Ideating XAI: An Exploration of User's Mental Models of an AI-Driven Recruitment System Using a Design Thinking Approach

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***Abstract*— Artificial Intelligence (AI) is playing an important role in society including how vital, often life changing decisions are made. For this reason, interest in Explainable Artificial Intelligence (XAI) has grown in recent years as a means of revealing the processes and operations contained within what is often described as a black box, an often-opaque system whose decisions are difficult to understand by the end user. This paper presents the results of a design thinking workshop with 20 participants (computer science and graphic design students) where we sought to investigate users' mental models when interacting with AI systems. Using two personas, participants were asked to empathise with two end users of an AI driven recruitment system, identify pain points in a user's experience and ideate on possible solutions to these pain points. These tasks were used to explore the user's understanding of AI systems, the intelligibility of AI systems and how the inner workings of these systems might be explained to end users. We discovered that visual feedback, analytics, and comparisons, feature highlighting in conjunction with factual, counterfactual and principal reasoning explanations could be used to improve user's mental models of AI systems.**

Keywords - Artificial Intelligence; Explainable Artificial Intelligence; Design Thinking; User-Centred AI.

I. INTRODUCTION

AI is reforming the way that many processes and services are delivered in society. From deciding who is granted access to credit, who gains a place in third level education to which CV is chosen to progress to interview for employment [1]. Complex algorithms processing big data sets, which would otherwise be beyond the scope of human processing, are often making life-changing decisions with little human intervention and with even less explanation. This has given rise to an emerging field of XAI in which the results of AI systems and algorithms can be understood by humans. Of the XAI solutions which currently exist, many are designed by software developers for other software developers to explain how computer code and algorithms work [2]. Such approaches often rely on developers' own *"intuition of what constitutes a 'good' explanation"* [3]. Some useful solutions have been developed around text classification including the TextPlanation demonstrator which uses graphical means to display the results for different Machine Learning (ML) libraries including LIME, SHAP, LRP, SKATER and ELI5 [4] and the XPlainIT tool which visually explains the decision-making process of deep learning models [5]. Few XAI solutions are aimed at the end users of AI systems. This can be problematic when we consider the diversity of users who engage with AI systems, many of whom may have no technical knowledge of such systems. Other modalities have been explored such as the potential of virtual agents [6] and saliency based explainability models [7], which show potential and highlight areas of further research. To better understand end users' mental models of AI systems, cross collaboration and a more user-centred approach have been suggested [8]-[10], as well as drawing from Human Computer Interaction (HCI) philosophy and psychology [9]. Ultimately, understanding people informs explaining AI [9].

This paper seeks to describe our investigation into users' mental models for AI and ideate XAI solutions using cross collaborative, interdisciplinary participants using a design thinking methodology. Design thinking workshops were conducted using an AI design problem statement within a relevant discipline - recruitment, that could be well understood by lay users. Design Thinking activities were carried out with participants from both graphic design and computer science backgrounds which were used to explore how users understood the proposed AI system and to uncover blind spots in their understanding and associated challenges. We hoped to explore what users' "internal representations" [11] of AI systems that might be based on their real-world experiences and build on this to develop ideas as to how these AI systems might be more usefully explained. The rest of this paper is structured as follows: In Section II, we describe related work on Design Thinking and mental models, in Section III, we describe our approach to ideating XAI using design thinking, in Section IV, we describe the results of the design thinking session including users' approaches to solve AI system pain points. We conclude by highlighting areas for future work.

II. BACKGROUND

2.1 Design Thinking

Over the course of the last century, the professional practice of design has evolved to include a much wider range of disciplines including addressing social problems, business management and within the world of information technology design. It has been suggested that those who are non-designers could benefit from thinking like designers [12]. One approach which has emerged within the field of user experience design to help bridge this gap is design thinking. Design thinking can be described as a problem-solving approach which prioritises users' needs using a non-linear or iterative process with well-defined stages: empathise, define, ideate, prototype, test [25]. Our study focuses primarily on two stages: empathising and ideation as two of the most useful stages for determining users' mental models. Further research will concentrate on other phases. Fundamental to design thinking is the concept of empathy, connecting with those who use our products or services on a deeper level by considering what a user might do, say, think and how they might feel whilst engaging with a product or service. Persona development and empathy mapping are two design thinking activities which can be used to facilitate this [15] in conjunction with pain point identification, big ideas ideation and prioritisation [16].

