Measuring machine learning harms from stereotypes requires understanding who is being harmed by which errors in what ways

Angelina Wang[*], Xuechunzi Bai[†], Solon Barocas[‡§], Su Lin Blodgett[§]

Abstract

As machine learning applications proliferate, we need an understanding of their potential for harm. However, current fairness metrics are rarely grounded in human psychological experiences of harm. Drawing on the social psychology of stereotypes, we use a case study of gender stereotypes in image search to examine how people react to machine learning errors. First, survey studies show not all machine learning errors reflect stereotypes nor are equally harmful. Then, experimental studies randomly expose participants to stereotype-reinforcing, -violating, and -neutral machine learning errors. We find stereotype-reinforcing errors induce more experientially (i.e., subjectively) harmful experiences, while having minimal changes to cognitive beliefs, attitudes, or behaviors. This experiential harm impacts women more than men. However, certain stereotype-violating errors are more experientially harmful for men, potentially due to perceived threats to masculinity. We conclude that harm cannot be the sole guide in fairness mitigation, and propose a nuanced perspective depending on who is experiencing what harm and why.

[*]Department of Computer Science, Princeton University
[†]Department of Psychology, Princeton University
[‡]Department of Information Science, Cornell University
[§]Microsoft Research

Introduction

Machine learning systems are increasingly playing a central role in everyday life. They revolutionize how humans communicate information, generate ideas in arts and science, and make decisions in hiring, education, medical diagnosis, and beyond. Accompanying this rapid proliferation is an increasing attention on the potential harm these systems may cause, and movements toward developing them in a fair, ethical, and inclusive way [5, 6]. The first step in mitigating harm is to be precise about who exactly experiences what kind of harm and why [5, 10, 11, 21, 43, 47, 87]. Despite the importance of human psychological experiences in thinking about harm, we know relatively little about how humans react, evaluate, and reason about machine learning classification outputs and their potential harms during everyday interactions with these systems (with exceptions in decision-making systems such as credit assignment, job allocation, etc. [19]). Drawing on psychological theories of social stereotypes, this paper presents empirical evidence that underscores the complexity of harmful experiences when machine learning models inevitably make mistakes.

Stereotypes are frequently invoked to explain why some machine learning classifications are more harmful than others [1, 4, 9, 88]; however, researchers rarely investigate the concrete connection between stereotypes and harm. Without fully interrogating this relationship, false assumptions slip through the cracks, both in terms of where the stereotypes come from and how they relate to harm. Some studies overly rely on researchers' own worldviews. For example, researchers identified an object recognition model as harmful because it amplifies the degree to which labels for kitchen items like "knife, fork, and spoon" are incorrectly assigned to photos featuring women, and labels for technology-related items like "keyboard and mouse" are incorrectly assigned to photos featuring men [96]. This rationale not only extends to incorrect assignments of even more neutral objects like tables, but these remarked-upon errors themselves may not even be genuinely harmful: While computer scientists working in

the male-dominated technology space tend to find technology-related items like keyboards highly male-stereotyped, broader audiences do not actually share this idea, as we find in our study. Other studies heavily rely on occupation data from the American Bureau of Labor Statistics, e.g., WinoBias [97]. While more grounded than relying on researchers' assumptions, this approach has one large limitation (beyond only representing occupation data in America). It primarily captures descriptive stereotypes, meaning actual overrepresentations of groups in an occupation. However, it misses prescriptive stereotypes, which entail beliefs about what occupations people of different groups should be in. Prescriptive and descriptive stereotypes often diverge in practice [14, 58]. While some prior work has annotated or drawn from more grounded stereotypes [12, 16, 17, 80], researchers commonly assign equal levels of harm to every stereotype, or even to every misclassification. Our study does the necessary work of explicitly connecting stereotypes to harm [8]. This connection is pivotal because, without a deeper understanding grounded in psychological experiences, bias mitigation may inadvertently *increase* the number of harmful errors in a well-intentioned but ultimately misguided attempt to reduce other kinds of errors.

