Transcending XAI Algorithm Boundaries through End-User-Inspired Design

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Abstract

The boundaries of existing explainable artificial intelligence (XAI) algorithms are confined to problems grounded in technical users’ demand for explainability. This research paradigm disproportionately ignores the larger group of non-technical end users of XAI, who do not have technical knowledge but need explanations in their AI-assisted critical decisions. Lacking explainability-focused functional support for end users may hinder the safe and responsible use of AI in high-stakes domains, such as healthcare, criminal justice, finance, and autonomous driving systems. In this work, we explore how designing XAI tailored to end users’ critical tasks inspires the framing of new technical problems. To elicit users’ interpretations and requirements for XAI algorithms, we first identify eight explanation forms as the communication tool between AI researchers and end users, such as explaining using features, examples, or rules. Using the explanation forms, we then conduct a user study with 32 layperson participants to elicit their interpretations and requirements for XAI algorithms, in the context of achieving different explanation goals (such as verifying AI decisions, and improving user’s predicted outcomes) in four critical tasks. Based on the user study findings, we identify and formulate novel XAI technical problems, and propose an evaluation metric verifiability based on users’ explanation goal of verifying AI decisions. Our work shows that grounding the technical problem in end users’ use of XAI can inspire new research questions. Such end-user-inspired research questions have the potential to promote social good by democratizing AI and ensuring the responsible use of AI in critical domains.

1 Introduction

As the research development of explainable artificial intelligence (XAI) or interpretable machine learning algorithms comes to a steady state (Molnar, Casalicchio, and Bischl 2020), it becomes increasingly difficult to propose novel XAI algorithms. Concurrently, despite many XAI algorithms being proposed, it is unclear how to use and evaluate them for their real-world impact. Lipton (2017) criticized this phenomenon as “a surfeit of hammers, and no agreed-upon nails”. This is partially due to the sole motivation that drives XAI algorithm development (Miller, Howe, and Sorensen 2017): XAI algorithms are designed by AI people for AI people, with the explanation problem grounded in model debugging, understanding, and improvement.

Meanwhile, designing XAI algorithms for end users to support their critical tasks has high demand and significant social impacts, but receives disproportionately little attention in the current XAI research paradigm (Umm-E-Habiba, Bogner, and Wagner 2022). As AI becomes pervasive in high-stakes tasks – such as in supporting end users’ medical, legal, financial, or driving judgments – making AI explainable to its end users is crucial to ensure the safe, ethical, and legal use of AI in critical domains. The non-technical end users, or end users for short, do not have technical knowledge in AI, machine learning, or programming. They could be laypersons or domain experts, such as physicians, judges, drivers, bankers, and other critical decision-makers. Compared to technical users’ demand for XAI towards model debugging, end users have more diverse requirements for explainability. Prior evaluations showed that directly applying existing XAI algorithms to end users’ tasks failed to achieve the key function of explainability in detecting model biases (Adebayo et al. 2022), or lacked key information on feature description to support clinical reasoning (Jin et al. 2022). These issues make designing XAI techniques for end users a more challenging research problem, one that needs to be addressed to ensure that AI and its explanation effectively support end users’ critical decisions. Designing XAI for end users also has a significant social impact: it democratizes AI technologies to make AI more accessible to a larger group of users, who use AI to perform critical tasks. The unmet needs and impactful research problem of designing XAI algorithms for end users has the potential to expand the algorithmic boundaries of XAI.

In this work, we explore how incorporating users’ insights leads to the framing of new XAI research problems. To overcome the technical communication barriers between XAI techniques and end users, we identify a shared vocabulary of the abstracted explanation forms, which serve as a bridging tool between AI researchers and end users. Explanation forms weave human-interpretable features into their individual reasoning process, as represented by the form of feature- (feature attribution, feature shape, feature interaction), example- (similar, typical, and counterfactual example), and rule-based explanations (decision rule and decision tree). Using the visual representations of the explanation forms, we conduct a user study with 32 layperson participants to elicit their interpretations and requirements for XAI algorithms, in the context of achieving different explanation goals (such as verifying AI decisions, and improving user’s
predicted outcomes) in four critical tasks. Inspired by the user study findings, we formulate several novel XAI technical problems, and propose an XAI evaluation metric verifiability based on the users’ explanation goal of verifying AI decisions. This work is an example to show that understanding end users’ demand for AI explainability may be a source of inspiration for the proposal of new XAI algorithms with meaningful social impact. It also calls for a new research paradigm of designing end-user-oriented XAI algorithms.

