# **EUCA: A Practical Prototyping Framework towards End-User-Centered Explainable Artificial Intelligence**

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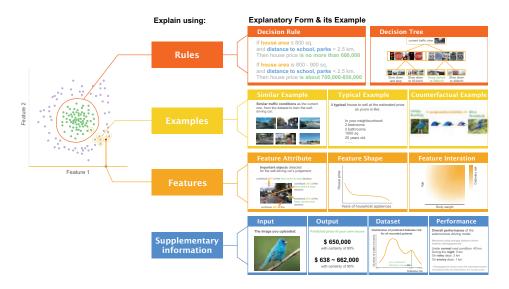


Fig. 1. **End-user-friendly explanatory forms in the EUCA framework**. The explanatory forms are shown on the right grids, each accompanied by a prototyping card example across four tasks used in the user study. The forms are a familiar language to both Al designers and end-users, thus overcoming the technical communication barriers between the two. The 12 explanatory forms are grouped into four categories to explain Al's prediction on a new data point (the red dot in the leftmost 2D feature-space plot), or the model's overall behavior: Explaining using features, examples, rules, and supplementary information. These categories correspond to the different aspects of showing Al's learned representations at the feature, instance, and decision boundary level, indicated in the plot.

The ability to explain decisions to its end-users is a necessity to deploy AI as critical decision support. Yet making AI explainable to end-users is a relatively ignored and challenging problem. To bridge the gap, we first identified twelve end-user-friendly explanatory forms that do not require technical knowledge to comprehend, including feature-, example-, and rule-based explanations. We then instantiated the explanatory forms as prototyping cards in four AI-assisted critical decision-making tasks, and conducted a user study to co-design low-fidelity prototypes with 32 layperson participants. The results verified the relevance of using the explanatory forms as building blocks of explanations, and identified their proprieties (pros, cons, applicable explainability needs, and design implications). The explanatory forms, their proprieties, and

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prototyping support constitute the  $\underline{E}$ nd- $\underline{U}$ ser- $\underline{C}$ entered explainable  $\underline{A}$ I framework EUCA $^1$ . It serves as a practical prototyping toolkit for HCI/AI practitioners and researchers to build end-user-centered explainable AI.

CCS Concepts: • Computing methodologies  $\rightarrow$  Artificial intelligence; • Human-centered computing  $\rightarrow$  User studies.

Additional Key Words and Phrases: Explainable Artificial Intelligence; Machine Learning interpretability; Usability Study; Human-AI Collaboration; User-Centered Design

#### 1 INTRODUCTION

*Problem statement.* Doctors, judges, drivers, bankers, and other decision-makers require explanations from artificial intelligence (AI) when they use AI for critical decision support. As AI becomes pervasive in high-stake decision-making tasks, such as in supporting medical, military, legal, and financial judgments, making AI explainable to its users is crucial to identify potential errors and establish trust [39]. The growing research community of eXplainable AI (XAI) aims to address such problems and "open the black box of AI" [32]. XAI literature generally divides its users into two groups according to their level of technical knowledge in AI: Technical users and non-technical users [21, 74, 75, 78, 86]. The primary focus of current XAI research, however, is on debugging, understanding, and improving AI models for technical users, such as data scientists, AI researchers and developers, leaving the largest and most diverse group of XAI users largely ignored: the non-technical end-users [21, 69]. Non-technical end-users, or end-users for short, can be either laypersons: such as drivers overseeing autonomous driving vehicles, or domain experts: such as doctors using AI-assisted technology in diagnostic tasks [26, 44, 47], judges using AI to support reaching a guilt verdict [51], and bankers using AI to assist in approving loan applications.

Challenges. Compared to developing for technical users that mainly needs to deal with technical challenges in XAI [33], developing XAI for end-users faces even greater challenges: 1) No technical knowledge: unlike technical users, end-users typically do not possess technical knowledge in AI, machine learning, data science, or programming, making some explanation methods which presume users' prior knowledge in AI (such as gradients, activations, neurons, layers) unviable. 2) Diverse users, tasks, and explainability needs: when developing XAI for technical users, users have a relatively unified need: they utilize explanations mainly for debugging, gaining insights on the model, and improving it accordingly [45]. In contrast, developing XAI for end-users must adapt to the variability in the end-users' roles, tasks, and needs for explanation. For example, A doctor may demand distinct explanations from AI when using it as a diagnostic support system, whereas a human resources specialist resorts to explanations to support her hiring decisions (different end-users and tasks). Even if an XAI system is built for the same task, the needs and requirements for explanation may vary. For example, a house seller may leverage the explanation of AI predictions to boost her property value, whereas a realtor may need an explanation to verify why AI's prediction diverges from her own judgment.

Research gaps. Given these challenges, there is an urgent need for end-user-centered XAI design guidance to support AI practitioners' and researchers' XAI design process on critical decision support tasks. Although recent years have witnessed booming research on XAI in both human-computer interaction (HCI) and AI communities [12, 32, 78], research on end-user-centered XAI is still at its infancy. The AI community lacks and calls for such user-centered perspective [62, 68]. In the HCI community, the existing user-centric XAI design guidance [57, 61, 67, 85] utilized a traditional user-centered approach informed by users' requirements only, which may lead to

<sup>&</sup>lt;sup>1</sup>The EUCA framework is available at http://weina.me/end-user-xai

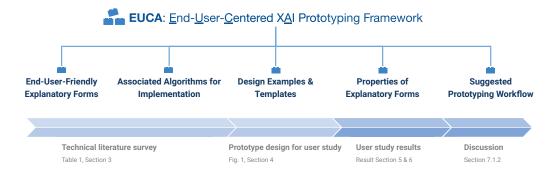


Fig. 2. **EUCA framework components and creation process.** *Top*: EUCA contains 5 components to support XAI prototyping process. *Bottom*: The length of each arrow covers the creation of a EUCA component and its corresponding paper sections. The light blue arrows are preparation stages before the user study, and dark blue arrows indicate the user study phase.

technically-unachievable solutions limited by current AI capacities or training data availability [94]. They also lack support for prototyping, participatory design, and UX/UI (user interaction/user interface) design, which are the most desired support identified by prior user studies with XAI design practitioners [57, 92, 93].

Solution. To address the above challenges and research gaps, we propose the  $\operatorname{\underline{E}nd}\operatorname{\underline{U}}\operatorname{ser}\operatorname{\underline{C}}\operatorname{entered}$  explainable  $\operatorname{\underline{AI}}$  framework EUCA as a practical prototyping framework to support the design and implementation process of end-user-centered XAI. The EUCA framework (Fig. 2) contains a suggested prototyping workflow (Section 7.1.2), a series of end-user-friendly explanatory forms (Section 3) that consider both end-user literacy and technically-viable solutions, their design examples and templates (Fig. 1), their identified proprieties (pros, cons, applicable needs for checking explanations, and UI/UX design implications) from our user study for prototyping support (Section 5), and their associated XAI algorithms for implementation (Table 1). The full content of the framework is in the Appendix, and key messages are summarized in Table 1.

The process of creating the EUCA framework is illustrated in Fig. 2. To tackle challenge 1) lack of technical knowledge, we screened existing XAI techniques, summarized their final representation forms for explanation, and selected those forms that do not require any prior technical knowledge to understand. We finally curated twelve end-user-friendly explanatory forms (Fig. 1): Explaining using features (including feature attributes, feature shape, and feature interaction), examples (similar, prototypical, and counterfactual examples), rules (decision rule and decision tree), and some necessary supplementary information (input, output, dataset, performance). Since they were derived from technical works, the explanatory forms naturally link design representations to XAI algorithms. They enable designers to fully explore the technical feasible solution space, and not have to worry about their design solutions are technically infeasible. Those forms are also a familiar language for end-users, thus providing opportunities to involve users in the prototyping and participatory design process.

To address challenge **2**) **end-user's roles, tasks, and needs diversity**, EUCA incorporates user-centered design in its prototyping process, so that users' context-specific requirements are fully understood and addressed in prototypes. To do so, we first instantiated the explanatory forms as prototyping cards on four AI-assisted critical decision-making tasks across health, safety, finance, and education, and conducted a user study with 32 layperson participants. The interview and card sorting demonstrated using the prototyping cards as building blocks of explanation. And

through a participatory design process, designers and users could discuss and identify the suitable strategy to combine the prototyping cards to construct XAI prototypes that address users' needs for explanation. The user study also identified the strengths, weaknesses, applicable explanation needs, and UI/UX design implications for the explanatory forms.

Contribution. The main contribution of EUCA is that it provides a practical prototyping framework for **AI practitioners** (UX designers, developers, etc.) to build end-user-centered XAI prototypes. The prototyping workflow and tangible design examples/templates support user-centered prototyping and co-design process, and enable end-users to communicate their context-specific explainability needs to practitioners. The suggested prototyping process (illustrated in Fig. 10) is intuitive to follow even for people outside the HCI/UX community. The explanatory forms are simple and familiar for both technical creators and non-technical users, thus can easily invite all stakeholders to the co-design conversation. The coupled XAI algorithms facilitate to implement the low-fidelity prototypes to functional high-fidelity ones.

In addition to the above support for XAI practitioners, **HCI and AI researchers** may prototype using EUCA to propose novel XAI interfaces/algorithms, with the idea of using explanatory forms as building blocks. The user study findings uncovered the strengths, weaknesses, and design implications for each explanatory form, providing opportunities to improve and create new ones.

Besides bridging the communication gap between XAI creators and their end-users, EUCA is also a boundary object [3] that bridge the knowledge gap between AI and HCI/UX expertise. Designing end-user-centered XAI is challenging since it requires both expertise in HCI and AI [90]. EUCA is built with a collaborative effort of combining AI and HCI expertise, and XAI creators working in either field can use EUCA to compensate for the missing expertise, or to scaffold the conversation and collaborate with team from the other field. HCI designers and researchers use the prototype since it's the representation of the underlying algorithm ("form followed by functions"). For HCI/UX designers who lack constant access to AI experts, we provide design method that abstracts XAI techniques into tangible design patterns and exemplars. By having a tool to directly talk to users, EUCA introduces the notion of prototyping and user-centered design to AI researchers and the AI community. It joins the recent effort in XAI field to synergize the HCI and AI community to facilitate interdisciplinary collaboration and communication [12, 90].

In addition to the EUCA framework contribution, the user study also identified fine-grained end-users' requirements in different explainability needs, such as to calibrate trust, detect bias, resolve disagreement with AI, and to improve the outcomes.

### 2 BACKGROUND AND RELATED WORK

#### 2.1 Explainable AI and User-Centered Perspective

Explainable artificial intelligence (XAI), or interpretable machine learning (ML), is usually regarded as a sub-field of ML. XAI can be narrowly defined as revealing the model decision making process. But a broader definition includes all necessary background information to make the AI model and its decision-making process transparent and understandable [72], including the training data and model performance. We adopt the broad definition of XAI in this paper.

Unlike other ML fields that rarely involve end-user in the technical development and evaluation phase, XAI inherently has a close relationship with its end-users: In the end it is the users who will interpret the explanations resulting from XAI techniques. Although in the past few years, the XAI field is booming (largely due to the pervasive use of AI in critical tasks and the legal and ethical requirements on model transparency and accountability [1]), and many XAI techniques were proposed, most works remained at an algorithmic level. It is unknown whether or how they will work in practice, and what are their suitable use cases. As Lipton criticized, "with a surfeit

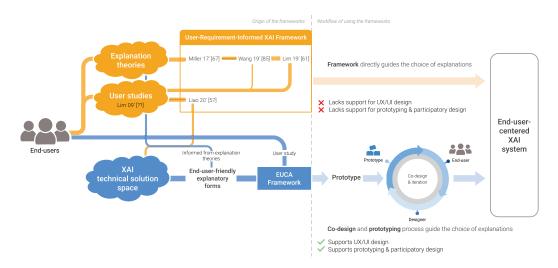


Fig. 3. Visualizing the distinction between EUCA and prior frameworks regarding their user-centered origin The left half shows two distinct streams of developing the user-centered XAI frameworks: informed by users' requirements only (top: existing frameworks), and informed by both technical capabilities and users (bottom: EUCA). The curved and straight lines indicate knowledge sources or prior works they originated from. The right half outlines the workflows of using the two types of frameworks in practice. While user-informed frameworks imply a linear workflow that does not provide opportunities to incorporate users' feedback before implementation, EUCA framework supports an iterative prototyping process. A detailed comparison regarding the two workflows is expanded in the next figure.

of hammers, and no agreed-upon nails,"..."we fail to ask what end the proposed interpretability serves" [62]. Although a number of XAI technical taxonomies [72], surveys [41, 87], and technique selection guidance [18] were proposed, they only support the technique selection process in the back-end, not the whole system design including the front-end UI/UX design and user requirements analysis. These technical guidelines also mainly consider the technical aspect rather than usability requirements, and are technique-oriented, not end-user-oriented.

The ML and XAI community realized such pitfalls and calls for a human-centered perspective and collaboration between HCI and AI fields [62, 68]. The explanation problem is also regaining visibility in the HCI field in recent years. Based on extensive literature analysis, Abdul proposed an HCI research agenda on XAI [12]. Vaughan and Wallach discussed the importance of taking a human-centered strategy when designing and evaluating XAI techniques [90]. Furthermore, XAI is usually part of an AI system with XAI being the main component or an embedded feature. Therefore, the human-AI interaction guidance may also be applicable to the XAI system design process as general design principles [14, 94].

# 2.2 User-Centered XAI Design Guidance

2.2.1 Analysis of prior works. To inform the design of user-centered explanations, existing works identify human-centered insights from explanation theories and human-subject studies. We illustrate the comparison of existing user-centered XAI frameworks with EUCA in Fig. 3 and Fig. 4, and state the details below.

