AI-Ethics by Design. Evaluating Public Perception on the Importance of Ethical Design Principles of AI.

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Abstract

Despite the immense societal importance of ethically designing artificial intelligence (AI), little research on the public perceptions of ethical AI principles exists. This becomes even more striking when considering that ethical AI development has the aim to be human-centric and of benefit for the whole society. In this study, we investigate how ethical principles (explainability, fairness, security, accountability, accuracy, privacy, machine autonomy) are weighted in comparison to each other. This is especially important, since simultaneously considering ethical principles is not only costly, but sometimes even impossible, as developers must make specific trade-off decisions. In this paper, we give first answers on the relative importance of ethical principles given a specific use case — the use of AI in tax fraud detection. The results of a large conjoint survey (n=1099) suggest that, by and large, German respondents found the ethical principles equally important. However, subsequent cluster analysis shows that different preference models for ethically designed systems exist among the German population. These clusters substantially differ not only in the preferred attributes, but also in the importance level of the attributes themselves. We further describe how these groups are constituted in terms of sociodemographics as well as opinions on AI. Societal implications as well as design challenges are discussed.

Key words ethical principles · artificial intelligence · public perception · design preferences · trade-offs

1 Introduction

Artificial intelligence (AI) has enormous potential to change society. While the widespread implementation of AI systems can certainly generate economic profits, policymakers and scientists alike also highlight the ethical challenges accompanied by AI. Most scholars, politicians, and developers agree that AI needs to be developed in a human-centric and trustworthy fashion, resulting in AI that benefits the common good, respectively the whole society (Berendt, 2019; Cath et al., 2018; European Commission, 2020; Floridi et al., 2018; Jobin et al., 2019). Trustworthy and beneficial AI requires that ethical challenges be considered during all stages of the development and implementation process. While plenty of work considers ethical AI development, there is surprisingly little research investigating public perceptions of those ethical challenges. This lack of citizen involvement is striking because developing ethical AI aims to be human-centric and of profit for the whole society. Filling this research gap, we set out to shed light on public perceptions of ethical principles outlined in ethical guidelines. Particularly, we investigate how people prioritize different ethical principles. Accounting for the trade-offs between the different ethical principles is especially important because maximizing them simultaneously often proves challenging or even impossible when designing and implementing AI systems. For instance, aiming for a high degree of explainability of AI systems can conflict with the ethical principle of accuracy, since a high degree of accuracy tends to require complex AI models that cannot be fully understood...
by humans, especially laypersons. Thus, taking the goal of ethical AI development seriously requires decision makers to take the opinions of the (affected) public into account.

This paper gives first answers to the relative importance of ethical principles given a specific use case — here, the use of AI in tax fraud detection. In a large (n=1099) online survey with a conjoint design, we asked participants to rate different configurations of tax fraud systems; the proposed systems varied in how they comply with the seven ethical principles that are most prominent in global AI guidelines (Jobin et al., 2019). As we aim for high external information value of our results, we decided not to rely on one specific ethical guideline, but on the ethical principles that are most referred to on a global scale.

2 Ethical Guidelines of AI Development

AI increasingly permeates most areas of people’s daily lives, whether in the form of virtual intelligent assistants such as Alexa or Siri, as a recommendation algorithm for movie selection on Netflix, or in hiring processes. Such areas of application are only made possible by the accumulation of huge amounts of data, so-called Big Data, that people constantly leave behind in their digital lives. Although these AI-based technologies aim to take tasks off people’s hands and make their lives easier, collecting and processing personal data is also associated with major concerns. Boyd and Crawford (2012) emphasize the importance of ethically responsibly handling Big Data. Scandals such as the NSA affair or Cambridge Analytica have recently caused great public outcry. The public attention was, therefore, once again drawn more strongly to the issue of privacy. Policymakers are increasingly reacting to these concerns. For example, shortly after the Cambridge Analytics scandal became public, the European Union’s General Data Protection Regulation (GDPR) came into force. This is considered an important step forward in the field of global political convergence processes and helps to create a global understanding of how to handle personal data (Bennett, 2018).

However, Big Data not only leads to privacy concerns, but can undermine transparency for users of online services. This lack of transparency is further exacerbated by the fact that algorithms are sometimes too complex for laypersons to understand, which is often referred to as a black box (Shin and Park, 2019). Questions regarding comprehensibility and explainability are therefore at the core of algorithmic decision-making and its outcome (Ananny and Crawford, 2018). These questions become particularly relevant when algorithms make biased decisions and systematically discriminate against individual groups of people. For example, the COMPAS algorithm used by United States (US) courts systematically disadvantaged black defendants by giving them a higher risk score for the probability of recidivism than white defendants (Angwin et al., 2016). In contrast, a hiring algorithm used by Amazon systematically discriminated against female candidates (Köchling and Wehner, 2020). Algorithmic discrimination can be caused by flawed or biased input data or by the mathematical architecture of the algorithm (Shin and Park, 2019; Zou and Schiebinger, 2018). Thus, AI systems run in danger of reproducing or even exacerbating existing social inequalities with detrimental effects for minorities. Such algorithmic unfairness then leads to the question of who is accountable for possibly biased decisions by an AI system (Busuioc, 2020; Diakopoulos, 2016). All of these questions have been extensively discussed in the fairness, accountability, and transparency in machine learning (FATML) literature (Shin and Park, 2019). The different concepts are closely intertwined. For example, Diakopoulos (2016) points out: “Transparency can be a mechanism that facilitates accountability” (p. 58).