Our first conceptual contribution is in differentiating between machine learning errors which are stereotype-reinforcing, stereotype-violating, or neutral. We posit that errors which reinforce social stereotypes can be more harmful than errors that do not. While stereotypes are cognitive beliefs in people's minds, they can have an influence on attitudes (i.e., prejudice) and behaviors (i.e., discrimination) [2, 42, 45, 51, 56]. For example, people may have *cognitive beliefs* that women are more warm but less competent, and thus *emotionally* express protective attitudes and pity for women [38]. People then *behave* in ways that maintain women's warmth and discount their competence, such as being less likely to promote women to leadership positions [30, 33]. Therefore, stereotypes of certain social groups can prompt shifts in attitudes and behaviors that can ultimately harm the stereotyped group. Although researchers implicitly

acknowledge the mediating role of stereotypes in machine learning harm, we draw on the psychological framework of stereotypes to provide a concrete and systematic assessment (Fig. 1).

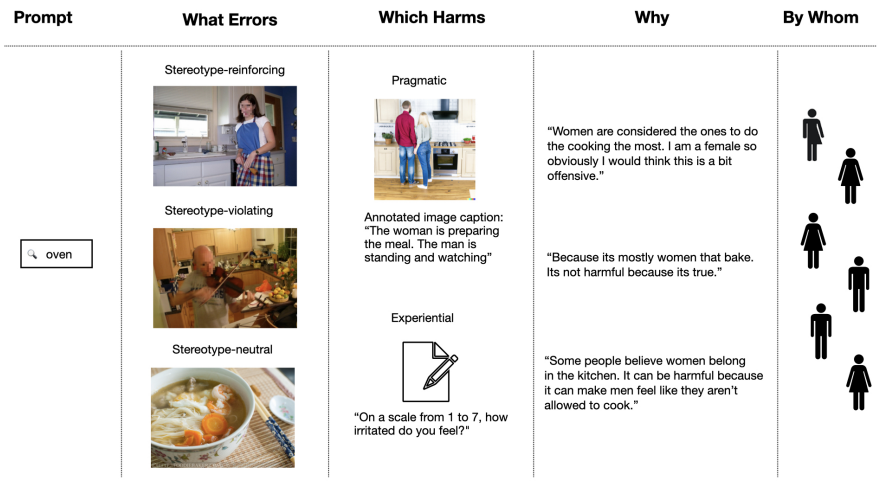

Fig. 1 Summary of our work. We distinguish false positive errors to be those that are: stereotype-reinforcing, -violating, or -neutral. This label comes from human annotators, and depends on what gender group the prediction target (e.g., *oven*) is marked to be associated with. Then, we measure two types of harms: *pragmatic* which are changes about a stereotyped group in cognitive beliefs, attitude, or behavior and *experiential* which are personal self-reports of harm. We find that participants find stereotypes to be harmful for a number of contrasting reasons, and also that this harm is different between different gender groups. While we rely on the social categories of men and women in this work due to the prevalence of stereotypes about both groups, we acknowledge this as a limitation and do not endorse the binarization of gender.

Our second conceptual contribution is in defining harm. Prior work in the machine learning fairness space has rarely been concrete about what harm actually means [10]. We distinguish between two types of harm as the most likely to result from stereotype-reinforcing errors: *pragmatic harms* involve measurable changes in someone's cognitive beliefs, attitudes, or behaviors toward the group being stereotyped, while *experiential harms* involve self-reports of negative affect (Fig. 1). Pragmatic harms are motivated by prior research showing that, for example, people express envy and passively harm groups that are stereotyped as competent but untrustworthy (e.g., lawyers), or express

contempt and actively attack groups that are stereotyped as incompetent and unreliable (e.g., homeless [20]). In the domain of machine learning, prior work has considered components of this framework and found that exposure to gender-biased image search results can lead to more biased estimations of gender representation of that occupation and decreased sense of belonging [52, 60]. To examine if people experience pragmatic harms, we measure cognitive, emotional, and behavioral changes between people who experience machine learning outputs containing stereotype-reinforcing errors compared to those who experience stereotype-neutral or stereotype-violating errors. We hypothesize that the former will result in pragmatic harm.

