adjust strategies for future advertising campaigns (Haleem et al., 2022). Thus, AI plays a significant role along the entire spectrum of actors involved in the personalization of online advertising as it supports data acquisition and analysis, the targeting of users and the continuous monitoring and recalibration of all the processes described above.

Mapping, seeing through and grasping the various organizational and technical levels that frame the actor landscape in personalized advertising is challenging. However, even though actions revolve around personalization, **online users are not at the center of this system but normally marginalized** to their roles as consumers. Besides many automated and largely 'invisible' data transfers, there are, of course, also opportunities for individual users to consciously and actively share personal information and preferences. Online users subscribe to channels, feeds, profiles, newsletters, etc. that suit their interests. However, such conscious selections usually feed into an AI system as an addition at the most. The data provided are often not reasonably connectable to the 'conclusions' AI-driven personalization mechanisms draw from them. As an example, there are ML models to infer passwords with an accuracy of 93 % from the sound of keystrokes in video conferences (Harrison et al., 2023). In this case, the visible context for a user is the video call. Merely in passing, a person signs in to an account – and with a probability of 93 % some other person is able to get access to the password as well. Similar to how the victim of that data theft is unlikely have suspicions about the video conference, a recipient of a personalized ad is incapable of relating an ad to the data that underlie its targeting. As a spreader of inconspicuous digital particles, individual users in the targeted advertising ecosystem are not only elementary for its functioning but also largely passive and powerless ad recipients. In turn, players at the top of the online marketing business are anything but powerless. As illustrated in Figure 3, the largest shares of advertising revenue are owned by a relatively small number of the well-known "Tech Giants" (Zulaikha et al., 2020, p. 9) Alphabet, Amazon and Meta.[3]

[3] Meta Platforms is the parental company of Facebook and Instagram.

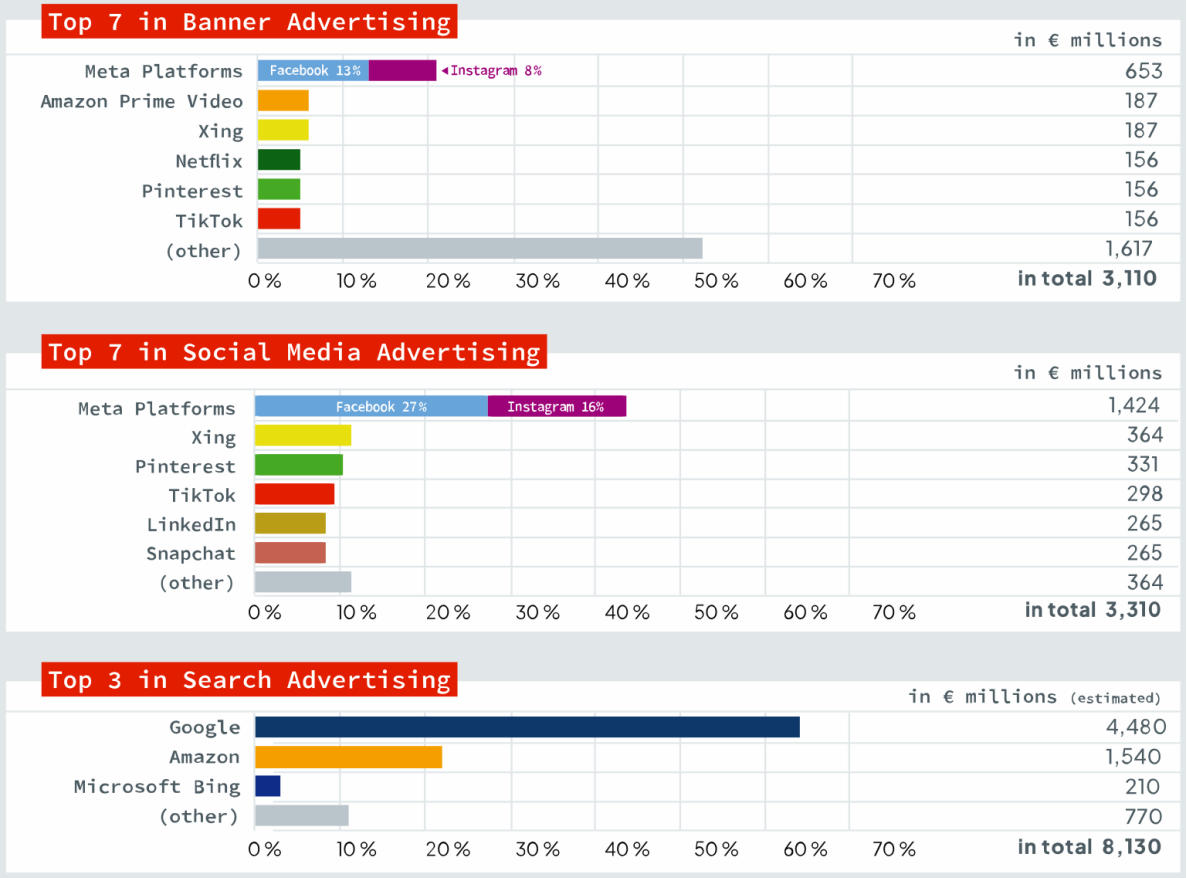

Figure 3: Selected market shares (percentage of total revenues) in German online advertising markets (own illustration, IÖW, based on Statista 2023a, 2023b)
(Market shares reflect 2022 spending by companies on advertising in Germany. Overlays, pre-/mid-/post-rolls and web-/app-based video ads are not included. Amounts in search advertising are estimated based on the size of the entire German market and global percentages.)

In the German market (Statista, 2023a), more than one fifth of banner ad revenue (approximately 650 million EUR per year) and almost half of social media advertising (approximately 1400 million EUR per year) is distributed between the Meta-owned companies Facebook and Instagram. With almost two thirds of estimated profits,[4] Google leads the particularly voluminous business of search advertising, making ca. 4500 million EUR every year. It is followed by Amazon, which is also third in banner advertising, and Microsoft, whose wholly owned subsidiary LinkedIn is sixth in social media advertising. More than that, there are only a few notable competitors. In banner and social media advertising there are – by total profit in descending order – Xing[5], Pinterest, TikTok, Snapchat and Netflix. It does not seem possible to determine which proportion of these massive turnovers is being generated with the help of AI systems. However, as set out in Section 3.2, the spark that led to exploding online advertising markets – personalization – is mainly enabled and fueled by AI technologies.

[4] For search advertising, our estimations of absolute market shares in Germany are based on relative market shares worldwide, multiplied with total spending in this domain in Germany (Statista, 2023a).

[5] Xing is a career-oriented social network, similar to LinkedIn, which is relatively popular in German-speaking countries.

4 Sustainability assessment of AI-based personalized advertising

Several studies have tried to assess the impacts of (AI use in) personalized advertising for the environment, people and economy. These studies, however, often only focus on one dimension of sustainability, for example the environmental side (e.g., Dhar, 2020; Hermann, 2021; Pärssinen et al., 2018) or the socio-economical side (e.g., Amnesty International, 2019; Armitage et al., 2023; Bjørlo et al., 2021; Christl, 2017; Forbrukerradet, 2020; McCann et al., 2021), thereby lacking an integrative perspective. One study tries to combine social, economic and ecological factors, but it lacks a clear conceptual background (Kingaby, 2020). This study takes first steps towards **a multi-dimensional sustainability assessment of the impacts of AI-based personalized marketing** and investigates how different actors such as businesses, marketing agencies, civil society organizations and the German population perceive these impacts.

The assessment involved adapting the holistic **sustainability criteria framework** for AI developed by Rohde et al. (2021) and applying it to the case of personalized online marketing. Rohde et al. (2021) distinguish between three relevant sustainability dimensions (ecological, social, economic) and one cross-sectional dimension concerning the general AI design. Through a literature review (Section 2.1) and expert interviews (Section 2.3), the key challenges in online marketing within the three sustainability dimensions were identified, clustered and associated with the sustainability criteria framework. The cross-sectional dimension was excluded as it is more concerned with the design process than with the impacts of AI.

Rhode et al.'s (2021) ecological criterion 'sustainability potential in application' has been adapted as it was too unspecific for this context. In this analysis, it was understood as the indirect ecological risks of 'increasing consumption' and 'misinformation and greenwashing'. For the latter an additional criterion 'Disinformation and Alternative Facts' was introduced because no counterpart was available in the existing framework but it appeared to have relevance beyond the online marketing context (e.g., for ChatGPT applications). Although the sustainability challenges are presented separately, it is important to keep in mind that they are interdependent and interrelated. For example, the risk of market concentration and monopoly is linked to the challenge of disinformation and danger for democracy. Also, general disinformation and climate disinformation are also hardly separable, even if Figure 4 suggests the separation is possible.

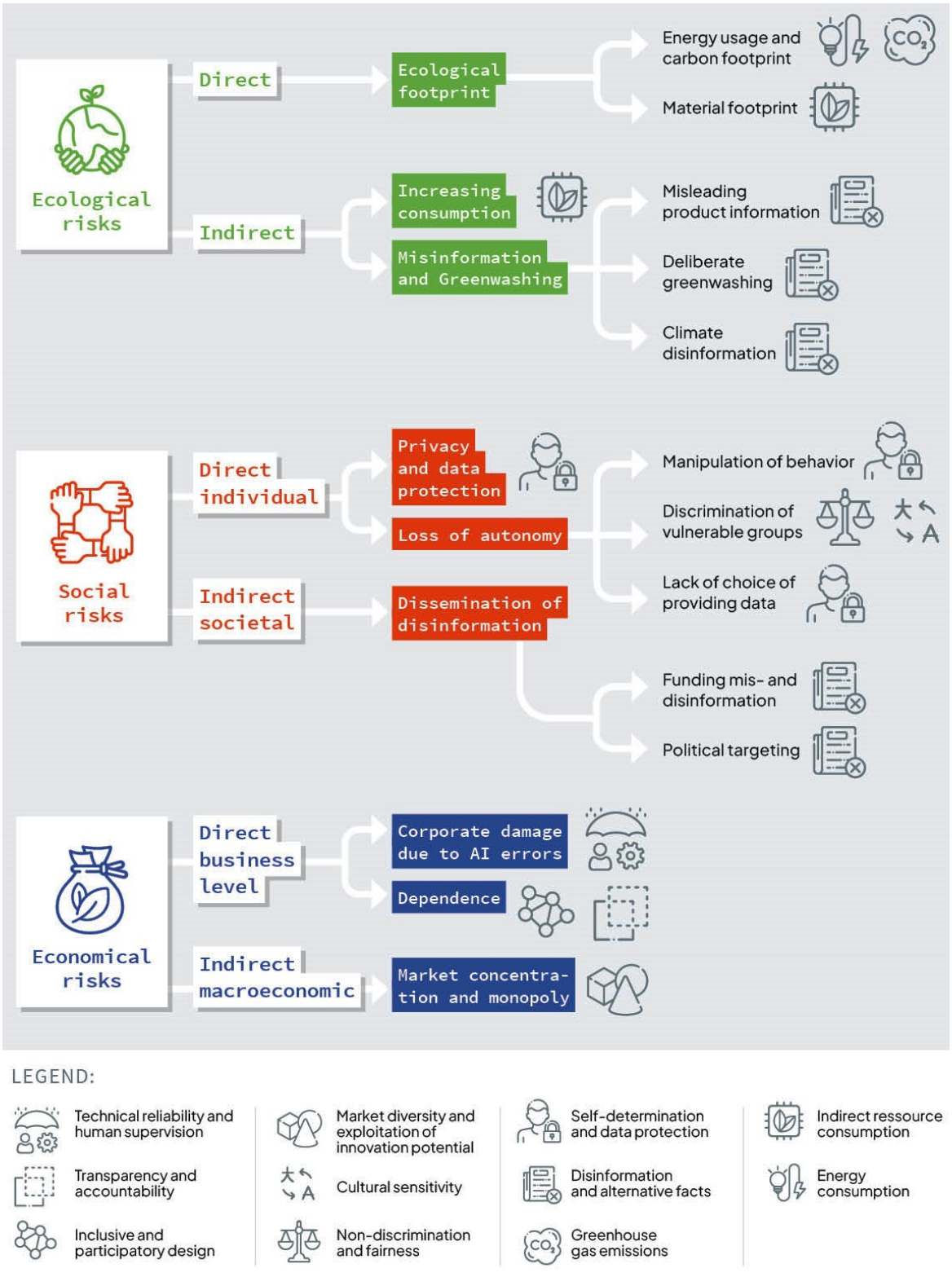

Figure 4: The sustainability risks of AI-based personalized advertising (own illustration, IÖW)

In brief, the assessment shows that AI-based **personalized advertising faces an urgent need to address sustainability challenges as major risks have been identified** in all categories of social, economic and ecological sustainability. Although the tech industry praises the benefits of AI, the assessment indicates that the risks and dangers in the field of online marketing outweigh the

advantages. In total, nine challenges with ten characteristics have been identified (see Figure 4). The identified risks overlap with 10 of the 13 sustainability criteria of Rohde et al. (2021), showing that there is a need to tackle sustainability challenges in AI-based online marketing. Only the two economic criteria 'distribution effect in target markets' and 'working conditions' do not appear to be relevant – in the sense that they have not yet played a role in the online marketing literature or were not mentioned in the interviews. This finding, however, only means that they have not yet been discussed or prioritized in the academic, business and public debate and that there would be a need for further studies to investigate their relevance in this field.