2.2 Mental Models

Mental models describe what a user believes they know about a system such as an information system. The ultimate goal of any software designer or developer is to build a system where users can build accurate and as a result useful mental models [17]. In essence mental models refer to a user's expectation of how a system should work [18]. In the case of predictable systems within digital technology the theory of mental models has proven useful [19]. However, within AI where systems are complex, less predictable and change over time this approach can be difficult to apply. It has been argued that explainability and comprehensibility, with regard to user interaction, should employ the use of specific use cases, putting the user at the centre of XAI [20]. As well as the ethical need for explanations in AI, legislation such as the EUs General Data Protection Regulation (GDPR), the USAs Algorithmic Accountability Act 2022 and the UKs Digital Regulation Plan demonstrate that lawmakers realise the importance of accountability and transparency of algorithms [21]-[23].

III. PARTICIPANTS

We conducted a design thinking workshop with students from an Irish College of Further Education. University ethical approval for the workshop was sought in advance and consent forms acquired. Inclusion criteria for the study included expertise in Computer Science and/or Design. Participants were invited to partake via email. The final participants included 20 students. Prior to the workshop, a Microsoft Forms survey was distributed to establish demographics and their knowledge, if any, of AI, XAI and Design Thinking. 20 participants in total were divided into 4 groups of 5 participants.

Group 1: 2 designers & 3 computer scientists, 5 males: Andrew Wilson Persona.
Group 2: 2 designers & 3 computer scientists, 1 female & 4 males: Andrew Wilson Persona.
Group 3: 3 designers & 2 computer scientists, 3 females & 2 males: Maria Atkins Persona.
Group 4: 2 designers & 3 computer scientists, 5 males: Maria Atkins Persona.

The participants comprised 11 computer science students and 9 design students supporting our interdisciplinary, collaborative approach [9]-[12]. 11 participants identified as undergraduate students while 9 identified as mature student / professional returned to education. 11 participants were aged 18-24, 5 were aged 25-34 and 3 were aged 35-54. 4 participants were female and 16 were male. See Figure 1. 4 groups of 5 participants were formed for 1 design thinking workshop.

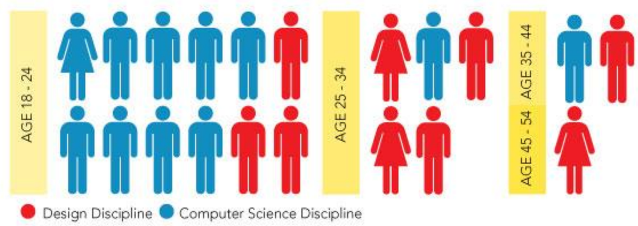

Figure 1. Participant Profile.

IV. METHODS

4.1 Persona Design

It has been estimated that at least three quarters of all CVs submitted for jobs in the US are processed by AI [14]. Efficiency and cost savings are the main motives for employing AI in candidate selection; however, a recent report from Harvard Business School showed that 88% of employers agree that suitable candidates are vetted out of the system because they do not match exact criteria [29].

After selecting the problem domain, 2 design problem statements were presented which introduced participants to 2 personas: How can we help Maria (a recruiter) understand the CV filtering systems she is using and ensure possible suitable candidates aren't slipping through the net? And, how can we help Andrew (a job seeker) understand the process involved in how his CV is being screened for interview selection and increase his confidence in the system? Personas are an important tool which are used to align designers and developers to user experience and in at least some settings can be used to great effect [13]. To better understand end user problems related to AI systems for employment and recruitment, we designed two personas reflecting differing user experiences. Andrew Wilson was designed as a job seeker engaging with a recruitment application whereas Maria Atkins was designed as a

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recruiter using the application for processing candidates for interview. See Figure 2.

Figure 2. Personas referenced during workshops [30][31].

Andrew is a recent highly qualified computer science graduate but has some characteristics which may be considered atypical, for example, his relatively older age and his background when compared to other university graduates. These characteristics were by design as such features may exacerbate historical biases in datasets used by AI systems [1]-[14]. Maria was designed to reflect the experiences of many working in the recruitment sector where algorithms are now commonly used to filter candidates without providing explanations of why candidates are selected or not [1].

4.2 Design Thinking

The design thinking process begins with empathising, followed by pain point definition and finally ideation and evaluation.

