

# A Critical Survey on Fairness Benefits of XAI

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In this critical survey, we analyze typical claims on the relationship between explainable AI (XAI) and fairness to disentangle the multidimensional relationship between these two concepts. Based on a systematic literature review and a subsequent qualitative content analysis, we identify seven archetypal claims from 175 papers on the alleged fairness benefits of XAI. We present crucial caveats with respect to these claims and provide an entry point for future discussions around the potentials and limitations of XAI for specific fairness desiderata. Importantly, we notice that claims are often (*i*) vague and simplistic, (*ii*) lacking normative grounding, or (*iii*) poorly aligned with the actual capabilities of XAI. We encourage to conceive XAI not as an ethical panacea but as one of many tools to approach the multidimensional, sociotechnical challenge of algorithmic fairness. Moreover, when making a claim about XAI and fairness, we emphasize the need to be more specific about *what* kind of XAI method is used and *which* fairness desideratum it refers to, *how* exactly it enables fairness, and *who* is the stakeholder that benefits from XAI.

## 1 INTRODUCTION

The integration of artificial intelligence (AI) into decision-making processes has raised concerns about reinforcing societal inequalities [17, 150]. Moreover, much progress in AI comes at the cost of increased complexity and opacity, which may impede human understanding [38]. Explainable AI (XAI) is commonly conceived as a remedy to both of these emerging challenges [25]. However, the implicit link between XAI and fairness has been challenged due to inconclusive evidence and a lack of consistent terminology [23, 122].

Our critical survey explores the complex relationship between XAI and algorithmic fairness by reviewing 175 recent papers and identifying seven archetypal claims on the alleged fairness benefits of XAI. Organizing the scattered debate into meaningful sub-debates, we discuss caveats and provide an entry point for future discussions on the suitability and limitations of XAI for fairness. We find that literature from various domains is highly optimistic about the usefulness of XAI for several fairness dimensions and stakeholders. However, many claims in the literature remain vague about how exactly XAI will contribute to fairness, and disregard technical limitations, conflicts of interest between stakeholders, and normative grounding. Highlighting central caveats as well as nascent approaches to address these caveats, we contribute to a more nuanced understanding of the interplay between XAI and fairness in AI-informed decision-making.

This paper is structured as follows: we start by establishing key concepts that we use to structure the debate and interpret claims. Next, we describe how we identified and organized claims from 175 papers into 7 archetypal categories. Afterwards, we introduce each archetypal claim at face value by verbalizing the underlying intuition from the literature. Based on that, we organize a meaningful, structured debate and take a critical perspective on these claims. Finally, we synthesize patterns of critique and caveats to embed the alleged fairness benefits of XAI in a bigger picture. Through this thorough and systematic study, we hope to bring clarity to the entangled relationship between XAI and fairness, and inform future efforts aimed at leveraging XAI to tackle algorithmic unfairness.

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## 2 BACKGROUND

*Related work.* While XAI and fairness have both separately produced a large body of research [45, 200], some recent publications note a lack of research at the intersection [23, 139]. Langer et al. [122] extract different desiderata of XAI (with one of them being fairness) from over 100 peer-reviewed publications and point out that only a subset of papers substantiates their claims with empirical evidence. Balkir et al. [23] survey challenges in the application of XAI for fairer language models and call for more precise conceptualization on how exactly XAI relates to fairness. Zhou et al. [234] provide an overview of XAI methods for fairness objectives and highlight the consideration of contextual factors as well as the need for interdisciplinary research. Our work adds to this stream of literature by adopting a systematic and critical approach similar to Blodgett et al. [36], who analyze and criticize the use of the term “bias” in the context of natural language processing.

*Dimensions of XAI and fairness.* Both XAI and fairness are multifaceted concepts that can be conceptualized along various dimensions [45, 200]. In this work, we understand XAI as any mechanism that “produces details or reasons to make [the] functioning [of an AI system] clear or easy to understand” [25]. We adopt the term *desideratum* from Langer et al. [122] to differentiate several roles and objectives of XAI. We explicitly examine desiderata in the context of fairness and distinguish between formalized notions of fairness (*formal fairness*) and human perceptions (*perceived fairness*), similar to Starke et al. [203]. Formal fairness criteria are captured in mathematical and statistical frameworks [24, 42] that may or may not be aligned with human fairness perceptions [66, 151, 202]. Formal fairness notions are often distinguished into group and individual fairness: group fairness criteria typically require a form of parity between demographic groups, for example, along sensitive attributes like gender or race [50]. Individual fairness criteria typically demand to treat similar people alike [69]. Perceived fairness is a subjective human attitude that is highly context-sensitive [203] and related to complex moral deliberations [31]. It requires fundamentally different measurements than formal fairness, for example, based on psychological constructs [55]. From Colquitt [55] we also adopt the decomposition into *distributive*, *procedural*, and a *informational* dimension. Distributive fairness is only concerned with the decision outcome whereas procedural fairness refers to the underlying decision-making process. Informational fairness accounts for aspects of the communication accompanying a decision.

Regarding the purpose of XAI, we further delineate *substantial* from *epistemic* goals [122]. An epistemic goal refers to the capability of humans to observe fairness properties of a model (e.g., XAI providing insights into a model’s reliance on sensitive attributes), whereas a substantial goal actively aims to alter fairness dimensions (e.g., mitigating formally unfair model characteristics). This distinction is helpful to understand the multifaceted role of XAI across many application contexts. For example, an epistemic usage of XAI may be to *inform* about a given fairness desideratum (e.g., group fairness), whereas a substantial usage of XAI aims at directly or indirectly *affecting* (un)fairness properties of an AI system. We also adopt the taxonomy from Langer et al. [122] on human stakeholders of XAI, which includes developers, deployers, regulators, users, and affected parties (i.e., decision subjects).

## 3 METHODOLOGY

Similar to Blodgett et al. [36], we systematically identified and scrutinized claims of recent publications—in our case about the fairness benefits of XAI. We first conducted a structured literature review guided by Kitchenham and Charters [112] to identify entrenched claims on the alleged capabilities of XAI for fairness. This process yielded 175 papers and is depicted in Figure 1. We supplemented our deductive literature review with inductive coding [228] at the level of

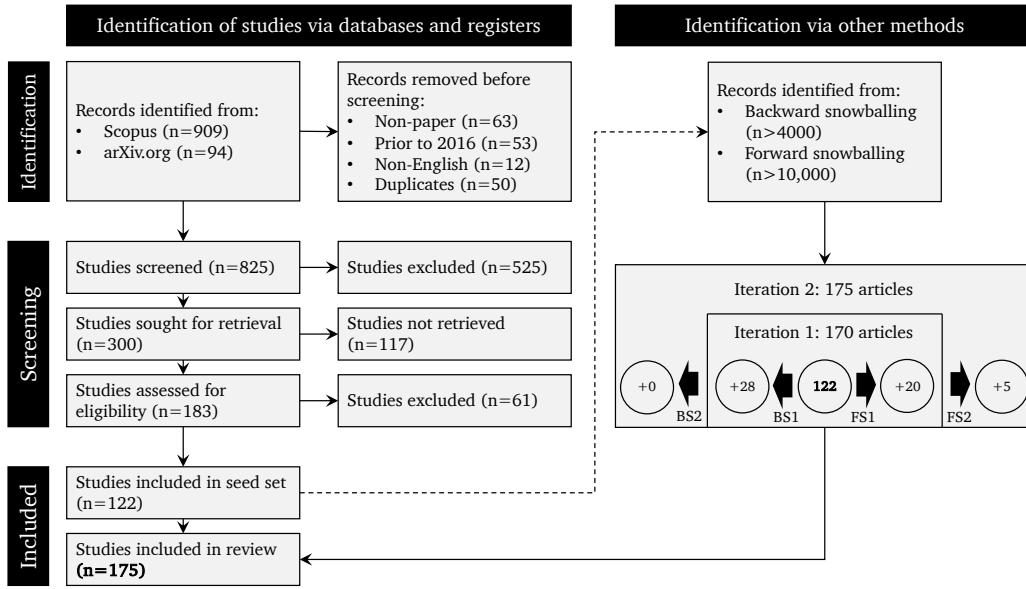


Fig. 1. PRISMA flowchart describing the article selection procedure.

individual claims. A rigorous qualitative analysis of these claims using a grounded theory approach [52] yielded seven archetypal claims, summarized in Figure 2.

