# Why Don't You <u>Do</u> Something About It? Connecting AI Explanations & User Action

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#### Abstract

A core assumption of explainable AI systems is that explanations change what users know, thereby enabling them to act within their complex socio-technical environments. Despite the centrality of action, explanations are often organized and evaluated based on technical aspects. Prior work varies widely in the connections it traces between information provided in explanations and resulting user actions. An important first step in centering action in evaluations is understanding what the XAI community collectively recognizes as the range of information that explanations can present and what actions are associated with them. In this paper, we present our framework, which maps prior work on information presented in explanations and user action, and we discuss the gaps we uncovered about the information presented to users.

#### **Author Keywords**

explainable AI; actionability; human-centered design

## **CCS Concepts**

•Human-centered computing  $\rightarrow$  User centered design;

### Introduction & Background

Artificial intelligence systems are increasingly involved in high-stakes decision making, such as healthcare, financial, and educational systems [32, 9, 26, 14]. Many have called

Permission to make digital or hard copies of part or all of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for third-party components of this work must be honored. For all other uses, contact the owner/author(s).

Copyright held by the owner/author(s). *CHI'23*,, April 25–30, 2023, Honolulu, HI, USA ACM 978-1-4503-6819-3/20/04. https://doi.org/10.1145/3334480.XXXXXXX for explainable AI (XAI)—AI systems that provide explanations for their reasoning or responses in a way that humans can understand [32, 9, 26]. Through the explanations, developers and researchers aim to create systems that support user trust [26, 36, 20, 41, 24], transparency [26, 24, 29, 3], and control and agency [3, 40, 21, 13, 33, 8, 19, 38].

Explanation systems are often organized and evaluated based on technical aspects. For example, many papers [2, 6, 7, 35, 4] organize and address explainability based on families of methods that are either inherently explainable (e.g. rule-based models, decision trees) or help with posthoc explainability (e.g. Partial Dependency Plots, counterfactuals, sensitivity analysis). Some have noted the overall lack of papers evaluating XAI methods and quantifying their relevance [37], and those proposing models often focus on technical quantiative measures [2, 4, 35], such as accuracy when performing a task [4, 35, 37], F1, and sensitivity [4].

While technical aspects are important for verifying algorithmic correctness, they don't speak to the core assumption of XAI systems: explanations change what users know, thereby enabling them to act in response to AI decisions [33, 38, 12]. The terms **actionability** and **actionable insight** are used to reference explanations' abilities to enable pragmatic action via the information they provide [28, 34, 11, 27, 42, 44, 39]. However, Liao, Gruen, and Miller [30] note the gap in delivering satisfying user experiences. Researchers are increasingly calling for greater consideration of users' actions when designing and evaluating XAI systems [28, 19]. Similarly, Ehsan et al. [17] propose incorporating social transparency—making visible socio-organizational factors that govern AI to help users more effectively take action.

Not only is there no consensus on what kinds of information can and should be presented to users, but there is also a relative lack of connection between types of explanations and what the resulting user actions are expected to be. Several papers [32, 26, 15, 43, 5, 1, 9] attempt to categorize information that explanations communicate, but many don't elaborate expected user actions. Others make a connection with user action by evaluating explanations on users' ability to act on unexpected behaviors [11], change an outcome [36, 27, 10], or achieve a desired result [39, 18, 22]. But these evaluate specific technical solutions.

We argue that the evaluation of the effectiveness of explanations be tied directly to the actions a user can take in response. Establishing action as a new heuristic for judging explanations is key to forcing designers to consider the explanation's integration with users' broader system factors. However, the lack of consensus on information that XAI systems present and what corresponding user actions one should want or expect can make the design and evaluation of XAI systems challenging.

We help reorient the evaluation of explanations by creating a framework that attempts to tie information presented by XAI systems to user action. We use existing literature to synthesize 10 categories of information that can be presented by XAI systems. For each category, we explicitly list actions users can take in response. Through our framework, we provide a more unified starting place to examine the relationship between information provided in explanations, user actions, and ultimate XAI interaction goals of trust, transparency, control, and agency.

