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An Analysis of Personalization Factors in Explainable Artificial Intelligence (XAI) and Its Correlation with Decision Making

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Abstract. This study delves into Explainable Artificial Intelligence (XAI), aiming to address two crucial questions: what aspect we should focus in personalization and how can we make XAI more individualized based on it? What the relationship between XAI and decision making and how should we balance it? A systematic literature search and backward snowball method were used to collect 44 core literatures. In this experiment, four types of personalized feature classifications were summarized: knowledge, character, XAI understanding, need. Four common methods to implement Personalized XAI were identified: correctness rate, interaction, visualization, and segmentation. The study found that blind pursuit of XAI's credibility can have detrimental effects, suggesting building human - machine systems and using XAI as a tool, which allow users to question and overturn XAI's wrong decisions. This study also found that XAI's effectiveness in decision - making varies with user's personalization. For users with limited knowledge, providing more understandable explanations can be beneficial. For the users only want to make decision quickly, XAI can provide them with correctness rate and simple explanation instead of detailed explanation to help them make decision quickly. However, it acknowledges limitations such as potential sample bias from the snowball backwards and subjective inferences. This research offers a theoretical basis for future personalized XAI research and calls for a more balanced view on XAI's role in decision making.

Keywords: explainable artificial intelligence (XAI), personalization, decision making

1. Introduction

In contemporary technological landscapes, artificial intelligence(AI) has become an important tool to help us to make decisions. However, users' trust remains a main barrier for users to trust AI. explainable AI(XAI), an AI that can show how it makes decisions to users, then appeared and has attracted widespread attention because it can improve users' trust [1-3]. Based on it, how to make XAI more convincing becomes a key. Personalization has shown great potential in it. However, it isn't clear what aspect we should focus on in personalization [4].

In different fields, XAI has different objectives. In the field of health, its primary goal is to increase the confidence of patients and healthcare professionals in AI-assisted medical decision-

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making by increasing the level of trust. In the financial and military sectors, its focus is on risk avoidance and ensuring the safety of the decision-making process; In the case of a recommendation system, the main focus is to improve system transparency and user satisfaction, so as to optimize the recommendation effect. In the academic research environment, it also covers multiple motivations such as promoting human-machine synergy and symbiosis, and promoting academic innovation [5]. We can know that in most of situations, trust isn't the ultimate goal, but making the right decision is. a lot of research focusing too much on trust so that they ignore the accuracy of decision making.

In this research, l focused on two problems: what aspect we should focus in personalization and how we can make XAI more individualized based on it? What is the relationship between XAI and decision making, and how should we balance it?

I gather literature in the field of XAI. To solve the first question, I count the Personalized differences that work in the paper and the way to improve trust in XAI, then I analyze and summarize so that I can find the personalization that really needs to be focused. To the second, I will narrate my point of view based on the paper I found.

2. Methodology

2.1. Literature search

In this study, in order to comprehensively and accurately obtain the literature closely related to the research topic and build a solid research foundation, I conducted a systematic literature search, and finally identified 44 core literatures. This literature search process is described in more detail below.

In this study, Literature search and backward snowball methods were employed. Firstly, I identify the keywords: XAI, explainable AI, explainable artificial intelligence, personality trust, and decision making. Then, limit the time frame to 10 years. The search operation is then performed in the Web of Science and the Hollis database. After that, I found some authoritative literature in XAI. Then use the backward snowball method for these documents. After removing duplicate documents, I find 185 original articles.

2.2. Literature screening

Firstly, I filter by article title and abstract. The screening criteria are as follows: Literature must be directed around the research topic, XAI is explicitly involved, Empirical research literature is preferred, Individualized differences or XAI decisions are used as research content. After this round of screening, I excluded 102 articles that were not related to the research topic, and the remaining 83 articles entered the full-text screening stage.