### 3.1 Systematic Literature Review

In order to gain an understanding of the domain, test the effectiveness of keywords, and identify relevant publishers, we initiated an exploratory review by crawling the Google Scholar database. Our search string is chosen to reflect on various dimensions of both XAI and fairness and to restrict the results to AI contexts. For XAI, we relied on the taxonomy of Barredo Arrieta et al. [25] and also incorporated the related terms *understandability*, *comprehensibility*, *interpretability*, *explainability*, and *transparency*, as well as their inflections of the same stem. After screening around 400 individual papers, we finally decided on the following search string—note that the asterisk as wildcard character allows us in each case to consider words of the same stem, including adjectives and nouns:

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(xai OR explanation OR understandab* OR intelligib* OR comprehensib* OR interpretab* OR explainab* OR
transparen*) AND fair* AND (ai OR "artificial intelligence" OR "machine learning")
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Relying on recent recommendations to combine two popular search strategies, database querying and snowballing [227], we followed proven guidelines for systematic literature reviews in the domain of software engineering [112, 226]. Scopus was the natural choice for our database search because it is an effective tool to generate seed sets for snowballing [145], and it includes all relevant publishers for our task. To account for recent, unreviewed publications, we also applied our search string to the arXiv.org database. Following the documentation guidelines of Kitchenham and Charters [112] and the PRISMA standard [154], we provide a transparent and replicable documentation of the selection process: Figure 1 depicts how a total body of 1,003 identified records (as of September 2022) was condensed to a seed set of 122 with explanations on the filter criteria for each step. Because the goal of this critical survey is to characterize the *contemporary* discourse on XAI and fairness, we focused on papers from 2016 onwards.

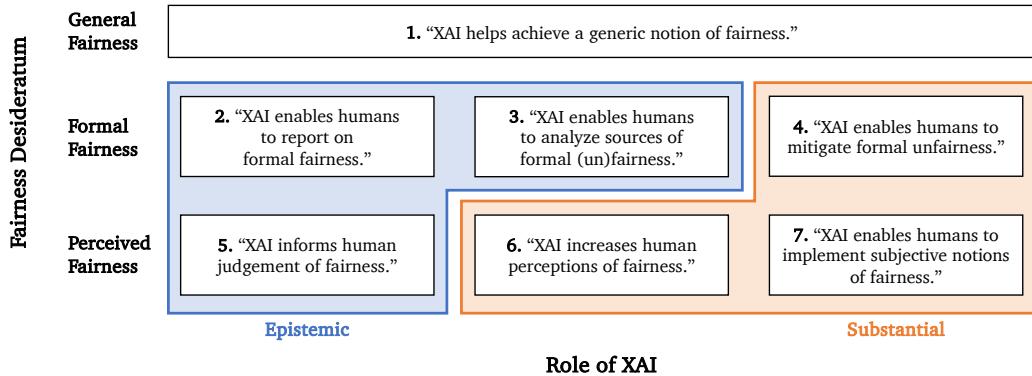


Fig. 2. The seven identified archetypal claims on the role of XAI for fairness desiderata.

At the initial identification level we only considered scientific papers and excluded records such as courses, keynotes, etc. Here, we manually inspected all abstracts and only retained papers examining dimensions of both XAI and fairness fitting into the broader scheme of our definitions. Consequently, we discarded papers having too broad or deviating notions of the XAI terms (e.g., using the term *explain* in a different context), papers using the term *fair* in different contexts (*fairly*, FAIR principles, etc.), and papers where fairness or XAI are not the object of research. Proceeding to full-text analyses, we heuristically scanned the entire paper for explicit claims on XAI and fairness. We focused on unique statements as opposed to straightforward summaries or paraphrases of previous work, which eliminated most literature review papers. Finally, we discarded papers where the direct relationship of XAI and fairness was not considered or remained too vague to infer any claims. For example, Shin [187] examines the influence of explainability and fairness on trustworthiness but does not address the interaction of explainability and fairness.

Starting from the seed set of 122 papers, we performed iterative backward and forward snowballing [226]. Using the citation crawling tool Citationchaser [94], we accelerated the snowballing procedure and focused on the most frequently referenced papers. We stopped whenever the third iteration had not generated any further hits. Please refer to Appendix A.1 for a comprehensive overview of the gathered papers categorized according to their underlying methodology.

### 3.2 Inductive Claim Analysis

In a subsequent step, we inductively identified dominant themes by analyzing commonalities and grouping claims into meaningful categories. We found grounded theory to be an appropriate methodology and followed the research design framework by Chun Tie et al. [52], employing MAXQDA for claim extraction, coding, and memoing [118]. To reiterate, we built our grounded theory around the following two questions:

- What does recent literature claim about the relationship between XAI and fairness?
- On what kind of evidence are these claims grounded?

We started by skimming the full texts of our 175 selected papers to comprehend the respective methodology and key results. In parallel, we scanned for claims with a strong focus on the most relevant and promising article sections. For example, introduction, discussion, and conclusion often provided more expressive claims than the method and results sections, which we usually only considered to retrace methodology or reasoning. Throughout the coding procedure, we

used memos to note down important insights, augment the claims with contextual information (such as textual context, meaning of abbreviations, authors' reasoning, etc.), and document the coders' line of thought.

In the first iteration we kept the codes as specific as possible to maintain a maximum amount of information. During coding we did not only consider the verbatim content of the claims but also their context and, if possible, their underlying reasoning. We used this information to categorize the type of evidence leading to the claim, which we recorded in our coding system. In the subsequent iterations we identified higher-level concepts and started grouping the claims into mutually exclusive categories. To achieve theoretical saturation, we ensured that the identified categories were sufficient and the assignment was plausible and correct by re-checking each claim.

#### 4 CRITICAL SURVEY

Figure 2 shows the result of our coding process and highlights the different roles XAI may take to address fairness desiderata. We use the concepts introduced in Section 2 to organize the claims and relate them to one another. This allows us to differentiate between claims about formal or perceived fairness, and claims on what we call "general fairness," which do not specify what kind of fairness is pursued. We also differentiate whether the claims relate to an epistemic or a substantial role of XAI. In what follows, we introduce each archetypal claim by verbalizing the underlying intuition and providing representative quotes from the literature. We then organize a structured debate and take a critical perspective. Please refer to Appendix A.2 for a comprehensive overview of archetypal claims including representative examples and a complete list of references.

