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Lay User Involvement in Developing Human-Centric Responsible AI Systems: When and How?

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Artificial Intelligence (AI) is increasingly used in mainstream applications to make decisions that affect a large number of people. While research has focused on involving machine learning and domain experts during the development of responsible AI systems, the input of lay users has too often been ignored. By exploring the involvement of lay users, our work seeks to advance human-centric responsible AI development processes. To reflect on lay users’ views, we conducted an online survey of 1121 people in the United Kingdom. We found that respondents had concerns about fairness and transparency of AI systems which requires more education around AI to underpin lay user involvement. They saw a need for having their views reflected at all stages of the AI development lifecycle. Lay users mainly charged internal stakeholders to oversee the development process but supported by an ethics committee and input from an external regulatory body. We also probed for possible techniques for involving lay users more directly. Our work has implications for creating processes that ensure the development of responsible AI systems that take lay user perspectives into account.

CCS Concepts:
• Human-centered computing → HCI theory, concepts and models; Empirical studies in HCI; Collaborative and social computing.

Additional Key Words and Phrases: Human-centric AI, responsible AI, AI recruitment system, lay users, AI development lifecycle

ACM Reference Format:

1 INTRODUCTION

Artificial Intelligence (AI) systems now make decisions that affect a large number of people, for example, in clinical decision support systems, in loan [68, 83, 98] and bail decisions [8, 23]. In these settings and others, there have been increasing calls for developing human-centric AI systems that are fair, accountable and transparent [101, 102]. Various efforts are underway to establish standards, methodologies and guidelines that aim to help designers and developers build responsible AI systems across the AI development lifecycle [3, 7, 16, 27, 37, 38, 55, 69, 78]. Regulatory frameworks, such as the European Union’s AI Act [107], are also being drawn up to ensure AI is developed responsibly.

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In addition, tools, techniques and methods have been proposed to help AI experts to address fairness and transparency, mainly during model development and evaluation [2, 9, 13, 18, 47, 79, 85, 109, 113]. However, relying on AI experts, designers and developers ignores the perspectives that lay users can bring to responsible AI development. By lay users we refer to those who may have no or moderate knowledge of AI but who will be the likely people impacted by AI technology. It has been shown that the views of AI experts differ substantially from such lay users in the development of AI systems [54] and in response there are already some positive steps toward lay user involvement, for example through value-sensitive design practices [5, 62], technology demonstrators [115], or participatory design practices [67, 90].

Our work aims to extend these human-centric responsible AI developments and help shape suitable methodologies and techniques that allow lay users with little to no AI-related technical skills or domain knowledge to contribute to creating responsible AI systems. Specifically, in the work we report, we set out to investigate

- (RQ1) who lay users believe should be involved in the AI development process to ensure fairness and
- (RQ2) how lay users envisage being involved in a responsible AI development process to allay their concerns.

To address our research questions, we conducted a large-scale online survey with 1121 participants, sampled to be representative of the population of the United Kingdom (UK). This method allowed us to gain a rare high-level perspective—with opinions from a large number of participants—on where people see value in their involvement in the development pipeline of responsible AI systems. From this, our objective is to lay the ground for future policy, governance and design research and provide an informed basis for what, where and who to target.

To ground responses, we focused on the development of a hypothetical AI job recruitment system, a high-stakes domain in which most people have some experience. Furthermore, AI’s use in this domain has attracted controversy. Organisations have used AI to aid in the screening of large applicant pools and such recruitment tools have been found to be discriminatory, often reinforcing intersecting, societal biases [106, 119]. Our findings reveal that respondents had wide-ranging concerns about creating a fair AI system at all stages during development, focusing on transparency and validity of the data and corresponding models. They expressed a desire to see internal stakeholders oversee the development process, supported by ethics committees, and saw a place for input from external regulatory bodies. Furthermore, respondents suggested the need for greater education around AI to underpin more direct involvement by lay users.

Our paper makes the following contributions:

- a better understanding of the views and needs of lay users about how AI can be developed fairly and responsibly;
- identification of stages at which to involve lay users in AI design and development;
- a discussion of possible methods, techniques and tools for how to gather lay users’ feedback and values and how to include these in responsible AI development practices;
- input into growing implications for policy and governance of responsible AI.

This work is structured as follows. Firstly, we describe related work in this area. We then outline our methods for gathering and analysing responses. We present the findings of our analysis and discuss the limitations and implications of our work. We conclude with a brief synopsis of our study.
2 RELATED WORK

Many issues are currently covered under responsible AI; most commonly a responsible system is understood to be an AI system that is transparent and fair, and that has been developed so that both its design and development are accountable. We first describe concepts of transparency and fairness and then provide an overview of proposals that have been put forward to develop responsible AI systems in an accountable manner. The argument we draw from this related research is that despite the objectives of fairness and transparency in responsible AI, relatively little work has been invested in understanding the distinct priorities of lay users. In particular, there is little insight from those lay users who will be immediately impacted by AI systems and what they view responsibility to mean, who they believe should take responsibility, and where in the AI pipeline they believe responsibility should be taken.

2.1 Transparency and Fairness

Major strides have been made to develop transparent AI through Explainable AI (XAI) [47]. Explanations of AI systems can help users understand why decisions were made [32], improve their mental models [63, 64], and calibrate their trust in the system [47]. Extensive work has been carried out to develop explanations both attending their content and presentation [10, 70, 95, 105, 111]. Parallel research has focused on the impact of providing explanations for users in terms of, for example, trust, reliance, and mental model soundness [17, 51]. Much of the work on explanations underpins and supports fairness by identifying biases in the data or making models transparent, and many of the tools to investigate fairness, covered in section 2.2.2, take advantage of XAI approaches.