Our contributions are: (1) We conduct a user study that enables AI researchers to understand end users’ interpretations and requirements for XAI algorithms. (2) Based on insights gained from end users, we formulate several new XAI technical problems, and propose a computational XAI evaluation metric verifiability. From these, we call for a new research paradigm of end-user-oriented XAI for technical innovation as well as social impact. (3) We identify explanation forms as a bridging tool to support technical communication between AI researchers and end users. We also provide human-centered design methodological support for AI researchers to use the tool in end-user-inspired XAI algorithmic design.

2 Related work
This interdisciplinary work utilized research methods and was inspired by ideas from the following domains on XAI:

End-user-inspired XAI techniques We summarize works with the technical problem formulation grounded in end users’ use of XAI. Wang and Rudin (2015) proposed the falling rule list that prioritizes high-risk predictions, which aligns with human decision-making patterns in critical tasks. Biran and McKeown (2017) used natural language to generate human-centered important feature explanations focused on domain knowledge and human reasoning. Adebayo et al. (2022) conducted computational evaluation and a user study that identified post hoc explanations as ineffective in helping end users to detect unknown spurious patterns that a model relies on. Jin, Li, and Hamann (2022) proposed a computational evaluation metric grounded in physicians’ clinical image interpretation patterns, and conducted a systematic evaluation on 16 saliency map algorithms. Results showed the examined algorithms were ineffective in helping clinical users appreciate the AI model decision process or gauge the decision quality. These works show the importance of and research gaps in end-user-oriented XAI algorithms.

Human-centered XAI: design principle and user study The human-computer interaction (HCI) community calls for human-centered XAI, which uses human-centered design methodologies to propose and assess XAI techniques based on the understanding of users and their tasks. Liao and Varshney (2021) proposed an explanation rule-based visualization RuleMatrix for end users to understand, explore, and validate black-box AI models. Wang et al. (2019), Liao, Gruen, and Miller (2020). Specific user studies were also conducted to understand users’ perceptions on various XAI techniques, such as laypersons’ interpretations of similar and counterfactual examples (Cai, Jongejan, and Holbrook 2019), counterfactual examples in recommendation systems (Shang, Feng, and Shah 2022), rule-based explanations (Huysmans et al. 2011), and decision sets (Narayan et al. 2018); and pathologists’ interpretation of similar examples (Cai et al. 2019), feature attribution, typical, and counterfactual examples (Evans et al. 2022).

Our work is built upon prior human-centered XAI efforts to understand users’ requirements, but differs in that we conduct the first user study on a comprehensive subset of XAI techniques that are end-user-friendly. This study design enables users to directly compare all available XAI techniques in the same setting. It also differs by taking a step further and directly framing new technical problems inspired by end users’ requirements. To the best of our knowledge, this is the first work that aims to close the loop from user understanding to XAI algorithm design, and bridge AI research with human-centered XAI.

Requirements engineering for XAI Studies in the field of requirements engineering focus on using different human-centered methodologies to elicit users’ requirements for XAI (Chazette et al. 2022; Umm-E-Habiba, Bogner, and Wagner 2022), such as using interview, prototyping (Eiband et al. 2018), focus groups, observations, questionnaires, and scenario-based design (Wolf 2019). Our user study design mainly utilizes methods of interview and card sorting.