##### 4.1 Claim 1: "**XAI helps achieve (a generic notion of) fairness.**"

This type of claim treats fairness as a monolithic concept without specifying *how* XAI will lead to *which* kind of fairness for *whom*. While phrasing and determinism vary by reference, we identify three tendencies. The first suggests XAI as a *necessary* condition for fairness. For example, a popular belief is that a decision has to be understandable in order to be fair:

*"First and most evidently, understanding the logic and technical innerworkings (i.e. semantic content) of these systems is a precondition for ensuring their safety and fairness"* [127, p. 40].

XAI is sometimes even treated as *sufficient* for achieving fairness. An exemplary intuition is that revealing the underlying mechanisms of a decision is all it takes to guarantee fairness:

*"From a social standpoint, explainability can be considered as the capacity to reach and guarantee fairness in ML models"* [25, p. 9].

Many others remain *tentative* insofar as they suggest vague capabilities of XAI for fairness but are less assertive:

*"Explainability and interpretability: these two concepts are seen as possible mechanisms to increase algorithmic fairness, transparency and accountability"* [44, p. 2].

*Critique: Futility and danger of vague claims on generic fairness notions.* Fairness is a multidimensional concept [55, 146] with many conflicting notions [78, 116]. Hence, it is easy to come up with counterexamples for such strong and simplistic claims. For example, distributions of classification rates can be used to show that models conform with formal fairness criteria without XAI methods [50]. Moreover, a transparent model can be perfectly scrutable and still be deemed unfair by some stakeholders, which precludes the suggested sufficiency [143]. The central underlying assumption behind these claims appears to be that XAI is valuable to *some* dimensions of fairness. This (perhaps plausible)

intuition is also reflected in all ethical AI principles reviewed by Floridi et al. [74]. However, we argue that suggesting a universal link between XAI and fairness is misleading and threatens a meaningful debate that should account for the multidimensionality of fairness and incorporate essential needs of relevant stakeholders [122]. Perpetuating these overly general claims threatens to produce unwarranted trust and reliance towards current XAI technology, and fails to recognize the multitude of interests with regard to fairness. By disentangling the multidimensionality of fairness into more fine-grained scopes, our work organizes the debate in a way that fosters more precise claims and nuanced arguments.

#### **4.2 Claim 2: “XAI enables humans to report on (formal) fairness.”**

A large share of papers is concerned with using XAI to measure and report on formal (un)fairness, often phrased as “identifying bias” [85] or “detecting discrimination” [106]. One central intuition behind these claims is that conventional evaluation of model outcomes (e.g., testing for demographic parity) may fail to consider the underlying mechanisms leading to this outcome [131]. XAI is expected to fill this gap by providing insights into these mechanisms, which may then be related to formal fairness criteria [67]. Since the anti-discriminatory motivation of formal fairness criteria typically relates to sensitive group attributes such as gender or race, XAI is commonly employed to examine how models make use of these sensitive attributes. Inspired by the legal notion of disparate treatment [132] and the idea of “fairness through unawareness” [120], one form of individual fairness deems any explicit use of sensitive attributes as unfair (e.g., [12, 96, 105]):

*“An algorithm is fair if the protected features are not explicitly used in the decision-making process.”* [105, p. 850].

Moreover, in cases where we have clear guidance on which features are legitimate and fair to use, prior work has argued that feature importance can be employed to validate whether models actually rely on these features; for example, in computer vision tasks [15]. Prominent XAI methods that have been employed to gauge the use of sensitive attributes are feature importance measurements using LIME [171] and SHAP [134] (e.g., [13, 46, 106]), or inherently interpretable models (e.g., [139, 169, 209]). Because sensitive attributes are often correlated to other (seemingly) legitimate features, many papers additionally account for correlations and causal relationships of sensitive attributes (e.g., [61, 87]). One work, for example, aims to “nullify the influence of the protected attribute on the output of the system, while preserving the influence of remaining features” [87] through XAI and post-processing techniques.

Another common form of individual fairness focuses on “contrastive explanations” [198] to identify instances where the outcome changes only based on “flipping” a sensitive attribute. Papers differ in their exact methodology but often rely on similarity-based measures (e.g., [35]) or counterfactually constructed data points (e.g., [60]) to identify data pairs where this behavior occurs.

*Critique: Misconceptions of feature importance for group fairness.* Logical conclusions between feature importance and formal fairness criteria require utmost caution. For a thorough discussion on formal relationships between sensitive attributes and various formal fairness metrics we refer to Castelnovo et al. [42]. Some prior work interprets low feature importance of sensitive attributes as a guarantee for demographic parity (e.g., [106]), and others claim that “feature importance measures do quantify both group and individual fairness” [46]. However, low feature importance of sensitive attributes is neither a necessary nor a sufficient criterion to satisfy formal group fairness metrics due to redundant encoding [65, 142] or differing base rates [69, 132]. Redundant encoding (i.e., correlations between sensitive features and other “task-related” features) is problematic because many popular post-hoc XAI methods, such as LIME and SHAP, do

not account for correlations. When demographic groups have differing base rates (e.g., higher average scores in credit risk scoring), achieving demographic parity would require the decision to account for these group inequalities—which would justify the purposeful use of sensitive attributes. Dwork et al. [69] coined this as “fair affirmative action,” and Lipton et al. [132] shows that this form of disparate treatment can be normatively justified depending on the societal context (see also Section 4.4). Recent empirical findings also indicate that various stakeholders tend to approve of the inclusion of sensitive attributes if it benefits historically marginalized groups [151].

*Critique: Normative grounding of applying XAI to individual fairness.* We further question the normative grounding of many cases where feature importance techniques are used to allegedly promote individual fairness. Prior work has interpreted low feature importance of sensitive attributes as a form of “fairness through unawareness” (e.g., [105]). This approach not only disregards the possibility of redundant encoding but also makes implicit normative assumptions about the world. According to Binns [32], this form of individual fairness is based on the assumption that any group disparities in task-relevant features stem from “personal choices,” as opposed to structural injustice. These assumptions also become paramount when contrastive explanations are employed to test whether similar individuals are receiving differing outcomes based on their sensitive attributes (e.g., [35, 72]), because such approaches disregard any relationships between sensitive and legitimate features. Binns [32] argues that the specified similarity norms in these techniques reflect specific worldviews ranging from “raw metrics” (attributing differences to personal choices) to group-adjusted metrics (attributing disparities to unjust structures).

Causality-based and correlation-based XAI methods (e.g., [61, 87]) may resolve the problem of redundant encoding and reveal statistical relationships between sensitive and legitimate features. However, using the information captured in sensitive attributes is not always morally wrong [151]. For example, consider the use of standardized tests to predict college success: financial ability to retake the exam and access training means that the relationship between test score and target outcome may vary across demographic groups, and thus including sensitive information may in fact be *desirable* from a fairness perspective [114]. Observing group-specific differences in the predictive relationship between covariates and outcomes is known as *differential subgroup validity* [104], and is common across domains, including hate speech prediction [91]. These caveats underline the need to not misuse XAI as a “fairness proof” but to interpret the fairness reports based on contextual factors and normative deliberations, as we further discuss in Section 4.5.