#### **Creating the Framework**

Using existing XAI literature, we consolidated a framework mapping the kinds of information in explanations to associated actions. Papers focused on cataloging technical methodologies as opposed to information in explanations were excluded. After reading the abstracts in the search results, the authors selected 30 survey papers for deeper reading. Of these, 11 met the inclusion criteria: [1, 9, 26, 31, 25, 32, 16, 30, 4, 45, 23]. We iteratively developed the categories in our framework. We began with the categories listed out by the ICO & Turing Institute [1], cataloguing information types and any actions mentioned as intended or potentially resulting from the information provided. If a paper included a type of information that could not be clearly classified, we redefined our framework's categories, and then re-classified all information types and corresponding actions. Our framework isn't exhaustive, but a starting point.

#### The Framework

Our Framework, displayed in Figure 1, has 10 categories of information that are thematically grouped. Explanations with information on **Model Exposure** (pink) categories communicate how the model relates to the Al's decision to the user. Explanations with providing information on **Model Accountability** (orange) communicate about the creation, verification, and implications of the Al model. Finally, explanations providing information on **Model Context** (purple) communicate how the model aligns with externally produced information and its assumptions about users' context.

To the right of each category we list actions users can take in response. Jørnø & Gynther [28] and Fanni et al. [19] argue that an actor's "action capabilities" encompass mental actions or choices, which can impact physical actions or interactions. Thus, actionability can manifest as mental or physical actions. Consequently, we define three classes of actions. (1) Mental State Actions are changes in users' mental state that impact what they understand or believe about the system and how they can act in response. (2) XAI Interactions are the interactions users have with the XAI interface features, such as clicking buttons or toggles to request more information. Finally, (3) External Actions are actions users can take in response to and outside of the XAI system, such as reaching out to another person for help or ceasing to use the system. We acknowledge Mental State Actions are not traditionally considered part of "actionability". However, they constitute responses that potentially influence XAI Interactions and External Actions. For example, deciding on the continued usage of a system is neither an XAI Interaction nor an External Action but can impact both. Consequently, Mental State Actions are an important part of actionability that need to be considered.

While the user has a broad range of explanation types and resulting Mental State Actions, there are surprisingly limited potential XAI Interactios or External Actions. There are only 7 distinct XAI Interactions and 6 distinct External Actions. Further, the distribution of papers presenting explanations with information types across the typology revealed several gaps. Almost every paper (12 total) mentioned explanation(s) with Individual-Centered, Modus Operandi, Comparison, and Model Fairness information. However, only about half (4-6) of papers mentioned explanations with Model Performance and Model Input Environment information. Explanation examples with information on Model Implications, Model Responsibility, Externally Produced Knowledge, and Usage Assumptions were mentioned in no more than 2 papers. This may indicate a need for AI creators to expand the kinds of information and actions they can provide to users.

#### Conclusions

A core underlying assumption is that explanations are useful to users and that usefulness consequently manifests itself in the potential for action, both mental and physical. Through the examination and synthesis of existing literature, our framework contributes a first step in developing transferable evaluations centered on assessing explanations based on users' actions, and we uncovered several gaps in the literature around the kinds of information provided by explanations. Addressing the gaps may result in a richer design space of XAI systems that afford a greater range of actionability to users. The framework places actionability as the locus of successful XAI systems and suggests new opportunities to evaluate the effectiveness of explanations as an increase in the action potential of users.