In contrast to pragmatic harms which focus on external impositions towards a stereotyped group, experiential harms consider the subjective feeling of harm directly experienced by the stereotyped group member [91]. Subjective experiences of emotion have long been discounted as a legitimate source of knowledge, especially when expressed by social groups like women who are associated with emotion [48]. Additionally, these feelings can influence one's own behaviors. For example, when women are given a math exam and told that the exam is diagnostic of their own intellectual abilities, stereotypes of women as less capable of math negatively impact their performance on the exam [81]. In conceptualizing the experiential harm of machine learning errors which may seem individually minor, we draw a parallel to the concept of microaggressions. Microaggressions are "small act[s] of insult or indignity, relating to a person's membership in a socially oppressed group, which seems minor on its own but plays a part in significant systemic harm" [72]. Just like how a machine learning model's classification error (e.g., of an `oven` on an image of a woman) may seem small on its own, and are "easily interpretable as inadvertent errors rather than as malevolent actions," their negative effects on the target are real and should not be neglected [72]. Important in this measure of harm is who the respondent is. Standpoint epistemology emphasizes the importance of the experiences of the individuals being stereotyped,

and the difficulty in establishing the legitimacy of this as a measure of harm thus far can be at least partially attributed to testimonial injustice [31, 35, 67, 93]. Hence, we hypothesize greater reports of experiential harm on stereotype-reinforcing errors for the stereotyped group.

Our third and more nuanced conceptual contribution is a call for an increased appreciation of the diversity of reasons that can lead to the same measured harm (Fig. 1). While prior work often uses human judgments, they do not always incorporate the potential divergent reasons that individuals have which may lead to the same annotation. In our work, we find complexity in what people find to be stereotypical and harmful. This complements prior work studying how human annotators bring different subjective experiences in their labeling of data [22, 23, 65, 89], introducing strong associations between annotator identity and annotations [76]. In more subjective tasks such as labeling text as toxic or not, annotations are often divergent. While taking the majority vote is a common way to reconcile differences in annotations, there is a growing consensus to use a more representative system [26, 41, 50, 71]. Understanding harm faces similar nuances when incorporating divergent perspectives on the same issue. However, simply incorporating representative annotations is not enough; it misses the personalized reasonings behind each response. For example, in a heterosexual gender normative society, some people think that men wearing skirts is harmful and should be regulated [15, 74]. Careless incorporation of this perspective could lead to a system that treats misclassifications of skirts on men as harmful errors on par with those which reinforce sexist stereotypes. If not carefully examined, naive additions of more voices may even exacerbate bias.

We conduct human studies to concretely measure the presence of harms when people experience machine learning errors. As a concrete application to ground our human studies in, we consider gender stereotypes in the popular machine learning task of object recognition as used in photo search engines. We use the COCO [55]

and OpenImages [54] datasets (Fig. 2), and design survey experiments with online American participants from Amazon Mechanical Turk through Cloud Research [57] (Methods). We first ask participants whether objects in COCO and OpenImages are stereotypically associated with different gender groups in order to distinguish which kinds of errors are stereotype-reinforcing, stereotype-violating, or neutral (Results - Study 1). Using those unveiled distinctions, we then expose participants to synthesized search result pages which contain different kinds of errors. We find little immediate evidence of pragmatic harms, but sizable evidence that stereotype-reinforcing errors are experientially harmful – a finding that is more pronounced among participants who identify as women compared to those who identify as men (Results - Study 2). In addition to stereotype-reinforcing errors (e.g., `oven` on women), we explore stereotype-violating errors (e.g., `oven` on men), which have received scarce attention in the machine learning fairness literature. We find that while the stereotyped group (e.g., women) generally finds it more harmful for the error to reinforce rather than violate stereotypes, this is not true when it comes to clothing-related items typically associated with women (e.g., `cosmetics`, `necklaces`) being misclassified on men. Here, we see a backlash towards violations of the norms around gender presentation where men tend to find these misclassifications of, e.g., `cosmetics`, more harmful on men rather than women, calling into question the idea that it is always normatively desirable to reduce errors perceived as more harmful due to their relationship to stereotypes (Results - Study 3). Finally, our qualitative analysis reveals the plurality of why participants think certain objects are stereotypes, and why those stereotypes may be harmful or not (Results - Study 4).