Miller summarized the characteristics of explanations from philosophy, psychology, and social science [67]: users prefer simple, *selected* (but may be biased), and *causal* explanations; explanations are *contrastive* to other related predictions, and people tend to seek causal reasoning in

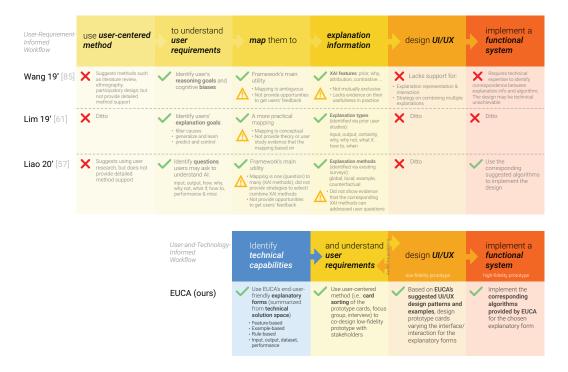


Fig. 4. Workflow comparison of using the two types of frameworks in practice. Prior frameworks imply a user-requirement-informed workflow as shown on the top: user requirement  $\rightarrow$  design  $\rightarrow$  implementation, while EUCA follows a user-and-technology-informed workflow (bottom) by considering technical capabilities. EUCA replaces the direct mapping from user requirements to explanation information, with a iterative prototyping and co-design process (indicate by the back-and-forth arrow in the workflow). For each step in the workflow, we highlight the key actions or results using bold font.  $\checkmark$  and  $\times$  indicate whether a step is supported or not supported by a framework content, and  $\wedge$  indicates the limitations of applying a framework in a certain step.

a *counterfactual* fashion, i.e.: what would the prediction be if certain features of the input had been different. The explanation is a social process in that humans tailor explanatory contents to different explainability needs and audiences.

Following this line, Wang et al. conducted a review on explanation theory literature, and further provided a theory-driven, user-centered XAI framework that describes how human reasoning process and explanation theories guide explanation system requirements [85]. They suggested the XAI system should support reasoning while mitigating heuristics and bias. Their work is a first attempt in developing user-centered XAI design guidance, but remained at a conceptual and abstract level, and lacked actionable guidance on how to practically implement explanation theories for context-specific tasks and needs.

In their follow-up paper, Lim et al. [61] extended the framework by detailing the explanation types (input, output, certainty, why, why not, what if, how to, and when), and proposing pathways to link these types to users' three explanation goals: filter causes, generalize and learn, and predict and control. The explanation type taxonomy was first identified by Lim and Dey in 2009, by surveying users' questions in crowdsourcing user studies for context-aware systems [60]. Our

explanatory forms overlap with their taxonomy in our category of "supplementary information": input, output, and certainty. As a position paper, their proposed linkage is mainly conceptual and lacks user study evidence. They also did not provide practical guidance or implementation support to illustrate its usefulness in real-world tasks. In contrast, we included a variety of explanation needs/goals in our user study, and backed our findings on explanatory forms and explanation needs correlation with qualitative and qualitative user study data.

Liao et al. [57] further explored the idea of providing mapping guidance between users' requirements and explanation types to facilitate human-centered explanation design. The explanation types were identified based on questions users may ask to understand AI. Their framework also provides an additional mapping from explanation types to algorithmic implementation, saving practitioners the efforts and needed expertise in identifying the right algorithm to implement. Using the question list and explanation types as a study probe, they further conducted a user study with 20 UX designers to explore the opportunities and challenges of putting XAI techniques into practice. Their results revealed rich details on users' needs for XAI, but failed to show evidences (such as user studies with users) that the corresponding XAI methods will answer users' questions. Different from EUCA that focuses on the prototyping process, their framework directly guides the choices of explanation types, and it does not provide opportunities to take in users' feedback on design solutions before the system being implemented.

2.2.2 User-Informed vs. User-and-Technology-Informed Paradigm. While prior frameworks utilized a general user-centered approach by proposing design solutions based on users' requirements, such a direct user-requirement-informed paradigm may not be applicable in the context of XAI, or generally, AI system development. If we abstract the human-centered technology development process as the following workflow:

User requirements 
$$\xrightarrow{\textcircled{1}}$$
 Design  $\xrightarrow{\textcircled{2}}$  Implementation Workflow (1)

For common technological development, usually the user-centered challenge is in Step ①: to guide design by getting informed from users, which is the focus of previous frameworks. This approach implies that once we find the design solutions, such design can be easily fulfilled by technique implementation (Step 2)). This is usually the case for traditional technology development, as the functionality of the system can largely be specified and determined by design, but not the case for AI [94]. Yang illustrated it in a case study on designing an AI-driven clinical decision support system [92], where considering users requirements only led to a technically unachievable solution (Step 2) is blocked), due to designers' and end-users' limited understanding of current AI's technical capabilities, or lack of training data to train the proposed AI model. In real-world practice, since UX designers usually "know very little about how AI works", to come up with a technical-viable design, UX designers need to work closely with technical teams to incorporate technical solutions in the craft of design, which is the central stage in the AI system design process. And such relatively novel and unique workflow is the most challenging and unsupported part for design practitioners, and made "working with AI took much longer than when designing other UX products and services", according to Yang et al.'s interview with 13 UX designers who are experienced in AI products [93].

To sum up, the unique of AI and XAI system design requires to take into consideration not only the user side, but fully consider the viable technological solution space [94]. The workflow of designing a user-centered AI or XAI system thus becomes:

As analyzed in previous Section 2.2.1, prior XAI design frameworks [57, 61, 85] follows user-requirement-informed paradigm (Workflow 1), whereas ours is informed by both end-users and technical capabilities (Workflow 2) (Fig. 3, 4). Although previous frameworks tried to address the unique challenge of technical capability in XAI design, by regulating users' requirements in a predefined space (such as pre-defined XAI goals or questions), and provided direct mappings from user's requirements to design solutions, such approach had to compromise design possibilities reside outside the pre-defined space, and limit users' choices, hence may not fully address users' needs. It also makes many existing technical solutions under-explored. In contrast, the EUCA framework is a strategic synergy of both XAI techniques and user-centered design methods. And to the best of our knowledge, we are the first to take the user-and-technology-informed paradigm to develop the end-user-centered XAI framework.

2.2.3 Solution-first design vs. Prototyping. In addition, prior frameworks implicitly suggested using the framework to directly guide the choice of explanation information. The explanation selection and design processes do not provide opportunities to take in users' feedback until the candidate solution has been designed or implemented. The shortcoming of such a solution-first design approach is that the initial premature solution becomes hard to get over, as the effort in crafting design and implementation becomes an expensive sunk cost [79]. In contrast, prototypes, especially the low-fidelity ones, enable quick and inexpensive trial-and-error, allowing full exploration of the solution space before implementation. We discuss the prototype topic further in the next section.

# 2.3 Prototyping and Co-Design as Necessary Processes towards End-User-Centered XAI

Given the complex scenario in real-world design and development practice, using the one-size-fits-all mapping between user's requirements and explanation information provided by existing frameworks may not be applicable. Prototyping provides a quick-and-dirty way to help XAI system designers understand user-, task-, and scenario-specific requirements, to assess and improve their design. It also sensitizes designers to the scope of AI capabilities, "it is through sketching and prototyping that designers understand what the technology is and can do" [94]. Prior works demonstrated using prototypes and involving stakeholders in the co-design processes in various user-oriented XAI development settings.

To bridge technical XAI with their ambiguous and dynamic real-world use, Wolf [89] proposed to apply scenario-based design [79], an HCI method that mimics prototyping idea without a tangible prototype [46]. It creates a narrative description to envision the user experience after deployment to guide the system design. Cirqueira et al. demonstrated applying scenario-based requirements elicitation in designing a user-centric XAI system for fraud detection [30].

Similarly, after a literature reivew, Eiband et al. found there is no consensus in prior works on what to explain, and users' demands vary case-by-case [34]. They then presented their six-month participatory design process on the transparency interface design for a commercial intelligent fitness coach, and demonstrated an iterative prototyping process to answer how to explain as follows: in a focus groups workshop with stakeholders, the team members brainstormed and sketched the UI and user workflow, followed by voting and discussion of the ideas to generate a list of promising implementation ideas. Next they implemented two most promising ideas as a series of low- and high-fidelity prototypes, and evaluated and refined the prototypes in several user testing. The process resulted in two high-fidelity prototypes.

Despite prior attempts in incorporating the prototyping process in XAI design, creating XAI prototypes is still a challenging task and requires technical expertise. Practitioners desire support

on prototyping tools and methodology, according to a number of user studies with UX designers [57, 92, 93]. Our EUCA framework provides prototyping tools and methodologies to facilitate the creation of low- and high-fidelity prototypes that are technologically feasible. This support is particularly useful for designers who do not have ML expertise or lack constant access to capable data scientists.

# 2.4 End-User-Oriented User Studies on Explanation Information

Existing user studies with non-technical end-user participants were conducted in a case-by-case manner, to understand users perception on the explanation information and provide insights for XAI design.

Cai et al. [25] examined the effect of *similar examples* and *counterfactual examples* (named comparative explanations in the paper) in a study involving 1150 layperson participants in an online drawing and guessing platform. They found users who received *similar example* explanations felt they had a better understanding of AI, and perceived AI to have a higher capability. *Counterfactual examples*, however, did not always improve the perceptions of AI as it exposed the limitations of AI and may have led to a confusing or unexpected result.

Narayanan et al. [71] conducted a controlled user study with 600 Amazon Mechanical Turkers to identify how varying different complexities of a *decision set* explanation affect users' ability to interpret it. They found that while almost all types of complexity resulted in longer response times, some types of complexity, such as the number of rules, or the number of new features introduced, had a much bigger effect than others such as repeated features.

While prior works provide individual evidences based on a specific XAI application, our study systematically compares and assesses the strengths, weaknesses, applicable explanation needs, and design implications of explanatory forms in a variety of tasks and explanation need scenarios.

#### 3 END-USER-FRIENDLY EXPLANATORY FORMS

Distinct from prior frameworks that the explanation information is informed from users' requirements only, by applying the EUCA framework, the design of explanation information is informed from both user requirements and technical capabilities. This ensures that the resulting design is technologically achievable. To do so, we began with the observation on existing XAI systems/taxonomies that, despite the XAI algorithms, models, tasks, and visual representations vary, their resulting explanation information can be abstracted as several recurrent forms, such as feature attributes generated by linear model or algorithms mimic linear model [13, 63, 76], similar examples from different content-based retrieval algorithms [52], or decision tree and rules. And some of the forms may be consumed by non-technical users without technical knowledge as a prerequisite. Since the explanatory forms are the final resulting explanation information from existing XAI algorithms, and the number of explanatory forms is a finite set, we may use the explanatory forms to guide the choice and design of explanations in an XAI system. Because the explanatory forms are originated from existing XAI algorithms, once the forms are decided, it is straightforward to implement their associated algorithms, i.e.: form followed by function (we reverse the famous design maxim "form follows function" [7]). Our approach also echoes the matchmaking design process that identifies potential user domains ("nails") for numerous existing XAI techniques ("hammers") [22].

Based on the above insights, we explored the XAI solution space by extracting the resulting explanation information from existing technical literature in AI, HCI, and information visualization fields via literature review, then selected and summarized end-user-friendly explanatory forms based on the following criteria:

(1) The explanatory forms must be end-user-friendly, i.e., users are not required to possess technical knowledge to understand the explanation.

(2) The explanatory forms are mutually exclusive regarding the information they represent. We noted sometimes the explanation information can be attributed to different XAI types and concepts that entangle with each other, e.g.: *causal* explanations may be expressed as feature attributes or rules; *counterfacutal* explanations can be represented as counterfactual features, examples, or rules; feature attribute can be *global* as well as *local*. We selected forms that are mutually exclusive, so that they can act as building blocks, represent the elemental explanation information and their combination would not be redundant/repeated in an XAI system.

The literature review process and the list of surveyed literature are detailed in Supplementary Material S1. We ended up with 8 explanatory forms in three categories: explaining using features, examples, and rules. In addition, we added necessary supplementary information to make the explanation complete, including input, output, dataset, and performance. A total of 12 end-user-friendly explanatory forms are included in the EUCA framework.

The end-user-friendly explanatory forms are familiar and mutual language to both end-users and XAI practitioners, so that they can facilitate the communication on users' requirements and co-design process. Since the forms are summarized from technically achievable solution space and shown as UI design patterns, it also bridges the expertise gap between HCI/UX designers and AI developers. Next we introduce each explanatory form, accompanied by their possible visual representations summarized from the surveyed literature to facilitate UI/UX design. Figure 1 shows their visual examples.

Table 1. The End-User-Friendly Explanatory Forms. We indicate whether a form is a global (explaining the model's overall behavior), or local explanation (explaining the decision to the individual instance). We also give its applicable input data types: Tabular - tabular data, Img - spatial-structured data (e.g., image, graph), Txt - sequential data (e.g., text, signal). The \* indicates our rated user-friendly level (1: least friendly, 3: most friendly). Its pros, cons, design implications, and applicable explanation needs are summarized from the user study findings, followed by associated algorithms for implementation.