Then, I download and read the full text of 83 articles, thoroughly evaluate the content of the literature, the research methodology, the reliability of the conclusions, and the degree of contribution to the research topic. Literature that is too broad in content and does not delve into the core issues of the research topic are excluded. Finally, 44 high-quality articles were identified as the core references of this study. These documents can provide sufficient theoretical support and empirical basis for our research

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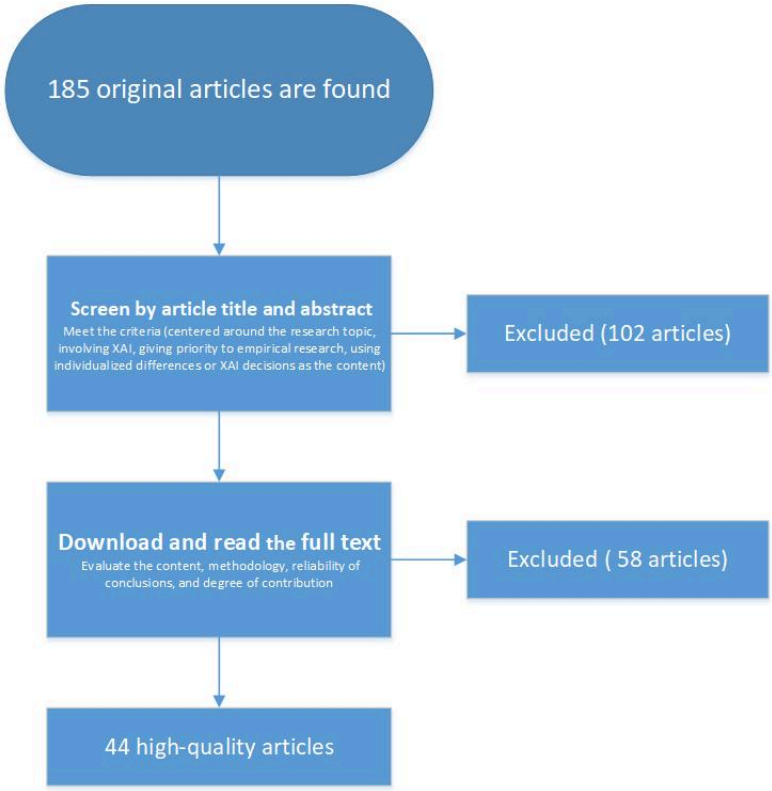

Figure 1: Literature screening process

3. Personalization

3.1. Personalized categorization

Based on the articles I found, I made figure 1, which shows the degree to which each individualization factor has received attention in the literature, and figure 2, which shows the degree to which each method has received attention in the literature.

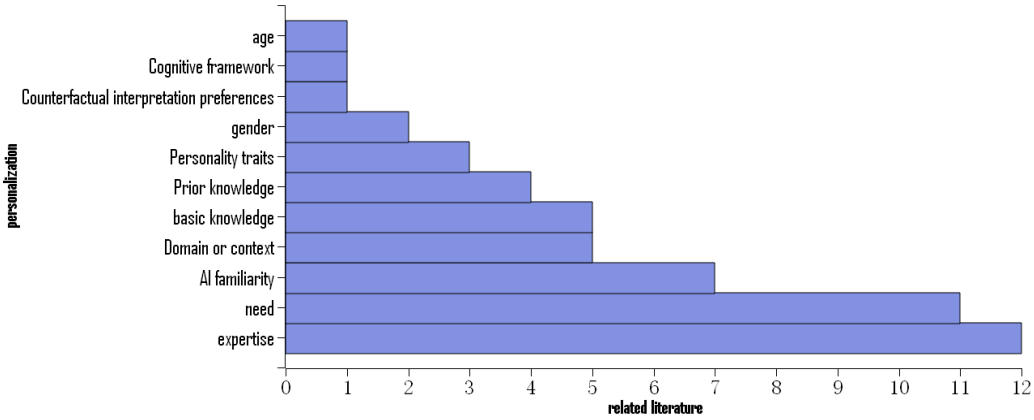

Figure 2: Personalized characteristics and the number of relevant literatures

At first, an explanation of the concepts in the figure is as follows: in Figure 2, expertise means how specialized users are in a field when it comes to solving problems in this field with XAI. Need