Fairness is often equated with justice and its two main principles, liberty and equality. The overarching notion here is that all people should be entitled to basic rights and freedoms and have equal opportunities [94]. Previous work has attempted to differentiate and taxonomize notions of justice [12, 26, 34, 66], including equity (i.e., equal distribution), procedural (i.e., relating to a fair decision-making process), interactional (i.e., relating to people’s treatment), and informational (i.e., that a decision is well-justified) fairness. A common way of defining fairness is at group and individual levels [50]. Group fairness ensures equal treatment of or outcomes for different groups or members of groups [8]. Groups are often defined using ‘protected attributes’ which are enshrined in law, such as age, disability, gender reassignment, marriage and civil partnership, pregnancy and maternity, race, religion or belief, sex, and sexual orientation [36]. However, discrimination against a group can be indirect, for example, by linking a protected attribute (e.g., race) with non-protected attributes (e.g., post code) [8, 19]. A different way of judging fairness is through individual fairness, which relates to the similar treatment or outcomes of two similar individuals [33]. The trade-off between individual and group fairness widely used in legal situations has been considered a difficult issue to resolve [33]. Moreover, there are different ways to think about fairness that are influenced by people’s backgrounds [85], such as gender [74, 112] and environment and stakeholder roles [66, 108, 120].

AI development processes present numerous opportunities for bias and unfairness to arise [8, 20, 31, 40, 48, 55, 88]. For example, bias and unfairness can be introduced through the choice and characteristics of the dataset, feature engineering and selection, or choice of learning model. Various fairness metrics have been developed to investigate and counteract bias in AI systems. In the last few years, over twenty different types of metrics have been identified [85], including group [57, 109] and individual fairness [33], subgroup fairness [59, 117, 118], counterfactual fairness [65], and many more. Applying these metrics is difficult in practice because there is no agreement on which metric is best to use [7, 8, 23, 109], and because statistical bias is often a poor proxy for human fairness values [27, 80, 85, 98, 108]. For example, it has been found that while fairness outputs were
perceived by participants as statistically fair, some participants were not comfortable with an AI system making high-stakes decisions without a human in the loop [12].

2.2 Responsible AI Development Methods, Techniques and Tools

2.2.1 Design Methodologies and Methods. To ensure the design and development of responsible AI systems, many different frameworks have been developed [56]. The most well-known of these have been Microsoft’s Guidelines for Human-AI Interactions [3], Google’s Responsible AI practices [79, 89], IBM’s Everyday Ethics for Artificial Intelligence [53], Fujitsu’s AI Ethics Impact Assessment Practice Guide [71, 87] and the European Commission High-Level Expert Group on AI’s ethics guidelines for trustworthy AI [25]. In all these guidelines, design and development teams are asked to consider responsible development at different stages of AI development, with some providing ‘checklists’ that can be used to apply these guidelines to practice. Many of these guidelines emphasise a human-centric approach to AI design, and engaging with users at some point during AI development. While guidelines can stimulate discussions within design and development teams, it has been noted that these guidelines are fairly abstract and can be difficult for designers and developers to implement in practice [73].

Methods that could be employed during AI development are relatively scarce. Most of the design guidelines mentioned in this section suggest adopting a User-Centred Design (UCD) process in which users are consulted throughout. Value-sensitive Design for AI [5, 62, 122] echoes the involvement of lay users to determine how AI systems should be shaped. Participatory Design has also been proposed as a method for giving voice to lay users [90] while co-design has been put forward to shape AI systems by involving lay users [82, 83, 103].

2.2.2 Tools and Techniques for Responsible AI Design. There are now a number of toolkits available to investigate and mitigate fairness issues, for example, FairML [1], AI Fairness 360 [9], Fairness comparison [39], and Google’s What-if tool [113]. Previous research has also proposed tools to investigate fairness, for example, FairSight [2] and FairVis [18].

While, these tools have largely been directed at data scientists, some steps have been taken to involve lay users more directly. A tool, coupled with an interview protocol, has been proposed to elicit fairness notions from stakeholders who have no technical background in AI [22]. Silva [116] is a tool that visualises casual relationships in data and their effect on fairness, understandable and usable by lay users. WeBuildAI [67] proposes a series of steps that involve lay users directly in designing AI models, by being able to highlight attributes the AI should pay attention to, and by evaluating, comparing and choosing models to be used. More recent work has also looked at human-in-the-loop fairness tools for lay users [83] in which lay users can mark up decisions which they consider fair or unfair, for inclusion in further training of the model.

2.3 Focusing on lay users and their views of responsible AI processes

Set against these related threads of responsible AI research, the work we report on aims, specifically, to draw further insights and lessons from lay users as those likely to feel the immediate effects of AI systems. Our work remains grounded in notions of transparency and fairness [47, 94] and very much aims to ensure biases, discrimination and inequity are limited in AI systems, or at least in some way made visible to lay users who are impacted by the AI systems [8, 20, 31, 40, 48, 55, 88]. The point of departure in the work we present is to start with the views of those lay users to determine where action to achieve more responsible systems should be taken and by whom. This shift to account for lay users, as well as domain experts and those skilled in ethical or responsible practices, is an attempt to widen, enrich and democratise responsible AI practices [100].
Such a starting point resonates with more recent methods, techniques and tools that have involved lay users, often through participatory or co-design methodologies (e.g., [58, 104]). The prevailing orientation in these human-centred approaches, however, has been to engage with lay users to improve transparency (e.g., [72, 86]) or deepen understandings of bias, discrimination and inequity and to some extent how these forms of unfairness might be addressed (e.g., [43, 99, 114]). Our work differs from this previous research in that we investigate where and how lay users want to contribute throughout the AI design and development process. It also seeks lay users’ views on possible ways of approaching AI, responsibly, in order to inform new approaches that may better involve them.

2.4 Research Gap
In contrast to previous research, we focus on the voice of lay users in the AI development lifecycle. Prior work has started to look at how to empower and involve lay users, for example through participatory design practices and human-in-the-loop model development and evaluation. This work addresses the research gap of gathering views of lay users to determine where action to achieve more responsible systems should be taken and by whom, in order to democratise responsible AI [100].