4.2.1 Empathy mapping & As is scenario

Participants engaged in two empathising activities

1. Empathy mapping: considering persona's thinking, feeling, saying and doing
2. As is scenario: Identification of steps and persona's thinking, feeling and doing

These activities are to facilitate pain point identification.

4.2.2 Pain Point Identification

Pain point identification was carried out using 5 sticky dots per participant. This was followed by a playback or presentation of each group's main findings.

4.2.3 Big ideas & Prioritisation

Ideation in the form of big ideas and prioritisation follows pain point identification. This involves:

1. Grouping of similar pain points
2. Identification of 4 pain points
3. Design of 3 solutions and 1 absurd solution for each pain point
4. Voting using 5 sticky dots on most feasible and important solutions
5. Prioritisation using XY grid, X Axis = feasibility for us, Y Axis = importance to the user. This categorises solutions into no brainers (High Importance to the user & High Feasibility for us), big bets (High Importance to the user & Low Feasibility for us), unwise (Low Importance for the user & Low Feasibility for us), utilities (Low Importance for the user & High Feasibility for us).

4.3 Data Collection and Analysis

At each stage of the design thinking workshop, data was collected using digital photographs of each activity sheet with post its and voting sticky dots included. Playbacks of critical moments were recorded for transcription post workshop. The workshop concluded with a short group interview with questions designed to ascertain participants' engagement with the processes and to further explore their mental models regarding XAI. Audio was also recorded of post workshop interviews. Content analysis followed identifying common categories linked to pain points.

V. RESULTS

Results are divided into two parts. Firstly, we present an overview of the findings from the design thinking activities which includes participants' responses to empathy mapping and as is scenarios to identify pain points in users' engagement with AI. We follow with a content analysis of participants "big ideas" or ideation linked to pain points identified earlier. We interpret the findings of this analysis with an emphasis on presenting common categories identified during workshop exercises.

To categorise our results more effectively, we combined the findings for each persona. Findings for groups 1 and 2, those that empathised with Andrew Wilson, were grouped together as were findings for groups 3 and 4, who empathised with Maria Atkins.

5.1 Empathy Map & As is Scenario Groups 1 & 2

Groups 1 & 2 associated the process of making job applications and continually being rejected as being a negative experience, which is to be expected. Emotions such as "Depressed", "Upset", "Angry" and "Unmotivated" featured predominantly. Empathy mapping was followed by an As Is Scenario where groups broke Andrew's process into steps and delved further into the thoughts, feelings and actions associated with each. Group 1 broke a job application process for Andrew into the following steps: search, apply, receive replies, analyse, revise CV and call or reapply. Group 2 broke a job application process for Andrew into the following steps: Revise CV, Internship application, email the companies about what he should do and look outside this country.

5.2 Pain Point Identification

Voting followed using sticky dots where each participant used 5 sticky dots to vote on the areas of most pain for our persona. Both groups identified similar pain points which included the process of applying and reapplying, continually revising CV, receiving a negative response and lack of feedback.

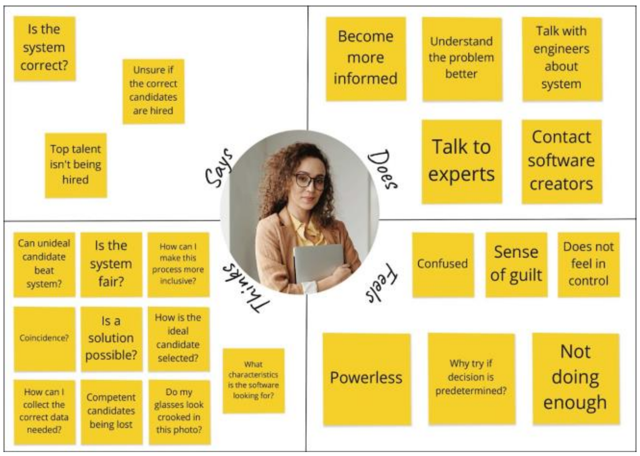

Figure 3. Graphical Representation of Empathy Map Group 4 [30].

5.3 Empathy Map & As is Scenario Groups 3 & 4

Groups 3 & 4 associated Maria's engagement with the recruitment system as being opaque and confusing. They described Maria as feeling "Confused", ``Powerless" and having a sense of "Guilt". See Figure 3.

Figure 4. Graphical Representation of As is Scenario with Pain Point Voting Group 4.