*Critique: A case for formal procedural fairness.* Balkir et al. [23] observe that XAI and formal fairness criteria take fundamentally different perspectives and argue that XAI focuses on the procedural dimension of fairness—that is, one that focuses on the fairness of decision-making processes rather than outcomes [88]. Whereas *formal distributive fairness* metrics (such as demographic parity and equality of opportunity) are well established in the literature and grounded on moral and political philosophy [19, 24], Balkir et al. [23] note that there is no shared conception of *formal procedural fairness*. Individual fairness criteria appear to get closest to a formalized notion of procedural fairness. However, as discussed above, the specific form of individual fairness is contingent on normative assumptions [32]. Morse et al. [144] propose the domain of organizational justice [55, 128] as another source of inspiration for formal procedural fairness. For example, Leventhal [128] defines six components of procedural fairness: consistency, accuracy, ethicality, representativeness, bias suppression, and correctability. For some of these components (e.g., bias suppression) XAI may in some instances be helpful; others (e.g., ethicality and correctability) would demand measures beyond formal fairness reports such as value transparency [133] and appeal processes [135] (see also Section 4.5).

*Critique: Technical limitations of XAI for formal fairness reports.* In a plea for intrinsically interpretable models, Rudin [174] argues how model-agnostic explanations of black-box models are fundamentally unfaithful to the original model and cannot explain decision processes sufficiently. This critique has been echoed in multiple studies demonstrating the susceptibility of such approaches to adversarial attacks on fairness reports, which produce innocuous explanations for (formally) unfair models. Major limitations of feature importance methods are “fairwashing” through, for example, rationalized surrogate models [6], reliance on input perturbations [197], or exploitation of redundant encoding [65].

Rudin [174] further questions the procedural character of many post-hoc XAI methods and argues that they do not reveal direct insights into the true underlying mechanisms of a black-box model. Accordingly, results from these XAI methods should be called “summaries of predictions”, ‘summary statistics’ or ‘trends’ rather than ‘explanations’ [174]. Indeed, post-hoc methods like LIME, SHAP, and contrastive explanations [198] provide little information about the decision-making process itself. A true procedural perspective on fairness may only be provided by model-specific explanations [41], such as intrinsically interpretable rule lists (e.g., [8]).

*Critique: Power asymmetries in XAI-enabled fairness reports.* The stakeholders (e.g., developers) in charge of producing fairness reports take a crucial role. By making important design choices on the transparency of a model, they shape the way a model is perceived by other, mostly less powerful, stakeholders in downstream steps. Many stakeholders without further access and knowledge must rely on the selective information provided by these XAI techniques. This power dynamic is critical since explanations can be manipulated to conceal the use of sensitive attributes (e.g., [6, 65, 121]). For XAI to become a valuable tool for fairness desiderata, it is, therefore, important to be explicit about the targeted stakeholders, their potential needs and objectives [122], as well as the normative deliberations that went into the development of relevant XAI techniques [133].

#### 4.3 Claim 3: “XAI enables humans to analyze sources of (formal) unfairness.”

Beyond descriptive fairness reports, XAI methods are often claimed to uncover patterns of formal unfairness and to pin down contributing factors.

“The investigations demonstrate that fair decision making requires extensive contextual understanding, and AI explanations help identify potential variables that are driving the unfair outcomes” [234, p. 1].

This extends the epistemic facet of XAI to provide deeper-level insights of how a specific notion of (un)fairness emerges. Such claims concern *instance-centric* or *feature-centric* approaches: instance-centric approaches focus on individual instances in the data that drive unfairness. For example, some prior works claim to identify discriminatory samples in the training data, which serve as a basis to mitigate formal unfairness (e.g., [3, 72]). Feature-centric approaches analyze how features relate to formal fairness. Some extend existing feature importance methods with the goal of quantifying the contribution of features to formal unfairness (e.g., [27, 142]). Others causally decompose the influence of sensitive features on outcomes into direct, indirect, or induced discrimination (e.g., [87, 231]).

*Critique: Using XAI to explore formal fairness.* Opposed to Section 4.2, the claims in this section are not using XAI as a “fairness proof” but rather as a tool to explore and understand problematic patterns. Still, some caveats from Section 4.2 apply here as well, especially with regard to the normative grounding of fairness desiderata. The idea behind formal fairness analysis is to contribute to a more profound understanding of unfairness than simple fairness reports, and many methods from the literature aim to identify “drivers” of unfairness—albeit at the cost of making strong assumptions such as knowledge of causal graphs [49], which may not always hold in practice. Moreover, Hu

and Kohler-Hausmann [103] argue that the validity of constructing counterfactuals based on sensitive attributes like sex may be questionable altogether. In Section 4.4, we describe how prior work has suggested to leverage insights on alleged sources of discrimination for *mitigating* formal unfairness. Some approaches also claim to provide a more “accurate” [83] and “robust” [27] picture of the usage of sensitive features potentially tackling issues of “fairwashing” raised by Aïvodji et al. [6]. However, future work must ascertain the reliability of these analytic tools and be cautious with the interpretation of the analyses.

*Critique: Formal fairness analysis contributes to a broader view on fairness.* Several papers in this category shed light on underrepresented facets of formal fairness that emerge with AI-informed decision-making. For example, Balagopalan et al. [22] and Dai et al. [58] argue that disparities in the quality (“fidelity”) of explanations introduce a novel kind of formal unfairness. This adds another layer to the relationship of XAI and fairness in that explanations are not only supposed to indicate unfairness but may themselves exert a form of unfairness. Moreover, Gupta et al. [92] and Karimi et al. [108] examine the fairness of recourse; that is, explanations that provide guidance to affected parties on how to turn a negative into a positive prediction. Recourse can be formalized by the distance to the decision boundary, which as well, can introduce disparities between demographic groups that conventional fairness metrics fail to reflect. By accounting for fairness of recourse, XAI might contribute to a more holistic view on formal fairness that not only considers discrete points in time but also addresses future actions of affected parties. However, Slack et al. [196] warn that counterfactual explanations can also be manipulated and show how several XAI methods are prone to concealing group disparities for cost of recourse (i.e., how much effort has to be invested in order to an individual’s outcome). Finally, Ghosh et al. [82] propose a framework that captures intersectional effects of multiple sensitive features. XAI targeted at intersectional fairness might pose a crucial step towards the hard problem of “fairness gerrymandering” [110]. As shown by Kearns et al. [110], a myopic focus on formal fairness metrics between individual groups is prone to conceal disparities between certain subgroups.

*Critique: Fairness analysis beyond currently available XAI methods.* Despite this broadened view, XAI methods might still suffer from blind spots beyond our attention. As Warner and Sloan [224] argue, there are facets to fairness that conventional XAI methods might never be able to reveal, such as contextual and societal factors that are not directly reflected in the data. For practical impact, XAI and fairness tools (e.g., [5, 98]) should extend towards underrepresented notions of formal fairness, and ethical AI frameworks (e.g., [80]) should provide guidelines to account for the societal context of fairness. Finally, Waller and Waller [219] contend that machine learning introduces a novel kind of bias (“assembled bias”) that does not emerge from societal data bias but from the process of feature creation. Assembled bias may extend beyond legally protected classes and poses novel challenges for XAI in the context of fairness.

#### 4.4 Claim 4: “**XAI enables humans to mitigate (formal) unfairness.**”

Several papers observing formal unfairness directly employ countermeasures to mitigate it (e.g., [139]) or propose mitigation as a next step for future work (e.g., [142]). The sequence of (i) detecting, (ii) analyzing, and (iii) mitigating unfairness aligns with the distinction between epistemic and substantial facets of fairness desiderata [122]. Beyond that, the facets can coincide when XAI methods like feature importance are directly integrated into training and bias mitigation algorithms:

“To inhibit discrimination in algorithmic systems, we propose to nullify the influence of the protected attribute on the output of the system, while preserving the influence of remaining features” [87, p. 1].