3 STUDY METHOD
To address RQ1 and RQ2 – who lay users believe should be involved and how – we conducted a large-scale online survey, focusing on the development of a hypothetical AI recruitment system. The AI recruitment system scenario was inspired by previous work on perceptions of AI algorithmic decisions [68], and real-world case studies which show discrimination against underrepresented groups (e.g., women, and people with disabilities) [29, 41, 106, 119]. As with similar studies [45, 54, 60], we adopted an online survey as an appropriate method to gather initial answers and input from a large number of people, and to ask where people see value in their involvement in the AI development pipeline. This methodology is intended to lay the ground for future qualitative work (e.g., focus groups, co-design activities, participatory design, etc.) to refine, follow-up and complement our results.

3.1 Online Survey Design
Before accessing the main survey, participants were able to view general information about the purpose and details of the study, and we sought informed consent to store and analyse the data of people over 18 years of age. We then screened out anyone who had any significant experience in AI or related areas to ensure we only obtained responses from lay users. Participants gained access to the survey if they passed the screening question.

The survey consisted of three parts (the full survey is available in the supplementary materials). We adopted a mixture of open, closed, multiple-choice, and ranking questions to capture participants’ responses and preferences.

3.1.1 Part 1: Background Knowledge about AI systems. We first explored participants’ prior knowledge of AI. Specifically, we asked participants to self-rate their understanding of AI using a scale of expertise from level 0 (ignorant which means “I have never heard of it”) to 5 (intermediate which means “I have used it for a year or more on a daily or regular basis, and am comfortable using it in moderately complex projects”), inspired by Jim McBeath’s scale [77]. See section 3.3 for a more detailed explanation of these levels and how participants were distributed across them. We did not use levels 6 to 10 because they refer to people with experience in the domain for 5 years or more.
3.1.2 Part 2: AI system and hypothetical use case introduction. In order to introduce a shared language and common understanding of AI and practices in the AI development process, we provided a short definition of what an AI system is, some examples of common AI systems, and an explanation of the difference between AI systems and traditional computer programs. Drawing on and synthesising well-established representations of the AI pipeline/life cycle (common in textbooks, e.g. Walsh [110]; Hechler et al. [49]; De Silva and Alahakoon [30]), we then explained how AI is developed providing an illustration and a detailed description of the different steps (see Appendix A.1).

Following this general introduction, we provided a recruitment scenario to motivate the use of a hypothetical AI system. We focused on a high-stakes domain in which most people have some experience. To design our scenario of study we were inspired by AI tools organisations have recently used to screen large applicant pools, and work that has shown concerns around these systems (i.e., discriminatory problems, often reinforcing intersecting, societal biases) [29, 41, 106, 119]. The participants were asked to imagine a scenario in which a new AI recruitment tool is to be developed to help an organisation’s HR team screen and rank applicants for a preliminary interview. The hypothetical tool would differentiate between candidates meeting or not meeting job criteria, processing CVs and cover letters to automatically email selected candidates for a preliminary interview.

At this point, we asked participants about their initial fairness attitudes and perceptions using a 5-level Likert scale. We also asked whether, in their opinion, AI should play a role in this scenario and describe any hiring situation where they had been treated unfairly and why they thought it was unfair. Finally, we captured participants’ perspective on AI fairness by ranking statements that encapsulate common fairness concepts currently found in the literature [12, 26, 34, 66], but also we provided an option to describe their own concepts. For instance, individual fairness was described as similar people will be treated in the same way. The complete list of fairness definitions and survey questions can be found in the supplemental material.

We then asked them what could be done to make the AI recruiting tool fairer overall, selecting all that applied from a list of statements, and allowing them to add their own suggestions. The list included, for example, providing an explanation of the reasons for building the AI in the first place, inspired by prior literature on Explainable AI [17, 32, 47, 47, 51, 95, 105, 111].

3.1.3 Part 3: Lay users’ involvement during AI recruitment system stages. The last part of the survey focused on how respondents thought fairness could be taken into consideration in the development lifecycle of an AI recruitment system. This part was divided into 4 sub-parts: 1) business case, 2) collecting and labelling data, 3) AI model training and evaluation, and 4) AI deployment and decision making.

The structure of each sub-part was very similar. Firstly, we further explained the relevant steps in the hypothetical AI recruiting tool scenario. For example, in the Business Case stage, we described that the AI recruitment tool was part of a business case which was discussed within the organisation in a meeting by hiring managers. In the meeting they questioned whether they should build a new AI recruiting tool to help the HR team speed up the recruiting process and reduce the workload when evaluating a very large pool of candidates for a position. After that, we asked participants to state their concerns about the fairness in the development of the tool, if they had any.

Next, we proposed a multiple choice question about who should be involved in that stage. The options (see Appendix A.2) for this question were always the same at each stage, and were based on prior literature and common real-world practices (e.g., [35, 69, 71, 89]). We then asked them to rank how they, as lay users, could be involved in that stage to ensure fairness. Answers were provided appropriate to that stage, but we allowed respondents to provide their own suggestions.
or express their preference of not being involved through “Other” option. We took great care to present and explain options in details for each question. An example for the Business Case stage can be found in the Appendix A.3.

All ideas, methods, and possible interactions with data and models we presented as options were drawn and extended from the literature. For instance, large scale survey or questionnaire is a common method to ask people for their opinions in the AI area (e.g., to ask people their perception on the importance of ethical design principles [60]). Further, in section 4.2.2, we proposed “helping with labelling data”, which is a current way to involve people in the AI development pipeline [28, 97], as well as “flagging” [83], “model card” [79], “proving their own data to include in the dataset” [6, 42], and so on. Finally, to ensure that we fully captured respondents’ ideas, we asked them for other ways to be involved and why this would be beneficial.

3.2 Data Collection and Analysis

Approval was granted prior to the study by the Computer Science Research Ethics Committee at City, University of London while the first author was based at the institution. Before conducting the survey we piloted the study with students with no prior knowledge of AI to test the survey’s duration and receive feedback. This helped us to improve the clarity of the survey’s structure, questions, and options addressed to a non-expert audience.

Participants were recruited through Prolific [91], a crowd-sourcing platform for researchers to recruit participants for their studies, in June 2022. People who accepted the ad were directed to our survey site, implemented using Qualtrics [92]. The survey lasted approximately 30 minutes, and participants received £5 for their time, in line with Prolific’s hourly minimum pay guidelines. In the main survey, we included three attention-check questions to ensure that people read each question carefully, and to promote the quality of the responses.