To address these concerns and to define common ground for (self-)regulation, governments, private sector companies, and civil society organizations have established ethical guidelines for developing and using AI. The goal is to address the challenges outlined by the scientific community and thus to ensure so-called “human-centered AI” (e.g., Lee et al., 2017; Shneiderman, 2020), or “human-centric” AI (European Commission, 2019). For example, the High-Level Expert Group on AI (AI HLEG) set up by the European Commission calls for seven requirements of trustworthy AI: (1) human agency and oversight, (2) technical robustness and safety, (3) privacy and data governance, (4) transparency, (5) diversity, non-discrimination and fairness, (6) societal and environmental well-being, and finally (7) accountability (European Commission, 2019). Along similar lines, the OECD recommends a distinction between five ethical principles, namely (1) inclusive growth, sustainable development, and well-being; (2) human-centered values and fairness; (3) transparency and explainability; (4) robustness, security, and safety; and (5) accountability (OECD, 2021).

Some researchers have taken a comparative look at the numerous guidelines published in recent years and have highlighted which ethical principles are emphasized across the board (e.g., Hagendorff, 2020; Jobin et al., 2019). There is widespread agreement on the need for ethical AI, but not on what it should look like in concrete terms. For example, Hagendorff (2020) highlights that the requirements for accountability, privacy, and fairness can be found in 80% of the 22 guidelines he analyzed. Thus, to a large extent, the
guidelines mirror the primary challenges for human-centric AI discussed in the FATML literature. At the same time, however, Hagendorff (2020) points out that it is precisely these principles that can be most easily mathematically operationalized and thus implemented in the technical development of new algorithms. Jobin et al. (2019) conducted a systematic review of a total of 84 ethical guidelines from around the globe, although the majority of the documents originate from Western democracies. In total, the authors identify 11 overarching ethical principles, five of which (transparency, justice and fairness, non-maleficence, responsibility, and privacy) can be found in more than half of the guidelines analyzed. Also, the attributes of beneficence and of freedom and autonomy can still be found in 41 and 34 of the 84 guidelines, respectively. The ethical principles of trust, sustainability, dignity, and solidarity, on the other hand, are only mentioned in less than a third of the documents (Jobin et al., 2019).

In this paper, we focus on the seven most prominent ethical principles, which are discussed in most of the existing guidelines, analyzed by Jobin et al. (2019). In addition to the aforementioned principles of transparency (or explainability), fairness, responsibility (accountability), and privacy Jobin et al. (2019) list non-maleficence, freedom and autonomy, and beneficence. They conceive “general calls for safety and security” (p. 394) as non-maleficence. At the core of the principles lies the requirement for technical security of the system, for example, in the form of protection against hacker attacks. In this way, unintended harm from AI should be prevented, in particular (European Commission, 2019). According to Jobin et al. (2019), the freedom and autonomy issue addresses, among other things, the risk of manipulation and monitoring of the process and decisions, as also addressed by the AI HLEG. In light of this challenge, implementing human oversight in the decision-making process can ensure that human autonomy is not undermined and unwanted side effects are thus avoided (European Commission, 2019). However, decision-making procedures are perceived as fair when the procedure guarantees a maximum degree of consistency on the one hand and is free from personal bias or, at worst, corruptibility of human decision makers could be suspected, i.e. in tax fraud detection (Köbis et al., 2021). In this sense, the use of AI can lead to less biased decisions (Miller, 2018). Finally, beneficence refers to the common good and the benefit to society as a whole. However, reaping this benefit requires algorithms that do not make any mistakes. The accuracy of AI is therefore decisive for societal benefit. This is because only a high level of predictive accuracy or correct decisions made by an AI can generate maximum benefit (Beil et al., 2019). Accordingly, AI systems used in medical diagnosis, for instance, can only improve personal and public health if they operate as accurately as possible (Graham et al., 2019; Yeasmin, 2019).

While all ethical principles highlighted in the ethical AI guidelines seem desirable in principle, they can cause considerable challenges in practice. The reason is that when designing an AI system, it is often infeasible to maximize the different ethical aspects simultaneously. Thus, multiple complex trade-off matrices emerge (Binns and Gallo, 2019; Köbis et al., 2021). Two examples help to illustrate this point. First, the more available information about a user’s wants, needs, and actions, recommendation algorithms on social media platforms can make helpful and more accurate recommendations. This information includes private data about a user, such as the browsing history, but also sensitive data, such as gender. Collecting this data and simultaneously improving the recommendation can result in accuracy-privacy (Machanavajjhala et al., 2011) or accuracy-fairness trade-offs (Binns and Gallo, 2019). Second, for a company to assess if its hiring algorithm discriminates against social minorities, it needs to collect sensitive information from their applicants, such as ethnicity, which may violate fundamental privacy rights, leading to a fairness-privacy trade-off (Binns and Gallo, 2019). By adding more variables like transparency, security, autonomy, and accountability to the mix, highly complex trade-offs between the various ethical principles emerge.