The following sections elaborate on the sustainability benefits and risks of AI-based advertising. In section 4.1 the direct and indirect ecological impacts 'Ecological footprint', 'Increasing consumption and unsustainable lifestyles' and 'Misinformation and greenwashing' are discussed. Section 4.2 presents the social risks of AI-based personalized advertising 'Privacy and data protection', 'Loss of autonomy' and 'Dissemination of disinformation and risk for democracy'. Finally, section 4.3 goes into detail about the economic dangers of AI in this field in the form of 'Corporate damage due to AI errors', 'Dependence of businesses and lacking possibilities of influence' and 'Market concentration and monopoly'.

4.1 Ecological Benefits and Harms

For the evaluation of AI applications, it has proved useful to distinguish analytically between **'Sustainable AI' and 'AI for Sustainability'** (Rohde et al., 2021). 'Sustainable AI' describes the impacts of AI systems on humans and the environment along the systems' life cycles, e.g., energy consumption or greenhouse gas emissions caused by the AI systems through training and operation. 'AI for Sustainability', in contrast, considers the purpose for which an AI system is developed, e.g., to make a positive contribution to social or environmental objectives. Here, we conceptualize 'Sustainable AI' as the direct, computing-related impacts of AI development, training and application in personalized marketing, thereby referring to the life cycle categories of production, use and disposal (Pohl et al., 2019). By also assessing indirect, application-related impacts of AI systems on the ecological dimension, we evaluate if AI in personalized marketing can be seen as 'AI for sustainability' (as a simplified adoption of the higher order effects introduced by Pohl et al., 2019).

4.1.1 Direct Ecological Impacts

Direct impacts on sustainability are related to the life cycle of an AI system including hardware and software. For the environmental effects, account is taken of inputs such as the natural resources and materials needed for the hardware and the energy required in running models, as well as of the resulting outputs such as carbon emission.

The environmental footprint of AI in online marketing

Representatives of the tech industry often emphasize the **potential of AI** development for reducing energy intake and emissions: "Training better models can actually save more energy over time. For example, NAS[6] can find very efficient models. Given the number of times they're used each day for inference, in less than a week they save more in energy than the old hand-tuned versions" (Burr

[6] Neural architecture search (NAS) is an automated model for designing ML networks.

cited in: Dhar, 2020, p. 424). However, efficiency gains are often neutralized by more frequent demand and application and the **carbon footprint** of training ML models is not negligible. For example, the carbon emissions of training a big language model[7] (300 000 kg CO_2 equivalents) equal around 125 round trip flights between New York and Beijing (Dhar, 2020; Strubell et al., 2019). A study by Pärssinen et al. (2018) estimates the overall energy consumption of online advertising as 106 TWh per year and that of the total infrastructure as 1059 TWh per year. This consumption results in 60 Mt CO_2 equivalents for online advertising – more than Greece emitted in 2021 (Ritchie & Roser, 2022).

Yet, these numbers are connected with uncertainties, as online advertising processes, and especially the AI share, comprise multiple steps and factors, which all contribute to the environmental footprint: First, collecting data in online marketing requires the transfer of user information from various sources such as websites, social media platforms and mobile applications. These **data transfer processes** of data transmission and routing involve energy-consuming network and computing infrastructures. Second, collected data is stored and managed over long periods of time, necessitating further energy, as data centers and servers for **data storage**, backups and retrieval are required. Third, data is used to train ML models. The models **analyze** future data inputs and provide personalized insights for advertising campaigns. Here, significant computational resources are used for training complex AI models since they require a high-performance computing infrastructure, including powerful servers or machine clusters. Energy is, thus, continuously being consumed by servers that are used for processing and storing data. Moreover, during operation constant **cooling** is needed, which is highly energy-intensive and accounts for a large part of data centers' overall energy consumption. Lastly, **real-time bidding** (see section 3.2) includes fast data processing and communication between multiple parties. Then, ad delivery – meaning the display of ads on the end device – often requires additional **rendering of multimedia content,** e.g., images or videos.

Our expert interviews show that marketing agencies and departments are **aware of these environmental impacts**. For example, a data scientist stated: "At least in my field, people know that machine learning is energy-intensive" (Int. 8). Two marketing department leaders confirm this for their businesses as well: "Just as we cause emissions when we produce products, we also cause emissions when we do marketing" (Int. 6); "This hunger for energy in these systems, it's scary, isn't it?" (Int. 5). Innovation in algorithm development, increased availability of data as well as improved and cheaper computational resources have facilitated increased use of AI systems in the past years (Dhar, 2020). This increase has also influenced energy consumption. As one interview partner explains:

> "Since generally the technology for computing is becoming cheaper, there is a tendency for being less mindful of the performance of certain algorithms. […] [Previously] it was not possible for you to run [certain models] because it would take a lot of time. Also […] these cloud providers make it very easy for you to scale up the resources […] if you need to. So then if you want, you can have a very energy-intensive algorithm and just run it and it will run fast." (Int. 8)

[7] AI language models (or NLP) are applied both in online marketing for 'data mining' processes in order to acquire consumer data from various sources, e.g., also spoken language, and for automated text generation, which can be used in ads, e-mails and other forms of marketing.

In addition to the easy accessibility of developing, training and implementing AI models, the **internal logics of the marketing and the tech business** also contribute to increasing energy consumption and carbon emission output. Overarching goals are fast, efficient and effective solutions: “We are aware that our work is energy intensive. We try to make it efficient. There are a lot of pipelines or code that we have to look at and try to run efficiently. But it's mostly looking at performance and not so much at ecological impact” (Int. 8). Especially the work of intermediary companies is fast-paced and under pressure, e.g., marketing agencies that are developing custom-made marketing solutions for their clients. Time to look at more environmentally friendly models is rare: “In the case of consultants, it’s already a lot of pressure to make these solutions for the clients because you work on an hour basis […]. It will never happen that someone will just work over hours just so an algorithm is more ecologically friendly“ (Int. 8). Achieving the model’s purpose and the client’s aim in an effective, fast and cheap way is the priority:

> “They [data scientists in marketing agencies] are more worried about the functionality. Unless the client is really worried about it [energy consumption], they will not spend time on that, unfortunately. […] Even though there are some resources in terms of understanding how energy-intensive certain algorithms or certain cloud processes are […]. There are a lot of different options that you can choose. Then normally we choose based on functionality.” (Int. 8)

But it is one thing to know that energy usage is high and increasing – and another to know how much energy and materials are used. A major **challenge lies in quantitative assessment of environmental impacts**. There are two main obstacles to accurate measurement: 1) Monitoring data is lacking and 2) various technical factors influence energy consumption.

1) Monitoring data is lacking: To collect and analyze data and to target the desired audience, most businesses rely on the services and infrastructures of big companies such as Google and Meta. These companies account for the largest share of material and energy consumption for computational hardware, servers, models and algorithms. Yet, even if usage data is monitored by Google and Meta, it is **not sufficiently disclosed** to the users. Advertisers are only capable of monitoring their individual consumption levels, but not those of their partners:

> “Yes, we also have our own cloud in use and we measure it there […] and make sure that we reduce energy consumption. But with the platforms, I have to say, it's difficult for us to get insights. And then also to be able to take countermeasures. […] What we can influence internally, we monitor and work against it, of course. But everything that we do together with external parties – we are aware of it, of course – but there are no levers for us to prevent it.” (Int. 7)

Another interview partner explains that the marketing agencies energy consumption is minor in relation to that of Google:

> “If you look at the energy bill of our office, it’s nothing. […] We do have a website, and you do need some physical infrastructure for companies. But most of our services, for example, the tools that I build, we run it on Google Cloud, so they are running on Google servers.” (Int. 8)

Google claims to be operating on 64 % carbon-free energy globally and aims to reach 100 % carbon-free energy by 2030 (Google, 2022). Also, service users are able to monitor their usage: “It’s true that Google has some services that allow you to calculate the CO_2 spend that you have while

running all these services" (Int. 8). However, the data are neither fully transparent nor verifiable: "They put a little green leaf that says it's filled with renewable energies or with solar or wind. But again, it's not very transparent and it's very easy to greenwash. Maybe it's a bit greener, but I don't know how much greener" (Int. 8).

Furthermore, Google's carbon footprint calculation service is not enabled by default and relatively difficult to access – even if it does not generate an extra cost. One interview partner elaborates:

> "I asked for having this service in our Google Cloud, but you need permission from the manager account. And I sent it to my supervisor and he said, 'I'll see what can be done'. And then nothing happened and I asked again. […] It's a service that they provide for free […]. And normally me, I have administrator rights so I can do everything that I want, but just for that, I cannot ask for this feature." (Int. 8)

Finally, indicators of carbon footprints or the use of renewable energies do not provide any information about the overall amount of energy and materials used. Even a data center run on renewable energies needs water for cooling, hardware and materials, which have to be sourced in the first place and which are not visible through a CO_2 indicator that only reflects the energy consumption of computing in certain data centers.

2) Technical factors influencing energy consumption: The required amount of energy also depends on various technical factors along the 'data life cycle'. After collection, data first have to be stored. The **type of data storage** influences the energy amount required. For example, a service user can choose the geographic location of the data storage: "I'm creating a data set where I'm going to store data […], I have the option to decide where the data is going to be stored. So, I can choose Amsterdam, I can choose US, I can choose Germany. And I imagine this has environmental consequences" (Int. 8).

This effect is due to varying **shares of renewable energy** in the respective domestic electricity mix. Also, the needed infrastructure and energy for the data transfer and the **accessibility of data** have to be considered. Data that needs to be frequently accessed, queried and analyzed has a higher energy consumption in the storage phase due to data transfer and retrieval as well as analysis processes and pace. One interview partner explains:

> "We have some predictive models that require to make predictions on demand. […] But you have also other models where maybe you don't need that immediate response and maybe you can calculate that answer once a day, for example. And then, I think, all these kinds of differences […] have an environmental cost." (Int. 8)

However, the respective environmental impact is not considered when deciding on one of the options: "I only see the money or the performance in how much time it takes me to query the data" (Int. 8). Therefore, when storing data and training ML models, carbon emissions vary according to "the location of the server used for training and the energy grid that it uses, the length of the training procedure, and even the make and model of hardware on which the training takes place" (Lacoste et al., 2019, p. 1).