XAI Algorithm Examples	LIME [76], SHAP [63], CAM [100], LRP [19], TCAV [50]	PDP [35], ALE [16], GAM [83]	PDP [35], ALE [16], GA2M [26]
Applicable Needs	To verify Al's decision	To control and improve the outcome; To reveal bias	To control and improve the outcome
UI/UX Design Implications	Alarm users about causality illusion; Allow users to set thresholds on feature importance score, and show details on-demand	Users can inspect the plot of their interested features; May indicate the position of local data points (usually users' input data)	Users may select their interested feature pairs and check feature interactions; or XAI system can prioritize significant feature interactions
Cons	Illusion of causality, confirmation bias	Lacks feature interaction; Information overload if multiple feature shapes are presented	The diagram on multiple features is difficult to interpret
Pros	Simple and easy to understand; Can answer <i>how</i> and <i>why</i> AI reaches its decisions.	Graphical representation, easy to understand the relationship between one feature and prediction	Show feature-feature interaction
Visual Repre- sentations	Saliency map; Bar chart	Line plot	2D or 3D heatmap
Explanatory Form	Feature Attribute Local/Global Tabular/Img/Txt * * *	Feature Shape Global Tabular **	Feature Interaction Global Tabular *
Explanation Category	<b>Feature</b> - based explanation		

Explanation Category	Explanatory Form	Visual Repre- sentations	Pros	Cons	UI/UX Design Implications	Applicable Needs	XAI Algorithm Examples
Example- based explanation	Similar Example Local Tabular/Img/Txt * * *	Data instances as examples	Easy to comprehend, users intuitively verify Al's decision using analogical reasoning on similar examples	It does not highlight features within examples to enable users' side-by-side comparison	Support side-by-side feature-based comparison among examples	To verify the decision	Nearest neighbour, CBR [52]
	Typical Example Local/Global Tabular/Img/Txt **	Data instances as examples	Use prototypical instances to show learned representation; Reveal potential problems of the model	Users may not appreciate the idea of typical cases	May show within-class variations; or edge cases	To verify the decision; To reveal bias	k-Mediods, MMD- critic [49], Generate prototype [64, 80], CNN proto- type [28, 56]
	Counterfactual Example Local Tabular/Img/Txt **	Two counterfactual data instances with their highlighted contrastive features, or a progressive transition between the	Helpful to identify the differences between the current outcome and another contrastive outcome	Hard to understand, may cause confusion	User can define the predicted outcome to be contrasted with, receive personalized counterfactual constraints; May show controllable features only	To differentiate between similar instances; To control and improve the outcome	Inverse classification [55]), MMD-critic [49], Progression [48], Visual [37]

Explanation Category	xplanation Explanatory ategory Form	Visual Repre- sentations	Pros	Cons	UI/UX Design Implications	Applicable Needs	XAI Algorithm Examples
Rule- Decision based Rules/ explanation Global Tabulan ***	Decision Rules/Sets Global Tabular/Img/Txt **	Present rules as text, table, or matrix	Present decision logic, Need to carefully "like human balance between explanation" completeness an simplicity of explanation	Need to carefully balance between completeness and simplicity of explanation	Trim rules and show on-demand; Highlight local rule clauses related to user's interested instances	Facilitate users' learning, report generation, and communication with other stakeholders	Bayesian Rule Lists [91], LORE [40], Anchors
	Decision tree Global Tabular/Img/Txt *	Tree diagram	Show decision process, explain the differences	Too much information, complicated to understand	Trim the tree and show Comparison; on-demand; Support Counterfactu highlighting branches reasoning for user's interested instances	Comparison; Counterfactual reasoning	Model distillation [36], Disen- tangle CNN [98]

# 3.1 Feature-Based Explanation

Feature-based explanations are the most common form of explanation information. We refer *feature* to a piece of information that can describe the input data. It could be raw representation of the input (such as image pixels, sound wave signals), or descriptive characteristics of the input summarized/designed by human (such as house features presented in tabular data), or features automatically learned by AI. For example, a real estate agent can describe a house by its size, location, and age, three descriptive features; The feature of an image can be each individual pixel, or a group of pixels highlighting the object of a car, or the explicit concept of "car".

To use features for explanations, the feature representation must be human-interpretable. Feature space is also the cornerstone of other explanatory forms: example-based explanations are instances with similar or contrastive features; and rule-based explanations are features connected by logic and conditional statements. The feature-based explanations consist of three explanatory forms:

*3.1.1* **Feature attribute**. It indicates which features are important for the decision, and what are their attributions to the prediction. For example, it can be a list of key features and their importance scores to the house price prediction, or a color map overlaid on input image indicating the important parts/objects for image recognition. It assumes the prediction is explainable (often locally) by linearly addable important features.

*Visual representation*: Its visual representations largely depend on the data type of features. For image and text data, overlaying a **saliency map** or color map on input is the most common visualization. It uses sequential colors to code the fine-grained feature importance score for each individual feature (could be a pixel for image input, a word for text data). For image/video input data, other popular visualizations include using *segmentation masks* or *bounding boxes* on important image objects/parts.

To visualize multiple feature attributes for tabular or text data, a **bar chart** is a typical choice. Variations of the bar chart include waterfall plot, treemap, wrapped bars, packed bars, piled bars, Zvinca plots, and tornado plot. Compared to bar chart that shows a point estimation of feature importance, *box plot* can be used to visualize the probabilistic distribution of the feature importance score. Its variations include violin plot and beeswarm plot that show more detailed data distribution and skewness.

*3.1.2* **Feature shape**. It shows the relationship between one particular feature and the outcome, such as the house size to the predicted house price.

*Visual representation*: For a continuous feature (such as height, temperature, i.e.: measurement on a scale), a **line chart** is the most common visualization, depicting whether the relationship between the feature and outcome is monotonic, linear, or more complex. The line chart can be accompanied by a scatter plot detailing the position of individual data points.

For a categorical feature (such as gender, season), a bar chart can be used.

*3.1.3* **Feature interaction.** When features interact with each other, their total effect on the outcome may not be a linear summation of each feature's individual effect. Feature interaction considers such an interactive effect, and shows the total interaction effect of multiple features to the outcome. It can be regarded as an extension of feature shape by taking multiple features (instead of one feature) into account.

*Visual representation*: **2D or 3D heatmap** is usually used to visualize the total effect of feature interactions on prediction. Limited by the visualization, a heatmap shows feature interaction for at most three features (using 3D heatmap). More complicated multiple paired feature-feature interactions can be visualized using matrix heatmap, node-link network, or contingency wheel.

# 3.2 Example-Based Explanation

Human uses examples to learn and explain. Examples carry contextual information and are intuitive for end-users to interpret. Three different types of examples are included:

- 3.2.1 **Similar example**. Similar examples are instances that are similar to the input data regarding their features. For example, for a house to sell, its similar examples can be houses in the adjacent area with similar features such as house size, age, etc.
- *Typical example*. A typical or prototypical example is a representative instance for a certain prediction. For example, a typical example of the diabetes prediction could be a patient who exhibits typical characteristics (such as a high blood sugar level, an abnormal hemoglobin A1C level) that could be diagnosed as diabetes.

*Visual representation*: For similar and typical examples, it is straightforward to show several examples with their corresponding predictions.

3.2.3 **Counterfactual example**. Its features are similar to the input, but has minimal feature changes so that its prediction is distinct from the input. For example, an instance C that is predicted as healthy is a counterfactual example for the input I that is predicted to have diabetes, if C has all the same features as I, except its blood sugar level is lower than I. We noted that counterfactual explanations can also be expressed as counterfactual features or rules. However, a counterfactual feature/rule can not be a standalone explanation in an XAI system, they must reside within contain context by assuming all other features are constant. To make the explanation information complete, we include counterfactual explanation in the form of example.

*Visual representation*: Counterfactual examples can be shown as two instances with their **counterfactual/contrastive features highlighted**, or a **transition** from one instance to the other by gradually changing the counterfactual features.

# 3.3 Rule-Based Explanation

Rule-based explanations are explanations where decisions of the model, in whole or in part, can be described succinctly by a set of logical if/else statements, mimicking human reasoning and decision making. It also implies the decision boundary, thus may be convenient for counterfactual reasoning. The rule-based explanation is a global explanation of the model's overall behavior. It includes the following two explanatory forms of decision rule and decision tree. We note rule and decision tree actually carry out similar explanation information. But since they are usually generated by different XAI algorithms, and their representation format (text vs. diagram) are distinct to the end-users, we included them as two separate explanatory forms.

*3.3.1 Rule.* The decision rules or decision sets are simple IF-THEN statement with condition and prediction. For example: IF blood sugar is high, AND body weight is over-weighted, THEN the estimated diabetes risk is over 80%.

*Visual representation*: Rules are usually represented using **text**. Other representing formats include table [27] or matrix [70] to align, read, and compare rule clauses more easily.

*3.3.2* **Decision tree**. Decision tree represents rules graphically using a tree structure, with branches representing the decision pathways, and leaves representing the predicted outcomes.

*Visual representation*: The most common representation is to use a node-link **tree diagram**. Other visual representations to show the hierarchical structure include treemap, cladogram, hyperbolic tree, dendrogram, and flow chart.

# 3.4 Supplementary Information of an XAI System

In addition to the above explanatory forms generated by XAI algorithms, an XAI system needs to present some necessary background or supplementary information to end-users, such as input, output, decision confidence/certainty, model performance metrics, training dataset information such as data distribution, etc. We included the following essential and common ones in our framework, and indicates whether they are global (explaining the model's overall behavior) or local explanation (explaining the decision on an individual instance):

- (1) **Input**, **output** (local): input is end-users' input data, and output is AI's prediction on the given input.
- (2) **Certainty** (local): Since the prediction from AI models is usually probabilistic, the certainty score shows the case-specific certainty level about how confident model is in making this particular decision.
- (3) **Performance** (global): Performance metrics (such as accuracy, confusion matrix, ROC curve, mean squared error) help end-users to judge the overall decision quality of the model, and to set a proper expectation on the model's capability, as suggested in the human-AI interaction guideline [14].
- (4) **Dataset** (global): It describes the information of the dataset where the AI model is trained on, such as the training data distribution. It may help end-users to understand the model and identify potential flaws in the data.

#### 4 USER STUDY METHOD

We conducted a user study with 32 layperson participants. The user study utilized interview and card sorting methodology. It is to demonstrate the process of using EUCA prototyping workflow to design XAI low-fidelity prototypes in different AI-assisted critical decision-making tasks. The primary goal of the user study is to identify the strengths, weaknesses, applicable explanation needs, and UI/UX design implications of the explanatory forms as their proprieties to incorporate into the EUCA framework. The secondary goal is to use EUCA as a study probe to understand the end-users' explanation needs for XAI. Our research questions are:

**RQ1**: What are the strengths, weaknesses, applicable explanation needs, and design implications for the end-user-friendly explanatory forms?

**RQ2**: What are end-users' requirements under various explanation needs?

#### 4.1 Participants and Recruitment

We recruited layperson participants via convenience sampling method by advertising posters at the public libraries, community centers and online community boards in the Greater Vancouver area over a 3-month period in 2019. The inclusion criteria were: 1) adult (19 years old and above); and 2) do *not* have prior technical knowledge in machine learning, data science, or artificial intelligence. A total of 32 participants were enrolled in the study (Female = 16; Age: 38.2±16.0, range 19-73). Participants' occupations covered a variety of industries e.g.: technology, design, car insurance, finance, psychology, construction, sales, food & cooking, law, healthcare, government/social services, retired. For participants who use AI in work or life (6 participants, 19%), they used AI software such as Google Assistant to play music, navigate traffic, chat with clients, and help drive investment decisions. Figure 5 shows the distribution of participants' age, educational background, familiarity with and attitudes towards AI. Participants' detailed demographics are in Supplementary Material S2. The participants were thanked with \$25 CAD for their time and effort in the study. The study is approved by the university's ethics board (Ethics number: 2019s0244).

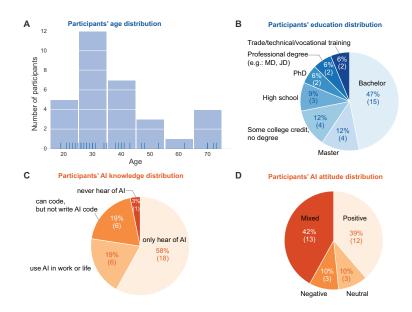


Fig. 5. **Participants' demographic information**. (**A**) Histogram of participants' age distribution. The sticks on the *x* axis show each participant's age. (**B**) Pie chart on participants' educational level. Numbers in parentheses represent the number of participants in that category. (**C**) Pie chart on participants' familiarity with Al. (**D**) Pie chart on participants' attitudes towards Al; Positive attitudes include "interested" in and "excited" to use Al; Negative attitudes consist of "skeptical" and "concerned" about Al; A mixed attitude means participants hold both positive and negative attitudes towards Al.

#### 4.2 The Interview Instrument

4.2.1 Critical decision-making tasks. We focus the scope of the study on AI-assisted critical decision-support tasks, where explanations have high utility as shown in previous research [24, 32, 59], and AI could not be delegated to have full automation because of the high-stake nature of the tasks and liability issue. We designed four decision-making tasks reflecting the diversity of AI-supported critical decision-making. The four tasks are: House task: users use AI to get a proper estimate of their house price. Health task: users use AI to predict diabetes risk. Car task: users decide whether to buy an autonomous driving vehicle. Bird task: users use AI bird recognition tool to prepare for an important biology exam. The tasks are critical decision-making scenarios, and the decisions have significant consequences on one's health and life (Health and Car Task), finance (House Task), or education (Bird Task). At this stage, we have not included domain experts in our study. Thus we deliberately designed the tasks so that decisions can be made based on common sense without requiring domain knowledge. The four tasks covered common input data types of tabular, sequential, image and video data, and their corresponding datasets are publicly-available (see Table ??), so that the resultant paper prototype from the user study can be actualized as a working prototype for case-specific studies in future work.

4.2.2 **End-Users' Explanation Needs**. Even for the same user and task, end-users' needs for explanation, i.e.: the trigger point or motivation to check the explanation of an AI system, may vary from time to time based on different contexts or usage scenarios. In our study, we aim to capture the fine-grained details of end-users' requirements in different explanation need scenarios. We summarized the following potential **explanation needs** from prior works [32, 39, 72, 78] as follows:

AI-Assisted Critical		HOUSE TASK	HEALTH TASK	CAR TASK	BIRD TASK
Decision-Making Tasks		Sell a house	Check diabetes	Buy a self-driving	Prepare for exam
200000	v 1/10/10/10/05 Tellerice		risk	car	
		The figure has		Fine Execution from the Control of t	Target est times;
	Trust	You doubt whether to trust the AI tool or not	You doubt whether to trust the software prediction on your diabetes risk		You don't know whether to trust the results from the website or not
	Safety			You need to know whether the autopilot mode is safe and reliable	
Explana Needs	<sub>iti</sub> B <b>i</b> as		You doubt whether the software will perform the same among people with different gender, age, or ethnicity group	You want to know if the autopilot mode performs robustly under varying road, weather, and light conditions.	
	Disagreement with AI	AI's prediction aligns/does not align with your own estimation	You maintain good health with no major diseases or a family history of diabetes/Diabetes tends to run in your family, and you're afraid of getting it someday, and Al predicts your chance of getting diabetes is low/high	You notice the car sometimes drives much slower than the expected speed limit	The results sometimes do not align with your knowledge
	Differentiation				In the exam, you need to write a short statement to differentiate different birds
	Learning				Is it a good tool to improve your learning and help you know more about bird taxonomy?
	Improvement	You need to decide whether to do a renovation or replacement of appliances to increase your house value, and which action is the most cost-effective	You want to know how to adjust your lifestyle accordingly to lower the risk of diabetes		
	Communicatio	You need to communicate    your decision with your    family	You need to need to inform family members and consult your doctor	You need to communicate with your family about your judgment on the car's safety	
	Report				In the exam, you need to write a short statement on how you recognize the bird as such species
	Multi-objective trade-off	s	You're aware that the insurance company may use such a prediction from the software to determine your insurance premium and benefits	You're easy to get motion sickness, and you notice you seem to get car sick more frequently in autopilot mode	
ML problem type		Regression	Regression	Classification	Classification
Input data type		Tabular data	Tabular/sequential data	Image/video data	Image data
Availab	le dataset	Boston	Diabetes	BDD100K [96]	CUB-200
		housing [11]	dataset [6]		dataset [88]

Table 2. The four tasks and their explanation needs used in the interview.