All studies are approved by our institution IRB, protocol number 14738. Studies 1 (https://osf.io/cpyn4), 2 (https://osf.io/m9akd, https://osf.io/v2w4m), and part of Study 3 (https://osf.io/xpv5j) are pre-registered on OSF, while Study 4 is more exploratory. By bringing greater clarity to different types of machine learning errors

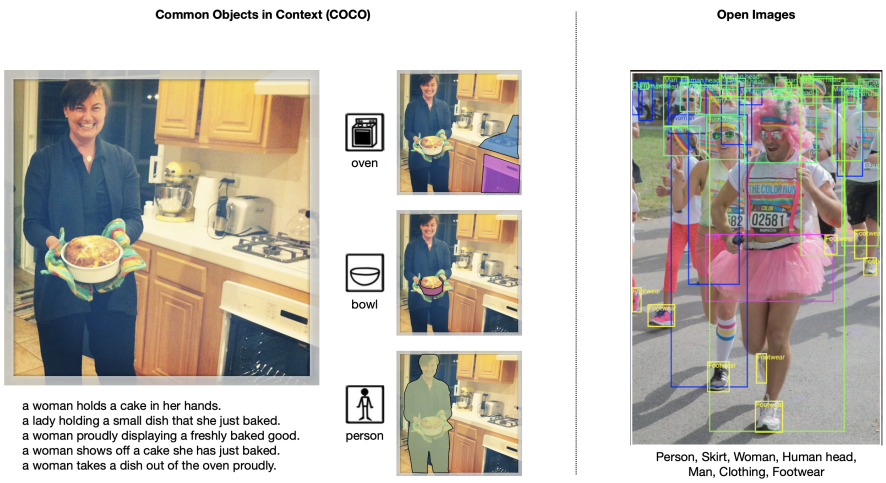

Fig. 2 COCO and Open Images object recognition datasets. We use two popular image recognition datasets in our work to represent the application of a photo search engine. Both datasets contain annotations for perceived binary gender expression of the people in the images as well as the objects present in each image. The left panel shows one example figure from COCO annotated with objects like `oven` and `bowl`. The right panel shows one example figure from Open Images annotated with objects like `person` and `skirt`.

based on their relationship to a stereotype and embracing the rich psychological experiences behind them, we urge researchers and practitioners to more carefully consider different kinds of classification errors, potential harms, and the relevant relationships between them. We believe that identifying psychological experiences with machine learning outputs is critical to understanding the potential harm of a system, and in turn, mitigating it. Without doing so, we may inadvertently prioritize an overall decrease of errors at the expense of increasing the number of harmful errors.

Results

We explore a popular task in machine learning known as object recognition (i.e., classifying the objects present in an image). To make it concrete for our human studies, we use it in the context of a smart phone's photo search engine, and examine gender stereotypes. Specifically, we consider one type of machine learning error called a false positive: when an object is predicted to be present in an image when it is in fact

not there. This causes the image with a false positive to be wrongly surfaced on an image search results page.[1] In our work, we are only concerned with the effect of the misclassification, and not why the model may have made the mistake, or what the participant thinks is the reason the model made the mistake. Unlike prior work auditing search engines [52, 60, 68, 69, 86], our sole focus is on tracing the concrete effects that search results can have.

Study 1: Distinguishing which machine learning errors reflect social stereotypes

To understand the social stereotypes held by American society relevant to our machine learning task, we first elicit human judgments ($N = 80$) on Common Objects in Context (COCO) [55]. COCO has 80 objects and perceived binary gender expression of pictured people annotated across the images [95]. In the survey, we ask the participants whether each object (e.g., `keyboard`, `zebra`) is stereotypically associated with men, women, or neither. As expected, not all objects reflect gender stereotypes. This is already in contrast to a somewhat common assumption in ML fairness research that any difference between groups is an amplification of a stereotype [11].

Among 80 objects, 13 objects are marked as stereotypes by more than half of the participants (Figs. 3). Some examples of stereotypically gendered objects are `handbag` with women, `wine glass` with women, `tie` with men, and `truck` with men. Among the remaining objects, 18 objects (e.g., `keyboard`, `carrot`, `traffic light`) are marked by zero participants as stereotypes with any gender group. If an object was marked to be a stereotype, we also asked participants whether they believed it was harmful in the abstract. Complete results are in the Supplementary Material, but we use these initial findings to select experimental stimuli in subsequent studies. In Study 2a the stereotype-reinforcing condition includes women and `oven` (marked to be most

[1] We note that false negatives are subsumed in this setting because enough false positives will crowd out the results page and ultimately have a similar effect as false negatives on images of the gender that does not have false positives.

harmful), women and `hair dryer` (marked to be least harmful), and the associated control conditions include women and `bowl`, women and `toothbrush`. In Study 2b we also include in the stereotype-reinforcing conditions of men and `baseball glove` (marked to be more harmful) and men and `necktie` (marked to be less harmful) with the control conditions of men and `bench` and men and `cup`.