3 Public Preferences for AI Ethics Guidelines

A human-centric approach requires that AI systems are used “in the service of humanity and the common good, with the goal of improving human welfare and freedom” (European Commission, 2019: 4). Thus, it is essential to account for the perceptions of those most affected by decisions made by algorithmic systems. A recent example from the United Kingdom (UK) illustrates that violating ethical principles when designing and implementing AI — in this case, an automated system that graded students in schools — can lead to substantial public outrage (Kelly, 2021). Empirical research further suggests that perceiving AI as unethical has detrimental implications for an organization in terms of a lower reputation (Acikgoz et al., 2020) as
well as a higher likelihood for protests (Marcinkowski et al., 2020) and for pursuing litigation (Acikgoz et al., 2020). Thus, to address the fundamental question of which kind of AI we want as a society, detailed knowledge about public preferences for AI ethics principles is key. A surging strand of empirical research addresses this question and finds that public preferences for AI are highly dependent on the context, as well as on individual characteristics (Pew Research Center, 2018; Starke et al., 2021). While people perceive algorithms to be acceptable in some domains (e.g., social media recommendation), they reject them in others (e.g., predicting finance scores). Also, judgments about AI hinge considerably on sociodemographic features, such as age or ethnicity. In the US, a study by the Pew Research Center (2018) identifies four major concerns voiced by respondents: (1) privacy violation, (2) unfair outcomes, (3) removing the human element from crucial decisions, and (4) inability of AI systems to capture human complexity.

The empirical literature further shows that people largely desire to incorporate ethical principles advocated for in the legal guidelines. First, people base their assessment of an AI system on its accuracy. The seminal study by Dietvorst et al. (2015) finds that people avoid algorithms after seeing them making a mistake, even if the algorithm still outperforms human decision makers. Along similar lines, people lose trust in defective AI systems (Robinette et al., 2017). However, studies have found that people still follow algorithmic instructions even after seeing them err (Robinette et al., 2016; Salem et al., 2015). Second, fairness is a crucial indicator for evaluating AI systems (Starke et al., 2021). When an AI system is perceived as unfair, it can lead to detrimental consequences for the institution implementing such a system (Acikgoz et al., 2020; Marcinkowski et al., 2020). Third, empirical evidence suggests that keeping humans in the loop of algorithmic decisions, i.e., ensuring human oversight at least at some points of the decision-making process, is perceived as fairer (Nagtegaal, 2021) and more legitimate (Starke and Lünich, 2020) compared to leaving decisions to algorithms. Fourth, in terms of transparency, the literature yields mixed results. On the one hand, more openness about the algorithm is essential to building trust in AI systems (Neuhaus et al., 2019), involving the users (Kizilcec, 2016), reducing anxiety, (Jhaever et al., 2018) and increasing user experience (Vitale et al., 2018). On the other hand, studies show that too much transparency can impair user experience (Lim and Dey, 2011) and confuse users, complicating the interaction between humans and AI systems (Eslami et al., 2018). Fifth, privacy protection can be an essential factor for evaluating AI systems, leading people to reject algorithmic recommendations based on personal data (Burbach et al., 2018). However, other studies suggest that users are often unaware of privacy risk and rarely use privacy control settings on AI-based devices (Lau et al., 2018; Zheng et al., 2018). Sixth, empirical research suggests that people perceive unclear responsibility and liability for algorithmic decisions as one of the most crucial risks of AI (Kieslich et al., 2020). Furthermore, accountability and clear regulations are viewed as highly effective countermeasures to algorithmic discrimination (Kieslich et al., 2020). Along similar lines, other studies found that perceptions of accountability increase people’s satisfaction with algorithms (Shin and Park, 2019) as well as their trust (Shin et al., 2020). Lastly, in terms of security, people consider a loss of control over algorithms a crucial risk of AI systems (Kieslich et al., 2020).

Only a few studies, however, compare the influence of different ethical indicators on people’s preferences. In several studies, Shin and colleagues tested the effects of three crucial aspects of ethical AI: fairness, transparency, and accountability. The results, however, are mixed. While fairness had the most substantial impact on people’s satisfaction with algorithms (followed by transparency and accountability) (Shin and Park, 2019), transparency was the strongest predictor for people’s trust in algorithms (followed by fairness and accountability) (Shin et al., 2020). Another study found that explainability has the most decisive influence on algorithmic trust (Shin, 2020). However, to the best of our knowledge, no empirical study has looked at different trade-off matrices between the various ethical principles and investigated people’s preferences for single principles at the expense of others. Therefore, we propose the following research question:

RQ1: How do varying degrees of consideration of ethical principles in the design of an AI-based system influence the public’s preference for prioritization among them?

However, considering the diversity of social settings and beliefs among society, it is probable that there are trade-off differences among the public concerning the prioritization of ethical principles, respectively ethical preference patterns of AI systems. Hence, we ask the following research question:

RQ2: Which preference patterns of ethical principles are present in the German public?

The literature suggests that human-related factors influence the perception of AI systems. For example, empirical studies have found that age (Grglić-Hlača et al., 2020; Helberger et al., 2020; Vallejos et al., 2017), educational level (Helberger et al., 2020), self-interest (Grglić-Hlača et al., 2020; Wang et al., 2020), familiarity with algorithms (Saha et al., 2020), and concerns about data collection (Araujo et al., 2020) have effects on the perception of algorithmic fairness. Hancock et al. (2011) performed a meta-analysis of factors influencing
trust in human-robot interaction and identified, among others, demographics and attitudes toward robots as possible predictors. Subsequently, we elaborate on this literature and test for differences among human-related factors concerning the emerging ethical design patterns. Hence, we ask RQ3.

RQ3: Which characteristics do people who favor a specific ethical design of AI systems share?

4 Method

4.1 Sample

The data were collected via the online access panel (OAP) of the market research institute forsa between March 16 and March 25, 2021. The OAP is representative of the German population above 18 years of age, which at least occasionally uses the Internet. Respondents from the panel were randomly invited to participate in the survey, with each panelist having the same chance to be part of the sample. Altogether, 1,204 people participated in the survey.