• Calibrate trust: trust is a key to establish human-AI decision-making partnership. Since users can easily distrust or overtrust AI, it is important to calibrate the trust to reflect the capabilities of AI systems [84, 99].

- Ensure safety: users need to ensure safety of the decision consequences.
- Detect bias: users need to ensure the decision is impartial and unbiased.
- Unexpected prediction: the AI prediction is unexpected, and users disagree with AI's prediction.
- Expected prediction: AI's prediction aligns with users' expectations.
- **Differentiate similar instances**: due to the consequences of wrong decisions, users sometimes need to discern similar instances or outcomes. For example, a doctor differentiates whether the diagnosis is a benign or malignant tumor.
- Learn: users need to gain knowledge, improve their problem-solving skills, and discover new knowledge.
- Improve: users seek causal factors to control and improve the predicted outcome.
- Communicate with stakeholders: many critical decision-making processes involve multiple stakeholders, and users need to discuss the decision with them.
- **Generate reports**: users need to utilize the explanations to perform particular tasks such as report production. For example, a radiologist generates a medical report on a patient's X-ray image.
- Trade-off multiple objectives: AI may be optimized on an incomplete objective while the users seek to fulfill multiple objectives in real-world applications. For example, a doctor needs to ensure a treatment plan is effective as well as has acceptable patient adherence. Ethical and legal requirements may also be included as objectives.

Each task is accompanied by several explanation needs as shown in Table ??. The tasks and explanation needs were presented in the form of storyboards using graphics and text. Supplementary Material S2 details the interview schedule and materials.

- *4.2.3 Creating Prototyping Cards from Explanatory Forms.* We demonstrated our process of creating low-fidelity prototyping cards out of the 12 explanatory forms.
  - (1) **Create prototyping card templates** We started by creating templates according to the visual representations in previous Section 3. The visualizations were the vanilla and most common format appeared in previous literature. For example, we used bar chart and color map to visualize feature attribute in tabular and image data respectively. Each card shows one explanatory form. For some explanatory forms (such as feature attribute and counterfactual example), we created multiple cards with different variations of their visual representations.
  - (2) Extract features as content placeholder We then manually extracted several interpretable features given the AI task. For instance, in the house prediction task, we extracted house size, age, etc. In the self-driving car task, we extracted saliency objects such as traffic signs, road markers, cars, and pedestrians. As quick prototyping, the feature content may not necessarily reflect the true content generated by XAI algorithms. They served as content placeholders.
  - (3) **Fill the prototyping templates with content placeholder** The extracted features were then used to fill in the prototyping card templates. The final prototyping cards are shown in Figure 1 and Supplementary Material S2.

After interviewing the first five participants, we revised some prototyping cards based on participants' feedback. For instance, we indicated the position of the input data point on the feature shape and feature interaction cards. We also removed several variations of the cards since participants found them harder to interpret.



Fig. 6. **The user study procedure**. The study consisted of two rounds corresponding to the two research questions. In the above example, we use the Bird task and the explanatory purpose of calibrating trust.

### 4.3 Study Procedure

The study session consists a one-to-one, in-person, open-ended, semi-structured interview and a card sorting.

4.3.1 Interview. The interview consists of two rounds (Fig. 6). The first round is to familiarize participants with the tasks and explanation needs, and to understand end-users' explanation needs for XAI (RQ2) before showing them the prototyping cards. The participant was first introduced to an AI-assisted decision-making task and its corresponding explanation need scenarios. Each task and need scenario were shown as storyboards color-printed on paper. For each explanation need, we asked the participants whether they accept AI as decision-support, and need AI to explain its decision. If explanations were needed, we then asked what explanations/further information they request.

After discussing all the explanation needs for one task, the participant entered the second round: card sorting, which is detailed in the next section. At the end of the interview, the participants filled out a demographic questionnaire. The average study session lasted for 65 minutes. (each participant's study duration is in Supplementary Material S2). We audio-recorded the interviews, made observational notes on the card selection and sorting process, and took pictures of the card sorting results.

4.3.2 **Prototyping via Card Selection and Sorting**. For each decision-making task, the participants first revisited the task. Then the researcher walked through the created prototyping cards showing the explanatory forms for that task. In this process, the participants could ask questions if they did not understand or need clarification. They could also comment on each card. Before we moved to the next step, we asked participants and made sure they had no questions or concerns with the cards.

Next, for each explanation need scenario, the researcher asked participants to select, rank, and combine the prototyping cards that they found were the most useful ones and could meet their explainability needs. They could also sketch on blank cards to create new prototyping cards, and add the newly created cards to the card sorting. After sorting the cards, they were asked to comment on why they selected or did not select a card, and their rationals for making such a sorting (**RQ1**). After the card sorting, they were asked whether the combination of cards would fulfill their explainability needs.

#### 4.4 Data Analysis

We utilized a mixed method to analyze the data.

For qualitative analysis, we analyzed the interview data using inductive thematic analysis approach [23]. About 2800 minutes of interviews were recorded and transcribed. We performed coding using Nvivo software. Three members of the research team started with an open coding

pass to individually create a list of potential codes. Two additional sets of codes were also applied: 1) the 10 explanatory *explanation needs* (listed in Section 4.2.2); 2) the 12 *explanatory forms* in our framework (listed in Section 3). Upon discussion and applying the affinity diagram process, a unified coding scheme was devised, and two team members independently coded one transcription using this scheme. The first pass of inter-rater reliability Kappa score was 0.43. After an in-depth discussion with the research team, we further clarified the code definition, merged potential overlapping codes, and removed redundant codes in the coding scheme. The second pass of inter-rater reliability Kappa score was 0.88 on two new transcriptions. The first author analyzed all interview transcripts twice, and the other coder analyzed half of the transcripts.

We also conducted quantitative analysis on card sorting, and on participants' responses to the questions asked in the interview. Since the quantitative results are less relevant to the research questions, we put the quantitative methods and results in Supplementary Material S2.

#### 4.5 Presentation of Results

To avoid redundancy, we present the quantitative and qualitative results together. The *explanation needs* are marked as blue, and *explanatory forms* are orange. The ratio of responses are shown as rule (12/15), which means out of 15 card-ranking responses, 12 selected the explanatory form rule. We highlighted key messages using **bold** font. Whenever necessary, we included participants' verbatim quotes despite some minor grammatical error. Some quotes had their current task and explanatory purpose indicated.

# 5 RQ1: PROPRIETIES OF THE END-USER-FRIENDLY EXPLANATORY FORMS

We present the primary findings from the user study, by detailing the fine-grained proprieties of the 12 explanatory forms (pros, cons, applicable explanation needs, and design implications).

#### 5.1 Feature Attribute

*5.1.1* **Pros.** In the study, we used a bar chart to represent feature importance score for tabular data, and color map and bounding box object detection for image data (Fig. 1). All participants **intuitively understood feature attribute**, and over half selected it (143/248) and ranked it at top positions.

"Feature attribute uses a simple way to highlight the most important parts, and you can see very clearly at your first sight how this can be recognized." (P04, Bird, Learning) "It's easy to read. ...And you have a bar (chart) here it's really clear information that people understand instantly." (P28, House, Trust)

By showing "finer details" (P10) and "breakdown and weights of features" (P23) "that AI took into account" (P31), participants perceived feature attribute can answer "how" and "why" questions.

"tells me why" (P20), "gives me the behind the scenes" (P24), "tells me how AI read things and how it makes decisions" (P03), "have an understanding of how much weight AI is giving to each of the factors" (P22), and "identify key aspect, ... support its reasoning" (P18).

- 5.1.2 Applicable Explanation Needs. By checking feature importance ranking, participants would instantly "compare with my own judgment, to see if that aligns with my feature attribute" (P01, Car, Safety), especially when participants need to verify AI's decision.
- *5.1.3 Cons.* Although a causal relationship may not be confirmed, some participants tended to **assume feature attribute is causal**, or simplify the relationship among features by assuming they are **independent from each other**. This was usually occurred when they were seeking explanation

to improve the predicted outcome. And participants were likely to be informed by the feature importance score to prioritize the most important features to take actions upon.

"Seeing that body weight is more important than exercise, I think I will focus on changing what I ate, instead of like responding by going to the gym everyday." (P16, Health, Improvement) – Relies on feature attribute to improve the outcome.

"It (feature attribute) shows what are the most important factors that AI has taken into account, so you could target the biggest factors." (P31, Health, Improvement) – Assumes a causal relationship and prioritizes the action.

"If my blood sugar puts me at a super high risk here, but my caloric intake doesn't actually put me at that higher risk, it's like a lower risk, then I would rather just focus on blood sugar." (P22, Health task) – Ignores the complex interaction between blood sugar and caloric intake.

*5.1.4* **Design Implications** . To avoid the above causal illusion, UI/UX design may need to **alarm users** either implicitly or explicitly that changing the important features may not necessarily lead to the outcome change in the real world, due to correlation does not necessarily imply causality.

For designing UI/UX of its prototyping card, designers may consider **varying different representations** of the feature importance, such as showing the feature ranking only and allowing users to check the detailed attribute scores on demand, or allowing users to set a threshold on the attribute score and only showing features above the cut-off value, as suggested by a few participants.

"If the percentage (of the feature) is below the cutoff value, the users does not need to see (the feature), reduce the cognitive load." (P04, Bird, Learning)

#### 5.2 Feature Shape

*5.2.1* **Pros**. Participants **liked its graphical representation** of showing the relationship between one feature and prediction.

"It (feature shape on exercise and diabetes risk) feels so easy to latch onto like it's something that you can impact and something that's very tangible." (P22, Health, Trust)

5.2.2 **Applicable Explanation Needs**. The slope of the curve in feature shape line chart allows users to easily check how changing one feature would lead to the change of the outcome, thus many participants intuitively used feature shape for **counterfactual reasoning**, especially to improve the predicted outcome.

"I would be interested to see how much like here (feature shape) increasing the exercise by a small amount actually makes a really big difference. So that's also helpful to decide what you should be focusing on to try to avoid it (diabetes). The shape of the curve actually helps. Coz if I was out here [pointing to the flat part of the curve], then it would not be as helpful for me to increase my exercise." (P16, Health, Improvement)

By showing the relationship between the protected feature and outcomes, it also helps to reveal bias, i.e.: to check if the different values of the protected features (such as male, female) will lead to differences in prediction (such as loan approval).

"If these features are related to diabetes, then it (AI) should present some (feature shape) cards to tell me if the gender, age and ethnicity (will affect diabetes prediction), so this image (feature shape) would be really helpful." (P02, Health, Bias)

*5.2.3 Cons.* One drawback of feature shape pointed out by a few participants is that it does not considerate feature interactions.

"This one (feature shape on house size and price) is not based on the bigger the house, the higher you can sell, because it is based on a lot of features. Let's say the house is 2000 square feet. It was built in 1980. Another one is 1000 square feet, but it's just built a decade ago. So its (the latter) price will be much higher than this one (the former). You cannot just base on a house area and then determine the price." (P30)

Another drawback is that since one feature shape graph can only present one feature, to show multiple features' feature shape the interface will need multiple graphs that may –

"make your page so **overloaded**, so people just get tired. You want to make it as clear as possible. So if (there is) some unnecessary information people just intimidated." (P28)

*5.2.4* **Design Implications** . One suggestion for the above weaknesses is that feature shape can be accompanied by other explanatory forms and **show on-demand**. Users can select their interested features from a feature list or other explanatory forms such as feature attribute, counterfactual example or rule, and choose to view feature shape diagrams of the selected features, as participants suggested:

"If I can click on this (feature attribute) and then I can get this chart (feature shape), I think that would be good. I don't think everyone is going to click it, but I think (if) people want more information, you will click it." (P20, House)

Many participants tended to check the **local position of their input data point** on the global feature shape diagram.

"It's good to see where exactly on a (house price) scale you are." (P20, House, Trust)

And P30 suggested feature shape could have the assumption that for all the other features that are kept constant, they should be as similar to user's input features as possible.

"The AI should assume all the other features are almost the same as mine, considering this hypothesis then this is the (feature shape) curve".

#### 5.3 Feature Interaction

5.3.1 Applicable Explanation Needs. Since feature interaction just adds one more feature to the (feature-outcome) diagram to show feature-feature interactions, it can be regarded as an expanded version of feature shape, and many of the above findings on feature shape apply to feature interaction as well. Similar to feature shape, feature interaction also supports **counterfactual reasoning** by including two or more features instead of one in feature shape.

"(feature interaction on age-body weight interaction) If you put yourself in a hypothetical guessing, you're in this age and this is your body weight, and you can already tell the chances (of diabetes) are high." (P23, Health, Trust)

- *5.3.2 Cons.* "*The graph is less accessible to understand*" (P22). In our study, only a few participants could correctly interpret the 2D heatmap of two feature interactions.
- 5.3.3 **Design Implications**. Similar to feature shape, participants would like to choose their interested feature pairs to check their interactions on feature interaction diagram. Since the combination of features is large, the XAI system may be able to **suggest interesting feature interactions and prioritize** the feature pairs which have significant interactions.

"If I click on any two of them (features), show the relationship between them. If I can choose age and blood sugar level, then probably there is some correlation between them.

If it is statistically significant, then I would want to know that. If there is no significance between, for instance, age and body weight, then I don't think it should tell me that. If the AI can tell me that this combination really is important for you to look into, then the priority would also make a lot of sense." (P23, Health, Unexpected)

# 5.4 Similar Example

In our study, most participants regarded both similar example and typical example as similar examples. Only a few participants got the idea of typical example that "you're getting the average" (P20). Thus in this section, we state the themes on similar example as well as the common themes of similar and typical example.