There are several studies that employ XAI methods with the goal of mitigating formal unfairness at the pre-processing, in-processing, or post-processing stage of AI systems (e.g., [8, 100, 165]). One common approach of using XAI for in-processing is to implement “interpretable” fairness constraints during model training, which has been done for rule lists (e.g., [8]), random forests (e.g., [4]), and deep neural networks (e.g., [218]). Post-processing methods include retraining algorithms that incorporate a fairness regularization term, which prior works compute with SHAP (e.g., [100]) or constructed counterfactuals (e.g., [59]). Aiming to resolve formal unfairness arising through concept drift, others have established a monitoring system that is claimed to automatically detect formal unfairness, attribute it to a responsible feature, and mitigate it [83]. Lastly, several papers [11–13, 29] propose feature dropout algorithms as a mitigation technique once an XAI method (e.g., LIME) detects reliance on sensitive features.

*Critique: Limitations of XAI to mitigate formal individual unfairness.* Many unfairness mitigation strategies suffer from the same shortcomings discussed in Section 4.2. Relying on LIME or SHAP to reduce the feature importance of sensitive attributes is prone to ignoring redundant encoding [142]. Further, employing XAI to increase individual fairness should be thoroughly grounded on normative assumptions about the source of existing group disparities [32]. Lastly, developers should make sure not to exacerbate issues of differential subgroup validity when using XAI methods for unfairness mitigation [91].

*Critique: Providing relevant cues for formal unfairness mitigation.* XAI techniques need to be designed to offer meaningful cues to human stakeholders, empowering them to effectively exercise their discretionary power in pursuit of specific objectives. With respect to formal distributive unfairness, recent work highlights concerns that widely used XAI methods such as LIME and SHAP may not provide such cues [179]. Instead, these techniques merely indicate whether an AI system utilizes sensitive information, which is insufficient for reasons outlined above. Emerging XAI techniques should empower human stakeholders to base their discretion on information that is both relevant and dependable, particularly for enhancing fairness objectives. A potential approach could involve directly conveying the pertinent individual or group fairness properties of the AI system to the relevant human stakeholder, as explored by Ahn and Lin [5] and Ashktorab et al. [21].

#### 4.5 Claim 5: “**XAI informs human judgment of fairness.**”

Whereas Section 4.2 summarizes XAI methods to provide descriptive information on formal fairness, this section discusses how humans interpret this information to make (non-formal) fairness judgments. Intuitively, if a model can justify its reasoning, a human should be able to judge whether it complies with normative standards or moral intuition.

*“Using XAI systems provides the required information to justify results, particularly when unexpected decisions are made. It also ensures that there is an auditable and provable way to defend algorithmic decisions as being fair and ethical, which leads to building trust”* [2, p. 52142].

Stakeholders may use information generated by XAI in multiple ways. First, *deployers* are interested in XAI to justify the decisions of their models in order to comply with legal frameworks and to foster trust and acceptance [56]. *Regulators* establish regulatory requirements on transparency and fairness to steer algorithmic decisions into a socially acceptable direction [170]. For example, human auditors might rely on XAI to judge the compliance with such requirements [225]. For example, Leslie [127] demands deployers to prove to an external auditor that their system is “ethically permissible, non-discriminatory/fair, and worthy of public trust/safety-securing.” Lastly, *affected parties* are addressed by XAI in multiple ways. Like other stakeholders, affected parties should also be able to make well-founded judgments about model

fairness, and XAI has been claimed to help in this regard [34]. However, addressing the limited access to information and lack of AI literacy, it is frequently demanded that affected parties should receive a dedicated set of information to engage in an informed discourse [175]. These demands are reinforced by Wachter et al. [217], calling for explanations that enable the understanding of decisions, support contestability, and provide guidance on recourse.

*Critique: The disputed value of XAI for auditing.* Several caveats on XAI for fairness reporting discussed in Section 4.2 have downstream consequences for auditing; for example, the capacity of XAI methods to intentionally or unintentionally conceal the feature importance of sensitive attributes. Also, delineating explainability from auditability, some works argue that XAI is not required to audit formal (distributive) fairness [201, 224]. Auditors should be aware of these limitations and embed the complementary insights provided by XAI in a broader sociotechnical framework to balance societal impacts of AI-informed decision-making [133]. By considering contextual factors, XAI may sometimes be valuable for fairness auditing. However, not in the form of “fairness proofs” but rather as a multifaceted tool to explore and indicate model characteristics that violate fairness expectations of involved stakeholders on a case-to-case basis [107]. Relying only on expert auditors to verify the fairness of AI systems as it is common practice in other high-stake domains [90] might promote dangerous dynamics for two reasons. First, current regulation is struggling to define specific fairness requirements [156]. Second, even with precise requirements and state-of-the art methods, code complexity [117] and “fairwashing” loopholes [6, 65] in combination with conflicts of interest [37, 77] pose threats to validity and robustness of expert audits.

*Critique: Right to explanation and informational (un)fairness.* Since the release of the GDPR, the implications for XAI and fairness are heavily debated [90, 93]. XAI is mostly seen as a valuable tool in the contexts of right to explanation [97], contestability [220], and recourse [92]. These desiderata are closely related to the concept of informational fairness, which has been defined as “adequate information on and explanation of the decision-making process and its outcomes” [181] as well as “informed self-advocacy” [215]. Prior work has observed that certain types of explanations support humans in acknowledging formal unfairness but also find that the context of deployment is a crucial moderator [34, 66]. However, to date there is not much guidance on how to design XAI towards informational fairness and informed self-advocacy. Asher et al. [20], Wachter et al. [217], and Watson and Floridi [225] provide conceptual starting points for formal requirements of explanations for affected parties but, to our knowledge, have not yet been tested empirically. Moreover, Schoeffer et al. [182] note that in some cases people seem to have no concerns with opaque decisions in the first place. In line with this, Schlicker et al. [177] find no effects for XAI on informational justice despite increased understanding.

Adding to this debate, research indicates that information can also be communicated in an *unfair* way. Aïvodji et al. [6] argue that the lack of specificity in XAI requirements creates incentives to provide deceptive explanations. Le Merrer and Trédan [124] formally show that remote explainability (i.e., indirect access to a single local explanation) makes it impossible for individuals to reveal untruthful manipulations. John-Mathews [107] proposes the concept of denunciatory power, which describes an explanation’s capacity to reveal an “unfair” incident. Based on an experimental study, it is shown how system providers are incentivized to always select the explanation with the lowest denunciatory power to minimize negative feedback. On the other hand, misleading explanations can even occur despite benevolent intentions [70]. Providing a game-theoretic framework, Watson and Floridi [225] conceptualize accuracy, simplicity, and relevance as the key properties of fair explanations, that is, the provided information should be trustworthy, understandable, and helpful to the explainee. They formally show that even accurate explanations can be misleading if they are incomprehensible or the information content is worthless. It remains an open challenge to empirically test

what kind of information XAI can provide to affected parties in order for them to *be* and *feel* treated “fairly” beyond the (currently) shallow concept of the “right to explanation” [216].

#### **4.6 Claim 6: “XAI improves human perceptions of fairness.”**

Beyond formal fairness, XAI is often touted to promote positive opinions and feelings about fairness of AI systems, which is closely connected with trust and acceptance [158, 191]:

*“The aim of local explanations is to strengthen the confidence and trust of users that the system is not (or will not be) conflicting with their values, i.e. that it does not violate fairness or neutrality”* [170, p. 5].