We cleaned the data according to three criteria: (1) low response time for the entire questionnaire (1 SD under average time), (2) high number of missing data in the entire questionnaire (2 SD above average number of missing data), and (3) low reading time of the introduction text for the conjoint analysis (under 20 seconds reading time identified through a pre-test). Participants were excluded when all criteria were met. Consequently, one participant was excluded. Additionally, we excluded all respondents who rated all proposed systems in the conjoint analysis equally (n=104). This data cleaning step was crucial, since those respondents showed no preferences for any configuration and, methodologically speaking, for those respondents, no variance can be explained in the conjoint analysis.

After data cleaning, 1099 cases remained. In total, our sample consisted of 593 (54%) women and 503 (45.8%) men, while 3 (0.3%) indicated binary. The average age of the respondents was 47.1 (SD=16.7). Furthermore, regarding education level, 192 (17.5%) hold a low, 362 (32.9%) hold a middle and 540 (49.1%) hold a high educational degree.¹

4.2 Procedure

Initially, respondents were asked to answer several questions concerning their perception and opinion on AI. To evaluate the preference of ethical principles in the design of AI systems, we integrated a conjoint survey with seven attributes in the survey. The use case addresses an AI-based tax fraud detection system. Such systems are already in use in many European countries, e.g., France, the Netherlands, Poland, and Slovenia (Algorithm Watch, 2020) and also in the state of Hesse in Germany (Institut für den öffentlichen Sektor, 2019). In our study, respondents were presented with a short text (179 words) describing the use case of AI in tax fraud detection. The text stated that these systems can be designed differently. Then, we described the seven most prominent principles in ethical AI guidelines that we derived from the review paper by Jobin et al. (2019): explainability (as measurement for the dimension “transparency”), fairness, security (as measurement for the dimension “non-maleficence”), accountability (as measurement for the dimension “responsibility”), accuracy (as measurement for the dimension “societal well-being”), privacy, and limited machine autonomy (for exact wording of the attributes, see Table 1). Notably, we chose to include machine autonomy as we assumed that in the special case of tax fraud detection, no human oversight might be preferred due to possible bias reduction. In the following, the ethical principles are also called “attributes”.²

After reading the short introductory text, respondents were told that an AI system can have different configurations of the different ethical principles. If the system satisfied a principle, it was indicated with a green tick; if the property was not met, it was marked with a red cross. Respondents were presented with a total of eight cards showing different compositions of AI systems in randomized order. The configurations only varied whether the seven ethical principles were satisfied (see Table 4 in the appendix). For each card, we asked respondents to indicate how much they preferred the configuration of ethical principles shown on the card. At the end of the questionnaire, respondents had to indicate some sociodemographic information.

¹ Five persons (0.05%) in the sample didn’t indicate their educational level.
² As the ethical principles outlined by Jobin et al. (2019) are rather broad, we consulted the guidelines of the EU commission (European Commission, 2019) for some formulations of the attributes. We take this measure as the German AI strategy is oriented on the EU guidelines and we aimed for a comprehensible design of the attributes.
Table 1: Description of the attributes

| Ethical Principle       | Description                                                                                                                                                                                                 |
|------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Explainability         | Explanation of the decision: each/any person concerned is explained in a generally understandable way why the system has classified him/her as a potential tax fraudster.                                      |
| Fairness               | No systematic discrimination: No persons (groups) are systematically disadvantaged by the automated tax investigation.                                                                                          |
| Security               | State-of-the-art security technology: The protection of the computer system against hacker attacks is always kept up to date with the latest security technology.                                              |
| Accountability         | Full responsibility with the tax authority: Should the automated tax investigation system lead to false accusations, the responsible tax authority bears full responsibility for any damage incurred.                         |
| Accuracy               | Virtually no errors in decision-making: The automated identification of tax fraud by the computer system works almost without errors.                                                                       |
| Privacy                | Exclusively earmarked use of data: Only the necessary data is used by the automated tax investigation system. Any other use of the considered data is excluded.                                                 |
| Machine Autonomy       | No human supervision: The identification of suspicious cases remains the sole responsibility of the automated tax investigation system.                                                                       |

4.3 Measurement

4.3.1 Conjoint-Design

The strength of conjoint analysis lies in its ability to analyze a variety of possible attributes simultaneously (Green et al., 2001). This is particularly relevant for attributes that can potentially offset each other in reality, as argued in the trade-offs of the ethical principles. While asking for the approval of the principles separately is likely to yield high scores across the board, conjoint analysis forces respondents to make a choice between the imperfect configurations of the principles. Furthermore, conjoint surveys can also be conducted with a partial factorial design. Thus, it is possible to predict respondents’ preferences for all combination possibilities, even if they only rate a small fraction of them. As described above, we treated the seven most prominent ethical design principles outlined by Jobin et al. (2019) as attributes (transparency, fairness, non-maleficence, responsibility, beneficence, privacy, autonomy). We chose sub-codes for some ethical principles to tailor the broad concepts to our use case of tax fraud detection. As attributed levels, we simply marked if an ethical principle was complied with or not.

To determine the different compositions of the cards used in our study, we calculated a fractional factorial design using a standard “order” allocation method and random seed. This method produces an orthoplan solution in which combinations of attributes are well balanced.

4.3.2 Measures

System approval. The approval of each system configuration was measured using a single item on a seven-point Likert scale (1=“do not like the presented system at all”; 7=“really like the presented system”).

Interest in AI. To gauge people’s interest in AI, respondents were asked to rate four items on a five-point Likert scale (1=“not true at all”; 5=“very true”); for instance, “In general, I am very interested in artificial intelligence” (see Table 5 in appendix for exact wording). We used the four items to compute a highly reliable mean index ($M=2.79; SD=1.07; \alpha=0.94$). Scale and wording was adopted from the Opinion Monitor Artificial Intelligence (Meinungsmonitor Künstliche Intelligenz, 2021).