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means that what users want in XAI, such as a simple explanation or a detailed explanation. AI familiarity means how often users use AI or users' degree of understanding of the logic behind AI, which shows users' proficiency in using AI. The domain or context is which field and what situation users face. For example, a user is a doctor, and he is about to give suggestions to a patient, so the field is healthcare. Then he may use XAI to make a decision, to convince his colleagues, or to convince his patient, it is in a different situation. Basic knowledge is the user's scientific knowledge, logic, or reading ability, which can help users to understand the explanation XAI gives. Prior knowledge is an understanding of a specific model, which may come from the user's knowledge or an introduction to this XAI. It means that users can predict how XAI gives an explanation and what explanation XAI will give. Personality traits are a user's personality based on the Big Five Personality [6]. Counterfactual interpretation preferences are whether users prefer counterfactual interpretation in the XAI explanation. Cognitive framework refers to a kind of mental structure or pattern that people use to understand, organize, and interpret information. It helps individuals perceive, process, and remember information, and also influences their views on things and decision-making.

Then I exclude some personalization factors from my further classification:

Age differences may contain differences in AI familiarity, basic knowledge, and expertise because users of different ages must have different times in learning and AI use, so it can't be a personalization with full trust, but it can still be used as an auxiliary means to judge the user's personality. The cognitive framework is too broad and difficult to quantify, so I don't think it is a good personalized judgment. Gender is like age; it contains different preferences in different aspects, it can't be personalized with full trust, but can also be used as an auxiliary means. Counterfactual interpretation preferences I will discuss in the following part: another find.

I divide the rest of the personalization into four categories: knowledge, character, XAI understanding, and need. Knowledge contains basic knowledge and expertise; it represents the user's ability to understand the explanations given by the XAI. Character contains personality traits; it represents a user's preference to the way XAI give an explanation. XAI understanding contains AI familiarity and prior knowledge; it represents the user's understanding to a specific XAI: How much do users know the general logic of XAI? how well do users understand how this specific XAI works, how will they explain it, and what kind of explanation will it give? It shows whether the user can use XAI Skillfully. Need to contain domain or context and need; it shows what the user really wants from XAI, in different domains, different situations, users may have different needs, use this to make personalized XAI can help a lot.

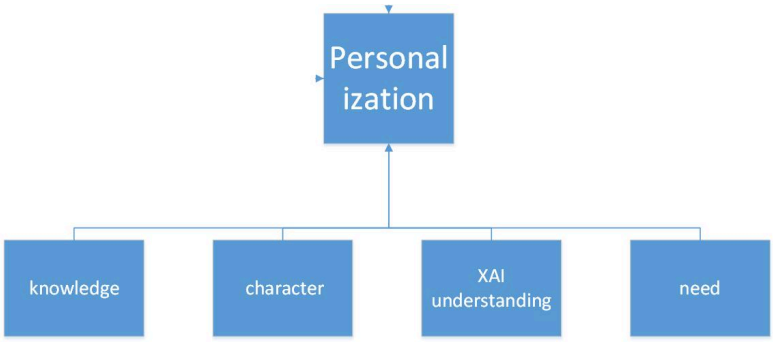

Figure 3: Classification of personalized features

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3.2. Ways to personalize XAI