In a recent survey, Starke et al. [204] find “tentative evidence that explanations can increase perceived fairness,” and note that fairness perceptions are moderated by a range of factors, including the context of deployment, political ideology, AI literacy, and self-interest. To disentangle the effect of XAI on perceived fairness, several studies build on the justice constructs of Colquitt [55] to decompose fairness perceptions into an informational, procedural, and a distributive dimension. Accordingly, prior work has suggested that explaining models to affected parties (*perceived informational fairness*) enables and moderates fairness judgements about the underlying process (*perceived procedural fairness*) and its outcome (*perceived distributive fairness*) [34]. There is some evidence that XAI is effective in increasing perceived informational fairness and trustworthiness, even over explanations provided by human decision-makers [181, 183]. However, findings on perceived procedural and distributive fairness are mostly inconclusive [34, 177]. This might be due to the dual effect of XAI for perceived fairness described by Lee et al. [125]: XAI can contribute to more understanding and transparent treatment (which relates to informational fairness); at the same time, XAI can unveil properties of the model that might conflict with people’s fairness beliefs (which relates to procedural or distributive fairness).

*Critique: The societal concern with maximizing perceived fairness.* Positive fairness perceptions may in several cases be desirable but can emerge for questionable reasons. For example, Shulner-Tal et al. [192] find that the effect of explanations on perceived fairness is primarily dominated by outcome favorability. Contrarily, negative outputs are generally regarded as unfair, regardless of the explanation [192]. Shin [189] finds that the mere act of providing explanations positively affects source credibility, which makes humans prone to form trust based on placeboic [71] or manipulative explanations [6, 121]. Similarly, it has been shown that explanations can increase participants’ trust and fairness perceptions even if the scenario primes the model as unfair [16]. From a societal perspective, this is concerning because users might inappropriately rely on unfair model output and affected parties might not recognize that they are treated unfairly. Therefore, a key desideratum of XAI in many cases may not be to foster *positive* fairness perceptions but *appropriate* (i.e., calibrated) fairness perceptions [180].

#### **4.7 Claim 7: “XAI enables humans to implement subjective notions of fairness.”**

It has been claimed that stakeholders can adjust a model towards non-formalized notions of fairness based on factors such as morale, domain-specific expertise, or other contextual factors. Throughout a series of co-design workshops, Stumpf et al. [207] especially highlight users and affected parties as key stakeholders to mitigate unfairness by incorporating feedback into the model. From the perspective of users, Schoeffer et al. [179] suggest that XAI should enable humans to calibrate their reliance behavior accordingly, but also identify a lack of empirical evidence for this. An example of theoretical support for this idea is provided by Chakraborty et al. [47], who propose an XAI method that visualizes the nearest neighbors of an unfairly classified data point:

*“We generate this tabular explanation for all test data points which are unfairly treated. A domain expert can easily evaluate our explanations and take decision whether to change the prediction or not” [47, p. 1231].*

Further, XAI is claimed to enable domain experts to make better trade-off decisions, for example, between fairness and accuracy [5, 7]. Some works have also proposed to have users directly incorporate domain-specific interpretable constraints into the model [232]. Moreover, some papers support the idea of actively integrating XAI-based feedback on fairness from affected parties into the design process of a model [75, 207]. Prior experimental work has explored how affected parties can identify unfair use of features that developers might overlook [211]. Others have shown that the implementation of feedback from affected parties overall increases various fairness criteria but warn that including affected parties into the model design can have detrimental consequences [148].

*Critique: The threat of uninformed “humans-in-the-loophole”.* Existing laws and regulations (e.g., the GDPR), assign an essential role to a human-in-the-loop as a safeguard for fairness and accountability [97]. Arguably, human points of contact are valuable for a sense of interpersonal fairness [55]. Also, human discretion may be required to make normative trade-offs [184] and to overrule intolerable outputs [220]. However, humans engaging in AI-informed decision-making should be provided with adequate tools to foster effective and responsible reliance behavior [26, 178]. Otherwise, real-world applications might be at risk of installing uninformed “humans-in-the-loophole” [33] that legitimate whatever the underlying logic of the model dictates. The scarcity of research in this section indicates that the practical potential of XAI this regard is currently questionable and under-explored [179]. We are in need of effective XAI tools to capitalize on the complementary capabilities of humans and AI for fairness tasks; for instance, whenever AI is superior in analyzing statistical patterns and humans are required to balance fairness desiderata based on the societal context.

## 5 THREE PATTERNS OF CRITIQUE

According to our survey, there is a prevailing optimism in recent literature regarding XAI as a catalyst for promoting fairness in AI-informed decision-making. However, we contend that several of these optimistic expectations are misplaced. Specifically, many claims on alleged fairness benefits of XAI exhibit three distinct types of shortcomings.

First, despite being highly optimistic, we find that many claims on the relationship between XAI and fairness are **vague and simplistic**. In Section 4.1, we have seen that prior work has claimed XAI to be a necessary or even sufficient condition for fairness. However, such blanket claims are prone to promoting a misguided reliance on XAI for fairness. While prior work has shown that XAI might in some cases contribute to a better understanding of AI systems [129], it is questionable why explainability would be a “precondition for ensuring their safety and fairness” [127] if we, for example, are only interested in fair outcomes. Such claims may sometimes be based on an implicit assumption that XAI can enable humans to audit or rectify AI systems. However, this gives rise to another limitation concerning a disparity between the anticipated benefits and the actual capabilities of XAI techniques, a topic we will delve into shortly. Further, the idea of “ensuring” [127] or “guaranteeing” [25] fairness often fails to consider the multidimensional and conflicting nature of fairness [62, 78, 146]. A one-size-fits-all fairness notion simply does not exist [50, 116]. We hope that our work can cultivate a more nuanced language for future research on potential capabilities of XAI for fairness.

Second, many fairness desiderata pursued with XAI methods are **lacking normative grounding**. For example, several papers treat “reliance on sensitive features” [12] as a form of unfairness without offering a normative rationale for why such reliance might be problematic. Binns [32] argues that this notion relates to a very confined form of unfairness that assumes a worldview where group disparities are solely due to personal choices. While this view might

be valid in (hypothetical) societies where no structural disadvantages occur, it is crucial to critically reflect upon this fundamental assumption. In fact, prior work has shown that actively *considering* sensitive attributes, such as gender or race, may significantly improve performance for historically marginalized groups like Black people and women and reduce algorithmic bias [114, 132, 138, 164, 194]; and this is closely connected to the presence of differential subgroup validity [104]. Finally, claims suggesting XAI as a means to improve fairness perceptions often fail to explain why positive fairness perceptions are a desirable goal in themselves—particularly in light of prior work showing that human perceptions are easily misled [51, 121, 197]. Instead, in many cases a more ethically justifiable goal might be to foster *appropriate* fairness perceptions, which are positive if and only if the underlying AI system is fair [180].

Third, even in cases of specifying and motivating a valid fairness desideratum, some claims are **poorly aligned with the actual capabilities of XAI**. For example, if the goal is to achieve formal distributive fairness, it is unclear how exactly XAI should promote this. In fact, prior research has shown that popular feature-based explanations like LIME and SHAP are unreliable mechanisms for enabling humans to enhance formal distributive fairness through leveraging their discretionary power [178]. It has also been shown that many post-hoc XAI methods are not suitable for auditing AI systems due to their susceptibility to manipulations [6, 14, 65, 196, 197]. For example, Dimanov et al. [65] show that adversarial model explanation attacks can reduce the feature importance of sensitive attributes and still exacerbate distributive unfairness. Instead, XAI appears to be more suited to reflect upon the legitimacy of features (e.g., [14]), which, again, requires human intuition and normative grounding throughout the evaluation. Finally, explanations based on counterfactuals are often impractical in the real world due to their reliance on the knowledge of causal structures.