XAI and information visualization Information visualiation and visualization analytics (VIS) are indispensable components of XAI systems. However, current research is mainly motivated by technical users’ demands of XAI for model monitoring and debugging (Alcioglu and Sun 2022). To design for the larger and neglected group of end users, Ming, Qu, and Bertini (2019) proposed an interactive XAI visualization RuleMatrix for end users to understand, explore, and validate black-box AI models. Jin et al. (2019) proposed the end-user-centered XAI visual vocabularies, which summarize the visual representations of XAI algorithms in an effort to bridge AI developers with end users. Their work inspired our work on the visual representations of explanation forms.

3 End-user-friendly explanation forms Since we cannot assume end users to have technical knowledge in AI, to effectively elicit their requirements for XAI algorithms, we identify the end-user-friendly explanation forms as a communication tool. An explanation form is the abstracted structure of information generated by an XAI algorithm. An explanation form has an end-user-facing property of its various visual representations, and an AI researcher-facing property of its different underlying XAI algorithms. Thus, it is a bridging interface that designed to categorize the XAI algorithm space according to end-user-centered properties. To identify the end-user-friendly explanation forms, we conduct a literature review and examine XAI surveys in the AI, VIS, and HCI domains, extract the output explanation forms from XAI algorithms, and filter out the forms that require technical background to interpret (such as dimensionality reduction or artificial neuron visualization) (detailed in Supplemental). The result comprises
eight end-user-friendly explanation forms categorized into three groups: feature-, example-, and rule-based explanations.

Before introducing individual explanation forms, we set up the general explainability problem: a predictive model \( f \) maps an input \( x \) in the input space \( X \) to a target prediction \( y_t \) in the output space \( Y \), i.e.: \( y_t = f(x) \). An XAI algorithm generates explanations on how the model \( f \) makes predictions. For local explanation on a certain input \( x \), the to-be-explained outcome \( y \in Y \) can be the target prediction \( y_t \), or the prediction difference \( \Delta y \) comparing the prediction \( y_t \) with a baseline \( y_b \).

We observe that for an end-user-friendly explanation form, the human-interpretable feature \( t \in T \) is the elemental component (where \( T \) denotes the human-interpretable feature space). Different explanation forms weave features into their individual logical chain or reasoning process to describe the model decision process. Feature-based explanations describe features \( t_1, t_2, \ldots \in T \) and their relationship with the outcome \( y \) quantitatively; example-based explanations present features \( t_1, t_2, \ldots \) within their context as instances \( x_m, x_n, \ldots \in X \); and rule-based explanations organize features \( t_1, t_2, \ldots \) and outcomes \( y \) by logical and conditional statements. Next, we describe each explanation form, its XAI algorithm examples (oriented to the AI researcher), and visual representations (oriented to the end user).

3.1 Feature-based explanations

1. **Feature attribution** decomposes \( y \) into a set of important features \( t_i \in T \), each having a marginal attribution \( a_i \) to \( y \), \( y = \sum_{i \in T} a_i t_i \). Examples of XAI algorithms that generate feature attribution explanation include \( \text{linear or scoring models (Ustun and Rudin 2016), Shapley value (Shapley 1951), SHAP (Lundberg and Lee 2017), TCAV (Kim et al. 2018)} \). Its visual representations (Fig. 1) include bar plots for tabular data or concepts, and saliency maps (Adebayo et al. 2018) for high-dimensional data (image or text).

2. **Feature shape** describes the marginal effect of a feature \( t_i \) to the outcome \( y \): \( f_t(t_i) \). Algorithm examples include: GAM (Tian et al. 2018); PDP (Friedman 2001), and ALE (Apel et al. 2020). Feature shape visual representations include lines (for continuous features) or bar plots (for categorical features) that show the relationship of \( t_i \) w.r.t. \( y \).

3. **Feature interaction** is an extension of feature shape by describing the joint marginal effect of more than one feature to the outcome: \( f_{t_1t_2}(t_1, t_2) \). Algorithms include GA2M (Caruana et al. 2015); PDP, and ALE. Its visual representation is a 2D or 3D heatmap to visualize the effect of \( t_1, t_2 \) w.r.t. \( y \).