The vast number of factors influencing the environmental footprint (especially material and energy usage and the carbon emissions) of AI-based online marketing make the quantification of it complex and difficult. Within the context of sustainability and online marketing, our study is limited to

investigating in more detail the environmental footprint of end devices by simulating the energy consumption associated with the deployment of personalized online advertising.

Modelling the environmental impact of tracking technology and ad display

To assess the impact of (personalized) online advertising on energy consumption, we ran **automat-ed browsing simulations**. A key aspect when looking at the ecological impact of personalized online advertising is the energy that is consumed for fitting the content and appearance of an advertisement towards targeted individuals and for delivering it to their devices. The energy for the ad creation and delivery process is consumed on two levels: the **network level and the device level** (González-Cabañas et al., 2023).

The network level includes all data processing steps and the communication and data transfer between intermediary actors involved in this process. User data are collected during browsing sessions and afterwards exchanged between involved actors (see section 3.3). The **traffic generated** by transmitting the data results in energy consumption on the network level. Data processing is generally performed through AI systems that allow the ever-growing amount of data available for marketing purposes. The technologies deployed in targeted advertising, above all the use of deep-learning models, often come at high computational costs, with **high energy consumption**. Since AI systems used for personalized online advertising are usually deployed by big companies that do not disclose information about the energy use of their systems, there are no tangible data on the environmental impact of using AI and data analytics in the marketing sector. Therefore, we limited our study on the network level to measurements that can be directly collected from browsing devices during webpage visits.

For the network level, we therefore analyzed the amount of data that is transferred through cookies when the 200 most popular German websites are visited. To deliver ads that are tailored towards an individual user, detailed information on the users' online behavior was gathered (see section 3.213). The device data were collected from **cookies and other tracking technologies** that are built into websites and applications. The use of these technologies, though stored on a user's device, is often not transparent to the user and thereby hard to detect, making it easy for large amounts of data to be collected. Despite their small size and concealed nature, these tracking technologies initiate numerous global-scale algorithmic processes with the help of user behavior data. They, thus, affect the power consumption of a user's device.

In our simulations, we recorded the **number and size of cookies** transferred while accessing each webpage, identifying an average of 155 cookies transferred per website visit. Most of them were issued by news and media content pages, followed by shopping pages (see Figure 5). The same two categories have the largest average cookie MB-size (see Figure 6), approximately 87 % come from third-party providers and have an average size of 139 bytes. When a webpage is called up, an average of 0.2 MB of data are transferred as cookies. Approximately 87 % come from third-party providers and have an average size of 139 bytes. Every time users reject 'non-essential' cookies, they reduce the number of cookies transferred and the resulting data transfer by 75 %.

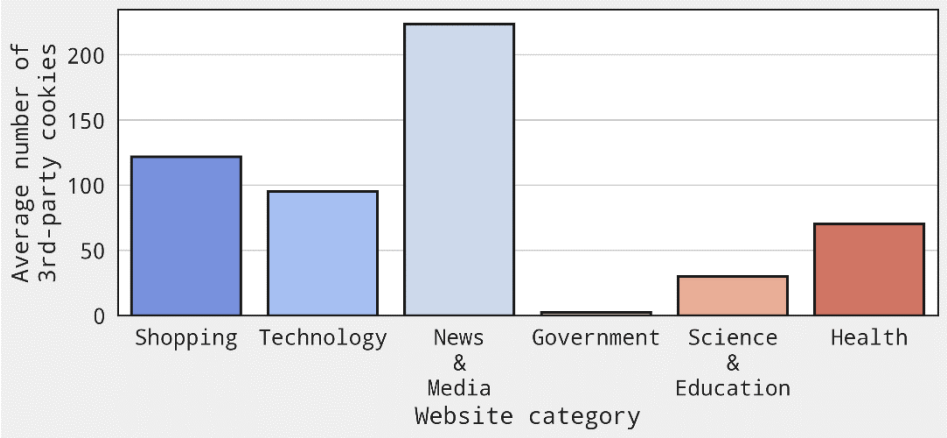

Figure 5: Average number of third-party cookies per website visit grouped into different website categories (own illustration, DAI-Labor)

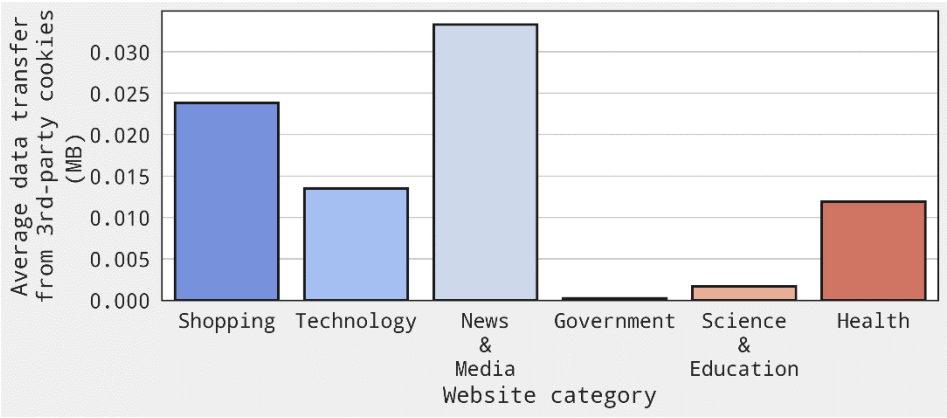

Figure 6: Average size of data (in MB) transferred by third-party cookies grouped into different website categories (own illustration, DAI-Labor)

The power consumption from accessing individual webpages and respective data transfers through cookies seems relatively low. However, the approximately 200 German webpages examined here are accessed over 4.5 billion times per month. In our study, only start pages were visited. Since several subpages are usually called up during typical online sessions, the effects of ad placement and data transmission are amplified. Thus, the traffic volume recorded in this study must be interpreted as a conservative estimate. Studies suggest that the top one million most visited websites cause an average traffic of 197 trillion cookies per month, resulting in over 11,000 metric tonnes of CO_2 emissions (Cucchietti et al., 2022; Pachilakis et al., 2023).

The network part of the ad delivery process is decisive in terms of which ads will be shown to a user visiting a webpage. Once this part is completed, the URLs leading to the ads are sent to a user's web browser. The advertisement is then downloaded and rendered. This process increases the computational workload of the CPU and graphics card in the device and thereby increases the energy required to load a specific webpage. The results from our simulations show that the **time required to load webpages is reduced by 14 % when ads are blocked** (see Figure 7). This can reduce the energy consumption of the end device's central processing unit by 10 %. We found that the greatest savings could be achieved on websites from the news and media category. This is a plausible result because news and media sites are often financed by the placement of advertisements. Additional energy consumption on the device level is caused by the graphics card for rendering the ads. On average, this results in a power consumption of 0.005 Wh per ad.

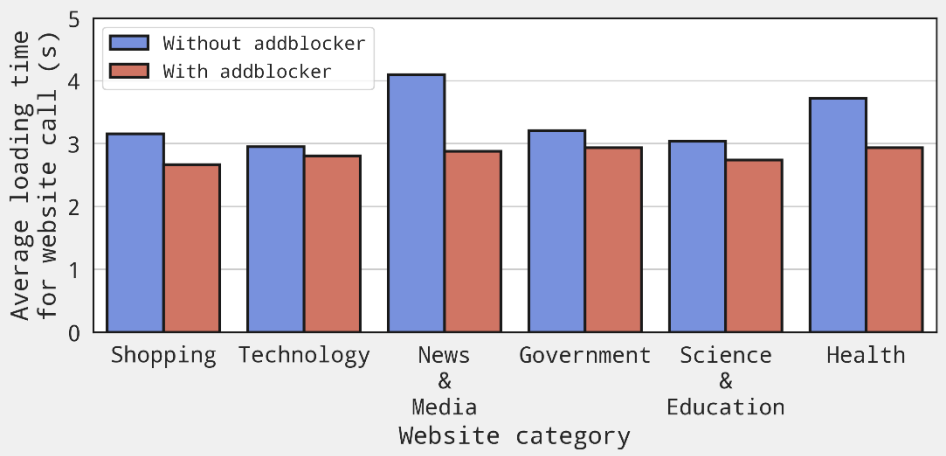

Figure 7: Difference of webpage loading time (in seconds) with and without using an ad-blocker for each website category (own illustration, DAI-Labor)

The automated browsing simulations thus show that multiple processes run on the network and device level in the background when loading a website or displaying an ad. A large share of energy consumption when browsing the internet could be saved if advertising and cookie tracking were limited.

4.1.2 Indirect Ecological Impacts

In many fields, AI is used as a tool or is developed to reduce negative environmental impacts, e.g., through a low-carbon infrastructure or smart grid design (Dhar, 2020). In general, AI is widely seen as part of the solution rather than as part of the problem (Akyürek et al., 2022). Also in marketing, AI is considered **a potential for sustainable development**. This view becomes apparent, for example, in the domain of sustainable marketing, which is defined as

> "the development and promotion of products and services that meet customers' needs in terms of quality, efficiency, price, and convenience without having a detrimental effect on the environment, society, or economy. It involves high technologies that communicate the offer and promote sustainable lifestyles and operations in companies." (Nozari et al., 2021, p. 1)

Marketing can thus be used to promote sustainable products, services and lifestyles and to help consumers make sustainable consumption choices. One of the interview partners confirms that the potential of AI-based advertising lies

> "in selling people better products and services or encouraging people to do things – like engage with the circular economy. [There are] some really good examples of eBay and Love Island in the UK partnering up and encouraging people that would never buy second-hand clothes to do that and to get their outfits from there. If we can apply AI to that to make it better, then I'm up for that." (Int. 1)

Data are seen as a key factor in improving (sustainable) marketing performance (Nozari et al., 2021). AI technologies represent an effective way to produce new data about the interests and preferences of consumers, and thus they may also contribute to sustainable consumption in a sense of promoting the 'best and sustainable choice': "Using these data can positively impact the growth of business activities and help customers achieve their desires and obtain the best products

and services" (Nozari et al., 2021, p. 1). Marketing technologies can help, to make the consumer aware of a certain sustainable company, product or service: "Normally display or YouTube ads […] rarely lead to conversion, but they are more tailored towards awareness that this company exists" (Int. 8). Additionally, they can match offers with presumably interested consumer groups: "In the sustainability field, it can lead to bringing together the offer and someone who is interested" (Int. 5), and AI may contribute to ecological sustainability. As another interview partner emphasizes: "I think we should be using the tools at our disposal to make that lifestyle shift happen. […] I can see AI and advertising is very helpful to that if it can make these things more persuasive whilst it's legal" (Int. 1). However, these potentials obviously hold true for virtually any product – be it more sustainable or not.

Increasing consumption

From a more critical perspective, the concept of 'sustainable marketing' itself is questionable[8] as the main **purpose of marketing is to increase product sales** and, therefore, to convince consumers to make purchases. The argument is valid that, if personalized marketing helps a consumer find the most suitable product, this can reduce returns. A research group at the University Bamberg estimated that the carbon footprint of approximately 530 million return packages equaled 795.000t CO_2 equivalents in the year 2021 in Germany, the same amount of CO_2 as is emitted when driving 5.3 billion kilometers with a car (Achter, 2022). Reducing return shipments could significantly contribute to mitigating climate change:

> "So, returns are a huge problem in e-commerce. If you can avoid returns by, among other things, only showing advertising to those who are unlikely to return the sweater or the bike, then that's a good thing." (Int. 4)

This reduction in returns can, therefore, have a positive ecological impact, even though return reduction is currently considered by companies mainly from a financial perspective: "The cost of returns is much, much higher than the cost of online marketing. So, managing marketing so that returns don't go up unnecessarily, that's a good idea" (Int. 4). While the financial burden of returns is closely monitored, the carbon footprint of returns is only measured by a fraction of companies (Achter, 2022).