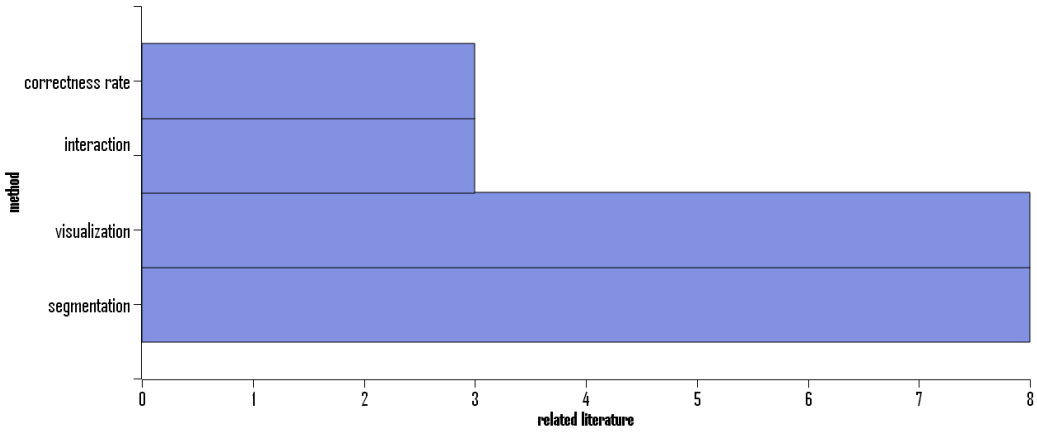

Figure 4: Way to implement personalized XAI

In the literature I find, it has 4 majority way to implement XAI personalization: correctness rate is showing the possibility of making the right decisions to users; interaction is allowing users to interact with XAI to change the degree of professionalism of the explanation, the method of giving the explanation and so on, which make a tailor-make XAI to users. Visualization is providing users with pictures to varying degrees in the explanation, because users with less knowledge or shallower XAI understanding may more like pictures than users with more knowledge or deeper XAI understanding [7]. Segmentation means that it give different explanations to users with different knowledge, XAI understanding or needs.

3.3. Another found

In the process of literature collation, I find that 8 articles mentioned the type of interpretation in different way [8,9]. Counterfactual explanations are more effective than descriptive explanations in helping people understand system decisions [10]. Counterfactual explanations are comparatively more understandable to medical experts [11], but it has individual differences [12]. Attributive and deductive explanatory styles work well in stock trading tasks [13]. Different expert has different attitudes to different methods of interpretation [14]. The initial level of trust was affected by the explanatory type, which was higher in the intentional and mixed conditions, and satisfaction with causal explanations was the lowest. The overall level of trust decreased over time and remained relatively stable under mixed conditions [15]. It shows that the type of interpretation has the potential to help users make decision by XAI.

4. Decision making and XAI

XAI now faces a lot of problems in decision making and trust.

For experienced clinicians, the XAI system allows them to get more help from their interpretations, benefit more from the diagnostic process, and increase their confidence and trust in the diagnosis. Clinicians with less experience benefit more from ordinary AI support. The study found that there was a slight correlation between clinicians' improved diagnostic accuracy and dermoscopy experience, with physicians who were more involved in the scientific discussion of dermoscopy benefiting more from XAI support, and physicians who rarely performed dermoscopy

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were likely to experience reduced accuracy when using XAI [16]. In this study, XAI reduced decision-making accuracy in doctor with low knowledge and Shallow XAI understanding instead of improving it. However, AI helps them more than XAI. This is also the case in other literature [17-20]. It is because users with low knowledge and Shallow XAI understanding can't really understand the explanation or even mistakenly think they understand [21].

Based on it, users may also blindly trust XAI though they not understand the explanation. For example, the simple exposure effect will increase people's confidence in machine predictions due to the presence of explanations [22]. Which leads to the exacerbation of some cognitive biases, then leads to wrong decisions. In contrast to that, some users require the system to be 100% accurate in order to be fully trusted.

Most of the above questions originate from user's low knowledge and Shallow XAI understanding. To the users with more knowledge and deep XAI understanding, XAI helps them a lot, even XAI may give error suggestions [14,23,24]. It is because users with more knowledge and deep XAI understanding can find the error in the explanation or contradiction between the suggestion and explanation, which help them to overturn the wrong decision of XAI. In this process, they may also find Information they left out so that they can make better decisions.

Subjective measures such as trust and preference do not accurately predict a user's performance in an actual task. In the actual decision-making task, although the participants trusted and preferred the AI of deductive explanation, when the AI recommended the error, their decision-making accuracy under the inductive explanation was higher [8].