3.2 Example-based explanations

4. **Similar example** is an instance \( x_s \) that shares similar features with the query input \( x \) regardless of their predictions. Mathematically, similar examples are instances that have minimal distance to the query: \( \arg \min_{x_c \in X} d(x_c, x) \), where \( d \) is the distance or dissimilarity measure. Algorithm examples include \( k \)-nearest neighbors, graph-based approach (Kawahara, Moriarty, and Hamann 2017), and case-based reasoning (Kolodner 1992).

5. **Typical example** or prototypical example is a representative instance of a prediction class, i.e.: an instance \( x_t \) that maximizes the probability of the target prediction \( y_t \): \( \arg \max_{x_t \in X} p(f(x_t) = y_t) \). Algorithm examples include \( k \)-medoids, MMD-critic (Kim, Khanna, and Koyejo 2016), and CNN prototype (Li et al. 2018; Chen et al. 2019). For both similar and typical examples, their visual representation is to show the example with its prediction.

6. **Counterfactual example** is an instance \( x_c \) whose features are minimally dissimilar to those of the query input \( x \), yet its outcome \( y_c \) is different from the target outcome \( y_t \) of \( x \), i.e.: \( \arg \min_{x_c \in X} d(x_c, x), s.t. \max p(f(x_c) = y_c) \neq y_t \). Algorithm examples include visual counterfactual (Goyal et al. 2019), and pertinent negatives (Dhurandhar et al. 2018). Its visual representations can be shown as two instances \( x \) and \( x_c \) and their predictions \( y_t \) and \( y_c \), with their counterfactual/contrastng features highlighted, and/or a transition from one instance to the other by gradually changing the counterfactual features.

3.3 Rule-based explanations

7. **Decision rules and decision sets** are IF-THEN statements with conditions and predictions. Algorithms include Bayesian rule lists (Yang, Rudin, and Seltzer 2017); LORE (Guidotti et al. 2018), and Anchors (Ribeiro, Singh, and Guestrin 2018). Rules are usually represented using the IF-THEN text. Other representations include table (Castron and Bertini 2019) or matrix (Ming, Qu, and Bertini 2019) to align, read, and compare rule clauses more easily.

8. **Decision tree** represents rules graphically using a tree structure, with branches representing the decision pathways, and leaves representing the predicted outcomes. Algorithms include disentangled CNNs (Zhang et al. 2018); and model
distillation (Frosst and Hinton 2017). Its most common visual representation is to use a node-link tree diagram.

4 User study method

We conduct a user study to understand end users’ generic interpretations and requirements for XAI algorithms regarding our proposed explanation forms. We include four AI-assisted critical tasks: House – users use AI to estimate their house price; Car – users use AI to predict their diabetes risk; Bird – users use AI to recognize an important biology exam. For each task, we create a set of visual representation cards that cover all applicable explanation forms. Since users’ need for explanation is usually a subtask in their whole decision-making process, we elicit participants’ comments for the explanation forms in different subtasks as the following explanation goals: calibrating trust, ensuring safety, revealing potential biases, when AI’s prediction is expected or unexpected, differentiating similar instances, learning from AI, improving user’s predicted outcome, communicating with other stakeholders, generating reports, and trading-off among multiple objectives. We indicate the explanation goals with underline.

The study is an in-person, semi-structured interview. The participant is first introduced to one task and its explanation goals randomly. We ask the participant what information s/he requires for an explanation goal. After that, we give a 5-min tutorial on the visual representation cards of explanation forms, ask the participant to select and sort one or a combination of explanation form cards for a given explanation goal in a task, and their reasons for selecting or discarding an explanation form. The detailed study method is in Appendix 3. Following the approval of the university’s Research Ethics Board (Ethics number: 2019s0244), we recruit 32 adult participants (P1-P32) who do not have prior technical knowledge in machine learning, artificial intelligence, or data science. Their demographics are: female: male = 1:1; age range 19-73, age mean±std = 38.2±16.0. We perform qualitative data analysis (Braun and Clarke 2012) on the transcripts of 2,175 minutes (>36 hrs) of audio recordings, by annotating transcripts with labels of explanation forms and goals, and identifying recurring themes. We also perform quantitative data analysis on the 248 sets of data on participants’ selection and ranking of explanation forms. Quantitative and qualitative data, and data analysis Python source code are provided in the Data and Code Appendix.