Yet, an often-used argument is that it is in the interest of consumers to be offered the, for them, most suitable, interesting, attractive products and services. The argument is, thus, implicitly based on the assumption that every person who is online actually wants to buy something. From a seller's point of view, this is comprehensible as every user is also a potential customer who may only need to learn about the company or be convinced to buy (keyword "conversion"). However**,** from an environmental perspective, **every additionally purchased product means additional environmental impacts** in terms of consuming resources such as raw materials, energy and water as well as pollution, environmental degradation and CO_2 emissions (e.g., from manufacturing or transportation). One interview partner explains how AI-based marketing contributes to a conversion and 'purchase decision':

> "What we try to do is statistically make kind of a path of touching points. So, we know some person saw an advertising on YouTube, and then they maybe google the name of the company or they saw another advertising on Facebook. And then we try to see the different touchpoints and individually assess how much each touchpoint contributed

[8] In the same sense as 'marketing ethics' and 'advertising ethics' have been called an oxymoron (Drumwright, 2018).

> to the end conversion, for example. So, then it's really about trying to understand the different paths and show those paths in a statistical way. […] Then the customer can see that some points are important because if you don't have this initial touchpoint, then you don't go through the later point that leads to the conversion." (Int. 8)

Personalized online advertising is not only about showing the most suitable offers to interested consumers with purchase intention. It is about convincing people on the internet that a certain company, product or service is interesting, useful or helpful when they did not have a certain need or purchase intention before. The head of marketing of a large German online retailer confirms this:

> "Does marketing create needs or does marketing satisfy needs? If you say marketing creates needs, then marketing is bad because the consequence would be, without marketing, no purchase, no use of resources. If you say marketing satisfies needs or [the company] satisfies needs, then it's different. [...] That's probably a bit of a philosophical or political question. [...] If you look at the development of the automobile or if you look at what an iPhone is. It satisfies needs that we didn't even know we could have 20 years ago. In my opinion, this speaks more for the awakening of needs through marketing." (Int. 4)

Another interview partner describes the phenomenon that advertisement creates new needs as '**psychological obsolescence**' (see also Proske et al., 2016). Similar to 'planned material obsolescence', psychological obsolescence aims at increasing purchases and sales:

> "That's when they came up with the idea of so-called psychological obsolescence. This means that although I have a great smartphone that works and does everything I need, I see advertisements everywhere in my environment for the latest device, for the latest trend, which tells me that my device is actually no longer state of the art, and then I buy the next one. And we have this most strikingly in the area of fashion. Fast fashion. There used to be spring fashion, fall fashion, maybe even winter. Now there's new fashion every month. [...] But in the end, we can only manage this by imprinting in people's minds that this is no longer in. And that ultimately works through advertising." (Int. 3)

Therefore, **personalized marketing is a substantial contributor to increasing consumption** (Kish, 2020). Further, AI-based technologies for personalization only reinforce this development. Lasty, even from a socioeconomic perspective, the argument of supporting internet users to find their most suitable product match does not hold true: social advertising conglomerates are seeking to meet the needs of their customers and shareholders. However, the customers of advertising companies are not internet user but the multitude of "advertisers competing for space on users' screens" (Kish, 2020, p. 3).

Misinformation and Greenwashing

The use of AI can lead to misinformation on three levels when creating and promoting content: 1) Incorrect representation (by a service provider) of product sustainability information (from the product provider), 2) Falsely displaying a product as more sustainable than it is (greenwashing) 3) Promoting and financing disinformation on climate change.

First, the problem with the automatic generation of ad content is that there is no guarantee that the information about a product is displayed correctly. The companies do not necessarily create their

ads but provide Google or other service providers with the relevant information such as product characteristics, price, materials and sometimes long descriptions about the product but also images, videos or headlines. Additional information such as delivery conditions or sustainability facts can be entered as well. The service provider uses this material to assemble and create advertisements tailored to a specific target group. One interview partner of a sustainability-oriented company reports that they had cases of **ads created by Google that had false or misleading information**: “Placed ads, where simply wrong information is contained or where certain keywords have been misinterpreted” (Int. 7). For companies that aim at producing and selling sustainable products, this is a problem as they want to provide their customers with trustworthy and verifiable information. If consumers are misinformed about the characteristics of a product or service, making an informed purchase decision is more difficult for them. One example mentioned was that a material that has been deliberatively excluded when manufacturing a product had been specified in an advertising as product material:

> “That was about [...] recycled polyester. [...] It was about an ingredient that the brand excluded. So, where it explicitly stated that it is not included. So, [this information] was also included in the product texts. And Google has just [falsely] declared it as an ingredient.” (Int. 7)

For companies using these automated content creation services, it is almost impossible to keep track of whether their advertisements are transporting the correct sustainability information. The content creation processes work so quickly and the amount of created ad content is so large that checking every advertisement is not an option: “We do random sample checks, but of course it's not possible in its entirety, to be honest. And that's also [...] the danger of AI, of course, that just such things happen and we don't even notice it, right?” (Int. 7). Another interview partner confirms: “I can't even check the texts the AI writes” (Int. 6).

Second, AI-based personalized marketing can contribute to **Greenwashing**, when a product or service is portrayed as more sustainable than it is. Marketing does not only already have multiple tools at its disposal that allow a distorted, ‘greener’ image of a company, product or serve, e.g., using the color green, placing a product in a natural surrounding or using vague green claims. In addition, an automated creation of advertising without control mechanisms can easily lead to a random combination of products and services with images, colors, descriptions, keywords. A product can be matched with a sustainability claim without proof or a check that the product meets any criteria. As one interview partner remarks, “sustainability is more of a buzzword here and will be used inflationary in the future and [therefore] differentiation will become very difficult” (Int. 5). One interview partner sees greenwashing next to climate denial and climate delay as one part of climate misinformation. She explains:

> “Then the third one is false solutions because that's what a lot of the greenwashing is. So, saying: ‘Carbon capturing storage will save us all’. When it's unproven technology. […] So, greenwashing is a lot of the false solution stuff.” (Int. 1)

The promotion of ‘false solutions’ via greenwashing, as the interview partner calls it, makes consumers buy products and leads them to think to have made a sustainable choice. But on the contrary, this product is most likely to have a significant environmental burden. Also, the consumer does not buy the product of a truly sustainability-oriented company. However, rather than having concerns, one of the interview partners working at a company with longstanding ecological motives sees the potential of an AI technology to consider all relevant information:

> "As a [sustainability-oriented company], one has […] been in the media for 30 years. Of course, one has entirely different references, so even the neural network already knows the difference today. The question is of course: Who is looking for it and how relevant is it? So, if I look for the sustainable distributors at ChatGPT today [...] you just look at the literature [...] we have more awards, we have newspaper clippings, the literature provides it all. So, the data, [...] is available and therefore also available in the networks." (Int. 5)

However, it is also a question of budget. Large companies can present themselves as much more sustainable through a stronger internet presence than can companies with a smaller budget.

Third, as the advertising industry provides the most important funding model for the internet, it is also a **funding and promotion model for climate disinformation,** which impedes fast and dedicated climate action by contributing to "highly fragmented information ecologies that intentionally obscure scientific facts regarding ecological emergencies" (Kish, 2020, p. 1). One of the interview partners addresses the problem directly: "At the moment we are, in my opinion, in the middle of an information war about climate change. And AI is being weaponized in that thing, and advertising is the massive part of that whole system" (Int. 1). AI-based personalized advertising is involved in two ways. First, by providing ad space, many websites can finance their activities independently, this has created numerous fake news and disinformation websites. Second, AI-based recommendation algorithms tend to especially promote sensational information such as climate change denial or fake news: "Hate and misinformation work really well in our online spaces because they work well with recommendation algorithms and because recommendation algorithms signal to advertisers that content is engaging" (Int. 1). The personal recommendation systems have already significantly impacted political campaigns (Amnesty International, 2019), which is why they also represent a threat to tackling big societal issues such as climate change.

4.2 Social Benefits and Harms

Discussions on the social effects of AI often highlight the promises and the direct and indirect advantages of the technology for consumers. Advertisers claim that the use of AI directly enables **more efficient, interactive and personalized advertising,** which makes ads more entertaining and relevant for consumers (Bjørlo et al., 2021; Kingaby, 2020). Also, it has been argued that AI-based decision aids benefit consumers as they "reduce search costs for consumers, making their decision-making process shorter and more efficient" (Bjørlo et al., 2021, p. 2). They help in processing large amounts of information, reduce the overabundance of online choices and, thus, alleviate frustration and dissatisfaction of consumers (ibid.). Indirectly AI-based online marketing provides consumers with **online resources such as information, products, services and content** as advertising is the main funding source. In this case study, not only the marketing representatives but also the experts of civil society organizations recognized this fact: "So many of our products and services are funded by advertising, which I do think has its merits" (Int. 1).

However, the opacity, surveillance, manipulation and discrimination exercised by AI-enhanced personalized advertising has been the top issue discussed in this field – far more than ecological or economic effects. Especially the scandal of Cambridge Analytica, the Trump elections and the Brexit referendum have shown how collecting and using personal data points can be used for political campaigning, thus, affecting even the shaping of public opinion and putting democratic foundations at risk (Amnesty International, 2019). But how are AI-based marketing activities connected to broader social risks and how do the involved companies perceive these risks?

The rising concerns can be systematized as **direct individual and indirect societal risks** of using AI in advertising. Direct individual risks occur on the level of the internet user or the consumer and include risks to privacy and data protection and the loss of autonomy. Indirect societal risks result from the loss of individual privacy and autonomy and affect society as a whole. They include the dissemination of disinformation and a risk to democracy and are closely related to the economic risks of AI in personalized online marketing (see section 4.3). In general, both business representatives and civil society organizations recognize the social risks of AI-based advertising. However, civil society actors articulate their concerns more critically. Marketing representatives are aware of those risks but do not call into question data-based marketing as a whole but first and foremost strive to comply with social regulations. Only one marketing manager explains that he does not see big disadvantages of AI-based marketing for their consumers: "I would rather see the advantages [of personalization] or the possibilities that arise from it. [...] For the users, for now, I don't see any great danger" (Int. 7).

Privacy and data protection. The industry of personalized advertising relies heavily on collecting and analyzing (partly highly confidential) personal data across sites, platforms and devices (see section 2). How the data are collected and used through various tools such as identifiers, cookie IDs, mobile IDs, fingerprinting and accounts remains unclear and opaque to users (Armitage et al., 2023; Christl, 2017). This opacity is problematic because, first, the **users often do not know which information is being transferred by whom to whom** and, therefore, unwittingly often provide data they do not want to share. Our representative online survey illustrated this clearly: only 28 % of participants stated that personalized advertising was (rather) well identifiable as personalized, whereas most of them did not agree (see Figure 8). Further, only around one fifth of respondents found online advertising interesting or helpful. Over half of the respondents explicitly stated they found online advertising (rather) unwanted and manipulative.