We gathered 1302 responses in total, but we excluded participants who: (i) had an AI background, (ii) failed multiple attention checks, (iii) attempted to take the survey multiple times, (iv) completed the survey too quickly (less than 10 minutes), (v) showed regular patterns in their responses (e.g., always selecting the first option). After this step, we included 1121 respondents in our analysis.

We analysed the quantitative data through descriptive statistics. Statistical testing is not appropriate in this study, as we do not have any baselines or conditions for comparison. For multiple-choice questions, we give the percentage of all responses. For ranking questions, we calculated the rank score of each choice by adding the rank values assigned by participants multiplied by the number of respondents who gave that rank and divided by the total number of respondents. Choices were ranked with 1 being the highest rank, so a lower rank score means the answer was considered more important across respondents. We also show graphs that give a breakdown of the ranking questions. In these graphs, choices are ordered by the rank score in decreasing order. The first position gives the highest overall ranking, and the last position gives the lowest ranking. Within a choice, we report the percentage of all respondents who ranked that choice for each rank value.

For questions with open answers, we used a qualitative thematic analysis [24] to extend the analysis of multiple-choice and ranking questions. Firstly, we went through each open question and we cleaned our data, cutting off blank or irrelevant answers (e.g., “Happy with the above”, “I don’t think I would want to be involved in different ways”, or similar). After that, we started classifying and grouping in themes the remaining answers to find new, common, and frequent preferences expressed by participants. For instance, in “Who else should be involved” question, several participants expressed the involvement of a legal team, trade unions, and other external stakeholders. We finally discussed, revised, and refined the themes within the research team, for instance incorporating similar themes or splitting a theme into 2 different instances.
Table 1. Demographic Information

<table>
<thead>
<tr>
<th>Factor</th>
<th>N</th>
<th>% Sample</th>
<th>% UK</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gender</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td>592</td>
<td>53%</td>
<td>51%</td>
</tr>
<tr>
<td>Male</td>
<td>529</td>
<td>47%</td>
<td>49%</td>
</tr>
<tr>
<td>Ethnicity</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Asian</td>
<td>66</td>
<td>6%</td>
<td>8%</td>
</tr>
<tr>
<td>Black</td>
<td>30</td>
<td>3%</td>
<td>3%</td>
</tr>
<tr>
<td>Mixed</td>
<td>26</td>
<td>2%</td>
<td>2%</td>
</tr>
<tr>
<td>White</td>
<td>976</td>
<td>87%</td>
<td>86%</td>
</tr>
<tr>
<td>Other</td>
<td>23</td>
<td>2%</td>
<td>1%</td>
</tr>
<tr>
<td>Age</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>18-39</td>
<td>330</td>
<td>29%</td>
<td>37%</td>
</tr>
<tr>
<td>40-59</td>
<td>438</td>
<td>39%</td>
<td>34%</td>
</tr>
<tr>
<td>60+</td>
<td>353</td>
<td>31%</td>
<td>28%</td>
</tr>
</tbody>
</table>

Table 2. AI background of participants

<table>
<thead>
<tr>
<th>Question</th>
<th>N</th>
<th>% Sample</th>
<th>% Sample</th>
<th>N</th>
<th>% Sample</th>
<th>% Sample</th>
<th>N</th>
<th>% Sample</th>
<th>% Sample</th>
</tr>
</thead>
<tbody>
<tr>
<td>AI Expertise level</td>
<td></td>
<td></td>
<td></td>
<td>Use of AI system</td>
<td></td>
<td></td>
<td></td>
<td>Fairness of AI</td>
<td></td>
</tr>
<tr>
<td>0 – Ignorant</td>
<td>35</td>
<td>3%</td>
<td>3%</td>
<td>Yes</td>
<td>616</td>
<td>55%</td>
<td>55%</td>
<td>Very Fair</td>
<td>68</td>
</tr>
<tr>
<td>1 – Interested</td>
<td>691</td>
<td>62%</td>
<td>62%</td>
<td>Not that I am aware of</td>
<td>505</td>
<td>45%</td>
<td>45%</td>
<td>Fair</td>
<td>459</td>
</tr>
<tr>
<td>2 – Pursuing</td>
<td>315</td>
<td>28%</td>
<td>28%</td>
<td>AI role in hiring process</td>
<td></td>
<td></td>
<td></td>
<td>Neutral</td>
<td>339</td>
</tr>
<tr>
<td>3 – Beginner</td>
<td>66</td>
<td>6%</td>
<td>6%</td>
<td>Yes</td>
<td>519</td>
<td>46%</td>
<td>46%</td>
<td>Unfair</td>
<td>236</td>
</tr>
<tr>
<td>4 – Apprentice</td>
<td>5</td>
<td>0%</td>
<td>0%</td>
<td>No</td>
<td>280</td>
<td>25%</td>
<td>25%</td>
<td>Very unfair</td>
<td>19</td>
</tr>
<tr>
<td>5 – Intermediate</td>
<td>9</td>
<td>1%</td>
<td>1%</td>
<td>Non-responded</td>
<td>322</td>
<td>29%</td>
<td>29%</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

3.3 Participants

The 1121 participants were representative of the population in the UK across three demographics: age, gender, and ethnicity. The background and sampling were provided by Prolific. When using a representative sample, Prolific takes the intended sample size and stratifies it across the demographics, using census data from the UK Office of National Statistics\(^1\) to divide the sample into subgroups with the same proportions as the national population (or as close as they can deliver). Note that while we recognise that it can be reductive to consider ‘gender’ as a binary variable, this data was collected by Prolific to meet the distribution of the national census data. Participants had to be 18 years old or over, speak English, and not have an AI/ML background. Here we report background data gathered in Parts 1 and 2 of the main survey.

Table 1 provides an overview of the gender, ethnicity, and age group of our sample. The sample was fairly balanced in terms of the gender of the respondents, with a slightly larger number of females than males. In terms of ethnicity, this reflected the demographic distribution of the UK population. Our sample also reflected the UK distribution in terms of age profile. We noted that a third of our respondents were over 60; this is slightly higher than the UK population and contrary to the usual age profile of crowdsourcing platforms.