## 6 CONCLUSION AND OUTLOOK

We conducted a critical survey organizing and scrutinizing claims about alleged fairness benefits of XAI. Despite many optimistic positions on XAI in the recent literature, we notice that the claimed fairness desiderata are often (*i*) vague and simplistic, (*ii*) lacking normative grounding, or (*iii*) poorly aligned with the actual capabilities of XAI. To facilitate a meaningful debate and move the field forward, our work stresses the importance of embedding XAI in a sociotechnical decision-making context that considers normative motivations and societal circumstances. Concretely, we emphasize the need to be more specific about ***what*** kind of XAI method is used and ***which*** fairness desideratum it refers to, ***how*** exactly it enables fairness, and ***who*** is the stakeholder that benefits from XAI. We hope that future work will build on our survey to address and overcome the fairness-related limitations of XAI.

By structuring the debate and building on the differentiation of fairness dimensions from prior literature, we hope to inspire a more nuanced and precise language for future research. A distinction between formal metrics and human judgement helps to keep in mind that formal fairness criteria are often only meaningful when put into context and related to a moral principle. This is especially relevant for XAI-informed fairness reports where the use of sensitive attributes can indicate discrimination but can just as well be normatively justified. The distinction between epistemic and substantial facet [122] clarifies the role XAI is meant to play: are XAI methods used to explore unfairness or do we employ it to directly alter the model’s fairness properties? Finally, the distinction between informational, procedural, and distributive fairness [55] allows a closer look at specific aspects of an entire decision-making interaction. For example, we expect informational fairness to provide an intriguing perspective on XAI with a focus on *fair explanations* as opposed to fair decisions. Moreover, we encourage future work to center around our raised questions of ***what***, ***which***, ***how***, and ***who*** in order to map opportunities of XAI for different human stakeholders along the full lifecycle of AI systems. Our archetypal claims may provide an entry point for such a framework.

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## A SUPPLEMENTARY MATERIAL

### A.1 Overview of the Literature

Consistent with Langer et al. [122], the literature identified from our systematic approach is highly diverse with regards to methodologies, pursued desiderata, and addressed stakeholders. To provide an overview of the examined set of papers, we start by describing the methodology used in these papers. The key point of this is not a perfectly distinct categorization but rather an emphasis of the types of evidence for the respective claims. Table 1 breaks down the methodologies used in the 175 papers and provides prominent examples to clarify the categories. Note that the counts add up to more than 175 due to some papers using more than one method. For example, Ahn and Lin [5] propose a design framework, instantiate it on real-life data, and additionally conduct user studies to demonstrate its use for practitioners.

Table 1. Methodologies used in the 175 reviewed papers.

Methodology	Count	Exemplary papers
<b>Conceptual contributions</b>	<b>76</b>	
Framework	35	[74, 115, 122]
Argumentation	24	[117, 131, 174]
Literature review	20	[25, 67, 126]
<b>ML evaluation</b>	<b>84</b>	
XAI/fairness method	63	[61, 87, 231]
Case study	12	[84, 119, 141]
Applied framework	9	[5, 98, 186]
<b>Human subject studies</b>	<b>29</b>	
Quantitative study	23	[34, 66, 107]
Qualitative study	14	[66, 125, 182]

*Conceptual contributions* comprise literature reviews and argumentations (such as position papers) building on prior work and reasoning. Elaborate recommendations for design, evaluation, or regulation as well as conceptual or formal models also fall into this category, labeled as frameworks. *ML evaluation* work comprises all studies that empirically evaluate an ML method or framework on real-world datasets. By far the most prevalent type of research is the empirical evaluation of an XAI and/or fairness method. This also includes work that scrutinizes existing XAI methods by performing adversarial attacks. Case studies applying existing methods in a specific domain or context are also included in this category. Further, if a framework is empirically evaluated on data, it additionally appears in this category as applied framework. Finally, *human subject studies* involve empirical examination of human perceptions, needs, or feedback. While quantitative methods mostly test statistical significance of hypotheses on fairness perceptions, qualitative methods explore reasoning and opinions of various stakeholders.

### A.2 Tabular Overview over Archetypal Claims and Literature

Table 2. Overview of evidence and references for claim 1: “*XAI helps achieve (a generic notion of) fairness*”.

Evidence	Exemplary claims	References
<b>Intuition</b>	<i>Necessary</i> : “First and most evidently, understanding the logic and technical innerworkings (i.e. semantic content) of these systems is a precondition for ensuring their safety and fairness.” [127, p. 40]	[10, 127, 149, 198, 205]
	<i>Sufficient</i> : “[F]rom a social standpoint, explainability can be considered as the capacity to reach and guarantee fairness in ML models.” [25, p. 9]	[1, 2, 25, 40, 73, 84, 214]
	<i>Tentative</i> : “Explainability and interpretability: these two concepts are seen as possible mechanisms to increase algorithmic fairness, transparency and accountability” [44, p. 2]	[39, 44, 54, 80, 176]
<b>Conceptual caveats</b>	“[A] perfectly auditable algorithmic decision, or one that is based on conclusive, scrutable and well-founded evidence, can nevertheless cause unfair and transformative effects, without obvious ways to trace blame among the network of contributing actors.” [143, pp. 14–15]	[122, 143]

Table 3. Overview of evidence and references for claim 2: “*XAI enables humans to report on (formal) fairness*”.

Evidence	Exemplary claims	References
<b>Intuition</b>	“These explanations are important to ensure algorithmic fairness, identify potential bias/problems in the training data, and to ensure that the algorithms perform as expected” [85, p. 1]	[1, 25, 28, 64, 67, 68, 85, 93, 101, 102, 106, 131, 139, 140, 158, 166, 170, 173, 174]
<b>Conceptual support</b>	“Actions driven by algorithms can be assessed according to numerous ethical criteria and principles, which we generically refer to here as the observer-dependent ‘fairness’ of the action and its effects. An action can be found discriminatory, for example, solely from its effect on a protected class of people, even if made on the basis of conclusive, scrutable and well-founded evidence.” [143, p. 5]	[37, 77, 84, 98, 122, 143, 198, 214]
<b>ML evaluation support</b>	“[F]eature importance measures are connected both with consistency and equality of opportunity. Consequently we see that feature importance measures do quantify both group and individual fairness.” [46, p. 9]	[3, 9, 12, 13, 15, 27, 35, 43, 46, 59, 61, 72, 76, 79, 87, 95, 98, 105, 106, 137, 139, 141, 142, 152, 157, 160, 163, 167, 169, 186, 206, 208–210, 213, 221, 230]
<b>Conceptual caveats</b>	“The excluded or ‘protected’ attributes can often be implicit in other nonexcluded attributes.” [117, p. 685]	[23, 87, 117, 139, 185]
<b>ML evaluation caveats</b>	“[M]any prominent XAI tools lack features that could be critical in detecting bias.” [9, p. 1]	[7, 9, 27, 65, 95, 139]

Table 4. Overview of evidence and references for claim 3: “*XAI enables humans to analyze sources of (formal) unfairness*”.