#### What kind of information is provided?

## What actions can a user take with this information?

	Information Categories	Examples	Mental State Actions	XAI Interactions	External Actions
Model Exposure	<b>1. Individual Centered</b> How the user's data relates to the model and/or its decision	Your loan application failed because of your credit score.	<ul> <li>Understand the way my data fits into the model as a whole</li> <li>Understand what factors/features in my data influence the decision</li> </ul>	<ul> <li>Request more/different information</li> <li>Request a different presentation mode</li> <li>Contest decision</li> </ul>	
	<b>2. Model Operation</b> The logic/process the model uses to reach an outcome	When considering your loan application, the top 5 factors considered were credit score, location, applicant age, loan size, and past housing purchases.	<ul> <li>Understand model logic to reach outcomes</li> <li>Better understand influential factors in a model</li> <li>Understand what process the model is taking to reach outcomes</li> </ul>	<ul> <li>Request more/different information</li> <li>Request a different presentation mode</li> <li>Contest decision</li> <li>Report a bias</li> </ul>	
	3. Comparison Similarities/differences, alternate outcomes/scenarios, advantages between data inputs	Below are the profiles of the most closely matching applicants who had their application approved.	<ul> <li>Choose one option over another</li> <li>Compare the outcome in my case to other outcomes</li> <li>Find similarities/differences between myself and other similar points</li> <li>Notice differences/similarities between data points (not necessarily myself)</li> </ul>	<ul> <li>Request more/different information</li> <li>Request a different presentation mode</li> <li>Request an audit</li> <li>Report a bias</li> <li>Contest decision</li> <li>Request different points of comparison</li> </ul>	
	<b>4. Model Fairness</b> Aspects of design and implementation ensuring decisions are unbiased	The race and resident status variables were removed from data used to train the model. The model optimized heavily based on credit score as requested by company directors.	<ul> <li>Explore/understand steps taken across design and implementation to ensure decisions are unbiased</li> <li>Detect biases</li> <li>Notice missing pieces in the model</li> <li>Know all possible outcomes</li> <li>Explore/understand the original training datasets</li> <li>Understand what data is excluded for the model and why</li> </ul>	<ul> <li>Request more/different information</li> <li>Request an audit</li> <li>Report a bias</li> <li>Contest decision</li> <li>Input more/alternate data</li> </ul>	<ul> <li>Change a behavior producing outcome(s)</li> <li>Consult another person about outcome</li> </ul>
Model Accountability	<b>5. Model Responsibility</b> Who to contact for responsibility of a decision	To understand more about how this decision was made email BoALoanApplication@bank.us	• Know who to contact for the responsibility of a decision	Request more/different information	<ul> <li>Support another person's understanding</li> <li>Collaborate with another person</li> <li>(Re)Collect and input new data</li> <li>Report system to an admin/tech help</li> <li>Stop using system</li> </ul>
	<b>6. Model Implications</b> Wider impact on taking an action directed by the system's recommendations	Your bank loan is approved, but improving your credit score by 20 points, you may significantly reduce interest rates.	<ul> <li>Understand impact of system on individual or wider society</li> <li>Decide/Justify continued usage of system given impacts</li> </ul>	<ul> <li>Request an audit</li> <li>Report a bias</li> <li>Report unforeseen consequences</li> </ul>	
	<b>7. Model Performance</b> Metrics for accuracy, reliability, security, etc. of the system	On the training/validation dataset the model correctly classified 95% of profitable loan applications.	<ul> <li>Judge consistency/performance</li> <li>Decide on continued usage of system given certainty around predictions</li> </ul>	<ul> <li>Request more/different information</li> <li>Request an audit</li> <li>Report a bias</li> </ul>	
	8. Data Input Factors Factors impacting what data is collected and input	Due to existing privacy laws, data only collected from Southwest United States.	<ul> <li>Understand broader information about factors impacting current environment/explanation</li> </ul>	<ul> <li>Request more/different information</li> <li>Request an audit</li> <li>Report a bias</li> <li>Input more/alternate data</li> </ul>	
Model Context	9. Externally Produced Knowledge Other information originating from outside the current input data or organization	Here are the average interests rates charged across banks for home loan applications as listed by Fidelity.	<ul> <li>Validate claims from current model</li> <li>Gain confidence in system findings</li> <li>Uncover other areas of data to explore</li> </ul>	<ul> <li>Request more/different information</li> <li>Request a different presentation mode</li> <li>Contest decision</li> <li>Report unidentified (by system) consequences</li> </ul>	
	<b>10. Usage or User</b> Assumptions Assumptions the system makes about its users and how it will be used	Model trained on 10,000 application samples from banks across the Southeast United States. May not be representative of other regions.	<ul> <li>Transfer learning between domains</li> <li>Understand system assumptions about data</li> <li>Recognize patterns across data</li> </ul>	<ul> <li>Request more/different information</li> <li>Request a different presentation mode</li> <li>Contest decision</li> <li>Report an unforeseen consequence</li> </ul>	

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