Acceptance of AI in domains. Respondents were asked whether they support the use of AI in 14 different domains on a five-point Likert scale (1=“no support at all”; 5=“totally support”). For every domain, we grouped the support values (4 and 5) as support for AI in the specific domain. Afterwards, we calculated an acceptance sum index; thus, the sum index ranges from 0=“support in none application domain” to 14=“support in all application domains”, $M=3.96$ ($SD=2.96$). The measurement was adapted from the Opinion Monitor Artificial Intelligence (Meinungsmonitor Künstliche Intelligenz, 2021).
Risk awareness of AI. We measured risk awareness of AI with three items by asking respondents: “You can associate both advantages and disadvantages with artificial intelligence. Completely independent of how big you think a possible benefit is: How great do you think the risk posed by artificial intelligence is?” Respondents gave their opinion toward their risk perception for the whole society and themselves, as well as for family and friends. The items were measured on a ten-point Likert scale (1=“no risk at all” to 10=“very high risk”). We adapted the measurement by Liu and Priest (2009) and calculated a highly reliable mean index ($M=4.9; SD=1.92; \alpha=0.91$).

Opportunity awareness of AI. Along similar lines, respondents were asked to rate three items on a ten-point Likert scale to the question: “Completely independent of the risk, how great do you think is the benefit to be gained from artificial intelligence.” Again, they had to rate the benefit perception for the whole society, themselves, and friends and family. We adapted the measurement by Liu and Priest (2009) and computed a highly reliable mean index ($M=5.82; SD=1.76; \alpha=0.87$).

Trust in AI. We measured trust in AI with four items to the question “How much do you trust systems of artificial intelligence already today...” on a ten-point Likert scale (1=“do not trust at all” to 10=“trust completely”). An example item read as follows: “...recognize patterns in large data sets”. We calculated a reliable mean index ($M=5.81; SD=1.73; \alpha=0.76$). The question wording was adapted from Lee (2018). The items are based on the dimensions proposed by Kieslich et al. (2021).

5 Results

All calculations were performed in R (V4.0.3). The analysis code, including R-packages used, is available on request.

5.1 Relative Importance of Ethical Principles

To answer RQ1, we calculated a conjoint analysis in R. In particular, we computed linear regressions for every respondent with the attributes as independent variables (dummy coded) and the ratings of the cards as the dependent variable. Thus, 1,099 regression models were calculated to show the preferences of every respondent; the regression coefficients are called the part-worth values (Backhaus et al., 2016; Härdle and Simar, 2015). Then, we computed the average score of the regression coefficients to retrieve the preferences of ethical design of the German population.

5.2 Part-Worth of Attributes

Predictably, all regression coefficients (part-worths) were positive ($b_{Accountability}=0.8; b_{Accuracy}=0.64; b_{Explainability}=0.57; b_{Fairness}=0.66; b_{Autonomy}=0.32; b_{Privacy}=0.66; b_{Security}=0.66$). Hence, the compliance with every ethical principle, except for limited machine autonomy, positively influences the approval rating of an AI system. As mentioned earlier, machine autonomy can be seen as conducive to objectivity in some cases. Hence, it can be preferred to human oversight. In the given case, the respondents aim at average for a solution where tax fraud is arguably detected unbiasedly.

We further zoomed in on the differences between the importance of satisfying the ethical principles, or, in other words, people’s preferences for some ethical principles over others. For that, we calculated the importance weights for each attribute (see Figure 1). Importance weights can be obtained by dividing each mean attribute part-worth by the total sum of the mean part-worths.

The results suggest that accountability is, on average, perceived as the most important ethical principle. Fairness, security, privacy, and accuracy are on average equally important to the respondents. Explainability of AI-systems is slightly less important. Lastly, machine autonomy is least important for the respondents. Thus, the importance weights of the attributes are, overall, relatively balanced in the aggregate.

5.3 Preference Patterns Among the Public

To answer RQ2 and RQ3, we conducted k-means clustering in R. K-means clustering is a method used to split observations into k mutually exclusive groups, called clusters, whereby group members within a group are as similar as possible and as dissimilar as possible from other groups (Boehmke and Greenwell, 2020). Thus, k-means clustering provides solutions for a differentiation of respondents based on a given set of properties.
We used respondents’ regression coefficients as cluster-forming variables. The number of clusters was determined using the within-cluster sum of square (“elbow”) method with Euclidean distance measure. Euclidean distance measure was chosen since the cluster variables follow a Gaussian distribution and have few outliers. The results suggest a solution of k=5 or k=11 clusters. Since we aim for a comprehensible cluster solution and k is commonly determined on convenience (Boehmke and Greenwell, 2020), we decided to choose the five-cluster solution in our analysis, as it is clearer to interpret and allows for further description and comparisons of the groups. Afterwards, we computed the k-mean clusters using the algorithm of Hartigan and Wong (1979) using 20 different starting points.

Figure 2 shows the preference profiles of the five cluster groups. The yellow group includes people who do not seem to care much about the ethical design of systems. The purple group values fairness, accuracy, and accountability. The green group demands privacy, security, and accountability. The blue group considers all ethical principles equally important. Finally, the main characteristic of people belonging to the red group is described through high disapproval of machine autonomy.

In the next step, we labeled the clusters and calculated the cluster sizes. Cluster 1 (red) was labeled as “Human in the Loop” cluster 2 (blue) as “Ethically Concerned” cluster 3 (green) as “Safety Concerned,” cluster 4 (purple) as “Fairness Concerned”, and cluster 5 (yellow) as “Indifferent”. Table 2 depicts the average approval ratings for each cluster group per card and in total across all cards.