Evidence	Exemplary claims	References
<b>Intuition</b>	“If your AI model is not sufficiently interpretable—if you aren’t able to draw from it humanly understandable explanations of the factors that played a significant role in determining its behaviours—then you may not be able to tell how and why things go wrong in your system when they do.” [127, p. 39]	[1, 3, 9, 25, 68, 127, 141, 165, 193, 209]
<b>Conceptual support</b>	“The investigations demonstrate that fair decision making requires extensive contextual understanding, and AI explanations help identify potential variables that are driving the unfair outcomes.” [234, p. 1]	[5, 58, 84, 142, 193, 234]
<b>ML evaluation support</b>	“We derived the Causal Explanation Formula [...], which allows one to understand how an observed disparity between the protected attribute and the outcome variable can be decomposed in terms of the causal mechanisms underlying the specific (and unknown) decision-making process.” [231, p. 2044]	[3, 5, 9, 14, 22, 27, 35, 47, 53, 61, 72, 79, 81–84, 86, 87, 137, 141, 142, 147, 152, 155, 165–167, 169, 172, 193, 197, 209, 210, 213, 230, 231, 233, 234]
<b>Conceptual caveats</b>	“[E]xplainable systems can be unfair in ways explainability will not reveal.” [224, p. 31]	[224]
<b>ML evaluation caveats</b>	“[LIME] still lacks the skills to detect issues of biased data and detect issues in the selection or processing of the model.” [9, p. 12]	[9]

Table 5. Overview of evidence and references for claim 4: “*XAI enables humans to mitigate (formal) unfairness*”.

Evidence	Exemplary claims	References
<b>Intuition</b>	“A consequential next step to this analysis is to look for methods that mitigate unfairness in the ML methods and at the same time maintain the accuracy gains.” [209, p. 7]	[30, 64, 77, 96, 101, 106, 122, 130, 139, 142, 193, 209, 218, 231]
<b>ML evaluation support</b>	“To inhibit discrimination in algorithmic systems, we propose to nullify the influence of the protected attribute on the output of the system, while preserving the influence of remaining features.” [87, p. 1]	[4, 7, 11–13, 29, 59, 72, 81, 82, 87, 92, 95, 100, 111, 123, 147, 155, 160, 165, 175, 218, 222, 229, 232, 233]
<b>Conceptual caveats</b>	“[W]e observe unfair recourse even when the predictions are demographically-fair.” [108, p. 14]	[77, 219]

Table 6. Overview of evidence and references for claim 5: “*XAI informs human judgement of fairness*”.

Evidence	Exemplary claims	References
<b>Intuition</b>	“Using XAI systems provides the required information to justify results, particularly when unexpected decisions are made. It also ensures that there is an auditable and provable way to defend algorithmic decisions as being fair and ethical, which leads to building trust.” [2, p. 52142]	[2, 28, 34, 44, 48, 56, 63, 66, 67, 84, 93, 97, 101, 113, 124, 133, 136, 159, 169, 175, 188, 199, 212, 217, 225, 235]
<b>Conceptual support</b>	“In offering an explanation to affected stakeholders, you should be able to demonstrate that considerations of ethical permissibility, non-discrimination/fairness, and safety/public trustworthiness were operative end-to-end in the design and implementation processes that lead to an automated decision or behaviour.” [127, p. 35].	[20, 34, 56, 63, 74, 77, 92, 96, 100, 107, 108, 125, 127, 133, 153, 181, 185, 192, 201, 217, 224, 235]
<b>ML evaluation support</b>	“The explanations can be used either as justification in case the decision is challenged or as a feasible action that the individual may perform in order to improve the outcome in the future (‘recourse’).” [79, p. 581]	[79, 92, 186]
<b>Human subject studies support</b>	“The results from a within-subjects study suggest that standards clarity and outcome explanation allowed people to judge whether the fairness properties of the algorithm were in line with their fairness concepts.” [125, p. 18]	[16, 18, 34, 66, 89, 107, 125, 148, 181]
<b>Conceptual caveats</b>	“A perfectly auditable algorithmic decision, or one that is based on conclusive, scrutable and well-founded evidence, can nevertheless cause unfair and transformative effects, without obvious ways to trace blame among the network of contributing actors.” [143, p. 14]	[6, 27, 47, 48, 57, 63, 80, 84, 85, 89, 90, 99, 107, 109, 117, 124, 126, 133, 136, 143, 174, 179, 180, 184, 185, 189, 191, 197, 201, 217, 220, 224, 225]
<b>ML evaluation caveats</b>	“[W]e show that it is possible to forge a fairer explanation from a truly unfair black box through a process that we coin as rationalization.” [6, p. 2]	[6, 14, 22, 27, 57, 65, 196, 197]
<b>Human subject studies caveats</b>	“[D]epending on how and when they are deployed, explanations may or may not help individuals to evaluate the fairness of such decisions.” [34, p. 10]	[6, 14, 16, 22, 34, 57, 65, 107, 196, 197]

Table 7. Overview of evidence and references for claim 6: “*XAI improves human perceptions of fairness*”.

Evidence	Exemplary claims	References
<b>Intuition</b>	“The aim of local explanations is to strengthen the confidence and trust of users that the system is not (or will not be) conflicting with their values, i.e. that it does not violate fairness or neutrality.” [170, p. 5]	[158, 170, 180, 189, 191, 192]
<b>Human subject studies support</b>	“Requiring organisations to explain the logic behind their algorithmic decision-making systems (informational justice) enables affected individuals to assess whether the logic of the system is just (procedural justice), which in turn might moderate their assessments of fairness of the decision outcomes (distributive justice).” [34, p. 3]	[16, 18, 34, 66, 107, 125, 161, 162, 181–183, 188–192, 212, 223]
<b>Conceptual support</b>	“The literature further yielded tentative evidence that explanations can increase perceived fairness.” [203, p. 9]	[203]
<b>Human subject studies caveats</b>	“Distributive justice was not affected by the different agents and there were no effects of the types of explanations.” [177, p. 13]	[34, 125, 168, 177, 181, 190]

Table 8. Overview of evidence and references for claim 7: “*XAI enables humans to implement subjective notions of fairness*”.

Evidence	Exemplary claims	References
<b>Intuition</b>	“There is no generally acceptable criteria[sic] for evaluating the tradeoff between fairness and utility over decision outcomes. Therefore, it is desirable to have a decision-making tool that helps incorporate the domain knowledge and human judgment to achieve fair decision making.” [5, p. 9]	[4, 5, 48, 64, 66, 179]
<b>Conceptual support</b>	“Our work is concerned with investigating design methods for user interfaces that can help with making the fairness of AI algorithms transparent, and then help with mitigating fairness issues by incorporating user feedback back into the algorithm.” [207, pp. 3–4]	[48, 75, 136, 207, 218, 230, 235]
<b>ML evaluation support</b>	“We generate this tabular explanation for all test data points which are unfairly treated. A domain expert can easily evaluate our explanations and take decision whether to change the prediction or not.” [47, p. 1231]	[4, 5, 7, 47, 119, 157, 195, 229, 232]
<b>Human subject studies support</b>	“The perceived unfairness of specific predictors can be used to exclude predictors or identify biases in the dataset. These biases may not necessarily be apparent to those developing the AI, for example due to a lack of domain expertise, diverging social backgrounds, or personal predisposition.” [211, p. 15]	[5, 148, 162, 207, 211]
<b>Human subject studies caveats</b>	“However, we also noted that some user input could make fairness worse. This is obviously a concern for human-in-the-loop learning as it is only as good as the input the end-user provides.” [148, p. 23]	[148]