5 User study result

5.1 Explanation forms

The quantitative results (details in Appendix §4) on explanation forms selected for different explanation goals are shown in Fig. 2, which indicates users may have different preference patterns of explanation for different explanation goals. The underlying reasons are described in the qualitative results. Next, we present the qualitative results to showcase the rich details of the participants’ interpretations and requirements for XAI algorithms, with selected key sentences quoted verbatim. Key findings are summarized in Table 1 and are highlighted in bold.

1 Feature attribution Participants intuitively understand the displayed feature information and prefer the “simple way to highlight the most important parts” (P04, for saliency map), and “outline of everything (features)” (P10, for feature bar plot). By showing “finer details” (P10) and “breakdown and weights of features” (P23) “that AI took into account” (P31), participants think feature attribution can answer how and why AI makes decisions. Users also tend to assume features are independent of each other, and have causal effect towards the outcome.

For the attribution information, users have various perceptions and requirements on the level of detail, including suggestions to set a user-defined threshold to “reduce the cognitive load” (P04, learning); and show feature ranking only, with the numeric attributions showing on demand. Regarding applicable explanation goals, users tend to “compare (AI’s feature attribution) with my own judgment, to see if that aligns with my feature ranking” (P01, safety). Users also use the feature importance ranking to prioritize their action to improve user’s predicted outcome.

2 Feature shape The graphical representation of showing the relationship between a feature and the prediction makes users “feel so easy to latch onto, it’s something that you can impact and something that’s very tangible” (P22). Thus, many participants use it for counterfactual reasoning to improve user’s outcome. In addition, by showing the re-
Table 1: Summary of user study findings (Section 5) on users’ interpretations and requirements for XAI algorithms regarding the explanation forms, and the formulation of technical problems (Section 6) based on users’ requirements.

| Explanation form | Users’ interpretation | Users’ requirement | Example of inspired technical problem |
|------------------|-----------------------|--------------------|----------------------------------------|
| Feature attribution | • Simple and easy to understand  
• Assessing AI by comparing features with user’s prior knowledge | • Users may require different level of details on the attribution information | • The proposal of evaluation metric verifiability |
| Feature shape | • Easy to understand  
• Support counterfactual reasoning | • A local or personalized feature shape | • Generate local feature shape on the identified subgroup |
| Feature interaction | • Difficult to interpret | • Prioritize significant feature interactions | • Ditto |
| Similar example | • Easy to understand, similar to human decision-making | • Support side-by-side feature-based comparison among examples | • Indicate feature-level information on examples |
| Typical example | • May be misinterpreted as similar example | • Atypical example to show edge cases for safety and biases check | • Anomaly detection for atypical examples |
| Counterfactual example | • Can suggest improvement  
• Help users differentiate similar instance | • Users can define the counterfactual outcome, the counterfactual feature type and range | • Be able to receive user-defined constraints |
| Decision rule | • The decision logic is simple and understandable | • Need to balance explanation completeness and simplicity | • Collapsible decision rule or tree |
| Decision tree | • Difficult to interpret  
• Can support counterfactual reasoning | • Need to highlight branches for user’s interested instances | • Ditto |

relationship between a protected feature (such as gender, ethnicity) and outcome, feature shape is also helpful to reveal potential biases.

For users’ requirements, despite being a global explanation, participants expect the feature shape plot to indicate the position of their input. Furthermore, P30 suggested constructing a personalized feature shape explanation by matching values of the remaining features with values from user’s input features: “The AI should assume all other features are more similar to mine, considering this hypothesis then this is the (feature shape) curve”. Participants also suggest attaching feature shape to other explanations as details and only shown on demand.