To further empathise with Maria an As Is Scenario exercise followed. Group 3 broke Maria's steps into the following stages: logs into system, researches, documents her concerns, contacts management, voices concerns. Group 4 took a slightly different approach and looked at Maria's initial steps in dealing with both successful and unsuccessful candidates. Group 4 steps included: review successful applicants, manually send out successful emails, review unsuccessful applicants, message unsuccessful applicants, call the IT person, inform senior management of concerns. Although slightly different, both groups ended with Maria documenting her concerns and voicing them to those in authority in the hope that a solution can be found. See Figure 4.

5.4 Pain Point Identification

Both groups continued to the next activity, pain point voting using 5 sticky dots each. Figure 4 represents the findings of Group 4 with pain point voting represented and 4 pain point areas circled. Similar pain points emerged from both groups which included the process of researching or reviewing the system, reviewing, and messaging unsuccessful applicants, identifying who can help and conveying her concerns. See Figure 5.

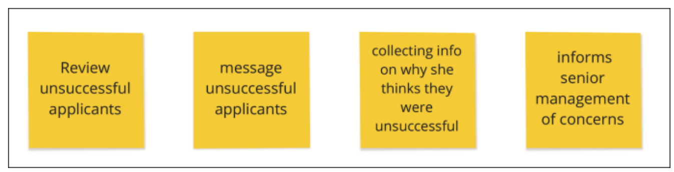

Figure 5. Graphical Representation of Pain Point Identification Group 4.

5.5 Big Ideas & Prioritisation Groups 1 &2

In response to these pain points groups 1 & 2 began the process of big ideas ideation and prioritisation. Each participant designed 3 solutions for each pain point and one absurd solution. After a second round of voting using 5 sticky dots each the most promising big ideas were identified. These were then placed on a prioritisation grid the main findings of which can be seen in Table I.

5.6 Big Ideas & Prioritisation Groups 3 & 4

Groups 3 & 4 carried out the same process of ideating on big ideas to solve the pain points for our persona Maria which were identified earlier. This followed with voting on the potential of these ideas and placement on a prioritisation grid. Table II documents the main findings of this process.

Participants' final task, playback of big ideas and prioritisation gave an opportunity for each group to explain in more detail their big ideas and reasoning for their choice of placement on the prioritisation grid.

We consolidated findings from our design thinking workshop and conducted a categorisation exercise to cluster or group common big ideas into similar topic areas. Our findings identified three categories associated with each persona and interestingly two overlapping categories for each. We coded each big idea as follows:

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- Visual feedback & analytics: 01
- Visual comparisons: 02
- Highlight problems & offer chances to rectify: 03
- Criteria manipulation / tracking: 04

Figure 6. Categories for both personas to understand AI system [30][31].

Visual feedback and analysis and visual comparisons were considered necessary for both Andrew and Maria to understand the AI-driven recruitment system. Highlighting problems and offering chances to rectify were considered necessary for Andrew and criteria manipulation and tracking was considered necessary for Maria. See Figure 6. Tables I & II document big idea categorisation.

TABLE I. BIG IDEAS, PRIORITY, CATEGORY GROUPS 1 & 2

Pain Point > Big Idea > Priority > Category			
Pain Point	***Big Idea***	***Priority***	***Category***
Negative replies & Rejection	Call for interview	No brainer	01
	Ask for feedback	No brainer	01
Revise CV	Compare past & present CV	No brainer	02
	Highlight problems on CV	Big bet	03
	Score in categories	Big bet	01
	Check CV similarity stand out	No brainer	03
Search & Apply	Create dashboard of applicants & show success	Big bet	01
	Template CVs	Utilities	02
	Guides	Utilities	02
Reapply / Apply again	Visual results	No brainer	01
	Rating (stars)	No brainer	01
	AI that creates data that helps person change parts in CV	Big bet	03
	Make it fun / a game	Big bet	03
Ask for feedback	Analytics / visual feedback	No brainer	01
	Virtual Agent / Concierge	Utilities	01
	Clippy	Unwise	01

Pain Point > Big Idea > Priority > Category			
Pain Point	***Big Idea***	***Priority***	***Category***
	Visual CV feedback	No brainer	01