All of the above show that current XAI needs users to understand and analyze its explanation, which means it is more suitable to users with more knowledge and deep XAI understanding. How about the users with low knowledge and Shallow XAI understanding? we can provide it with an explanation that is easier to understand, like put more pictures in it or providing them with natural language interpretation. To users who only want to make a decision quickly, we can provide them with the correctness rate and a simple explanation instead of a detailed explanation, which helps users with different needs.

In a word, trust is a side benefit of useful and reliable systems that use machine learning models, which evolve slowly over time. If trust is used as an indicator to evaluate the value of explanation, it may lead to artificially inflating the level of trust and harming the interests of users [25]. Thus, we should set up a human-machine system, give users the ability to overturn erroneous conclusions instead of blindly pursue to improve users' trust in XAI. Users with more knowledge and deep XAI understanding can use AI as a tool to help them. To the users with low knowledge and Shallow XAI understanding, we can provide them with more understandable explanations.

5. Discussion

This study has some limitations: the number of original documents is insufficient, and used the backward snowball method, which can lead to bias in the sample and thus not reflect the overall picture more accurately. The article contains subjective inferences, which may not accurately reflect the real situation due to cognitive biases. The research was mainly carried out through literature review and theoretical analysis, and no empirical research was conducted. The effectiveness has not been tested in real-world scenarios, and it is difficult to determine the effectiveness and feasibility of these methods under different user groups and task types.

For future study, it can design and implement empirical studies and collect actual data to validate theoretical hypotheses on the basis of the classification of personalization features and the methods to achieve personalization in this paper. For example, conducting tests provides users that have

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different levels of knowledge with different levels of explanation and discuss the impact to their decision-making, and provides a more scientific basis for practical application. Conduct an in-depth study of the types of explanations and explore the role they play in XAI. How effective are different types of explanations in different domains and contexts? Which types of explanations are easier to understand, and which types of explanations are easier to guide users to think deeply?

6. Conclusion

To the question of what aspect we should focus in personalization and how we can make XAI more individualized based on it? The answer is that we should focus on knowledge, character, XAI understanding, and need, and we can use correctness rate, interaction, visualization, and segmentation to get personalized.

To the question, What is the relationship between XAI and decision making, and how should we balance it? The answer is that we should build human-machine systems and think of XAI as a tool. The users with more knowledge and deep XAI understanding should truly understand and analyze the explanation so that users can make better decisions. To the users with low knowledge and Shallow XAI understanding, we can provide them with more understandable explanations. if users only want to make a decision quickly, XAI can provide them with a correctness rate and a simple explanation instead of explaining in detail.

The contribution to this paper is as follows: This paper summarizes the literature in different fields of XAI, and summarizes the universally applicable personalization characteristics across fields and the methods to achieve XAI personalization, providing a theoretical basis for the future of personalized XAI. The relationship between decision-making and XAI is discussed, cautioning researchers against blindly pursuing the credibility of XAI, reminding researchers to start building human-machine systems, using XAI as a tool rather than relying solely on it, so as to increase the probability of the right final decision

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Appendix

Table 1: Personalization and related literatures

Personalization	Related literatures
Age	[4]
Cognitive framework	[26]
Counterfactual interpretation	[12]
Gender	[27][28]
Personality traits	[4][29][30]
Prior knowledge	[14][27][31][32]
Basic knowledge	[28][29][33][34][35]
Domain or context	[7][9][12][14][32]
AI familiarity	[7][15][18][19][33][34][36]
Need	[17][18][19][29][30][34][35][37][38][39][40]
Expertise	[7][16][17][18][19][20][21][24][33][37][41][42]

Table 2: Method and related literatures

Method	Related literatures
Correctness rate	[9][12][20]
Interaction	[33][34][40]
Visualization	[7][19][20][33][40][41][42][43]
Segmentation	[17][18][34][37][39][40][42][44]