(3) Feature interaction Despite being an extension of feature shape, four participants find the feature interaction graph “less accessible to understand” (P22). Similar to feature shape, feature interaction also supports counterfactual reasoning.

For users’ requirements, participants would like to be able to select feature pairs to check their interactions, and expect AI to suggest or prioritize feature pairs with significant or interesting interactions.

(4) Similar example Similar example explanation “intuitively makes sense” (P16) to participants, as “it’s similar to how humans make decisions” (P02) by using analogical reasoning, “Even though these (similar and typical example) aren’t much specific about how it (AI) is actually doing the (decision) process” (P16), users, in their interpretation, automatically make up the model’s reasoning process by comparing instances: “it gives you comparables, like the houses that are similar to yours, you can compare the price” (P04).

To facilitate users’ comparison among instances, users request the example-based explanation to describe feature-level information, “to pinpoint things (features) that are similar or different between these cases” (P31), “I want to see if there are overlapped features” (P01), “I need to know what factors AI is taking into account in order to compare it with the others” (P16). Also, feature representation should support users’ side-by-side comparison. This is especially vital when the input data format is high-dimensional or difficult to read through.

(5) Typical example Participants may not well distinguish the meaning of a typical example from a similar example, and only seven participants explicitly understand the meaning of a typical example: “you’re getting the average” (P20). For participants who understand its meaning, typical examples help them learn from AI by revealing class-specific characteristics: “clearly separate each category, that helps people to differentiate the different categories” (P04). It also helps to reveal potential problems in the AI model or data, for example to reveal bias.

In some cases, participants expect examples to convey a richer context, such as several typical examples to represent within-class variations, or even atypical or edge cases that, albeit rare, may have stark consequences. This is to understand AI capabilities due to safety and biases concerns: “So they (similar and typical example) don’t really provide enough information about when the weather is different and when you’re driving at night, the results from non-typical conditions (do)” (P27, Car task, Bias).

(6) Counterfactual example It can serve different explanation goals depending on the context. In predictive tasks (House and Health), participants regard it as the straightforward explanation to suggest ways to improve users’ predicted outcome: “this one (counterfactual example) is the direct one telling you what to do to decrease your risk” (P16, Health). In recognition task (Bird), counterfactual example is suitable to show the differences to help users to understand and
differentiate two similar predictions.

Two participants did not understand the meaning of counterfactual example, and could not capture the nuance between it and feature attribution, since they both have features highlighted but for different reasons. It may also make users confused about similar instances, especially in recognition tasks.

Regarding users’ requirements, the two contrastive predictions in a counterfactual example can be user-defined or pre-generated, depending on the specific explanation goals. One prediction is usually from user’s input, and the alternative prediction could be: “the next possible prediction” (P18), users’ own prediction when there is a decision disagreement, the prospective prediction to improve users’ outcome, and the easily-confused prediction to differentiate similar instances. In addition, the counterfactual features may also receive user-defined or pre-defined constraints, such as constraints on only including user-controllable features; and constraints on the range of features.

(7) Decision rule Participants regard decision rule as able to “explain the logic behind how the AI makes decisions” (P27). Particularly, the text description format is “like human explanation” (P01), and “simple enough and understandable” (P11). The text format can be regarded as “more exact” (P05), and is helpful in report generation and user learning.

To reduce the cognitive load of complex rules and carefully balance between explanation completeness and usability, a few participants suggested trimming the rules by presenting shallow levels by default with a wide range of predictions, and showing more features and deep levels on demand with a narrow range of predictions; or “just show rules related to my own house features” (P30); or highlight local rule clauses related to user’s input on top of the global rule explanation.

(8) Decision tree Seven participants find it difficult to interpret the decision tree explanation. Four notice decision tree and decision rule provide “basically the same information” (P02), “all show the decision process” (P10), and are only different in their text or graphical representation. Participants mention an advantage of decision tree is to differentiate similar instances and support counterfactual reasoning by checking alternative feature values on adjacent branches.

Similar to decision rule, participants tended to focus on the branch pathway where their own input resides: “I know there are factors that could be other houses that lead to different prices, but i still see it as, ‘okay, I plug in my own numbers here and what’s my price?’ So it’s still specific to me” (P20, House task).