TABLE II. BIG IDEAS, PRIORITY, CATEGORY GROUPS 3 & 4

Pain Point > Big Idea > Priority > Category			
Pain Point	***Big Idea***	***Priority***	***Category***
Researching / Reviewing system	Provide visual statistics to explain AI system's decision	No brainer	01
	Category / criteria selection or manipulation	No brainer	04
	Hire someone else to fix system	Big bet	
Reviewing & messaging unsuccessful	Multiple job to candidate criteria matching	No brainer	02, 04
	Candidate pooling	No brainer	02, 04
	Double validation: checking successful and unsuccessful candidates' data for errors or untruths	No brainer	04
	Bias tracking	Big bet	04
	Theme identification related to unsuccessful applicants	No brainer	04
	Inform applicant how to improve	No brainer	02
Identify who can help	Clippy	No brainer	01
	Virtual agent	Utilities	01
Inform senior management of concerns	Visual Record	No brainer	01
	Audit report to share with management	No brainer	01
	Compare / track old system with new one	No brainer	02

One area of interest which we used to interpret our findings was the participants' use of drawing and visual ideation to explain their concepts in how both personas might better understand AI.

Figure 7. Participants visualisation of visual feedback & analytics.

Since drawing is encouraged as an integral part of design thinking activities, participants' visual interpretations

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of how AI might be explained resulted in thought-provoking ideas which informed our allocation of categories [24]. For example, participants described visual analytics showing a job applicant's score in categories related to keyword matching. *"Here are analytics with tables and charts so you can see if you want to hire someone…some sort of visuals or charts to say this is your rating for your employment history or this is your rating for your software skills…stars even"*. See Figure 7. Highlighting perceived flaws or poor keyword matching in an applicant's data was also considered. *"We looked at comparing past and present CVs and highlighting problems on a CV so if the person's CV is lacking or they have something written on it that they shouldn't, highlight those"* See Figure 8.

Figure 8. Participants visualisation of highlighting problems & offering chances to rectify.

VI. DISCUSSION

Our findings support research into the use of feature highlighting using factual explanations, for example, why the system produced certain results, versus counterfactual explanations, why the system produced one result over another, to better explain AI to users [26]. When a user's expectation is matched to the output of the system, in this case a job applicant believes they are suitable for a role or a recruiter expects certain applicants to receive an interview, factual explanations should be used. In the case of our personas, Andrew would expect CV rating, analytics or visual feedback if his application was successful or unsuccessful: "You scored 1 star in team working skills" or "You scored 20% in years' experience". However, a more useful explanation would be found in a counterfactual explanation when Andrew's expectation of the system is not met. Explanations highlighting why one decision was made over another would better explain the system's decisions [27]. "You were unsuccessful as your score of 1 star in team working skills should be at least 5 to progress to the next stage". This can be further explained using principal reason explanations where the factors which dominated the system's decision are explained but allow the user to act and receive a different result [27] which in Andrew's case would include being given an explanation highlighting features on his application which determined a negative result and allowing updates and reapplication. As such "You were unsuccessful for this job application because you only have one previous role which included team working skills. You should have at least 5 team working roles. Is this information correct?". For our recruiter, Maria, counterfactual explanations could be used to explain candidate selection not only for those that are successful but also for those that are unsuccessful and principal reason explanations to allow her to manipulate criteria and allow for a different result [30]. For example, "No female candidates were offered interviews due to CV gaps of over 6 months. Would you like to disregard CV gaps?" Although dealing with the domain of recruitment our findings could be useful within many other domains which utilise AI for data processing. Interestingly many of these mental models align with Nielsen's usability heuristics such as visibility of system status, match between system and real world and help users recognise, diagnose, and recover from errors [28]. Challenges encountered during workshops included logistical difficulties related to audio recording of large groups and photographing participants work. Audio tests carried out preworkshop concluded that one recording device located at each group, in this instance 4 audio recording devices, were necessary. Also, we found that recording of playbacks at significant stages, after empathising and pain point identification and after big ideas and prioritisation, was crucial in understanding participants contributions. Essential to successful data collection was the photographing of participants worksheets after each stage. We also engaged workshop facilitators to ensure that groups were focused on the problem statement, personas' engagement with the AI system, rather than solving the issue of recruitment in general.

VII. CONCLUSION

We present an exploration of user's mental models of an AI driven recruitment system where we put the user at the centre of our study. By engaging a design thinking approach with interdisciplinary participants, we discovered novel approaches for participants to communicate their understanding of AI systems and for researchers to understand their internal representations. Future work in this area should also centre around usability heuristics, more commonly referenced in HCI and user interface design, which should also be applied to more complex systems such as AI.

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