*5.4.1* **Pros**. Participants **intuitively understood** the concept of **similar example**. Similar example uses analogical reasoning to facilitate to the sense-making process.

"It just intuitively makes sense to me. ...similar and typical example are much easier. I don't have to think about them before figuring it out." (P16, Bird, Trust) "(similar and typical example) It's similar to how humans make decisions, like we compare similar images to the original (input) one." (P02, Bird, Trust)

- 5.4.2 Applicable Explanation Needs. Unlike other explanatory forms that reveal AI's decision-making process (such as rule-based explanations), "even though these (similar and typical example) aren't much specific about how it's actually doing the (decision) process" (P16), participants' minds automatically made up such a process by themselves by comparing instances. Such comparison mainly allow users to verify AI's decisions and to calibrate their trust. The common explanation needs in which similar example were selected are:
  - 1) To build trust, especially from a personal and emotional level.

This (similar example) made me trust on an emotional level. Because I'm thinking, 'Oh really? I am only 33 years old.' Like I probably not going to get diabetes. But then I'm reading about somebody that does (get diabetes), that sounds a lot like me, it kind of emotionally makes me feel like, 'Oh geez, maybe it is accurate.' So this (performance, output) is like using my brain, and this one (similar example) kind of got me in the gut like, 'Oh, okay. This could actually happen to me. It happened to this person who sounds a lot like me.'" (P16, Health, Trust).

2) To verify the decision quality of AI.

"It's like a proof for my final decision." (P30)

"Because AI has only 85% accuracy, I want to see similar ones, and what AI thinks they are." (P14, Bird, Trust)

"If it doesn't align (with my prediction), then I want to see some similar houses to remake the judgment." (P04, House, Unexpected).

**3**) To assess the level of disagreement when AI made an unexpected prediction, and to reveal potential flaws of AI.

"If my prediction appears in (a list of) <u>similar examples</u>, it allows me to judge whether AI is completely unreliable or just need some improvement." (P01, Bird, Unexpected)

*5.4.3 Cons.* Showing examples for comparison may not be applicable when input data is incomprehensible or **difficult to read and compare**.

"I think (similar and typical example) it's not important to me. Because I need to read other people's status, read their records." (P02, Health, Trust)

In addition, participants easily got confused when instances in similar example have **divergent predictions**. This problem might be solved by typical example which is stated in Section 5.5.

"(similar example) It's not really telling you if it (the input) is the one (prediction), so it could be this (prediction) or this or this [pointing to different predictions on similar example card]." (P26, Bird, Trust)

"This one (similar example) has too many choices (predictions), it's too confusing." (P05, Bird, Trust)

*5.4.4* **Design Implications**. As mentioned above, participants had to compare the features in similar example by themselves. It's important for the XAI system to support such **side-by-side feature-based comparison** among instances such as **input**, **similar**, **typical**, or **counterfactual example**, especially when the input data format is difficult to read through.

"I don't want to read the text (in <u>similar</u> and <u>typical example</u>), it is better to show those features and examples in a table for me to compare directly, also highlight the important features as an analysis process." (P29, Health, Trust)

"Maybe it could help the doctor to pinpoint things that are similar or different between these cases." (P31, Health, Communication)

"I would like a comparison. That's my own house (input), which probably will be off the top somewhere. And I'm comparing it with other information (typical example and counterfactual example). So in a column, and I can compare it. For the layout, maybe you can do a product comparison." (P03, House, Expected)

# 5.5 Typical Example

*5.5.1* **Pros**. One drawback of similar example is that it may make users confused about similar instances. Typical example may solve this problem since the typical examples for different predictions are more **distinct and separable** than nearest neighbors of similar example.

"(typical example) You actually made a category of each one. I remember in cognitive psychology, there's a theory. I don't remember the name, but if you clearly separate each category, that helps people to differentiate the different categories, then remember. But for this one (similar example), you have to read every one (instance) of them." (P04, Bird, Learning)

5.5.2 **Applicable Explanation Needs**. Since typical example represents the typical case for the outcome, it may help to reveal class-specific characteristics or even potential problems in the AI model or data, for example to **reveal bias**.

"If I'm concerned about what group the data is coming from, I would love if the typical case like the average that comes up says like, male, this age, and the factors were quite different from mine, then I kinda go, 'huh?' But if it could give me a typical case that's actually quite similar to me, then I would be less worried about it not performing well with my group." (P22, Health, Bias)

Unfortunately, most participants did not realize the meaning of typical example and did not make use of such "debugging" property.

5.5.3 **Design Implications**. In addition to show typical example of different predictions (between class variation), in some cases, it might be beneficial to show **different variations of typical example** for a particular prediction (within-class variation).

"It's showing different pictures of the same bird, and the colors even look different. So it's saying maybe, 'Oh, I get it, we have the male and female.' So it's showing different looks that the bird can have." (P06, Bird, Learning)

Opposite to typical example, some participants expected to see non-typical or edge cases that represent rare but severe consequences, mainly due to safety and bias 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." (P27, Car, Bias)

"I still don't know if the dog jumps out of nowhere. so maybe the (similar example) similar traffic conditions can see the extreme cases." (P03, Car, Safety)

# 5.6 Counterfactual Example

*5.6.1* **Pros and Applicable Explanation Needs**. In our study, counterfactual example was shown as two instances of different predictions, with their feature differences highlighted while keeping other features the same (Figure 1). This format can serve for different explanation needs depending on the task context. In predictive tasks (House and Health), participants regarded counterfactual example as the most direct explanatory form to **suggest an improvement**.

"For renovations, I think that's (counterfactual example) the only card I would choose. The only one that really tells me that I can do something to increase the price." (P20, House, Improvement)

While in recognition task (Bird), counterfactual example is suitable to **show the differences** to differentiate two similar predictions.

"Counterfactual example let me learn their relationship, highlight the difference between the two (birds). Help me remember the different features." (P11, Bird, Learning)

*5.6.2 Cons.* Some participants did not understand the meaning of counterfactual example, and could not capture the nuance between feature attribute and counterfactual example, since they both have features highlighted but for different reasons (feature attribute highlights important features for prediction, whereas counterfactual example highlights what features need to change for the alternative outcome to happen).

Counterfactual example may have the risk to make participants confused about similar instances, especially in recognition tasks.

"I think this tool (counterfactual example) will make me remember the wrong thing. I'm already confused. It shows information that is similar." (P11, Bird)

Thus it may not be the beginning explanations and may only show up on-demand, for example, for the two explanation needs of improvement and differentiation mentioned above.

5.6.3 **Design Implications**. The two **contrastive outcomes in counterfactual example can be user-defined or pre-generated** depending on the specific explanation needs. One outcome is usually from user's current instance such as input, and the alternative outcome can be: "the next possible prediction" (P18, Bird, Report), users' own prediction when there's a disagreement (Unexpected), the prospective outcome for improvement, and the easily confused outcome for differentiation.

The generating of counterfactual features may also receive user-defined or pre-defined constraints, such as: 1) constraints on the counterfactual feature type to include **controllable features only** (see Section 6.8 Improvement on controllable features); 2) generate **personalized counterfactual suggestions** based on features that users look upon: "the recommendation should be a

*lot based on what I do*" (P24, Health); and **3**) constraints on the range of specific counterfactual features: "AI should accept my personalized constraints on budget (P01, House, Improvement). Given these constraints, the XAI system can also provide multiple improvement suggestions for users to choose from (P01, P11), and may give weights or relative ranking on multiple suggestions.

#### 5.7 Decision Rule

Many participants noticed the three formats of rule-based explanations (rule, decision tree) provided "basically the same information" (P02, Health), "all show the decision process" (P10, Bird), and were only different in the text (rule) or graphical (decision tree) representation.

- 5.7.1 **Pros**. Several participants regarded rule can "explain the logic behind how the AI makes decisions" (P27). Particularly, the text description format is "like human explanation" (P01, House, Trust), and "simple enough and understandable" (P11).
- 5.7.2 **Applicable Explanation Needs**. The above pros make it suitable for verbal (Section 6.9 Communication) and written **communications** (Section 6.10 Report). Text format may also help to dispel confusion, since some participant regarded texts as being more precise than images, thus **facilitate learning**.

"In this case (Bird, Unexpected), I don't want to see the highlights (feature attribute). I want it to see points, the specific parts and give me some explanation. If I'm trying to prove myself wrong, or if I want to see how AI system can prove me wrong, I want to see more precise text, and precisely point out the important information." (P04) "The written helps because it's more exact, whereas the pictures, ...the blue in the picture might not be the blue that was in the written." (P05, Bird, Learning) "(rule) It's listing out something that a person might miss in the picture." (P18, Bird)

However, when the input is image data, some participants also mentioned providing text explanations only was not enough.

"(rule) It doesn't really show you the bird that you were looking at. Lots of birds have small thin bills short tails...if I can't see a picture of it, then it's not as helpful." (P06, Bird, Trust)

And many participants suggested "ideally you'd want both written and pictures" (P05) to complement each other.

*5.7.3* **Cons.** rule is **very sensitive to the degree of complexity** in text descriptions, as an increase in rule length or number of features will dramatically reduce its simplicity and the above advantages [71]. However, if the rule clauses are short, the explanation may not be precise and satisfying as well, as P06 pointed out,

"It (rule) is just too broad, it could apply to so many other birds."

Another concern is that since participants lack technical knowledge, some of them misinterpreted rule as instructions human fed to the AI.

"(rule) it is giving very clear instructions to the AI, like written text instructions, these are already fed into the system." (P09, Car, Safety)

*5.7.4* **Design Implications**. To reduce the cognitive load of complex rule, a few participants suggested **trimming the rules** by only showing the shallow level, or only showing rules containing the current input "just show rule related to my own house features" (P30), then users may query details on demand.

To carefully balance between explanation completeness and usability, if the full rule is shown, it's beneficial to **highlight** *local* rule clauses describing the current instance on top of the *global* rule explanation.

#### 5.8 Decision Tree

5.8.1 **Pros**. Similar to rule, participants regarded decision tree as "the most logical one" (P20) that "tells you the decision-making process" (P04):

"(decision tree) shows the process of thinking with AI, what it's going to do with the information." (P10)

"how the algorithm is working, what the machine is thinking about when it's coming up with the prediction." (P16)

*5.8.2* **Applicable Explanation Needs**. Participants mentioned an advantage of decision tree is to differentiate, possibly due to its unique tree layout:

"It explained very well what's the difference between them (the two confusing instances)." (P04, Bird, Report)

"It would show you how to pick up the different types of variants." (P10, Bird, Report) "I think this (decision tree) is the graphic comparison, like this beak might be sharper or smaller than this one, all those comparisons help" (P09, Bird, Unexpected).

Such advantage also supports **counterfactual reasoning** by checking alternative feature values on the adjacent branches.

"(Decision tree) can see how to improve. It has a comparison with different outputs." (P29, Health, Trust)

"Where does my house stands, if I'd be here, then I maybe try to change some of my features, to see how do these features affect my house price, or other houses compared to my own house." (P30, House)

*5.8.3* **Cons.** Several participants brought up its **weakness in communication and interpretation**.

"(Decision tree) is not natural language, it is more difficult to explain to my family." (P01, House, Communication)

"This is more like a logical thing for me to see. But I wouldn't use this as an explanation to family, because that's just weird. I don't want to rack their brains too much." (P20, House, Communication)

Indeed, in the study even with a two-feature two-layer decision tree, a number of participants commented:

"It's confusing." (P05, Bird, Learning)

"It got too much information." (P16, Bird, Unexpected)

"I don't really understand this one. I think it's a little bit complicated." (P08, Bird, Learning)

Since it is less interpretable than other forms, some participants suggested to show it on-demand.

"I don't think these two (decision tree, decision flow chart) are necessary to show in the first UI. Maybe these two can be hidden in an icon that says 'process'. Because it (decision tree) is more like a program in process." (P04, Bird, Trust)

Besides the tree structure, we used another flow chart visual representation (decision flow chart) in the study. In tasks that the inputs were images (Bird and Car task), quite a few participants

found neither the tree nor the flow chart structure helpful, and they only focused on the saliency features or objects the flow chart shows.

"I don't think it (the flow chart structure) matters, just the head and the belly (the highlighted region shown in the flow chart) matter." (P14, Bird)

*5.8.4* **Design Implications**. Similar to the suggestions in rule, to reduce its complexity, one participant suggested **trimming the tree** and just show the main branches, hiding the deeper branch details and only showing them on-demand.

"You could use this one (the two-feature decision tree) as a beginning, based on this, and you click (one branch) to another in-depth version of the price calculation. Because this (price prediction) range is still very far wide, and the features given is not enough, so if you want to (check details) maybe click and (it will) add more features to it (that branch), then get a narrow range (of prediction)." (P28, House)

Although rule-based explanations are *global* explanations, many participants tended to seek the branch pathway where their own input resides. It served as a *local* explanation on top of the *global* explanation. It suggested an XAI system may only show the branches containing interested instances, or **highlight branches for their interested instances**. They did so for the needs to verify AI's decisions, and for comparison with other counterfactual instances.

"I know there're 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, Trust) – Displays local as well as global explanations "The only thing we need is to indicate my own position on this (decision tree) branch. .... Then I can chase the features of my house." (P30, House, Unexpected) – Suggests to highlight the pathway for user's interested instance

# 5.9 Input

It serves as necessary background information, and participants regarded input as a "profile" (P24) that "stating the facts" (P20). It allows participants to understand what information Al's decision is based on, and can help "debug" to see "if AI is missing the most important feature" in input (P22, Health, Bias), and "whether or not the input is enough for it (AI) to make that decision" (P16, Health, Trust).

When checking input, participants tended to intuitively "look for certain features" (P14) to judge by themselves. And in the card sorting, some participants used input as an anchor, put it side-by-side with example-bases explanatory forms (similar, typical, and counterfactual example) for comparison. Quantitative results led to the same findings, as input was clustered together with other example-based explanatory forms (Figure 7, Supplementary Material S2 Figure ??).

#### 5.10 Output

In our study, the output card contained prediction information of a point prediction, a prediction range, and their corresponding uncertainty level (for regression tasks); Or top three predictions and their likelihood (for classification tasks) (Fig 1). For the output information presentation, some participants preferred to check the point prediction at the beginning, and check the detailed prediction range and uncertainty level on-demand or leave them at the end, since they "need a longer time to understand what these numbers mean" (P02).