5.2 Explanation goals

The qualitative and quantitative analysis of explanation goals (Appendix Fig.19) reveal two main clusters of users’ motivations to check the explanation:

To verify AI prediction for user’s optimal task performance The fundamental motivation for users to use an explanation is to verify AI predictions in case AI may err, understand AI’s capability of when, why, and how AI succeeds and fails, gain informed decision support, and ultimately improve user’s decision quality or task performance. This cluster includes the explanation goals of: calibrating trust, ensuring safety, detecting biases, and resolving disagreement.

To improve the user’s predicted outcome, and learn from AI After a user established proper trust or mental model of AI, AI and its explanation can be a knowledge source for users to learn from AI, or seek ways to improve user’s outcome. This cluster includes the explanation goals of: improving user’s predicted outcome, learning and discovering new knowledge from AI, differentiating similar instances, facilitating verbal and written communication, and balancing among multiple objectives.

6 End-user-inspired formulation of XAI technical problems and evaluation

Based on the user study findings, we formulate several novel technical problems and an evaluation metric of XAI. They are examples to show how users’ insights can inspire the proposal of new XAI technical problems.

6.1 XAI technical problem formulation

In (2) feature shape, a participant suggested seeing a local or personalized feature shape. A possible problem formulation would be to define or identify a subgroup of samples by similarity measure, and generate feature shape explanation based solely on the subgroup data. Some challenges on generating the subgroup explanation include sample size, and computational time for interactive personalized explanation (Yusuf et al. 1991).

In (5) typical example, participants requested to check atypical cases due to concerns about AI safety or biases. This can be formulated as an anomaly detection problem on how to detect rare but critical instances for explanation.

In (6) counterfactual example, participants suggested counterfactual examples receiving user-defined constraints on feature type and range. This suggests that AI researchers may need to consider receiving user-defined constraints on feature type and value range in the proposal of counterfactual XAI algorithms.

In (7) decision rule, based on user’s requirement to reduce cognitive load by showing shallow levels by default with a wide range of prediction, and showing more features and deep levels with a narrow range of prediction on demand, we formulate the technical problem of sparse and collapsible decision tree or rule. It receives the constraints that the outputs at shallow or deep levels are non-overlapping, and the similarity to within-branch supporting instances is greater than similarity to between-branch instances.

Based on the user study findings, we also raise open questions on designing end-user-oriented XAI algorithms:

For high-dimensional input data such as images or text, how can we effectively represent human-interpretable features, in order to embed those features as elements to utilize different forms of explanation, such as feature attribution, feature shape, feature interaction, decision tree and rules?
Prior works have explicitly represented features in deep neural networks as concepts (Kim et al. 2018) or typical examples (Chen et al. 2019; Nauta, van Bree, and Seifert 2021). Are there any other ways to represent human-interpretable features in deep neural networks? And how to effectively use the features to explain the model decision process?

A related question for high-dimensional data is how can we indicate feature-level information for example-based explanations, in order to facilitate users’ feature-based comparisons on similar or typical examples?

In the user study, participants tended to choose a combination of explanation forms for different explanation goals. Can we propose XAI algorithms that generate multiple explanation forms? Will the combination be more effective regarding their utility in helping the user achieve one or several explanation goals? In addition, how can we learn to generate the optimal personalized explanation based on prior user preference or interaction?

Can we propose XAI algorithms that can generate new types of explanation form, which use interpretable features more effectively to explain the model reasoning process? For example, using natural language explanation can express a rich decision logic that does not conform to a given structure of an existing explanation form.