The results show that the largest group cluster consists of people who treat all ethical principles equally and highly important, n=345 (31.39%). Hence, people in the Ethically Concerned group appreciate systems that satisfy all ethical principles. Otherwise, the approval ratings are quite low.

In contrast, the second largest group consists of people whose system approval ratings are only slightly affected by an ethical design of an AI-system, n=267 (24.29%). We label them as Indifferent. Those people
do not seem to care much about the ethical design of the system. However, persons in this cluster group show a medium acceptance for all presented systems.

A total of 167 (15.2%) respondents were considered as Safety Concerned. For those, AI systems must be safe, privacy has to be protected, and the responsibility of a specific entity has to be ensured. These ethical principles are far more important than fairness, accuracy, or explainability. Across all presented systems, the approval ratings are on a low to medium level.

The group of Fairness Concerned consists of 166 (15.1%) respondents who especially consider fairness and accuracy to be the important principles, whereas privacy and security hardly affected a positive rating. The Fairness Concerned are quite skeptical toward the presented systems if they do not follow their demanded ethical principles.

In the fifth cluster, people oppose machine autonomy and accordingly strive for human control, n=154 (14.01%). We term this group of respondents Human in the Loop as limited machine autonomy is the only factor that highly affects the ratings of the AI systems. Hence, for this group, it is relevant to build systems that are under human control. However, approval of the presented systems is on average on a medium level.

5.4 Cluster Description

We address RQ3 by describing the five cluster groups based on several characteristics, which we group into two categories: socio-demography (age, educational level) and AI opinions (interest, acceptance of AI in domains, risk awareness of AI, opportunity awareness of AI, trust in AI). We only included those respondents (n=913), who answered all included variables (no missing values). In the first step, we calculated the mean values for each explanatory variable for each cluster group. To test for significant mean differences between the clusters, we ran a MANOVA with the cluster group as the independent grouping variable and the seven
characteristics outlined above as dependent variables. We checked the assumptions and found homogeneity of variance-covariance matrices using Box’s M test, $M=137.62$, $p=0.05$. As Box’s M test is very sensitive, values lower than .001 are considered to be not trusted (Field, 2011). Further, we tested for normal distribution of the dependent variables with visual inspection and multivariate Shapiro-Wilk test. The Shapiro-Wilk test showed a significant deviance from normality, $W(913)=0.98$, $p=0.0$. Moreover, visual inspection revealed that the data were non-normal distributed. However, MANOVA is rather robust to a violation of normal distribution (Field, 2011). We used Pillais’ Trace test statistic, as it is the most robust test for violations of the underlying assumptions (Field, 2011).

As the MANOVA shows statistical significance, $V=0.11$, $F(4, 908)=3.74$, $p=0$, we performed subsequent ANOVA analyses for each of the dependent variables. Further, post-hoc tests with Tukey-HSD correction were used to test for mean differences between the groups for every dependent variable (see Table 3).

The ANOVA results show that the clusters significantly deviate from each other on all analyzed characteristics. In the following, we will describe the profile of each cluster group in further detail. All mean scores of all variables are displayed in Table 3 to visualize group comparisons.

### 5.4.1 Human in the Loop

The Human in the Loop group overwhelmingly demands human control and, thus, is strongly opposed to machine autonomy. Persons belonging to this group tend to be older and less educated. Regarding AI opinions, they are rather uninterested in AI and have a low acceptance of AI technologies. Moreover, they are comparatively more aware of risks, have quite low benefit perceptions, and low levels of trust in AI.

### 5.4.2 Ethically Concerned

People who demand high standards on all ethical principles are comparatively young and well educated. They also have a high interest and trust in AI systems. Furthermore, they tend to accept AI and have a relatively high benefit perception and a relatively low risk perception.

### 5.4.3 Safety Concerned

Respondents belonging to the Safety Concerned group are located in between the other groups regarding the sociodemographic variables and AI opinions. They are, of average age and education. Furthermore, they are somewhat interested in AI, accept AI in some application domains, are medium risk and benefit aware, and trust AI systems to an average extent.
5.4.4 Fairness Concerned

The *Fairness Concerned* group, which is concerned with the accuracy and fairness of AI systems, is comparatively young and well educated. Out of all clusters, the *Fairness Concerned* also perceive the lowest risks and the greatest benefits of AI. They further have the highest trust in AI systems, are most accepting of AI, and are one of the groups with the highest interest in AI.

5.4.5 Indifferent

The *Indifferent* can be described — together with the *Human in the Loop* — as the group with the most negative opinions on AI. People who do not demand ethically designed systems have relatively low acceptance, low benefit perceptions, and little trust in AI. Further, they have a high risk awareness and are comparatively uninterested in AI.

6 Discussion

This study sheds light on an under-researched area of ethical AI, namely the public perceptions of ethical challenges that come along with developing algorithms. On one hand, existing research focuses on normative and legal considerations for how ethical AI systems should be designed; on the other hand, the computer science literature elaborates on how ethical AI systems can be designed. However, empirical studies focusing on people’s assessment of ethical principles are relatively rare. However, as argued in this paper, accounting for the perceptions of those affected by AI systems is vital for a human-centric approach to AI.

Thus, we investigated opinions about the ethical design of AI systems by jointly considering different essential ethical principles and shedding light on their relative importance (RQ1). We further explored different preference patterns (RQ2) and how these patterns can be explained in terms of sociodemographics as well as AI-related opinions (RQ3).