Participants had divergent preferences and understandings on the prediction presentation form. Compared to a point prediction (e.g.: house price prediction is 650k), some preferred to see a **prediction range** in regression tasks (e.g.: house price is 638-662k), or top predictions list

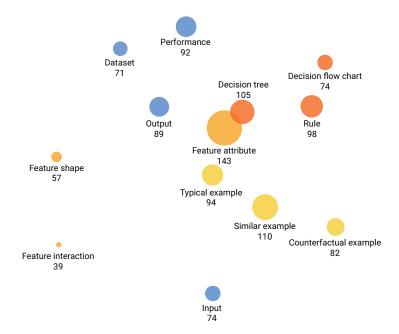


Fig. 7. **Visualizing the similarities of the explanatory forms**. The explanatory forms that are close to each other indicate they are more likely to be selected together to construct an explanation. The total number of times an Explanatory form was selected is indicated as the number below its name, also proportional to its dot size. The dot color indicates one of the four categories in the framework the explanatory form belongs to: feature, example, rule, and supplementary information. K-means clustering analysis on the 2D positional data yielded four clusters: Cluster 1: output, performance, dataset; Cluster 2: feature attribute, decision tree, rule, decision flow chart; Cluster 3: typical example, similar example, counterfactual example, input; Cluster 4: feature shape, feature interaction.

in classification tasks, because such prediction range "give choices" (P05, Bird classification task, Differentiation), "acknowledges a possibility" (P18, Bird, Unexpected), rank the decision priorities (P03, Car classification task, Safety), help them "(the range) to see how different between my and AI prediction" (P01, House regression task, Unexpected), and provide rooms for adjustment and negotiation:

"If I want to sell it higher, and I'll put 662k (the upper bound). Or if I wanted to sell it fast, then I'll put 638k (the lower bound). There's always a range, it's not necessarily just one price. And people will always bargain too." (P20, House, Communication)

And sometimes they "don't even need to know the (prediction) number exactly. This (range) tells me that (my diabetes risk) it's high. I have to do something. So that's what I want to know" (P17, Health regression task, Trust), and the range gives a higher certainty than a single point prediction which enhanced participants' trust.

In contrast, some other participants were more acceptable to a narrower range or a **point prediction**, because they saw a wider range of prediction had its drawbacks: "(the prediction range) shows too much fluctuation" (P07, House, Trust); And seeing the full predictions list (some with lower prediction likelihoods) may make them confused and discredit AI's decisions. Thus a narrower range may give them more confidence about AI's prediction.

"Seeing that the range is pretty small makes me a lot more confident that they've got enough data to actually be drawing conclusions." (P16, Health, regression task, Trust)

For the prediction likelihood/uncertainty/confidence<sup>2</sup>, some participants **had a hard time understanding the meaning of uncertainty** and required researchers' explanations. A high certainty "reassure AI's performance" (P22), "help a lot of persuading yourself into believing in AI" (P10), which is consistent with the recent quantitative finding on certainty level and trust calibration [99]. Especially for the explanation need where AI's prediction is unexpected, participants may abandon their own judgment due to AI's high certainty.

"If it had a high certainty, then I would want to know why my estimation is wrong." (P10, House, Unexpected)

# 5.11 Performance

After checking the performance information, most participants realized the probabilistic nature of AI decisions: "AI is not perfect" (P20), "they (AI) make errors sometimes" (P05). If the performance is within their acceptable range, participants would accept the "imperfect AI", and it helped them to set a proper expectation for AI's performance.

"I get it's downside. Performance warns me to, 'Hey, you know, it's not really accurate. There's some room for error.' " (P24)

And sometimes participants may calibrate their trust according to the error rate (in classification tasks) or error margin (in regression tasks).

"If there is a really big margin (of error), then it would probably demean the trust." (P23)

Almost all participants understood the meaning of accuracy (error rate) in classification tasks, whereas many participants had a difficult time understanding the margin of error in regression tasks.

"Performance is really in detail. I mean not everyone is familiar with statistics, like mean error." (P30, House, regression task)

Unlike the uncertainty level in output (Section 5.10) which is case-specific decision quality information, a few participants noticed performance is model-wide information, and just provides "general information showing the trust level of the system" (P04) is "too general, I would want to know specifically why (the speed) it's going down in this particular case of driving" (P05, Car, Unexpected). Thus they suggested there was no need to show it every time, "you should know before you use AI" (P11).

However, in some particular explanation needs such as to detect bias (Section 6.3), participants may require to check the fine-grained performance analysis on interested outcome.

"It (fine-grained performance on road/weather conditions) explains how often I should be confident in rainy days." (P19, Car, Safety)

#### 5.12 Dataset

In our study, the dataset card contains training dataset distribution of the prediction outcomes. Even after researchers' explanation, some participants did not well understand or **misunderstood** the information on this card (for example, some misinterpreted the distribution graph as feature shape), indicating it requires a higher level of AI/math/visualization literacy. For those who

<sup>&</sup>lt;sup>2</sup>Although the AI community has distinct methods to compute output likelihood and uncertainty level, in our study we used likelihood, confidence and uncertainty interchangeably to avoid participants' confusion.

comprehended the dataset information, some participants tended to link the dataset size with model accuracy and trust.

"The higher the (training data distribution) curve goes, then I would be more confident that they have a big pool of data to pull from." (P31, Health, Unexpected)

Some participants intuitively wanted to check their own data point within the training data distribution, and use it as a dashboard to **navigate, identify, and filter interested instances** (such as **similar**, **typical**, and **counterfactual examples**), to compare what are the same and different features between their input and the interested instances.

"I want to see which region I fall in the population, and compare with people around to see why my (diabetes) risk is only 10% with a family history." (P01, Health, Unexpected)

Nevertheless, in practice there may be some restrictions on reviewing the detailed dataset information due to data proprietary and privacy, as brought out by P19:

"I want to know the number of data and the details of it to verify. But I don't know if that's going to be able to be viewed. That's probably secret, right?" (P19, House, Expected)

# 6 RQ2: END-USERS' GENERAL REQUIREMENTS UNDER VARIOUS EXPLANATION NEED SCENARIOS

Although participants may have various motivations to check explanations, two main themes of explanation needs emerged in the interview. Quantitative clustering analysis confirmed similar trends as visualized in Fig. 9.

The first and fundamental driving force of checking explanations is to **verify AI's prediction**, and to gain trust and understanding of the AI system.

"Like boyfriend and girlfriend, I want to know what my boyfriend is thinking. Similarly, I want to know what the car's thinking before I'm with the car." (P32, Car task, Safety) – To gain understanding on AI

"I will also want to know how the software can predict the 80% chance that I'm going to have diabetes. And also, how did they come up with that numbers? Just giving me a number without justification or some verifiable reasons, it's just unlikely I would accept it because it may not be true." (P25, Health task, Trust)

The following explanation needs are more related to this motivation: calibrating trust (Section 6.1), ensuring safety (6.2), detecting bias (6.3), and resolving disagreement (6.4).

The second motivation to check explanations is for **personal improvement**, i.e.: to improve users' own welfare, such as to enhance personal problem solving skills and learning, or to improve the predicted outcome. This is built upon the trust and verification from previous experience, as one participant stated:

"(When trust has been established,) what has to be done in the next phase of the (AI) software, is how the software is being helpful to me. ... If I know the result, I don't think I would want to dig in to see why it is, but I would want to see how I can reduce the chances of diabetes." (P23, Health)

The following explanation needs are more related to this motivation: to seek suggestions to improve the outcome(6.8), to learn and discover new knowledge (6.7), to differentiate similar instances (6.6), to facilitate verbal (Communication, 6.9) and written communication (Report, 6.10), and to balance among multiple objectives (6.11):

#### 6.1 Calibrate trust

The process of calibrating trust involves multiple factors and their complicated interactions. We summarize the following key emerged themes participants requested to calibrate their trust toward AL.

(1) **Performance** Trust towards AI is fundamental to incorporate AI's opinion into the critical decision-making process [97], and many explanation needs below are built on trust. Since end-users usually do not have complete computational and domain knowledge to judge AI's decision process, model performance becomes an important surrogate to establish trust.

"Even if AI tells me how it reaches its decision, I cannot judge whether it's correct since it is a medical analysis and requires professional medical knowledge. I just know the accuracy and that'll be fine." (P01, Health)

Prior work identified two types of performance: stated and observed performance [95], and they were both mentioned in the interview. *Stated performance* or accuracy is performance metrics tested on previous hold-out test data, and it was mentioned by most participants as a requirement to build trust towards AI.

"I understand maybe AI is learning from past examples, and it may be finding patterns in the data that might not be easy to explain. So I'm less concerned about how it's getting there. I think I do have a trust that is doing it right, as long as there's something you can test after how accurate it's been." (P16, Health)

Compared to assessing the performance metrics, some participants tended to test AI by themselves and get hands-on *observed performance* to be convinced. This requires users to have a referred ground truth from their own judgment or reliable external sources.

"(My own test driving experience) is way more useful than watching a (test driving) video, because you shouldn't trust everything. The video might be just made to wait for you to buy the car. So talking from a customer perspective, I would like to try it myself, because I also sell things. So I would always like to try it myself instead of watching a video." (P21, Car)

(2) **Feature** The important features that AI was based on are the next frequently mentioned information.

"I would like to know the list of criteria that the AI chose the price based on, and which one weighs more." (P30, House)

(3) **The ability to discriminate similar instances** This information was requested by several participants to demonstrate AI's capability.

"(Decision tree) It's showing me that it's picking from a few similar ones, not just like a random ray of blue, purple, green birds. It's not random, it's a calculated response. More of that would help me trust AI." (P06, Bird)

"Typical example seems to be pretty good at picking up on differences. Similar example I can see that it's got a good variety of similar birds. So I found these ones make me trust it more. (P16, Bird)

(4) **Dataset** The dataset size that AI was trained on is another surrogate mentioned by some participants to enhance trust.

"To me what artificial intelligence does is just collecting a lot of data, and tries to make sense for behavioral patterns. So I would actually trust it, because I think it's just based on data, it is a more accurate measurement of what market rate is for house prices." (P03, House)



Fig. 8. **Heatmap of explanatory form—explanation need matrix**. The darkness level and number in the grid is the percentage of a explanatory form selected for that explanation need. The number under each need (on the horizontal top) is the total number of card sorting data collected for that need. The number beside each explanatory form (on the vertical left) is the total number of times an explanatory form was selected in the card sorting data.

"If I know that the AI comes from a large database, it seems like the database is actually the experience that AI has. So the larger it (dataset) gets, the more experienced AI would be, so I can trust it more." (P30, House)

- (5) **External information** This is another surrogate mentioned by participants to judge if AI is trustworthy. The external information could include:
  - (a) Peer reviews, endorsement, and AI company's credit.

"Since I'm not really a tech person, so I'm not sure how I look at it in a technical way. So that's why I just really depend on the company's reputation, and also how people feel about the website." (P28, House)

(b) Authority approval and liability.

"I trust more if the government themselves kind of stands behind it, getting some sort of government approval helps it a little bit more. So if there's some health authority like Health Canada or FDA support gives it more legitimacy." (P24, Health)

"For me personally, I would prefer if an actual person is there in the end, at least in the beginning stage. So if somebody is there to just say, 'hi, I'm so and so', and then AI takes control. Then we still know that there is somebody who's liable in the end for whatever happens." (P23, Health)

*Preferred explanatory forms.* The top three most selected forms for the need to calibrate trust were performance (20/40), output (20/40), and feature attribute (17/40). This quantitative results corresponds to the above qualitative themes (Figure. 8).

# 6.2 Ensure safety

To ensure safety and reliability of the AI system in critical tasks (the autonomous driving vehicle task in our study), participants frequently mentioned **checking AI's performances in test cases**, expecting the testing to **cover a variety of scenarios** to show the robustness of safety. Although it is impossible to enumerate a complete list of potential failure cases in testing, extreme cases or potential accidents were the main concerns and focuses of end-users.

"Potential crashes or just like someone speeding or a pedestrian jumping out of nowhere." (P19)

"There is likely to be someone running around, so it needs to show me the extreme cases. ... I need to see something like FMEA, failure modes and effects analysis, just to be like, 'okay this is how it works.' because I know nothing is foolproof. There are always to be something, but to what extent." (P03)

Similar to the need to calibrate trust, alongside the above *stated performance*, a few participants required *observed performance* to emotionally accept AI as an emerging technology.

"definitely I would want to be in one car. I think information is not helpful, it's not an intellectual factual thing, it's emotionally not acceptable. It (AI) is new and I have to learn to trust it." (P17)

*Preferred explanatory forms.* Regarding the specified information to present in the performance testing, participants would like to check the objects detected by AI (feature attribute, 9/13):

"It shows how it detects the important objects and how it makes decision" (P03, P05, P27)

"See if (the feature attributes) align with my own judgment of feature importance." (P01)

Performance (6/13) were also favourable to check the metrics summary of performance. A specified performance analysis in different test scenarios may also help as a safety alert by revealing the weakness of the system.

"Let's say I'm driving on a rainy day, then I know that I should be a lot more careful than when I'm with the car in a normal condition." (P27)

Similar example (7/13) were preferred since it showed "what's the condition or what kind of decision the car gonna make" (P32), although participants did not focus on its similarity nature, but rather assumed it can showcase a variety of cases including the extreme cases. Several participants chose decision tree (6/13) because it "gave me an overview of how the car makes decision" (P27).

#### 6.3 Detect bias

Participants were concerned about population bias [66], or distribution shift where AI models are applied to a different population other than the training dataset. Such concern is more prominent when a prediction is based on users' own personal data, and when users are in minority subgroups. Participants wanted to compare and see **if their own subgroup is included in the training data**.

"I know I'm in a class, they talked about how a lot of studies haven't been done specifically on women, even though they (diabetes) affect men and women differently. That is probably something I would want to know about, like if it gave me this result and then it had a little note that explained the research was done more on that demographic, so it may be more true for that demographic, but they're just trying to, what's the word, extrapolate to this group where I sit." (P22, female, Health)

Unlike the common bias and fairness problem in AI where the protected features should not affect the prediction, in our Health task on diabetes prediction, the protected features (age, gender,

ethnicity) do lead to a difference in diabetes outcome (referred as explainable discrimination in [66]). Participants who were aware of this point **required AI to account for such differences among subgroups**.