6.2 XAI evaluation metric formulation

Defining proper evaluation metrics is important for XAI algorithmic development. In addition to evaluating XAI on the technical aspects, we propose a computational metric verifiability \( V \) to evaluate an XAI algorithm regarding its utility in achieving one of the main explanation goals: verifying AI prediction for user’s optimal task performance. The way users use explanation to verify AI decision and judge AI decision quality or error is mainly to assess the explanation plausibility (i.e.: how reasonable the explanation is compared to user’s prior knowledge), and associate such assessment to AI decision quality. The verifiability metric \( V \) is a computational proxy for the above human assessment process. It evaluates the capability of an XAI algorithm \( M \) in fulfilling users’ explanation goal to verify AI decisions. We construct \( V \) as follows.

We assume users are knowledgeable in the task and their prior knowledge, which allows them to correctly predict the outcome, can be represented as a set of discriminative features \( t_u \in T \). Correspondingly, we assume \( t^*_u \) is the discriminative feature set covered by the explanation generated by \( M \) for \( x_i \) on its target prediction. We now quantify the explanation’s implausibility on \( x_i \) as the dissimilarity \( d \) between \( t^*_m \) and \( t^*_u \), which we denote as \( b_i = d(t^*_m, t^*_u) \). A larger \( b_i \) indicates higher implausibility (lower plausibility) assessment. We now postulate that when \( f \) is correct in its prediction, then the discriminative feature set \( t_m \) covered by \( M \) should agree with the feature sets \( t_u \) reflecting the user’s knowledge, i.e., lower prediction error should coincide with lower implausibility, and vice versa. We define verifiability \( V \) to capture this desired relationship through correlation \( \rho \):

\[
V = \rho(e, b)
\]  

where \( e = [e_1, \ldots, e_n]^T \), \( e_i \) is the prediction error or uncertainty on test data \( x_i \), and \( b = [b_1, \ldots, b_n]^T \). Finally, we note that the aforementioned setup requires the annotated feature set on \( n \) test data \( x_i \in X_{test} \).

7 Discussion

As shown in Section 6.1 user’s insights may inspire the proposal of new XAI techniques by: 1. User’s demands can be added as optimization constraints on XAI algorithms, such as in the case of (6) counterfactual example and (7) decision rule. 2. User’s perspectives can be a new heuristic for AI researchers to identify new research problems, such as in the case of (5) typical example where anomaly detection could be incorporated as part of the explanation. To facilitate AI researcher’s identification of end users’ needs, we provide human-centered design methodological support on prototyping methods and templates based on the explanation forms (in Appendix §2). Our user study aimed at identifying some generic user requirements, but not all of them. Future work in human-centered XAI may involve conducting more user studies focused on eliciting domain- or task-specific requirements with the potential of inspiring the design of user-centered XAI algorithms.

Evaluation is indispensable to validate whether an XAI algorithm can have a real-world impact. However, it is difficult to decide what to evaluate and how to evaluate when designing end-user-oriented XAI. Regarding what to evaluate, in the context of end users’ critical decisions support, we argue that explanation itself is not the end goal, but a means to help the users accomplish a series of downstream subtasks (i.e., explanation goals) while being tightly integrated into the user’s decision-making process. The focus of both computational and human subject evaluation should be the utility of explanation to users’ downstream subtasks, such as to verify AI decisions, and reveal biases. Regarding how to evaluate, in this work, we propose a computational metric verifiability \( V \) on the utility of explanation in verifying AI decisions. The metric can be used as a proxy of and prior to the human evaluation, as it is less costly, and one set of annotated test data can test multiple XAI algorithms. Future work may propose more evaluation metrics and conduct standardized computational and human subject experiments to assess the utility of XAI algorithms to users in achieving their explanation goals.

8 Conclusion

The current XAI research paradigm is mainly technical-user-centered, which disproportionately ignores non-technical end users’ high demand for explainability. To model the problem of designing XAI algorithms for end users to support their high-stakes tasks, we conduct a user study with 32 laypersons in the context of different explanation goals in four critical tasks. The user study findings identify rich details on end users’ interpretation and requirements for XAI algorithms, which can inspire AI researchers to discover new research problems. We further identify and formulate new technical problems by grounding the research problems in end users’ use of
explanation. This work calls for developing XAI techniques for end user-oriented problems to expand the XAI algorithm boundary and achieve significant social impact.

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