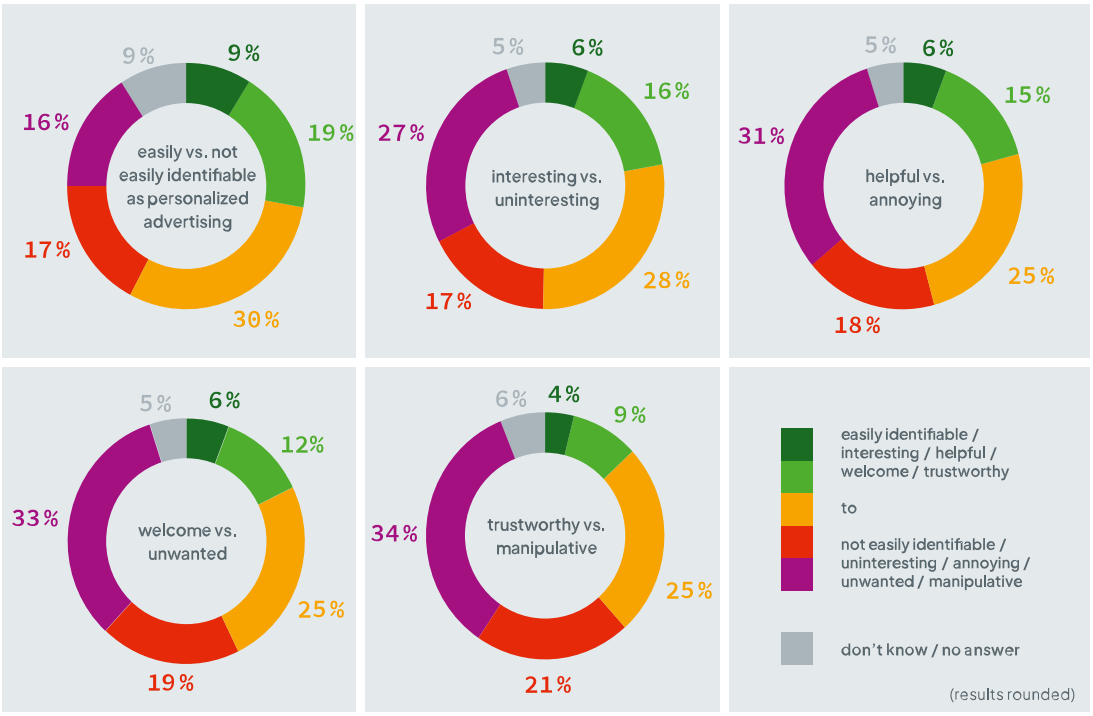

Figure 8: How users perceive personalized online advertisement (own illustration, IÖW)
"How do you view personalized online advertising?"

Second, this opacity is an issue because the data is not, in the first place, used for the users benefits but rather **exploited for private profits**. One of the interview partners remarks in regard to the big platforms such as Alphabet and Meta: “It's [AI-based personalized advertising] being pushed so strongly by the companies. And from my point of view, it's more the profit motive that is underlying, […] it is simply also in their own interest to collect even more data” (Int. 7). For the platform economy, the saying goes that, if a website, content or service is for free, then the user is either the ‘product’ or they pay with their personal data. In the case of the AI- and surveillance-based marketing industry, the economist Shoshana Zuboff goes even further and explains that the user is neither of the two but represents the “free source of the raw material that is converted into marketable products” (Zuboff, 2019, pp. 5-6, translation by the author). The individual can, thus, be exploited as much as any other source of ‘capital’ such as the natural environment as ‘natural capital’ or workers as ‘human capital’.

From that perspective, AI is just another tool to make this exploitation process more effective and to find new ways of collecting data and is, by design and purpose of the technology, socially unsustainable. While civil society organizations demand the end of using data for advertising and the labelling of AI usage in adverts, marketing managers try to tackle the issue by complying with the relevant social standards: “And the most important thing [...] is, before we do anything with AI, that we do it in compliance with data protection, we are extremely precise about that” (Int. 4). The **companies feeling of responsibility** in handling user data well is just one of the reasons for complying to the regulations such as the European General Data Protection Regulation (GDPR). **Avoiding fines for violation data protection obligations and a loss of reputation** are equally important:

> “Today Meta got a pretty big fine [...] because they transferred user data to the US without permission. And we don't want to pay this fine or have this bad press. And we don't think it's appropriate for us to handle customer data in such a way. So, everything we do is in the context of what the customer has allowed us to do and what is legally okay to do.” (Int. 4)

European companies put a lot of effort into meeting the GDPR data protection requirements. The marketing manager of a large German online-retailer explains: “There are a few teams, I'd say three teams of data scientists and computer scientists who are just busy implementing the parameters of the GDPR. So, anonymizing, informing and deleting” (Int. 4). Also, the **GDPR has changed how the marketing industry is working**. Certain methods and models of analyzing data are not possible anymore if users do not agree to sharing data or being tracked. Two marketing experts reflect:

> “GDPR […] has really changed a lot how the online marketing works […]. So, for example, a lot of the models that we used to have for personalization relied a lot on previous behavior on the website. And now if the user is not willing to share that information or is not logged in, then as a result […] a lot of our models are just not workable anymore. Because of that, a lot is changing in personalization now.” (Int. 8)

> “And this [GDPR] sometimes makes life a bit more difficult and complicated for those who want to implement a solution, which was also quite different in the past. There was also a time of the wild west on the internet, but now it's all legal and decent in any case.” (Int. 4)

This change means that there have been effective measures to improve the data privacy of individuals. Yet, under current circumstances, these measures do not lead to personal data not being

exploited. Part of the reason is a lack of individual knowledge of how to protect personal data better. Many users do not yet make use of the available possibilities, for example, objecting to the use of third-party cookies. The marketing manager of a sustainability-oriented company states that only 20 % to 40 % of the website visitors reject the use of cookies, even though he characterizes the customers of his company as being more sensitive to privacy topics than those of other companies.

In our representative survey of the German population, nearly 60 % declared that they used the option to reject analytic cookies (see Figure 9). However, here a social desirability bias is to be suspected. Of those who do not regularly use this option of data protection only 11 % stated that their privacy was not important to them. 13 % specified that they did not know about this option, 16 % stated that they did not know how to reject the cookies, 25 % said that it is too much effort and 27 % that they regard the process as useless. These results indicate a **lack of knowledge** among individuals about how to effectively protect data without too much effort.

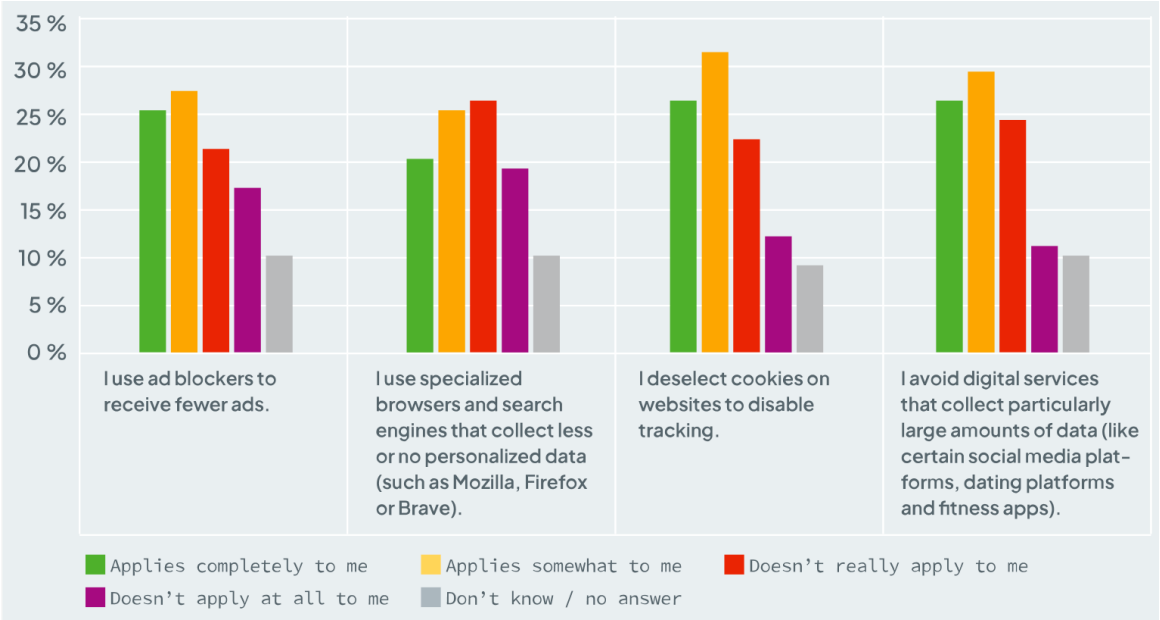

Figure 9: How online users protect their data (own illustration, IÖW)
("Which of the following measures do you take when you are online or to what extent do the following statements apply to your online behavior? Take into account all your online activities on your computer, laptop, tablet or smartphone.")

Another reason why personal data can still be exploited despite the GDPR regulations is the fast-moving and transforming tech industry, which is constantly looking for new ways to use personal data. For example, marketing agencies put more effort into other data collection strategies such as user accounts:

> "Personalization is changing a lot now […]. Before, we were more active in things like retargeting for example, but now because of the changes that are happening with the cookie and data regulation, we are moving more towards helping the client [to] understand the client's user base. So, the people that log into the website and […] give consent to share their data. How can we optimize this pool of people or help the client understand their customer base better?" (Int. 8)

So, most marketing intermediaries move quickly to find **ways around new data regulations**. As a lot of revenue depends on the data, website design often hinders the individual choice for data protection. **Dark patterns**[9] encourage or trick users into providing their data through incomprehensible and inaccessible data privacy options. So, a large barrier to serious data protection policies is that many companies claim to rely on the use of data and personalized advertising. Also sustainability-oriented companies emphasize that it is self-evident to use data for marketing purposes: “Just because we're sustainable doesn't mean we don't do modern marketing. And that simply includes the use of data” (Int. 6).

Loss of autonomy. The second risk on the individual level is the loss of individual autonomy when using online websites and services. In neoclassical economic theory, consumer autonomy represents a key condition for liberal market economies, next to consumer sovereignty and the principle of freedom of choice (Norkus, 2003). It can be defined as “the ability of consumers to make independent informed decisions without undue influence or excessive power exerted by the marketer” (Drumwright, 2018, p. 510). It has been argued that ML-based decision-aids have a positive impact on consumers as they simplify an oversupply of choice. However, a risk of this fundamental change in online decision-making is the **manipulation of online users’ behavior** and, therefore, the weakening of their autonomy (Bjørlo et al., 2021). Section 3.1 contains a discussion on the environmental risk due to advertising being used to nudge people towards more consumption and towards unsustainable lifestyles. AI-based personalized advertising uses individual data to induce the behavior that is best for the company, most often the purchase of a product, but not necessarily the behavior that is the best for the user. The more information is accessible about a target group, the easier a certain behavior is to provoke. One civil society representative warns:

> “The biggest risk is the possibility of manipulation. The more detailed a company or a party that has an interest has information about someone, the better they can use it to find out how to grip someone best. The more detailed someone is scanned [...], the easier it is to manipulate that person or to induce a certain behavior.” (Int. 2)

This exploitation poses a risk to users of the internet especially when they did not even intend to make a purchase or to perform a certain behavior. But even more so because it can be used to **discriminate against marginalized or vulnerable groups** (McCann et al., 2021). The expert elaborates:

> “It is used to exploit psychological vulnerabilities or illnesses. For example, a person wants to fly to his sick father, then the prices go up. So, the offer is tailored to the person. But to their disadvantage! It should be called surveillance-based advertising instead of personalized advertising.” (Int. 2)

The extent of the exploitation of personal data can be huge: Personalization based on place of residence can lead to price and supply discrimination. People who live in particularly vulnerable areas with a high proportion of poverty or crime can receive offers with disadvantageous conditions. Further vulnerabilities exist, for example, with children or people at risk of addiction and targeting of online gaming and addictive substances. Here, clear information asymmetries are in place where the marketing players know ‘everything’ about individuals while individuals do not even know which

[9] Dark patterns are manipulative designs or processes that are used to persuade website and app users to take a specific action, e.g., accepting cookies for data collection. They place information in a non-neutral way, hide certain relevant information and evoke instinctive behavior, e.g., by a certain color selection (Verbraucherzentrale, 2023).

data is collected and transferred to whom (Zuboff, 2019). These cases contradict the concept of autonomous consumers who are able to make informed decisions without the excessive influence of marketeers. One interview partner summarizes:

> “Classically, the theory assumes [...] that you have market participants who are equally informed […] and on this information basis you make your decision. Then it leads to the best product or the best-adapted product ultimately being purchased. But we live in a system in which the best product does not prevail because we have an information deficit among consumers, [who] [...] are also negatively influenced by too much advertising. That leads to the fact that it is no longer the best product that prevails in the market economy but the most or best advertised product. [...] If you look at AI, which is influencing [...] [the] consumer behavior more and more, we are ultimately […] on the way to a totalitarian capitalism.” (Int. 3)

Lastly, it is not only the manipulation of behavior and discrimination of vulnerable groups that are signs of the loss of consumer autonomy but also a **lack of choice in receiving advertisement**. The advertising industry relies on a digital system of dependency and ‘no exit’ (Zuboff, 2019). Leaving many online platforms such as Google or social media sites proves to be difficult as users rely on them for social interaction, work, education, health and access to products and services (ibid.). Under current circumstances, not providing any personal information would require users to quit large parts of online social life and – although it might be argued that most platforms are private – also parts of the public sphere. This loss would not be acceptable for a large share of the population. As using websites and services of the internet is directly connected with the collection of data and the display of advertising, it is almost impossible to make the autonomous choice against providing data and receiving advertisements. One interview partner introduces the legal concept of ‘**negative freedom of information**’, which he relates to advertisement in the non-digital public space and which refers to the fundamental right of rejecting (the display) of certain information:

> "It is of course my right as a human being to decide for myself when I want to see advertising and when not. [...] As a whole, it is legally derived from Article 5, freedom of communication. The so-called right to negative freedom of information. This has hardly been dealt with in legal literature. [...] Normally the right to freedom of information is understood as the fact that one can inform oneself from generally accessible sources. But every fundamental right also has a negative dimension. You can have an opinion, that is the positive freedom of opinion, but nobody can force you to form an opinion about something. In legal terms, this is called negative freedom of opinion. The same applies to freedom of information. I have the right to inform myself, but no one can force me to receive information in an unreasonable manner.” (Int. 3).

This argument is applicable to the online space where users should have the right of negative freedom of (advertising) information and display as well. However, this right is hard to implement as the online space is mostly private: “It can certainly be applied to the internet space, [because] I think the online space has also become a place of public discourse. For me, however, this is not the same as public space in the sense of our physical environment” (Int. 3). Also, in contrast to a public sphere, one can decide against using a private product, service or content. However, that this decision for most people is only a hypothetical choice has been discussed.

Dissemination of disinformation and risk for democracy. There are two ways through which AI-based personal-advertising contributes to mis- and disinformation[10] First, "the […] funding of hate and misinformation are massive risks and problems" (Int. 1), as one interview partner correctly states. Websites and platforms that are publishing 'fake news', conspiracy theories and false information have found a way to "monetize their content in an unprecedented way" (McCann et al., 2021, p. 22) through AI-based personalized advertising. To publish advertisements on such sites is even more attractive to advertisers as these publishing places are cheaper and highly engaging (McCann et al., 2021). One interview partner explains: "Hate and misinformation work really well in our online spaces because they work well with recommendation algorithms and because recommendation algorithms signal to advertisers that content is engaging and, therefore their advertising should appear next to it" (Int. 1).

Second, the same data, technologies, recommendation systems and algorithms that were developed for commercial targeting are building the **foundation for political targeting**: "Political microtargeting is the use of the tracking-based data driven advertising model to identify individuals or small groups to target them with specific tailored messages designed to appeal to them specifically" (McCann et al., 2021, p. 22). Internet users are thus being manipulated by content that is specifically designed for them to form a certain opinion, and they are only receiving a small share of available information and content as recommendation algorithms are trained on providing the user with content that is considered similarly interesting and relevant for them. Thus, they are nudged into certain viewpoints and opinions and, then, only receive supporting content, which prevents them from coming into contact with opposing views. A civil society representative states in one of the interviews: "And there are, of course, dangers for public discourse and for our democracy ultimately because of the formation of bubbles, of echo chambers" (Int. 3). The difficulty is to distinguish between trustworthy and false content, and the fact that only a small share of available information reaches the user impedes an informed and balanced shaping of public opinion, which in turn is the foundation of democracy. The dangerous influence of AI-and-data-based political targeting has been shown in the scandal of Cambridge Analytica, where the microtargeting is suspected to have had a substantial influence on the results of the US presidential elections and of the Brexit referendum (Amnesty International, 2019).

4.3 Economic Benefits and Harms

The economic benefits of using AI-based personalized advertising for businesses are widely known. Using ML technologies in personalized marketing promises to reduce costs for marketing campaigns, for customer acquisition and for customer service. It helps making advertising more efficient and to increase the return of investment. Generally, companies at all stages of the 'advertising lifecycle' are seen as the winners of personalized advertising. On closer look, this view does not prove to be accurate as a distinction between involved businesses has to be made and a broader look at the economy as a whole is required. In the following, we show that the use of AI in personalized online advertisements **poses risks on the business level as well as on a macroeconomic level**.

Corporate damage due to AI errors. On the specific company level, the use of AI poses a risk especially in content creation. AI is used for combining elements of texts and images in

[10] Misinformation refers to information that is stated falsely, inaccurately or incorrectly. Disinformation refers to the intentional spreading of false information such as deliberate greenwashing or propaganda.

advertisements in order to personalize the advertisement to the target group. This procedure is prone to errors, resulting in messages that were not intended to be sent to the potential consumers. The interview partners report that, at the given quantities of produced advertisements, there is no possibility of verifying them all, only a sample can be checked. This limitation can result in damaging the companies or the products image:

> “I can't even check what texts the AI writes anymore. And at the moment I don't have the certainty that this AI, no matter which one, will write the texts in such a way that they won't perhaps ruin my brand.” (Int. 6)

> “Text ads are put together where we say: ‘okay, that's not really what we want to convey as a brand.’” (Int. 7)

> “Placed ads, where simply wrong information is contained or where certain keywords, have been misinterpreted.“ (Int. 7)

While the danger of corporate damage due to AI is certainly a risk for businesses, it is one solely related to corporate sustainability in the sense of longevity of revenues and activities, but not directly a risk to socio-ecological sustainability. However, as this study was also interested in the impacts and perspectives of AI for businesses, it is still included here. The same applies for the following risk of dependence.

Dependence and lacking possibilities of influence. While some companies have immense influence in the data-driven marketing world because of their access to and power over data, technologies and infrastructures (see section 3.3), smaller companies have a much smaller scope of action. By deliberately driving and expanding AI- and data-based advertising, **the big players are forcing all other actors to follow their lead**: “Many companies that are not central players in this data-driven world, especially smaller ones, have no choice other than to accommodate themselves with the new rules, structures and standards set by the large corporate players” (Christl, 2017, p. 25). This compulsion is reflected in the fact that smaller companies are driven to participating in the modern advertising sector if they want to have a chance against the competition:

> “Certain things, if you want to participate in the market, you can't exclude at all. [...] For example, one of our most important sources is Google as a publishing medium. We have no influence there. [...] We simply have to [go] with the market, otherwise we wouldn't exist at all or at least not in the same size, if we didn't participate there.” (Int. 5)

> “We are a small player and [...] there are alternatives, but […] without Google and Meta, of course, our business success would also look different absolutely. So, to a certain extent we are also clearly dependent on the platforms.” (Int. 7)

It is as difficult for companies of a certain size to decide against personalized advertising and the use of data as it is for internet user to decide against providing data and receiving advertising. Further, smaller companies have little influence on how the collection and analysis of data as well as the design of (automated) advertising campaigns are implemented. Several interview partners state that there is **no transparency** about how certain campaigns are done or they cannot really control them. As one interview partner explains, personalized ads are generated “as Google then decides at that point. But of course, we don't have full transparency on how that works either” (Int. 7). The details on how Google designs AI processes, how data are analyzed and how it is used to create

personalized advertisements remains largely intransparent to the advertising companies. Especially sustainability-oriented companies try to control and implement more of the processes in-house in order to maintain control and also handle customer data responsibly; however, this in-house processing is not always possible and not the 'default' option:

> "Google […] has been driving automated campaign management for years and is actually pushing it more and more. Currently, there is already a trend that you decide less and less yourself, but rather that you provide Google, for example, with data or specify goals. And [...] Google then finds the best solutions. [This] is a double-edged sword for us. So, we also look at it with skepticism [and] [....] are more in the process of controlling it from our side and not handing over the control to the platforms. [...] [We] at least try to pull the strings and decide for ourselves what we do." (Int. 7)

Whether in ecological, social or economic issues, it is hard for companies to exert pressure and bring about change, for example, regarding the use, storage and transfer of consumer data, on ecological footprint data or on transparency. One interview partner admits: "It's difficult to push these big companies also like Google or Microsoft or Amazon" (Int. 8). This difficulty makes smaller companies dependent on the know-how, technology and infrastructure of the big players and limits their scope of action.

Market concentration and monopoly. Section 3.3 showed that the AI-based advertising market is – despite the many actors involved in the 'advertising life cycle' – dominated by two big players: Alphabet and Meta. They are usually better known for their subsidiaries Google and YouTube (Alphabet) and Facebook and Instagram (Meta). They are involved in collecting and analyzing data; they employ some of the biggest intermediaries for brokering advertising spaces and publish the personalized advertisings on their platforms. They, thus, have immense influence, as all three main activities of advertising, mediating and publishing lie within one and the same company. This development of extreme market concentration has often been referred to as a **'duopoly'** (Christl, 2017; Kingaby, 2020) and is problematic for several reasons.

Those companies concentrate large parts of data volumes and know-how within their company, making it impossible for other companies to compete and enabling a further power concentration: "[The] surveillance-based business model has in-built tendencies to exponentially increase the platforms' dominance and scale, and as such, the abuse of privacy and other rights has also helped concentrate power towards Google and Facebook" (Amnesty International, 2019, p. 41). Due to the lack of competition (McCann et al., 2021), they have **control over prices, practices and technical standards**, which they can take advantage of. Cases have become public where Google has, for example, manipulated the advertising market. As operators of the advertising space auction platform (auctioneer) and at the same time as co-bidder in the auction, they have a crucial information advantage by which they could deliberately decide the auctions in their favor (Tangens, 2021).

Also Amazon is known for favoring its own online retail business by evaluating data from third-party sellers or manipulating search results to its own advantage and, thus, establishing unfair trade practices (Künstner, 2023). The power concentration of the big players, the speed at which the advertising industry is developing and the **large information asymmetries** that exist between Alphabet and Meta on one side and governments and users on the other side have made it difficult to hold these actors accountable and put effective regulations in place (Amnesty International, 2019). Further, market power quickly translates into political power in the form of lobbying power, as companies with large financial means can influence political and public opinion-making processes

through donations, campaigns and lobbying activities (Künstner, 2023). The interviewed companies recognize the risks as well:

> **“**It's always more difficult to regulate these companies if they have a bigger pie or if they are the whole pie, regulation is more difficult. So, […] when these companies are too big, it's difficult to force them to have transparency. So, I think, it's just the general negative effect of having a monopoly.” (Int. 8)

The difficulty of regulating the big players and the lack of enforcement of current regulations in spite of recent attempts such as the European GDPR (Amnesty International, 2019) do not only pose a risk to the economy as a whole as **monopoly development and lack of competition impedes innovation and fosters exploitation**. They also represent a risk to fundamental human rights (Amnesty International, 2019). If this development continues and effective regulation is not put in place, the advertising economy is on its way to a “totalitarian capitalism” (Int. 3).

4.4 Perception of Sustainability Benefits and Harms

The representative surveys with citizens and decision makers in companies showed that not only marketing experts are concerned about the use of AI in personalized online advertising. However, knowledge about AI implementation in online advertising was limited among the survey respondents. Only 55 % of the households stated that they knew AI was used in personalization of online advertising. Accordingly, when asked in an open question which benefits and harms, they saw in AI implementation in online advertising, half of them did not name any. Companies seem to have limited knowledge as well: A third of them did not come up with any perceived benefits or harms when asked the same question.