"I know some ethnic groups just by genetic makeup could be more predisposed to diabetes. In order for it (AI) to arrive at this decision, I would think that it has maybe like a sample size of different people with different ethnicities to try to figure out. I would think there'll be years and years of research has already been done of the different groups, different ages that would then be factored in by AI. If I can see it (AI) is using that information, I'll be a lot more comfortable to actually using the AI's recommendation." (P17, Health)

In cases where the AI task is not related to personal information (in our study the self-driving car task), participants required AI to be able to detect objects and perform equally in all potential biased conditions.

"Now we are operating in night time, or different weather, but they (the self-driving cars) still have to be able to see the signs and identify the objects." (P13, Car)

*Preferred explanatory forms.* A fine-grained performance (12/24) analysis based on protected-feature-defined subgroups [66] can help users to identify potential biases.

"I would want to see the certainty and what the prediction error can potentially be for my demographic versus other groups. If it (the prediction error) is quite low, then I would probably worry less about that." (P22, Health)

Participants chose similar + typical example (12/24, means out of the 24 card-selection responses on Bias, 12 selected either similar or typical example) to help inspect the data and model, and to compare with other similar instances to confirm their subgroup is included in the model.

"You would want to know what the data that it's being drawn from, is it similar to you?" (P16)

Feature attribute (12/24) was also chosen since participants wanted to check if AI could still detection important features in minority conditions.

"I want to see how well AI is performing at night to see what it detected." (P05, Car).

#### 6.4 Unexpected: When Users Disagree with Al

When AI's predictions did not align with participants' own expectations, most participants would "question AI" (P16, P20) and "the contradiction may let me confuse" (P02). Some may lose trust with AI thus would not go further to check its explanations, if they were confident about their own judgment. Some would check "a trusted second opinion" (P06, P10), or refer to human experts (P12).

But for the majority of participants, **explanations were needed** "to know why" (P01) and to resolve conflicts.

"I'm feeling conflicted because it's giving me two different information, my own personal belief and AI. So in order to convince me that AI does know what it's talking about, you need to go through the mental validation step [pointing to the ranked explanatory cards]. So by the time I go through this (explanatory cards) and I come out of it, I am extremely convinced." (P24, Health)

Explanations help to identify AI's flaws and reject AI, or to check the detailed differences and to be convinced and correct user's own judgment, although "it might be harder to persuade me" (P31). Specifically, participants "try to understand what makes a difference (between AI and my

*prediction*)" (P03), which is similar to the need to differentiate (Section 6.6). To show why the predictions are different, many participants **required a list of key features**.

"Because AI cannot think like a human, so the reason that I ask for the criteria list is trying to think how similar to me is AI's thinking. So maybe AI is thinking better, or is seeing a wider range, so it's checking things that I've never thought about." (P03, House)

In case AI made errors, seeing what AI is based on can facilitate user's "debugging" process. Although end-users cannot debug the algorithmic part, they may be able to debug the input to see if AI "have the complete information" (P03) as users have. Furthermore, if some key input information is lacking in AI's decision, the system needs to allow users to provide feedback by inputting more information (P03, P24), or "correct the error" (P16) for AI.

*Preferred explanatory forms.* Feature attribute: 28/61, similar example: 25/61, decision tree: 23/61, performance: 20/61.

## 6.5 Expected: When Users Agree with Al

In contrast, when the prediction matched participants' expectations, participants "will trust the AI more" (P10), and the motivation to check explanations was "not as strong as the previous one (unexpected explanation need)" (P02). Some participants stopped at the prediction, willing to accept the "black-box" AI and may "not even waste my time (checking explanations)" (P20).

A few participants still wanted to check further explanations for the following motivations:

## (1) To boost user's confident.

"Even in this (expected) scenario, it would be nice to have some bullet points, like the reasons behind it the estimation being accurate, because if someone says that you're charging me way too much, I can have point by point reasons explaining to you why this house worth this price, it actually kind of as a confidence boost to think you are not overcharging or undercharging." (P03, House)

# (2) To **improve the outcome** (see Section 6.8 for more findings).

"If diabetes already runs in my family, (and AI predicts my risk of diabetes is 80%), it would probably make me more confident about the software. So I might want to ask for more information about which aspects of my health records were the most important for making this decision? Coz then maybe that can help me with my future activities and changing things in the future." (P31, Health)

*Preferred explanatory forms.* Feature attribute: 13/34, similar example: 12/34, typical example: 10/34.

## 6.6 Differentiate similar instances

To facilitate end-users' need to differentiate similar instances, AI is required to first have the ability to discern similar instances.

"Depends on how good it is...So I think you would have to improve how AI picks up the birds, like maybe these are the same color birds, but maybe they have slightly different characteristics. So if AI can pick that up, then I think it would be better." (P10)

And in case of doubtful prediction, participants expected AI to indicate how certain it is to the prediction.

"I would expect AI if it doesn't know, it would give choices. So it would say 100% or 99% that's an indigo bunting, and 89% it thinks it's a finch." (P05)

Based on that, AI needs to be able to "*pinpoint unique features* that made them really different from each other" (P06). In addition, the interface may also need to support users' own comparison.

"AI can tell you what the differences are. I guess it could be some list of the beak is longer for this and that. But I think visually bringing the differences up side by side, and then I can directly compare what the differences are." (P16)

*Preferred explanatory forms.* Rule (12/14) and counterfactual example (10/14) were the most preferable forms. Participants chose rule since "you could write that you differentiated the bird's tail were long or short, or beak thin or thick" (P10). The counterfactual examples "identify where specifically to look" (P16), and "describe the change, the progress" (P11).

#### 6.7 Learn

Using AI for user's personal learning, improving problem solving skills, and knowledge discovery, "depends on how reliable it (AI) really is" (P10). And participants expected AI to "receive human feedback to correct its error and improve itself" (P01).

To facilitate learning and knowledge discovery, "just looking at (input) pictures and (output) names isn't enough" (P10), and participants **expected a wide range of explanations** depending on the particular learning goal, such as "more details to systematically learn, go over that same bird, …a mind map to build a category of birds by one feature" (P02), "the specific characteristic about this bird, and how can I differentiate this bird from other birds" (P04). Other learning features mentioned by participants include: referring to external "respectable source" (P18), supporting personalized learning for unfamiliar terms (P04), and "collecting information about how well I'm doing on it, like if I guess wrong, does it record that? to see if I'm progressing" (P16).

Preferred explanatory forms. Rule-based explanations (rule: 12/14, decision flow chart: 10/14, decision tree: 8/14) were more favourable for the need to learn, since they showed "a learning process. It has like how you could recognize a bird. So help me to learn some new knowledge" (P02). Same as in Report, participants would prefer to see "the graphics and text combined" (P02): "It combines text and pictures, and they are relevant to each other. It's kind of a multi-modal learning" (P04).

## 6.8 Improve the predicted outcome

Participants intuitively sought explanations to improve the predicted outcome, when predictions are related to personal data (in our study, the House and Health tasks). However, they **tended to unwarrantedly assume the explanations were causal** (causal illusion [65], i.e., believe there is a causal connection between the breakdown factors and the outcome), even though the cause-effect relationship has not been confirmed, and AI largely relies on correlation for prediction [73]. Only a few participants required more solid evidence to support the explanations on improving the predicted outcome, especially when the action was related to critical consequences (personal health outcomes).

"I presume the recommendation (on improvement actions from AI) is also has been backed up by Health Canada, because I think I would tend to follow the recommendations if I know there's definitely medical support behind it." (P24)

"I would definitely want to know like what can I do to mitigate those risk factors or to address those things so that I can decrease the risk. I would really like to know if it had an explanation of how reliable each source was. Coz I know some studies, they might seem like a correlation, but it doesn't mean it's a direct cause. So I would really love it if it could potentially explain how powerful those studies are suggesting." (P22)



Fig. 9. **Clusters of the explanation needs** The explanation needs that are close to each other indicate they have similar patterns on participants' Explanatory form selection. Specifically, each explanation need is represented by a 12-dimensional vector, where each number in the vector is the total number of an Explanatory form selected for that explanation need. We visualize their relative distances in the 2D scatter plot using PCA dimensional reduction. explanation needs are marked by different colors indicating the cluster they belong to using k-means clustering: **Cluster 1**: Trust, Communication, Unexpected; **Cluster 2**: Safety, Multi-objective alignment, Bias; **Cluster 3**: Expected, Improvement; **Cluster 4**: Differentiation, Learning, Report.

Regarding the specific requirements on the explanations for improvement, participants were looking for **controllable features** and ignoring the features that cannot be changed.

"I can not change my age, but I'm able to reduce my weights." (P02)

Knowing the controllable features has a positive psychological effect to give users a sense of control, and vice versa.

"If I'm afraid of getting diabetes, and assume that I'm going to sentence, it feels like there's nothing I can do about it. But when I see this one (feature attribute), I think, 'oh geez, maybe there are other factors here that I can do something about.' So this may make me more positive about doing something about my condition." (P16)

"I know it (feature interaction) is comparing my house area and my number of rooms with other houses. I can understand 'okay if I increase my room number, the price will be increased that much.' But the problem is I cannot change any of them (the house features). It just gives me the feeling of disappointment." (P30)

To counterpoise the unchangeable features, users may intuitively apply counterfactual reasoning to compare different feature adjustment settings.

"If I make any change in my house appliance and renew, then I can still reach the same price as if my house was bigger" (P30).

Preferred explanatory forms Counterfactual example (18/26) and feature shape (13/26) were the top two selected forms. While counterfactual example (Section ??) provides how to achieve the target outcome change by adjusting the input features (counterfactual reasoning), feature shape (Section 5.2) (and feature interaction) allow users to adjust features and see how that leads to outcome change (transfactual reasoning [42]).

## 6.9 Communicate with stakeholders

To communicate with other stakeholders, some participants chose to communicate verbally about their opinions without mentioning AI. Others preferred to present stakeholders with more evidence by bringing AI's additional information explicitly to the discussion. For the latter case, the **other stakeholders need to establish basic understanding and trust towards AI** before discussing AI's explanations.

"I'd sit down and get my family together and explain about the artificial intelligence thing." (P12, House)

"I would try to get some evidence from it (AI) that I could take to the doctor to get them to buy into it." (P16, Health)

To do so, most participants chose to present AI's performance information to build trust.

"As long as the backstage is accurate and then I can just provide accuracy to my wife and she'll be able to get that. Trustworthy is the most fundamental." (P28, House)

Different audiences and explanation needs of communication may require distinct explanations, as described by P32:

"I'm pretty sure my husband or my mother has a different way to decide or they want to know different things."

In addition, in the Health task, we asked participants to communicate with family members or doctors about their diabetes predictions. Since the requested explanation covered a wide range of contents, we did not identify any distinct differences in the communicating contents between the two audiences.

A formal summary or report from AI may facilitate the communication with other stakeholders, as requested by many participants.

"A written report from AI that I would be able to reference to, in order to talk to my family about that. It would feel a little bit more official rather than just, 'oh, this is what somebody said', there's no real evidence, whereas this sort of creates that paper trail." (P31, Health)

*Preferred explanatory forms* While output (21/46) and performance (17/46) provide AI's result and help to build trust, feature attribute (27/46) and decision tree (17/46) show the breakdown factors and internal logic behind the prediction.

## 6.10 Generate reports

The content of reports may largely depend on the specific explanation need and readers of the report. In our study, participants frequently mentioned the report should include "key identifying features", "list of distinguishing characteristics or what makes it unique" (P09), or "a summary of factors that were part of the input led to the diabetic prediction" (P31). Users also mentioned including supporting information to back up the decisions, such as the training dataset size of the predicted class, and the decision certainty level (P01).

*Preferred explanatory forms* Rule(12/14), decision flow chart(7/14), and feature attribute(5/14) are the most frequently selected explanatory forms.

Rule descriptions can conveniently generate text reports.

"I have to write the explanation" (P08, P09)

"You can not only by looking at the images and get some explanation. You need some more specific description." (P08)

In addition, adding image to the text "would be complementary" (P10) to each other, and the format of image + text were more favourable by many participants.

"Rule is just describing and writing. It doesn't really show you a visual on how to compare them." (P06)

"Feature attribute and decision flow chart (presented in image format on bird recognition task) highlights what rule is saying, this knowledge complements your statement." (P10)

# 6.11 Trade-off multiple objectives

Usually it is the human user rather than AI to trade-off among multiple objectives in AI-assisted decision-making tasks. Thus when multiple objectives get conflicted (in our study, they are scenarios when car drives autonomously and passenger gets a car sick; and AI predicts diabetes and uses it to determine insurance premium), AI was required to allow users to take over or to receive users' inputs.

"It's the most important thing I would want to do is to allow me to stop, or asking to slow down if I'm feeling sick." (P03, Car)

Explanations are required if the multiple objectives conflict and need to trade-off. And users could use such explanations to defend for or against certain objectives.

"I think it's like a defensive thing, like if I'm expecting that they're going to cause an increase in my payments or whatever they're going to deny me (health insurance) coverage, I would be trying to find out what it's based on for the opposite reason maybe to discredit it." (P16, Health)

#### 7 DISCUSSIONS

We state how the EUCA framework supports HCI/AI practitioners and researchers to build enduser-oriented XAI systems/algorithms, and discuss our findings and compare them with prior literature.

# 7.1 Utilities of the EUCA Framework

7.1.1 Explanatory Forms as Building Blocks. In the user study, participants sorted the explanatory form prototyping cards, and combined them to construct a low-fidelity prototype. Participants rated the resulting prototype fulfilled majority of explanation needs (231 out of 279 responses, 83%). This shows that the explanatory forms in the EUCA framework may serve as building blocks that can be combined to complete an explanation. The finding resonates with previous user studies that an XAI system should support "integrating multiple explanations", as "users employed a diverse range of explanations to reason variedly" [85]. The combination helps to overcome the weakness of an individual explanatory form, and may make the explanation more robust, complete, and versatile. With multiple explanatory forms that complement each other, users may construct a whole picture about AI's decision process more easily, and may mitigate confirmation bias, attribution bias, and anchoring bias [58].