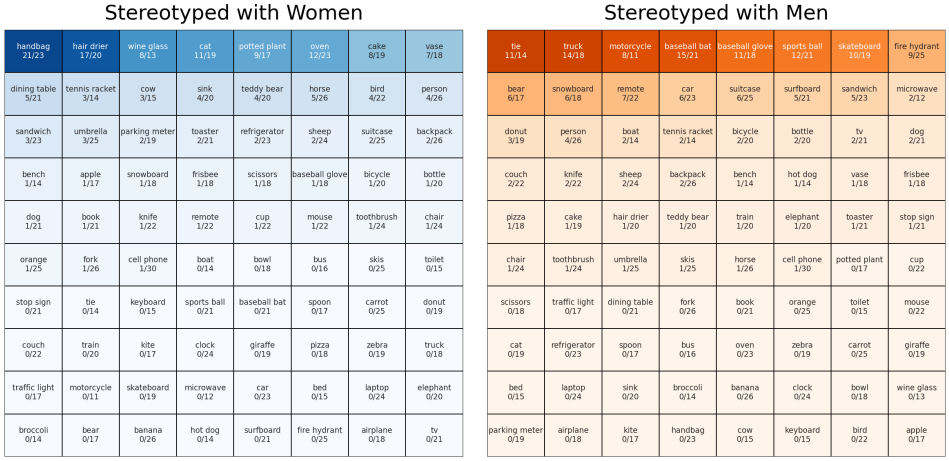

Fig. 3 Study 1 Object Results. Detailed participant responses for each of the 80 objects in COCO dataset. Fraction indicates number of participants asked about each object who marked it as stereotypically related to the gender group of women or men.

Study 2a: Stereotype-reinforcing errors show no pragmatic harm compared to both the stereotype-violating and neutral conditions

To test pragmatic harm in stereotype-reinforcing errors, we conduct a between-subject survey experiment, using the stereotype-violating and neutral errors as control conditions. The cover story instructs participants to look at our synthesized search result page, imagining it is their personal phone photo album, and find a picture they had taken of someone they saw with a particular object. The search result page looks different for each randomized condition. We randomly assign participants to one of the

three conditions ($N = 600$): the stereotype-reinforcing condition exposes an image search result page with stereotype-reinforcing errors, e.g., false positive of `oven` on images of women; the stereotype-violating condition contains the same for stereotype-violating errors, e.g., false positive of `oven` on images of men; the stereotype-neutral condition contains neutral errors, e.g., false positive of bowl on images of women. We then measure participants' cognitive beliefs, attitudes, and behaviors to see if there are any changes because of such exposure (Methods). The behavioral measure is of particular interest, as we ask participants to undertake a realistic task they are liable to encounter by virtue of their jobs as online annotators: data labeling. We choose this measure because online participants are often the source of training labels in large-scale machine learning datasets. We ask participants to perform two common types of labeling on image data: tagging and captioning. If stereotype-reinforcing errors have an influence on participants' cognitive representations, attitudes, and tagging or captioning behaviors, we should expect to see a statistically significant difference between participants who are exposed to search results with `oven`-women and those who are exposed to search results with `oven`-men or `bowl`-women.

Contrary to what we had expected, after adjusting for multiple comparisons we do not find hypothesized statistically significant differences. We run an Ordinary-Least-Square (OLS) regression with the control condition coded as 0 and the experimental condition coded as 1, composite scores for beliefs, attitudes, and behaviors respectively as the dependent variables. Results are shown in Fig. 4 with further details of the descriptive analysis of the captioning task in the Supplementary Material.