As a result of the initial screen question the majority of participants rated themselves low on our expertise levels (see Table 2). Three percent self-rated as "Ignorant". Most participants (62%) self-rated at level 1 (interested), meaning they had already heard a little about AI but did not know much. Twenty-eight percent of the participants responded that they had pursued the topic of AI, meaning that they had read an article or two about it and understood the basics of what it is,

\(^1\)https://www.ons.gov.uk
but lacked any depth of knowledge. The remaining 7% of participants ranged from beginner to intermediate (i.e., from 1 week to 1 year of AI-related practice).

With respect to immediate encounters with AI, 55% of the respondents reported having experienced an AI system, and the remaining 45% expressed they were not aware whether they had ever used an AI system. 46% of those surveyed indicated that AI should play a role in the hiring process, and 29% left this question unanswered.

We also probed respondents as to their attitudes toward fairness (Table 2, and Figures 1). In the survey, 47% of the participants stated that they expected that the AI will make very fair or fair decisions, and 23% thought that the AI’s system would make unfair or very unfair decisions. We found that the top most highly ranked fairness concepts were “People will be treated the same whether they are protected by law or not” and “The process to make decisions was logical and objective” (see Figure 1). This means that fairness through unawareness and procedural fairness were most important to a large number of our respondents. Surprisingly, “Similar people will be treated in the same way” appeared as one of the least highly ranked options; this means individual fairness was not important to a large majority of our respondents. The participants’ responses here also show that there was not one fairness concept that everyone agreed on, and that different people viewed fairness quite differently.

![Fig. 1. Participants’ ranked preferences on fairness concepts in an AI system. Top two ranked choices were people will be treated the same whether they are protected by law (e.g., gender, age, etc.), or not, and the process to make decision was logical and objective.](image)

4 FINDINGS

We analysed the survey responses to answer our two research questions. Our aim was to investigate (i) who should be involved in the AI development process to ensure fairness, from the perspective of lay users; (ii) concerns about developing fair AI systems, and (iii) how lay users could be involved to allay these concerns in a responsible human-centric AI development process.

Please note that labels in Figures (e.g., see Figure 4) and in-text references for options presented to participants have been abbreviated for readability. Please refer to the Supplemental Material for the full version of the survey.
4.1 RQ1: Who Do Lay Users think should be responsible for fairness the AI Development lifecycle?

Recall that we asked the same question of who should be involved across all four stages of the AI development lifecycle for our hypothetical scenario. Figure 2 illustrates the percentage of responses for these answers across different stages. Responses across stages within types of stakeholders remained relatively stable, however, there was an obvious preference by respondents for the top three stakeholders that respondents suggested should be involved in the AI development. These were in order of preference: the HR team who will benefit from the new AI recruiting tool platform (mean = 81%); an ethics committee within the organisation which is responsible for evaluating potential harms and risks in building such a system (mean = 73%); and AI experts of the organisation in charge of the AI development (mean = 73%). This was followed by an external regulator who vets important decision-making that might harm people protected by law (mean = 57%).

![Fig. 2. Clustered histograms by stage of the participants’ choices about who should be involved in the development of responsible AI systems. Top four choices, in decreasing order, throughout all stages were (B) the HR team, (D) an internal Ethics committee, (C) AI experts, and (F) an external regulator.](image)

4.2 RQ2: How to make the process more responsible?

Figure 3 shows participants’ preferences for what could be done to make the AI recruiting tool more responsible overall. The top choice was “Show how well the system performed during the evaluation” (69%). This practice refers to the AI model training and evaluation step and ensures the AI system’s robustness and fairness before it is deployed. Respondents were also interested in transparency. “Explaining how the AI model made its decision when you provide some information” was chosen by 68% of the respondents, alongside other explanations as to how the model was trained (48%) and how the model works in general (52%). Furthermore, participants placed value on the work done to make AI system development processes accountable, with 58% of the respondents choosing “Provide guidelines/principles that have been followed to build the AI system” as the third choice overall. None of the respondents thought that AI systems couldn’t be made fairer, underlining that there is still some way to go to ensure responsible AI development.

Next, we describe respondents’ answers for how lay users could be involved in each of the stages.

4.2.1 Business Case Stage. Concerns: Participants had concerns about the reasons and objectives of building an AI recruitment tool. In their responses, they pointed out that speeding-up the recruitment process in the organisation does not ensure quality and improvement in the hiring process. In
contrast, many respondents stated that such a system will advantage those who are already in power (e.g., cutting organisation cost, giving less responsibilities to HR team), reinforcing the general idea that an AI system will replace human roles and jobs (i.e., firing HR employees). Participants were worried that human interactions will take second place, instead they suggested humans should always be ‘in the loop’ when building this system. Several participants also mentioned that hiring managers’ involvement only at this stage would be concerning, and that asking feedback from external people, especially marginalised groups, could be a way to gain a different perspective.

Ways of involving lay users: Figure 4 shows the ranks of their responses. We found the most popular choice was (B) participating in a large-scale survey/questionnaire to express their views, benefits and risks (rank score = 1.6). This speaks to the suggestion that even the idea for AI development needs to be made transparent and accountable, and should involve external stakeholders. Less important was more direct involvement, such as helping the organisation with the co-design of the hiring AI system going forward, representing the view of lay users (rank score = 2.1) or vetting any major systems and data processing within the organisation (rank score = 2.3).

4.2.2 Collecting and Labelling Data Stage. Concerns: The main concern that participants noted in this stage was which data is collected and included in the dataset. Specifically, they mentioned...
the issues of gathering enough data, and collecting data only from past candidates, who might not be a representative sample of future job seekers. Other concerns were about information that might be collected and then labelled incorrectly. For example, some respondents feared that visual stylistic design choices of the CV might be represented as very important in the data and thus might disadvantage people with visual disabilities. Participants frequently mentioned unconscious bias and assumptions built into the data which might result in ripple effects in the next stages of AI development. As a remedy, respondents pointed out the need of a diverse group of people to verify how data is collected and labelled. This, in their opinion, could ensure that relevant information is not missed, and marginalised and protected groups are not disadvantaged.