6.1 From Ethical Guidelines to Legal Frameworks?

Our results show that regarding the relative importance of ethical principles no big differences among the German public exist. However, we find a slight accentuation of *accountability* as the most important ethical principle; moreover, the respondents consider *limited machine autonomy* slightly less important than the other ethical principles. Initially, these aggregate results indicate a balanced view on ethical AI. None of the ethical principles are strongly preferred over the other, leading to the conclusion that German citizens seem to have no critical blind spots. For a good rating of an AI system, all ethical principles are more or less equally important. Hence, developers and organizations should not neglect some ethical principles, while emphasizing others. Based on these results, it seems that compliance with multiple ethical principles is important for an AI system to receive a positive rating.

Thus, ethical guidelines are not only present in a vacuum, but also address the needs of the public. In the case of German citizens, accountability is foremost demanded. In the context of our study, accountability is equal to liability: hence, there is a need for a clear presentation of an actor, who can be accounted for losses and who — in the end — can be regulated. This is in line with empirical evidence showing that legal regulations are perceived not only as effective, but also as demanded countermeasures against discriminatory AI (Kieslich et al., 2020). As AI technology is considered a potential risk or even threat — at least among a share of the public (Kieslich et al., 2021; Liang and Lee, 2017) — setting up a clear legal framework for regulation might be a way to further enhance trust and acceptance toward AI. In this respect, the European Union (EU) has already taken on a pioneering role, as the EU commission recently proposed a legal framework for the handling of AI technology (European Commission, 2021). With this, they set up a classification framework for high-risk technology and even list specific applications that should be closely controlled or even banned. Considering the results of our study, this might be a fruitful way to include citizens, specifically, if it is made clear who takes responsibility for poor decisions made by AI systems. Besides, it is the articulated will of the European Commission to put humans at the center of AI development. Our empirical results suggest that ethical design matters and — if the EU takes their goals seriously — ethical challenges should play a major role in the future. Strictly speaking, ethical AI thus primarily requires regulatory political or legal actions. Hence, the implementation of ethical AI is a political task, which must not necessarily include computer scientists. However, from our results, we can also draw conclusions for the ethical design of AI systems in a technological sense.
6.2 Ethical Design and Demands of Potential Stakeholder Groups

Our results also suggest that citizens value ethical principles differently. After clustering the respondents’ preferences, we found five different groups that differ considerably in their preferences for ethical principles. This suggests that there might not be a universal understanding and balance of the importance of ethical principles in the German population. People have different demands and expectations regarding the ethical design of AI systems. Thus, these different preference patterns have implications for the (technical) design and implementation of AI systems. For example, the Fairness Concerned group should be addressed in different ways than the Safety Concerned or the Human in the Loop groups. Several studies have already been conducted on the inclusion of stakeholders in the design process, especially for fairness (Vallejos et al., 2017; Webb et al., 2018).

Concerning the results of our study, for example, given the case of an algorithmic admission system in universities (Dietvorst et al., 2015), system requirements articulated by the affected public (in this case, students) might widely differ from those of a job seeker categorization system (e.g., the algorithmic categorization system used by the Austrian job service (AMS)) (Allhutter et al., 2020). While students supposedly are younger, well educated, and more interested in AI, those affected by a job seeker categorization system are supposedly older and feel less positive about AI. Our results suggest that operators of AI systems should address the needs of the stakeholders differently if aiming for greater acceptance. For the admission system, it might be useful to highlight that such systems are precise and treat students equally, since students — based on their group characteristics — primarily belong to the group of the Fairness Concerned. For the job seeker categorization system, on the other hand, it might be more promising to focus on safety issues or the presence of human responsibility, as they may be assigned to the group of Safety Concerned or the Human in the Loop. It should be noted that we explicitly highlight that we believe that every ethical design principle is of great importance and that developers should address all issues accordingly. We simply outline that communication about such systems could differ concerning the affected public.

Notably, there is also a group of people of substantial size (the Indifferent), who are only slightly concerned with the ethical design of AI systems. This group does not oppose AI systems in general (in fact, they have on average the highest approval scores of all cluster groups for the presented systems), but they are not affected by compliance with ethical principles. This might be somewhat problematic, since this group arguably will not set high expectations for companies that develop AI systems. For example, Elzayn and Fish (2020) showed that achieving fairness in AI systems is very costly and that the market does not reward putting a massive amount of money in collecting data of marginalized groups, whether for monopolists or under competition. This becomes more alarming when considering the share of the Indifferent in society (24%). One might assume that the combination of lack of reward for ethical principles by the market and a potential lack of public outcry — at least in some parts of society — might lead to a sloppy implementation of ethical principles in practice. This is especially important to consider because ethical considerations are often left out of software development (McNamara et al., 2018). Again, Elzayn and Fish (2020) propose policy solutions to tackle this issue. Besides policy actions, organizations that are concerned with the ethical design of AI (e.g., Algorithm Watch) could actively reach out to the Indifferent and try to create awareness of the consequences of non-compliance with ethical principles. As it is part of the strategy of these organizations as well as the German AI strategy (Die Bundesregierung (2018)) to fuel public awareness and discussion about AI across all parts of society, it could be beneficial to reach out to people who are at the moment unconcerned about ethical issues. According to our results, generating at least some interest as well as trust in the capacities of AI could lead to greater engagement with ethical design challenges.