After the open question, the most-mentioned advantages and risks from the literature and the interviews were also assessed using seven items on a 5-point Likert scale. As shown in Figure 10, the participants from both the **companies and the households agreed to a greater extent with the items concerning the risks than they did for the items concerning the advantages**. On top of the list for both actor groups were the risks for users concerning data protection and privacy: 34 % of citizens and 29 % of companies strongly agreed, and another 24 % of citizens and 26 % of companies rather agreed that these risks existed. In contrast, only 9 % of citizens and 11 % of companies strongly agreed that users could benefit from personalized ads by finding the right product. Interestingly, the opinion of citizens and companies were not as different from each other as expected. In addition, most companies have a critical view on the risks for society and the environment. Notably, the percentage of citizens (between 11 % and 18 %) as well as companies (6-9 %) that did not know whether AI use in online advertising had any advantages or risks was relatively high. This finding shows that **knowledge on this topic is still limited**.

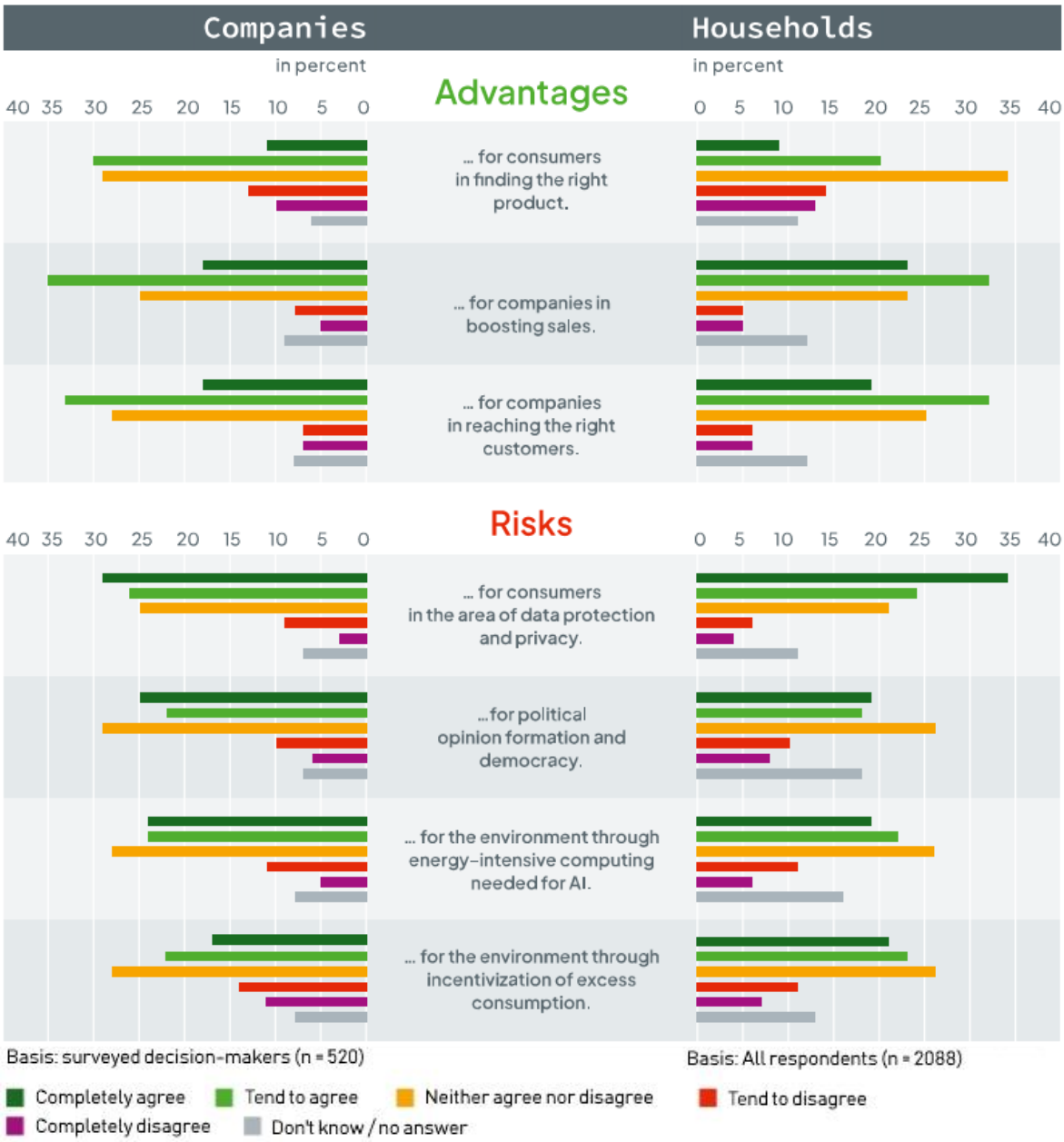

Figure 10: Perceived advantages and risks of AI in online advertising (own illustration, IÖW) ("How do you assess the advantages and risks of AI-supported personalized advertising?")

A further interesting result from the online survey was that not all companies were implementing AI-powered personalized advertising or the representative completing the survey for the company did not know it was already implemented (see Figure 11). Only 20 % of the companies stated that their company was implementing AI-supported personalized advertising, another 19 % said they were partly using it. Yet over half of them did not apply this form of advertising, or at least not knowingly for the person completing the survey. Furthermore**, personalized advertising seems to be especially attractive for larger corporations**. Whereas about 20 % of companies with a revenue of <100 million Euros were implementing AI in advertising, 34 % of companies with a revenue of >100 million Euros stated to do so. Similarly, from the companies with a revenue of < 10 million Euros, only 22-24 % thought doing without personalized online advertising would harm their business, 35-36 % of the companies with a higher revenue were worried about missing out on personal advertising advantages. And whereas 33 - 35 % of companies with a revenue of < 10 million Euros expected a more prominent role of personalized advertising in their marketing, a full 52 % of the

companies with > 100 million Euros revenues did think so. Yet overall, the lion's share of companies did not yet knowingly apply AI-supported personalized advertising, nor did they expect that it would harm their business if they did not apply it.

Figure 11: Participating German companies' implementation of AI in advertising (own illustration, IÖW)
("Now we are talking about the application of AI-supported personalized online advertising in your company. How much do you agree or disagree with the following statements?")

A surprisingly low number of companies (27 %) indicated that they were using the personalized ad services from Google or Facebook. Statistics from Eurostat (2023) show that, in 2021, 57 % of companies (with 10 employees or more) were using social media for marketing and to contact

customers. It seems likely that decision makers in companies are often not fully aware which technologies and data pools are used by third party advertisers. It seems that the smallest and largest companies are collaborating with Google and Meta most often: companies with a revenue of < 1 million Euros (31 %) and > 100 million Euros (39 %) use this form of marketing more often than the middle categories (22-23 %).

5 Pathways towards more sustainability in online advertising and beyond

The present case study has shown that AI application in personalized online marketing entails multiple risks and barriers for ecological, social and economic sustainability. This section discusses a selection of strategies and measures for more sustainability in and beyond the advertising industry. A summary of possible measures is presented in Table 4. While we distinguish between strategies on the policy, business and individual level, we want to emphasize the importance of effective policy measures because they represent a powerful lever for change and are to be favored – as the literature and the expert interviews have indicated. However, because we recognize that strong regulation takes effort and time, we also want to highlight the value of business and individual measures. The strategies considered to have the biggest potential to foster sustainability are marked in bold in Table 4.

Table 4: Strategies and measures for more sustainability in online advertising and beyond

	Strategies and measures	Sustainability dimension addressed
Policy	Enforcement of regulations and bans on data usage (e.g. GDPR)	Social, Economic
	Regulations and bans on environmental impacts (e.g. energy usage)	Ecological
	Regulation and ban of (AI- and data-based) advertising	Ecological, Social, Economic
	Labeling obligation for AI usage	Social
	Information campaigns and education on AI in advertising	Ecological, Social
	Development of a public digital infrastructure (e.g. public search index)	Ecological, Social, Economic
	Support of civil society organizations and independent journalism	Ecological, Social, Economic
Business	Adoption of corporate privacy and environmental self-declarations	Ecological, Social
	Internalization of environmental costs e.g. monitoring and compensation of CO_2 emissions	Ecological
	Usage of renewable energies	Ecological
	Adoption of third-party certificates and labels	Ecological, Social
	Implementation of open data and open source approaches	Social, Economic
	Implementation of data-sufficient marketing, e.g. privacy by design and default	Ecological, Social
	Adoption of new business models that do not depend on data	Ecological, Social, Economic
User	Use of ad-blockers	Ecological, Social
	Disclose little data e.g. through disabling cookies; using browsers, search engines and digital services that collect little amount of data	Social
	Political activism	Ecological, Social, Economic

Ecological Sustainability Social Sustainability Economic Sustainability

Policy measures

One of the most important and, in the literature, most often mentioned demands for policy measures is a ban on using and storing personalized data for advertising (Gossen et al., 2022; McCann et al., 2021) or, in other words, **the ban of surveillance-based personalized advertising** (Forbrukerradet, 2021; Lell, 2023). Successfully implementing and enforcing such a ban would lower the carbon emissions from the storage and transfer of data (McCann et al., 2021), tackle the issues of violations of privacy and data protection, lacking transparency, user manipulation, discrimination and disinformation (Forbrukerradet, 2021) and foster competition through creating a 'level playing field' where competitive advantages from personal data are diminished (Forbrukerradet, 2021; McCann et al., 2021). The European GDPR has enabled an important step forward in enhancing privacy protection. The policy requires that advertising companies obtain explicit consent from users when using, profiling, tracking and sharing their personal data. It, thus, aims at giving users back control over their own data (Forbrukerradet, 2021).

The GDPR has had a tangible effect on the advertising industry. An interview partner confirms: "I think there are good regulations, especially in the European Union with GDPR. This has really changed a lot how the online marketing works […] in Europe" (Int. 8). Another interview partner from the advertising business explains: "Self-commitment by the industry is not an effective lever if you want to make progress in this area. You have to regulate. So, the GDPR was important because it regulates. […] No advertiser said, 'We absolutely need a basic data protection regulation now'. The state has to set this framework" (Int. 4). Yet, **the GDPR faces several challenges** to putting an actual stop to the collection, storage and usage of personal data. It has been shown that consumers do not fully understand what it entails when they are consenting to tracking and profiling (Forbrukerradet, 2021; Kettner et al., 2018). Also, website and apps are intentionally designed in a way that users are nudged towards consenting to their personal data collection and usage, e.g., through dark patterns. Moreover, the advertising sector is fast-paced and companies are either deliberately not complying with the law or they are finding new technological 'solutions' to avoid the legislation. Further, substantial cross-border enforcement bottlenecks and the difficulty of enforcing and sanctioning companies make it challenging to control GDPR compliance (Forbrukerradet, 2021).

What are the (policy) alternatives or improvements to the current data handling processes in personalized online advertising? A first step would be the **prohibition of manipulative practices, such as dark patterns, and of the fragmentation of individual privacy settings**. This step could be achieved by enforcing 'privacy by design and default' (Gossen et al., 2022), for instance, as 'automated privacy signals' (McCann et al., 2021) and 'global, differentiated opt-in scenarios' (Kettner et al., 2020), where users would be able to set their privacy settings once in a browser extension or on a mobile device and which would automatically send these privacy signals to all websites and simultaneously remove all website specific privacy settings. In general, **Privacy by Design** incorporates data protection into the very architecture and framework of websites. **Privacy by Default** represents a proactive approach to safeguarding users' personal information while reducing the environmental costs associated with online services. This policy step would require website providers to prioritize privacy measures by default, promoting data minimization and thereby reducing the amount of user data collected. This reduction in data gathering directly correlates with decreased storage needs, resulting in lower energy consumption in data centers.