Ways of involving lay users: Figure 5 shows the respondents' ranking of the given options. The top ranked response (rank score = 2.7) was (B) investigating the existing training data for potential unfairness, which was rated by 34% of the respondents as the most important thing to do. In this option, the AI development team could make anonymised datasets available which lay users could inspect and ‘mark up’ with fairness issues that they identified. This was followed by (E) selecting information that might be problematic to include in any models (rank score = 3.3). While only 13% of respondents ranked this as their first choice, 21% ranked it second. In this option, the lay users could have the opportunity to again inspect an anonymised dataset and suggest attributes which were problematic to use in a model. While there are certain attributes that are protected by law, there are other attributes that are considered sensitive or are seen as problematic. For example, post or zip code is not a protected attribute but many people consider it as problematic to use in decision making. Promising steps towards involving lay users have been taken recently by developing interfaces that allow lay users to express fairness notions and issues in datasets [22, 83]. This would allow lay users to take much greater control of the development of AI models by directly influencing the data used to train a model and go some way to human-centric AI [101]. All other choices had very similar rank scores, from 3.6 to 4.2.

4.2.3 AI Model Training and Evaluation Stage. Concerns: Respondents were mainly concerned about transparency during training, testing, and evaluation. Specifically, they raised concerns about whether the dataset was large, accurate, and relevant enough to ensure that different cases were captured when the AI system was trained. They also were worried about testing, how data was selected for testing, and how many tests and testers were considered before deployment. One important aspect was the evaluation phase, and how fairness metrics were computed. They pointed out that different people are needed to define fairness, to whose interests, how fairness metrics are computed, and how often. Finally, they were also concerned about how developers might propagate their unconscious biases from training to evaluation.

Ways of involving lay users: Figure 6 shows the ranks of participants’ responses. We found the most popular preference was (C) investigating the existing model for potential unfairness (rank score = 1.7). This option was selected by more than 50% of the respondents. At second position, we found that 36% of the respondents chose option (D) (rank score = 2.4). What both these options have in common was that lay users would have access to an anonymised dataset that they could investigate and feed back on, either by flagging problematic decisions or changing model weights, representing a very active role in the development process. Instead, options where they would play a more passive role were ranked in general lower than more active participation. While model cards [79], Option (A) (rank score = 2.9), have been suggested as a way to increase transparency and accountability, it proved to be not that popular with our respondents. Option (B) (rank score = 2.4) also placed responsibility in the hands of the AI experts within the organisation to make the AI development more transparent. This suggests that participants preferred options where they are more actively involved at this stage (e.g., investigating, and reviewing).
Fig. 5. How users want to be involved in the Collecting and Labelling Data stage. The top 2 ranked preferences were (B) Investigating the existing training dataset for potential unfairness received the overall highest ranking, and (E) Selecting information in the applications that might be problematic to include.

Fig. 6. How users want to be involved in the AI model training and evaluation stage. Top 2 ranked responses were (C) investigating the existing model for potential unfairness, and (D) reviewing the dataset and adjusting the importance of the features.

4.2.4 AI Model Deployment and Decision Making. Concerns: In this stage, participants were concerned about the final decision made by the AI system, and how this decision is explained to the candidate. Respondents were of the opinion that all applicants should be treated fairly and not biased depending on age, race, sexuality, disability, etc. They reported ethical concerns about how the AI system could prevent discrimination against protected groups, and other people who are not
protected by law (e.g., non-native English speakers could be disadvantaged). If someone has been rejected, this should be done for good reasons. They pointed out that the AI system could miss important information about candidates, and this could lead to the rejection of good candidates. Again, as in the previous stage they were worried about how the system will process the CVs and cover letters. Participants stated that AI system might have too much power, instead more humans involvement is needed at this stage to verify AI system decisions.

**Ways of involving lay users:** Figure 7 shows their ranked responses. Option (C), Investigating the performance of the HR system for potential unfairness, was in the top position (rank score = 1.7) where almost 50% of the respondents ranked this practice as the most important for them, mirroring responses for investigating the training data set in the previous stage. with Option (B) in second overall rank (rank score = 2.1). This means that also in this stage participants wanted to be actively involved, through investigating and vetting datasets. Indeed, Option (A), viewing a ‘performance card’ (rank score = 2.6), which is similar to the model card idea in the previous stage, and Option (D) contact the organisation and/or regulator to do an investigation if you feel you have been treated unfairly (rank score = 2.9) did not allow lay users a voice in the deployment process. Respondents also suggested other options for their involvement which we did not present to them. Participants wanted to compare successful and unsuccessful applications to see if the AI system made a fair decision. This included setting up ‘test cases’ by sending fake CVs of minority candidates (e.g., people with disabilities) to see if they would be discriminated.

![Fig. 7. How users wants to be involved in the AI model deployment and decision making stage. Top 2 ranked responses were (C) investigating the performance and flagging potential unfairness cases, and (B) vet the performance after 1-month trial.](image)

5 **DISCUSSION**

In this section, we outline the limitations of our work. We then discuss implications for AI design and development processes, focusing on three aspects that our findings reveal: (i) diverse stakeholder involvement, (ii) end-to-end development process accountability (iii) active lay user participation, and (iv) the implications of our work on wider AI policy and governance.
5.1 Limitations
With respect to our study’s method, the way we introduced AI to participants prior to our survey (see 3.1.2) cannot be treated as establishing a baseline understanding for all participants. Though we targeted recruiting lay users, we are aware that participants came to the study with their own preconceptions and views of AI. Rather than establishing a baseline, the introduction to AI was used to establish a shared viewpoint and common language to progress with the survey. Related to this, the language and materials used to introduce AI and the AI pipeline/life cycle may have placed the emphasis on particular issues and concerns for participants and, in turn, influenced their responses to survey questions. The introduction to AI was developed using a common view of the AI development cycle often presented in textbooks and general AI materials – again, our goal was to frame the problem space using a shared/common language. The need for this could, arguably, be seen as a limitation of the relatively large survey approach we adopted. We recognise further, focused, qualitative research would be needed to deepen and developer richer insights into individual’s views and opinions and assess whether the survey method might have skewed results.