The largest share of the German population equally values all ethical principles and, thus, sets very high standards for ethical AI development. In fact, this leads to the observation that the bar for approval of AI systems is very high for this group. However, if the principles are complied with, ethical AI can lead to high acceptance of AI. Common characteristics of this group are a high level of education, young age, and high interest in AI as well as high acceptance of AI. This group is especially demanding in terms of AI design. This may lead to a serious problem for AI design. As outlined, some trade-off decisions must be made eventually, as the simultaneous maximizing of all ethical principles is very challenging. However, our results suggest that it will not be easy to satisfy the demands of ethically concerned people. If some ethical trade-offs are taken, it may very well lead to reservations against AI.

However, considering only the public perspective in AI development and implementation might also have serious ramifications. Srivastava et al. (2019) show regarding algorithmic fairness that the broad public prefers simple and easy to comprehend algorithms to more complex ones, even if the complex ones achieved higher factual fairness scores. As AI technology is complex in its nature, it is possible that many people
will not understand some design settings. In the end, this might lead to a public demand for systems that are easier to understand. However, it might very well be that a more thorough design of those systems would follow ethical principles to an even higher extent. Thus, we highlight that the public perspective on AI development definitely needs more attention in science as well as in technology development and implementation. We emphasize that the public perspective should rather complement and not dominate other perspectives on AI development and implementation.

### 6.3 Limitations

This study has some limitations that need to be recognized. We used an algorithmic tax fraud identification system as a use case in our study. Hence, our results are only valid for the specific context. However, as we wanted to describe preference profiles and cluster characteristics, we decided to present only one use case. This approach is similar to studies in the field of fairness perceptions, in which many studies only use one use case (Grigić-Hlača et al., 2018; Shin, 2021; Shin and Park, 2019). However, public perceptions of AI are highly context dependent. It might be that importance weights and cluster profiles differ concerning the particular use case. Therefore, further studies should test for various use cases simultaneously and compare the results regarding those contexts. Context-comparing studies have already been performed for public perception of trust in AI (Araujo et al., 2020) and threat perceptions (Kieslich et al., 2021).

A general limitation of vignette studies lies in the fact that we used an artificial use case and that the rating of the system has limited real-world implications. Without a doubt, more research is needed that focuses on stakeholders’ perspectives on AI systems that are or will be implemented soon.

Additionally, the survey was conducted only in Germany, and the findings are thus only valid for the German population. We encourage further studies that replicate and enhance our study in other countries. Cross-national studies could detect specific nation patterns regarding the importance weights and preference profiles of ethical principles. The comparison to the US, Chinese and UK population would be especially interesting, since those countries follow a different national strategy for the development of AI.

### 7 Conclusion

Ethical AI is a major societal challenge. We showed that compliance with ethical requirements matters for most German citizens. To gain wide acceptance of AI, these ethical principles have to be taken seriously. However, we also showed that a notable portion of the German population does not demand ethical AI implementation. This is critical, as compliance with ethical AI design is, at least to some level, dependent on the broad public. If ethical requirements are not explicitly demanded, one might fear that implementation of those principles might not be on the highest standard, especially because ethical AI development is expensive. However, we showed that people who demand high quality standards are interested in AI as well as aware of the risks. Thus, to raise demands for ethical AI, it would be a promising way to raise public interest in the technology.

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Appendix

Table 4 depicts the orthoplan for the conjoint analysis. Table 5 displays the item wording.

| Karten-ID | Explainability | Fairness | Security | Accountability | Accuracy | Privacy | Control |
|-----------|----------------|----------|----------|----------------|----------|---------|---------|
| A         | Yes            | Yes      | Yes      | No             | No       | No      | No      |
| B         | Yes            | No       | No       | Yes            | No       | No      | Yes     |
| C         | No             | Yes      | No       | No             | No       | Yes     | Yes     |
| D         | Yes            | Yes      | Yes      | Yes            | Yes      | Yes     | Yes     |
| E         | No             | Yes      | No       | No             | No       | Yes     | Yes     |
| F         | Yes            | No       | No       | No             | Yes      | Yes     | No      |
| G         | No             | No       | Yes      | Yes            | No       | Yes     | No      |
| H         | No             | Yes      | No       | Yes            | Yes      | No      | No      |
### Table 5: Item Wording

| Table 5: Item Wording |
|-----------------------|
| **Interest in AI**    |
| *How much do the following statements apply to you?* |
| I follow processes around artificial intelligence with great curiosity. |
| In general, I am very interested in artificial intelligence. |
| I read articles about artificial intelligence with great attention. |
| I watch or listen to articles about Artificial Intelligence with great interest. |

| **Acceptance of AI** |
| *Are you more in favor of or against the use of artificial intelligence...* |
| ...at banks and savings banks? |
| ...in the health care sector? |
| ...in industrial production? |
| ...in traffic? |
| ...in personal everyday life? |
| ...in schools and universities? |
| ...in public administration? |
| ...in political decisions? |
| ...in court? |
| ...in police and security agencies? |
| ...in journalism? |
| ...in personnel decisions? |
| ...in insurance companies? |
| ...in the military? |

| **Risk awareness of AI** |
| *How big do you think is the risk posed by artificial intelligence...* |
| ...for our society as a whole? |
| ...for you personally? |
| ...for your family, friends or acquaintances? |

| **Opportunity awareness of AI** |
| *How big do you think is the risk posed by artificial intelligence...* |
| ...for our society as a whole? |
| ...for you personally? |
| ...for your family, friends or acquaintances? |

| **Trust in AI** |
| *How much do you trust artificial intelligence systems already today to...* |
| ...recognize patterns in large data sets |
| ...make correct predictions about future developments |
| ...make appropriate recommendations for human actions |
| ...make high-quality decisions itself |