Different explanatory forms can be combined *statically* as different modules in the UI, or *interactively* combined and incorporated in the UX to show detailed explanatory forms ondemand [29, 81, 82]. The contents of combination can be *fixed* or *dynamically* generated, i.e., the XAI system learns to use different explanatory forms as vocabularies to respond to user's follow up questions, so that to construct an interactive explanatory conversation [87] with end-users.

7.1.2 **Suggested Prototyping Process**. Our user study demonstrated the prototyping and codesign process with end-users. To determine the most feasible combination of the explanatory forms to construct prototypes for a particular XAI system, we summarize the prototyping process from our user study, and suggest the following co-design and prototyping workflow.

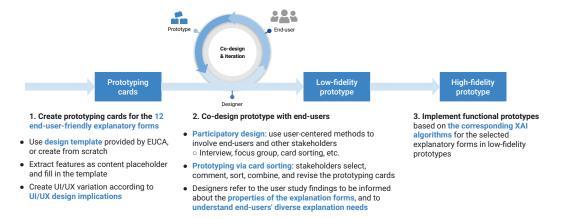


Fig. 10. **Suggested Prototyping Workflow using EUCA Framework** Blue bold text highlights the supporting contents provided by EUCA.

## (1) Create prototyping cards from explanatory forms

The designer starts by **manually extracting several interpretable features** given the AI task and input/output data type. For example, for tabular data, the features could be the column names that describing the input, such as house size, age, and location. For image data, the features could be saliency image part or object for recognition, such as cars, traffic signs, or pathological appearance of a disease on chest X-ray. As quick prototyping, the feature content may not necessarily reflect the true content generated by XAI algorithms. They served as content placeholders for the prototyping card design template.

Then the designer can use the prototyping card design template provided by EUCA, and **fill in the template with the above extracted features**. In the design template and example, we provide the basic visualization of the explanatory forms used in the user study. Designers can also create their own template from scratch by referring to the design examples. The EUCA framework website<sup>3</sup> supports designers sharing of their prototype design to expand the available design templates, and to encourage the reuse of design patterns on similar XAI applications.

For a particular explanatory form, the designer may **prepare multiple versions varying the visual representations** (e.g.: graphics or text) and UI layout, alternating contents from brief to details, and providing different options, such as whether to use pre-defined or user-defined contrastive outcome on **counterfactual example**, whether to give users the option to set a threshold level for **feature attribute**, or refer to the UI/UX design implications part in the user study findings (Section 5). Each explanatory form and its variations are presented on individual prototyping cards.

While designing UI/UX variations for the prototyping cards, designers may also consider and **apply the general human-AI interaction guidelines**. We selected the following design guidelines that are more relevant to XAI system: "remember recent interactions", "support efficient invocation, dismissal and correction", "remember recent interactions", "learn from user behavior", and "encourage granular feedback". Designers can refer to the guideline paper [14] for details.

<sup>&</sup>lt;sup>3</sup>http://weina.me/end-user-xai

(2) Co-design and iterate low-fidelity prototype with end-users With the prepared prototyping cards, the designers then can meet and discuss with the target end-users and/or other stakeholders of the XAI system, and apply user-centered methods informally or formally. Such methods may include interview, focus group, and card sorting. The communication aims to use the created cards as a prototyping tool to understand users' needs under potential explanation needs, and involve end-users in the co-design and prototype iteration process.

To quickly create a low-fidelity paper prototype from the prototyping cards, the **end-users can select, rank, combine, modify the prototyping cards**, and sketch new ones. In this process, designers may ask users why they selected or did not select a card, and their rationals for making such a combination, whether the combination could fulfill their requirements, and what is lacking in the current prototype. The users can easily manipulating the card positions to try out different layouts to examine different UI design possibilities (for example, on brewers, tablet or mobile phone).

Users can also comment on and revise each variation of the same explanatory form. With the tangible prototyping card examples, designers can know in-details about users specific requirements on the UI/UX design. The prototyping cards may facilitate the discussion of UX design, for examples, users may choose to hide some cards and only show them on-demand, or to present different explanatory information in different contexts.

After the initial communication with users, designers need to synthesize users comments and decide one or several prototype designs (such as using majority voting). Then based on the prototyping card ranking and combination, the designer may create low-fidelity prototypes, and continue to seek user and/or other stakeholders' feedback and iterate the prototype.

During the above process, the designer may refer to the user study findings to be informed about the properties of the explanation forms (pros, cons, applicable explanation needs, and design implications in Section 5), and to understand end-users' diverse explanation needs (to calibrate trust, detect bias, resolve disagreement with AI, etc. in Section 6).

# (3) Implement functional prototype

After co-design and several iteration, when the low-fidelity prototype is ready to implement, given that many existing XAI techniques are implemented as open-source toolkits (e.g.: [2, 4, 5, 8, 10, 17]), the development team can identify the most viable technical solution according to the corresponding XAI algorithms (Table 3) of the selected explanatory forms in low-fidelity prototypes.

- 7.1.3 Insights for novel XAI algorithms/interfaces. Our findings provide design implications and insights from end-users' perspectives. It would motivate HCI and AI researchers to develop novel interfaces/algorithms towards end-user-centered XAI. We give some examples for inspiration:
  - The design implication in similar example (Section 5.4) indicates users need to pinpoint the corresponding features among similar examples for easy comparison. This requirement can be regarded as a combination of the two explanatory forms similar example and feature attribute. Such insight may inspire UX researchers to design novel interfaces to support highlighting and comparing important features among instances on tabular data. However, this novel XAI interface is not applicable for image data, and new XAI algorithms need to be proposed, such as [28, 31].
  - Participants suggested to click features in feature attribute to check details of feature shape. It can be regarded as a combination of the two explanatory forms. Such a combination

can be achieved at the interface level, e.g.: Gamut [43], or at the algorithmic level, e.g.: COGAM [13].

• The advantages and disadvantages of similar example and typical example seem to be complementary to each other. A new type of example-based explanation may be proposed accordingly: it creates typical examples that are representative to the target class, while being as similar as possible to the input instance. Thus by taking the advantage of similar example, it is similar to the input instance to be easily understood, thus overcoming the disadvantage of typical example for being unrelated to the input instance; meanwhile it inherits the advantage of typical example for being distinctive and not confusing.

The above examples demonstrate using the explanatory forms as building blocks to create novel XAI algorithms/interfaces. In addition to the identified design implications in our study, XAI researchers can use the above prototyping method to identify users' requirements in their particular tasks, and propose new interfaces or algorithmic solutions accordingly.

Since explanation is a social process [67], an advanced XAI system may be trained to construct an explanation dialog [87] that mimics the human explanation process. New XAI algorithms can also be created in line with such a manner, for example, by using reinforcement learning to use different explanatory forms to respond to the user's current query and make such explanations adapted to users' preferences or explanation needs.

# 7.2 End-Users' Explanation Needs

XAI techniques are abundant, but understanding on end-users' needs is little. In this section, we present the user study findings on end-users' diverse needs for explainability within the context of explanatory forms. Our findings reveal two major themes of the need for explainability: explanations for verification/justification, and explanations for betterment.

7.2.1 "How do I know when my prediction is not an error?": End-users' verification of decision quality. After acknowledging AI's decision is probabilistic, most users need explanations for decision verification, so that they could incorporate AI into their own decision process on high-stake tasks. In our study, we discovered users frequently seek decision quality metrics, followed by explanations answering why or how questions (such as feature attribute and similar example) to verify the decisions. Users usually request such information 1) during the initial deployment stage [57] when trust has not been established so that users do not have knowledge on the observed performance [95], as in the explanation needs of safety and communicate; and 2) when AI's decision is being challenged, as in the explanation needs of bias and unexpected. Our quantitative results also revealed that the decision quality-related metrics (output, performance, and dataset) were frequently selected and ranked higher for the above explanation needs (Fig. 8).

In our study, we found that most participants accepted and understood the decision certainty in output, followed by performance. The training data distribution in a dataset was the least comprehensible form. Interpreting these metrics may require a certain degree of data analytic skills and could be time-consuming. The numbers may be contradicting and cause users' frustration. Thus, in real-world applications, it may not be feasible for end-users to check all the metrics. To indicate the probabilistic nature of AI, our findings (Section 5.10) suggest a possible workaround is to provide the range of prediction on-demand or a point prediction within its range. The range may bring additional benefits of leaving rooms for flexible and negotiable decisions for specific tasks. Another suggestion is to provide a unified and precise uncertainty estimation [20] metric that is case specific, incorporating all sources of decision uncertainty (such as performance on model capabilities, prior knowledge about the training data distribution, noises on input data, etc), to indicate the capabilities and limitations of AI prediction.

Alongside the above metrics, various other explanatory forms were selected by participants to verify AI's decision (trust, safety, bias, unexpected). The selection of explanatory forms largely depends on the specific task, the explanation need, and users' preferences, and there are no definite patterns. Previous quantitative results showed discrepancies of providing local explanations (feature attribute or similar example) and its effect on trust calibration and users' decision accuracy [54, 99], indicating explanations may play a complex role in the AI-assisted decision process. It may involve complex interactions among factors such as users' perception of the explanatory forms and their visual representations/layouts, AI and human's different error zones [99], explanatory information overload, users' cognitive bias when interpreting the explanations [9, 58], and how faithful the explanations are to the underlying AI model, etc. Future research is needed to explore these factors and their effects on human-AI collaborative decision quality. Because there lacks a universal model to predict various explanatory forms and their outcomes, our proposed EUCA framework could serve as a practical prototyping tool to quickly test the effects of various explanatory forms to guide the design process.

7.2.2 Explanations for betterment. The other major motivation to check AI's explanation is to move beyond decision verification, and to improve users' current status, such as to improve the predicted outcome, enhance users' learning and problem-solving skills, discover new knowledge, and trade-off among multiple objectives. Those explanation needs may emerge as users established trust and adopted AI into their decision workflow. As AI surpasses human performance in some critical tasks, AI can act as a knowledgeable source providing insights for humans to improve their own welfare. Although research in this direction is relatively limited, some prior works provide promising results on using machine explanations to improve users' knowledge and task performance [15, 53].

## 8 LIMITATIONS AND FUTURE WORK

The limitations and future work include:

- We summarized the end-user-friendly explanatory forms from technically-achievable solutions via a literature/critical review. We aimed to include the majority of existing explanatory forms with the information saturation criterion: i.e. no more additional explanatory forms could be identified. This process manifested in a conceptual model of the 12 end-user-friendly explanatory forms that served as a starting point for subsequent user study [38]. We did not aim to conduct an exhaustive, comprehensive systematic review, which is beyond what one paper could achieve. And since XAI techniques are fast evolving, the current framework may not necessarily cover all possible algorithms. The EUCA framework aims to serve as a moderate initial step towards a practical end-user-centered XAI framework, and is extendable to update with any emerging XAI technologies on the EUCA website<sup>4</sup>.
- Due to the high-stake nature and limited adoption of AI in critical decision-support, it is challenging to gain access to real-world AI systems in high-stake facilities (such as police offices, courts, clinics/hospitals, banks) to conduct user studies on multiple critical tasks, and recruit domain-specific end-users (such as physicians, police officers, judges, bankers). This is beyond the scope of one single paper could achieve. Therefore in the user study, we designed four fictional vignettes to represent the variability of AI-supported critical decision-making tasks, and participants' responses were based on conjecture rather than their real experience with AI. Our ongoing future work on XAI system design involves physicians as domain expert end-users using AI as support in their day-to-day clinical decision tasks.

<sup>&</sup>lt;sup>4</sup>http://weina.me/end-user-xai

Future work may apply the EUCA framework in other domain-specific XAI design and development practices to iterate and improve the framework.

• Bias may be involved in the card sorting of explanatory forms, as we noticed a few participants selected a card because it contained certain features rather than its distinguished form, despite in the follow-up questions we asked "what if the specific feature was or wasn't included". The explanatory forms, their contents, the particular visual representations, the task, user's current explanation needs, and user type all played a role in participants' selection choices under the specific study context, and our study design could not disentangle them. The quantitative results from card sorting are meant to serve as a reference only. They are not meant to be used directly to choose explanatory forms without the prototyping process, due to the above complex factors involved. Future work may design randomized controlled user studies to quantitatively examine the effects of the above factors in detail to guide the choice of explanatory forms in specific contexts. The EUCA framework website allows community users to share their prototypes, encouraging the reuse of design patterns on certain XAI applications.

## 9 CONCLUSION

Designing end-user-oriented explainable AI systems faces many challenges. From the user side, 1) End-users have diverse roles, tasks, and explanation needs. 2) End-users lack technological knowledge which is a prerequisite for some XAI systems in order to interpret the explanation. From the XAI practitioner side, 3) practitioners' expertise on AI or HCI/UXUI design usually does not overlap, and there lacks boundary objects to connect the two fields and facilitate collaboration between AI and HCI practitioners. 4) there lacks tools to support UI/UX design, prototyping, and co-design process.

To address the above challenges, we developed the end-user-oriented XAI framework EUCA with a collaborative effort of combining AI and HCI expertise. EUCA considers not only the human-centered perspective but also the technological capabilities, so that the design solutions are both end-user-oriented and technically achievable. It acts as a boundary object between AI and HCI fields and provides UI/UX design, prototyping, and co-design support.

To apply EUCA in practice, XAI designers can use the provided design templates to create prototyping cards for the twelve explanatory forms. The explanatory forms are end-user-friendly and were identified from a technically achievable solution space. They are a familiar and mutual language to both end-users and XAI practitioners. With the prototyping cards, designers can conduct a participatory design process that involves multiple stakeholders to receive their feedback and iterate the prototype. In this process, the stakeholders can comment, sort, combine, and revise the prototyping cards, to use them as building blocks to build a low-fielty prototype. Designers can also refer to the user study findings to be informed by end-users about the properties of the explanation forms (their strength, weakness, UI/UX design implications, and applicable explanation needs), and to understand end-users' diverse needs for explainability within the context of explanatory forms. The corresponding XAI algorithms for each explanatory form can facilitate developers to implement a functional prototype. As an initial step towards end-user-centered XAI, the EUCA framework provides a practical prototyping toolkit that supports HCI/AI practitioners and researchers to develop end-user-oriented XAI systems.

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