With respect to the survey’s design and the results, while we took great care to design our survey, the multiple-choice answers we provided may not cover all possible options for who to involve and how. Other practices which we did not capture in our survey might be relevant and appreciated by lay users. To counteract this to a certain extent, we provided open-text responses but often these were left blank. There were, however, two common themes running through the open responses for all stages. Firstly, many respondents reported that they did not have enough knowledge about the learning process to provide other suggestions on how else they would like to be included and that they would like to understand AI development better. This indicates that many respondents are currently in the dark about how decisions are made around AI systems and how they are developed. This reinforces calls for greater transparency and programs of education about AI development targeted at lay users. Secondly, participants also mentioned they would like to be informed of the general progress of the system. This again emphasises their desire to find out more about the development process but also suggests a greater need for accountability. Overall, we argue that the rankings and suggestions provided by respondents are of value as they allow us to get a sense of lay users’ perspectives.

Finally, with respect to representativeness, although we had over 1000 respondents to our survey, participants were drawn only from the UK. Therefore, findings might differ if this survey was transferred to other countries. Future work might explore a more geographically diverse sample to compare our initial results and investigate how cultural aspects across countries influence perspectives on involvement in developing AI systems. A step in that direction has already been taken by studying the influence of cultural dimensions underpinning fairness judgements [11, 14, 15, 61, 76, 83]. Additionally, although in our study, we investigated lay users of machine learning in general, the responses from various types of users should be compared in future work. This is because there are diverse stakeholders that should be included in the lifecycle of AI [53, 75], and in addition to that, even among lay users, their perceptions may vary depending on their expertise in their domain knowledge (especially knowledge on HR practices in this study), and whether or not they are directly affected by the outcome of a decision can affect their perception [82]. For example, if people are in a position where employment decisions are made or are currently seeking jobs and are immediately affected by the decision, their opinions might change [84]. Hence, comparisons among diverse stakeholders beyond investigating lay users’ responses should be made in the future.
5.2 Implications for responsible AI design and development

Our findings have four major implications for designing future responsible AI development processes.

5.2.1 Diverse stakeholder involvement. Our findings showed that, in addition to data scientists and AI experts, respondents also wanted to have the relevant internal domain experts involved. A close working relationship seems to be expected which is one of the key aims of human-centric AI development to ensure that these systems fit their context of use. Many guidelines for AI development already encourage involving these kinds of domain experts [3, 53, 71, 87] but more could be done to establish interdisciplinary teams that shepherd the design and development of an AI system.

From results in section 4.2.1, we can see that participants expected a close working relationship between domain experts, in this case, the HR team, and AI experts, all the while supported by an ethics committee, all internal to the organisation. This suggests a responsible, human-centric approach to AI, which is mentioned in several guidelines [3, 53, 89]. What is more, they also suggested input external to the organisation, through a external regulator. In fact, involving previous applicants or trade unions, as input frequently by respondents in “Other”, points to the importance of external stakeholders.

Most companies and organisations currently do not have an internal ethics committee set up that monitors AI development. If they do, usually in large organisations, an ethics committee is mainly involved at the beginning of the process, to approve work that involves humans and with a focus on the gathering of data and its security and privacy. What our findings suggest is a dramatic reorientation of the function of an ethics committee to provide much deeper scrutiny of the AI development process throughout. We believe that the ethics committee could help to identify and mitigate tensions between stakeholders’ views, concerns, and interests. This is also echoed by the suggested involvement of an external regulator which could vet the AI process if the work affects people protected by law, or if the AI system is being deployed in a high-stakes setting. However, this would also necessitate the establishment of common standards and practices against which AI development processes could be assessed.

Concrete actions to take: We suggest the following changes to practice for all organisations developing AI systems: (i) to put in place processes that ensure domain and AI experts work together to develop a solution, (ii) to set up internal ethics committees that take charge to represent the views of lay users affected by AI systems, and (iii) to open themselves up to scrutiny by regulators, if required.

5.2.2 End-to-end development process accountability. Currently, the primary focus when building AI systems is on the model building and evaluation stage but recent work has highlighted problems underpinning conventional AI practices, which focus mainly on model building [97]. Our findings show that attention needs to shift to cover all development stages, especially in early stages when a business case is developed as well as when the training data is collected [97]. Earlier involvement of stakeholders to gain perspectives on the business case and goals of the AI would go some way to incorporate human-centric principles for building responsible AI systems. Furthermore, in practice, most organisations fail to create or meet any data quality standards, even though AI experts recognise the value and importance of high-quality data and data processing practices [81]. Data plays a crucial role in training the AI system, and biases can be introduced at this stage. Our findings emphasise that more focus on this stage is required and that lay users have a role to play during the entire end-to-end AI development lifecycle. Finally, our findings in section 4.2.4 also revealed that respondents were highly concerned about what happens after deployment.
highlighted that even deployed systems need to be regularly evaluated and tested, to ensure that they remain fair. Specifically, one of the concerns was about how the system is tested to ensure it makes fair decisions over time, for instance, when the job description or requirement criteria change. Work in this area is still in its infancy but there are some encouraging steps being made to consider the systematic testing of AI systems involving lay users [21, 46] in addition to the user involvement during the use of AI systems over time [3].

**Concrete actions to take:** We suggest the following changes to practice for all organisations developing AI systems: to put in place processes that ensure lay users’ perspectives are sought and integrated across the entire AI development lifecycle.

5.2.3 *Active lay user participation.* Our findings suggest that there is scope for more actively involving lay users in all stages in the AI development process, from business case, collecting data, model building, and testing after deployment. Indeed, this is part of a greater democratization of AI [100], in which lay users play a crucial part to identify the problem to be solved with AI, generate and choose data to teach the AI model, and evaluate the training [93]. To do this, a combination of practices is needed that span design processes, interfaces, and algorithm development.

In terms of design processes, recent research has investigated the involvement of domain experts and lay users in the development of responsible AI systems through participatory and co-design practices [82, 83, 90, 103]. We encourage further uptake of these design practices in responsible AI development.