A more extensive alternative to personal-data-based advertising is **contextual advertising** (Forbrukerradet, 2021; IAB Europe, 2021; McCann et al., 2021). Contextual advertising means placing an ad based on where it will be displayed and not based on who will see it, e.g., placing an ad for

running shoes next to an online news article featuring the next marathon event (IAB Europe, 2021). This form of advertising does not require any third- or first-party personal data and has been found to be up to 7.5 times more effective than advertisements based on tracking (McCann et al., 2021). The legally supported re-introduction of contextual advertising would, thus, be advantageous for both users and businesses. It can be done automatically and programmatically using the existing, slightly redesigned auction infrastructure. However, the process of ad placements would be simplified for advertisers because data-management platforms, demand-side and supply-side platforms would no longer be needed, reducing the costs for advertising or resulting in more of the advertising budget reaching the publishers (McCann et al., 2021). Researchers consider that contextual advertising could tackle several of the mentioned risks of AI-based personalized advertising, for instance violation of privacy, bias and discrimination, competitive risks and national security risks, as well as direct environmental impacts (McCann et al., 2021).

For the environmental impacts, the case study has shown that significant knowledge is lacking on the actual levels of energy consumption and CO_2 emissions as well as on countermeasures. This missing knowledge is why regulation on the overall **monitoring and reduction of energy, material and water inputs as well as CO_2 emission outputs** is necessary. Regarding the indirect ecological impacts such as increasing purchases and consumption of products and services, only an overall limitation of online advertising can make a real environmental change. Online advertising ignores the limits of growth and the planetary ecological boundaries as long as it uses “commodified attention to (a) prey on the […] commodity fetishism of modern individuals to incite an ‘urge to splurge’ that fuels destructive conspicuous consumptions” (Kish, 2020, p. 3). With regard to the severe environmental challenges the world faces today and the call upon individuals to consume ‘sustainably’ and sufficiently (Gossen et al., 2022), there should also be a public debate on what needs are created by producers and the advertising industry in the first place, and how to fulfill the ‘good life’ for each and everyone without mass consumption.

Another field where regulation is needed concerns the current monopolistic structure of the advertising business and the resulting lack of competition. While the European Unfair Commercial Practices Directive has attempted to control how commercial actors engage in marketing, commercial practices and terms of use across markets, this directive is seen as insufficient when it comes to dealing with the challenge of AI-based personalized advertising (Forbrukerradet, 2021). Limiting the power of the few players in online advertising requires more ambitious initiatives. A good example is the Amazon case, in which Künstner (2023) examined to what extent it would be legal to carry out a **'decartelization' of the group** because it had been manipulating the market and established a practice of self-preferencing. A decartelization can be achieved by imposing an information restriction between segments of the company, by transferring the management to an independent organization or by parts of the company or assets being sold. The study on Amazon recommends a multiple, structural decartelization of Amazon’s own online trading, the e-commerce platform and the complementary services (webservice, fulfillment, logistics). Such measures should be considered and examined for the big online advertising companies as well, especially as, for example, Google has also repeatedly used self-preferencing practices (European Commission, 2017, 2018, 2019).

Further strategies should include a discussion on the **development of public digital infrastructure**, e.g., a public search index as an alternative to all private websites and spaces (Int. 2). Here, the parameters of energy consumption, used algorithms, anti-discrimination and manipulation measures, content quality, data protection and privacy could be governed and controlled. Only if this control is guaranteed can consumers have a true choice of using or avoiding certain services that are ‘data-consuming’ or energy-consuming. Currently, if users want to avoid certain search

engines, websites or social media, they have to decide against a big share of public life. This decision needs to be accompanied by broad **information and education campaigns** for all age groups on the use and dangers of data and AI in personalized online advertising (Gossen et al., 2022). Even if knowledge and awareness are not always sufficient to induce immediate behavior change in users, awareness and recommendations for actions are the necessary first step. Lastly, a change in the advertising industry is only possible if **civil society organizations and independent journalism** are supported, as they play a crucial role in public opinion-making processes and for democracy. They should not be dependent on revenues from advertisements and should fulfill the role of pointing out societal challenges.

Businesses strategies

Businesses are key actors on the path to more sustainability in personalized online marketing. The interviews of this study have shown that smaller companies perceive their scope of action as limited because they are dependent on the given infrastructure of the big players, which is difficult to influence. Civil society organizations, on the other hand, are skeptical about the impact that business action has: “It has to be regulation, not voluntary commitment! I no longer believe in that. It was only done to avert legislation” (Int. 2). While both positions have to be taken into account, it is of particular importance that businesses need to make a change. A first step would be implementing goals on data protection and privacy, material and energy consumption and fair corporate practices into **business strategy and guiding principles and to publish self-commitment statements**. Further, specific measures need to be implemented such as the **monitoring and compensation of CO_2 emissions**, the **use of renewable energies** or **data-sufficient marketing** (e.g., privacy by design and default on own websites and applications, reduced targeting of users with adverts). Also the switch to **open data and open source approaches** can make a difference when the companies’ big data, codes, algorithms and programs are shared and used for the common good (Gossen et al., 2022; Lautermann & Frick, 2023). However, here a debate is necessary as to which data and algorithm sharing can actually contribute to establishing fairer market practices in online advertising.

In addition, a company can decide to become certified by an **independent, third-party label or audit**. This certification would help in structuring internal corporate processes in meaningful ways and in choosing trustworthy business partners. Yet, as the interview partners mentioned, it is important to develop and create certificates and labels that are suitable for the digital marketing sector and its processes. Currently, common labels quickly lead to greenwashing as they cannot yet capture all the digital processes and material consumptions involved. Lastly, the most far-reaching action for ensuring the data protection and privacy and for lowering energy-related environmental impacts would be to **develop business models for advertisers, publishers and website hosts that are independent of data** collection, sharing and usage. Contextual advertising, subscription models for content-related websites such as online-newspapers and public infrastructures would be first steps towards data-independent online spaces.

Individual strategies

While individual strategies will rarely be able to change the workings of today’s advertising industry as a whole, they can be effective at the individual privacy level. Therefore, it is recommended that users who do not want to share personal data or to receive advertising **install ad blockers** and individually adjust privacy settings, e.g., **through rejecting cookies and using browsers, search engines and digital services that collect little data** (Kish, 2020)**.** Browser extensions can help to further restrict fingerprinting, tracking and advertising. Civil society organizations such as the

German association ‘Digitalcourage’ provide detailed information on how individuals can protect their data and move safely through the internet, which they call ‘digital self-defense’ (Digitalcourage, o.J.). Another example is the Electronic Frontier Foundation. The organization is located in the United States and provides hands-on information and tools for online users (EFF, 2023). Furthermore, it is essential that users inform themselves about the risks of personalized online marketing and stand up for their own personal rights and environmental protection through **political activism**. Only if citizens find a voice for their concerns and exert pressure on current politicians can a change in the legal framework be achieved.

6 Conclusion

It has been shown that AI systems suit manifold use cases in online marketing. Search engines, image processing applications and chatbots have become everyday companions, as in many other domains. Product design can profit from AI just like marketing intelligence or campaigning strategies. However, **probably the most strikingly influential use case within online marketing consists of AI-based targeting techniques, which enable personalized advertising.** Involved actors rely on the extensive mining of digital data, segmentation and the creation of user/customer profiles and the matching of specific ads to specific online users with the help of automated ad auctions in real time. The foundation for this business is the use of countless data points on users, their devices, the software they use, the online content they access and the individual temporally and spatially manifesting patterns of their online behavior.

These practices allow **conclusions to be drawn about further and potentially highly sensitive personal information**. Ad tech companies exploit the vast amounts of details we give away online and derive probabilities that are relatable to individual preferences, personality traits, financial situations, family statuses, political views and much more. Dominant criteria for the success of certain advertisements (such as engagement or conversion rates) incorporate the use of such information, even if it is not made explicit. As data sets have become richer and AI systems more powerful over the years, so have online advertising markets grown to such a great extent that the commercial Web as we know it relies on them to a large extent.

The structure and interplay of actors in personalized advertising is intertwined and opaque. Involved digital products and services are provided and used by stakeholders such as advertisers, publishers, recipients (online users) and various intermediaries such as marketing agencies, platforms and ad tech companies. An integral part of the inner functioning of personalized online advertising consists of continuous ad verification, evaluation and optimization for ad performance. **Online users take a largely powerless role in personalized advertising ecosystems while a few big economic players have significant influence** on the functioning and development of respective markets. Large shares of advertising revenue flow to a relatively small number of companies such as Amazon, Facebook, Google, Instagram, Netflix, TikTok and Pinterest (Statista, 2023a). AI can be expected to contribute a significant sum to their revenues as it facilitates today's quality and spread of personalization. From an advertising perspective, microtargeting works. From a consumer perspective, it is almost unavoidable. From a regulation perspective, it is hard to capture.

The fast-pacing developments in the advertising industry come at the expense of individuals, the environment and society. While a number of studies have already investigated one or another dimension of sustainability risks within online advertising, this study contributes to the existing body of research by adopting **a holistic sustainability assessment** perspective and examining direct and indirect environmental impacts, direct individual and indirect societal effects as well as economic consequences on a direct business level and on an indirect macroeconomic level. In total, nine harmful sustainability impacts with a further ten sub-effects were identified.

The results of our study show that the risks associated with personalized online marketing are not limited to privacy protection issues. **Web tracking, which is the backbone of AI systems used for personalization, has created a substantial demand for data transfer, processing and storage.** Data centers, which house the digital infrastructure of the Web, consume large amounts of electricity and contribute significantly to carbon emissions. It is estimated that the internet is

responsible for 5 % to 15 % of total global electricity consumption (González-Cabañas et al., 2023). Online advertising and the collection of user data are both big contributors. Furthermore, **material and energy intakes along the whole 'data lifecycle'** as well as **consumption increases on the consumer side**, caused by online advertisement, need to be taken into account when considering the environmental footprint of personalized marketing.

Although the implementation of the GDPR has substantially changed the online marketing sphere, there are still **immense challenges concerning individual privacy and data protection**, autonomy loss and manipulation of online users as well as the dissemination of disinformation including greenwashing and climate misinformation. AI use within personalized advertising has an intensifying effect on those dangers as processes are less controlled and comprehensible. And, while AI use and personalization are still soaring in the marketing world, businesses are starting to recognize the dangers. Especially smaller companies mention the **susceptibility to errors of automated messaging and the difficulties of being dependent on the few big players,** who are in control of most of the data, technology and infrastructure.

Overall we conclude in line with Kish (2020) that, for online marketing, the application of AI is more **a barrier to sustainability** than an opportunity. We, thus, argue that regulation in the form of a **ban on data- and surveillance-based personalized advertisement** is needed. Viable alternatives such as a shift towards **contextual advertising** are proposed for addressing privacy and data protection and direct environmental risks. To deal with the indirect environmental impacts of increasing resource consumption due to increasing purchases, there needs to be a public debate on what kind and how much advertising is desirable in general and how we, as a society, can **create public digital infrastructures**. However, as these are relatively long-term visions, we recognize the need for 'bridging solutions'. The flow and processing of data produced by online advertising can be limited through the technology deployed **(Privacy by Design**) and the settings chosen (**Privacy by Default**). Furthermore, more transparency about the AI systems used by companies in the digital marketing sector is required if the environmental impact of the digital marketing sector is to be fully assessed. Companies need to share the methods in use, how the models are trained, what data is used to train them and how much energy is consumed and carbon emissions are generated when developing and training these systems.

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ADDRESS AND CONTACT
Institute for Ecological Economy Research (IÖW)
Potsdamer Straße 105
10785 Berlin
Germany
Phone: + 49 – 30 – 884 594-0
Fax: + 49 – 30 – 882 54 39
E-mail: mailbox@ioew.de

www.ioew.de