Results from 4.2.2 and 4.2.3 suggest that new ways of involving lay users in data collection, model building and evaluation will need to be found, even before the system is deployed. This presents exciting research opportunities to design new interfaces for lay users to interact, understand, and manipulate datasets and resulting AI models [121]. Of course, investigating the quality of datasets might not be easy: they can vary in complexity and might require some domain expertise to interpret. However, we believe that the challenge is in developing interfaces that support these users to inspect data quality, especially with respect to fairness. Work in this direction is already ongoing, such as the Data Nutrition Project [52], SILVA [116], and FairHIL [82].

Some work is also already trying to involve lay users in model building and evaluation, by shaping the algorithms [67] or by developing interactive machine learning approaches that can take lay user feedback into account [63, 83].

We are not suggesting that all the methods, techniques, and tools we probed are applicable and usable across all domains. For example, consider the issue of developing an AI model that makes decisions about receiving organ transplants. While clinical input is obviously needed in developing a model that assigns a score to a possible recipient based on their history and likely outcomes, lay users’ input will need to be considered in determining the fairness of the AI model. Indeed, these approaches are already being put in place by either delegating the making of the final decision to a lay user committee [96] or through interfaces where fairness values can be gathered [4] to aid policy and model design. What we present in this paper is a call to action to consider how to increase the involvement of lay users in responsible AI development and governance.

A basis for all approaches to involve lay users is increased AI literacy. As we reported in our results, many respondents were unable to make their own suggestions because they felt they did not have enough knowledge about AI development processes. We urge that AI systems are made more transparent and accountable but that there is a substantial need for educating lay users about AI and its development.

**Concrete actions to take:** We suggest the following changes to practice for all organisations developing AI systems: (i) use participatory design approaches to actively involve lay users; (ii)
invest in building tools, targeted at lay users, that provide AI explanations, support sense-making and allow user feedback, and (iii) open up engagement with lay users that enhance AI literacy.

5.2.4 **AI policy and governance.** Increased attention is being paid to ensuring that high-stakes AI applications are developed responsibly. The EU’s AI Act [25] is likely to transform how AI systems are developed in critical domains such as jurisprudence, medicine, and hiring. The current UK strategy for regulating high-risk AI [44] is reflecting these efforts, and we will see laws around responsible AI development emerging over the next 10 years. The involvement of lay users – i.e., those affected by innovative AI technology – seems to us crucial to its success and acceptance.

**Concrete actions to take:** We suggest the following changes to practice for all organisations developing AI systems: (i) actively engage in discussions around standards and regulations that affect AI systems, (ii) seek lay user input about their concerns.

6 **CONCLUSION**

In this work, we investigated (i) who should be involved in the AI development process to ensure fairness, from the perspective of lay users; and (ii) how lay users could be involved to allay their concerns in a human-centric responsible AI development process. Through gathering the opinions of over 1000 respondents, representative of the UK population, we found that:

- respondents were interested in having their views reflected at all stages of the AI development lifecycle;
- they suggested internal stakeholders oversee the development process, supported by an ethics committee, and external regulatory bodies; and
- they also suggested more education around AI to underpin direct lay user involvement.

With these findings, we hope to evolve the ongoing discussion of how best to shape human-centric responsible AI development. Our work points towards greater involvement of lay users in AI systems that are fair, accountable, and transparent.

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**REFERENCES**


Lay User Involvement in Developing Human-Centric Responsible AI Systems: When and How?


Lay User Involvement in Developing Human-Centric Responsible AI Systems: When and How?


A SURVEY

A.1 AI system development steps description

Figure 8 represents an AI system development process. The steps illustrated in the flow chart were proposed to participants alongside the following detailed description.
Fig. 8. AI system development process.

(1) **Business Case.** The organisation discusses whether an AI system is needed, why the organisation should use resources for building it, and what the benefits and risks are.

(2) **Data collection and preparation.** This is an important step in the AI development process: data is collected into a dataset and pre-processed. That means data is ‘cleaned’ (e.g., put into the right format, incomplete data is thrown out) and possibly labelled (e.g., an image might be labelled with ‘cat’ or ‘dog’, or a loan application with ‘approved’ or ‘rejected’).

(3) **AI Modelling.** The dataset is then used as input for the AI modelling stage. The AI model is trained, which means that the model learns from the data. A successful modelling stage aims to create a robust model that can make accurate decisions based on the data.

(4) **AI testing and evaluation.** In the previous stage, a small portion of data is kept apart for evaluating and testing the AI model after training. The testing phase will provide information on how robust and accurate the model is, and if it works as expected. In general, models should not make too many mistakes, but they are never 100% accurate.

(5) **Deployment.** Once the AI model is ready to be deployed, it will be integrated into a system (for instance as part of a smartphone application) that users can interact with and use. The AI model is applied to the information a user inputs to produce an output or decision (e.g., cat or dog, loan approved or rejected, etc.).

### A.2 Who should be involved in each stage

In “Who should be involved in each stage” question, we included the following options:

(A) CEO and senior managers of the organisation;
(B) the HR team who will benefit from the new AI recruiting tool platform;
(C) AI experts of the organisation in charge of the AI development;
(D) an Ethics committee within the organisation, which is responsible for evaluating potential harms and risks in building such a system;
(E) current employees within the organisation who went through the recruiting process;
(F) an external regulator who vets important decision-making that might harm people protected by law;
(G) people who applied to the organisation but maybe did not get the job for some reason;
(H) people who enquired about the job but did not apply for some reason;
(I) a small team of stakeholders, including lay users, who are going to help with the design of the AI recruiting tool;
(J) with an option to specify their own answer.
A.3 How lay users can be involved in each stage to ensure fairness

In the Business Case stage, we provided the following 4 options:

(A) vetting any major systems and data processing within the organisation;
(B) participate in a large scale survey/questionnaire where the organisation explains their idea and you have the possibility to express your view and tell them about the benefits and risks you perceive;
(C) help the organisation with the design of the hiring AI system going forward, representing the view of lay users;
(D) other.