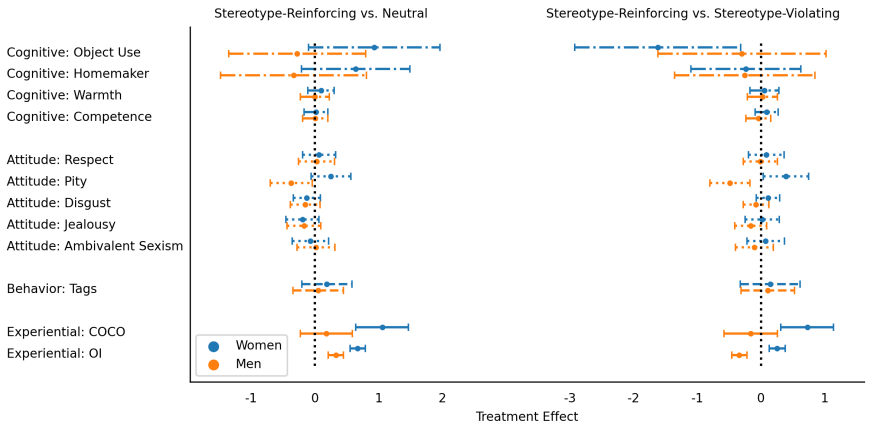

Fig. 4 Study 2, 3 Results The effect sizes and 95% confidence intervals are reported for 10 of our 11 measures of pragmatic harm (for the behavior measure of captioning, we provide a descriptive analysis), experiential harm on COCO, and experiential harm on our larger dataset of OpenImages. Deviations from zero indicate that exposure to the stereotype-reinforcing stimulus resulted in our measured harm compared to exposure to the control condition.

Study 2b: Stereotype-reinforcing errors show statistically significant experiential harm compared to both the stereotype-violating and neutral conditions

In terms of experiential harm, we design a within-subjects experiment ($N = 100$). We operationalize experiential harm by explicitly asking participants to rate how personally harmful they find different kinds of errors (which are stereotype-reinforcing, stereotype-violating, or neutral), on a scale from 0 (not at all) to 9 (extremely). This experience of error is analogous to situations where one reads in the news about the types of errors that artificial intelligence systems make [79], notices such a pattern of errors themselves, or is informed by a friend.

Comparing stereotype-reinforcing against neutral errors, an OLS regression shows participants rate stereotype-reinforcing errors to be more harmful than neutral ones ($b = .62$, 95% CI [.32, .91], $p < .001$). However, when disaggregating by gender this effect is only present among women participants (women: $b = 1.06$, 95% CI [.64, 1.47],

$p < .001$; men: $b = .18$, 95% CI [-.23, .59], $p = .393$). When we use the stereotype-violating error as the control condition rather than the neutral error, we again find participants rate stereotype-reinforcing errors to be more harmful, though to a smaller degree, ($b = .28$, 95% CI [-.01, .58], $p = .062$), with once again an effect only for women participants (women: $b = .73$, 95% CI [.31, 1.14], $p = .001$; men: $b = -.16$, 95% CI [-.58, .26], $p = .453$). Results are in Fig. 4.

In short, while we find little immediate evidence of pragmatic harms, we do find the existence of experiential harms resulting from stereotype-reinforcing errors, compared to both stereotype-violating and neutral errors. However, this pattern is present only among woman participants, and not men participants.

Prior work looking at a subset of what we call pragmatic harm has found very small effects in terms of cognitive belief changes about the representation of gendered occupations [52, 60], but we do not see the effects here, potentially because we have a coarser scale of measurement. Another line of work that finds a cognitive effect takes a different approach by studying occupations (e.g., peruker, lapidary) for which there are very few preconceived notions of stereotypes [86]. In our work, we focus on the activation of existing stereotypes, rather than the induction of novel stereotypes. Overall we find that the pragmatic harms are not measurable after exposure from repeated stereotypical errors in the current survey experiment, likely due to the fact that the effects of these harms are too diffuse and long-term, impacted by all of the facets of society we encounter in our lives [66]. Long-term observational studies are likely more well-suited to measure these kinds of impacts [34, 36, 49]. However, we do find consistent evidence that members of the oppressed group report a significant experiential harm in the form of negative affect on stereotypical errors made on them, consistent with the feelings of inclusivity in gender-biased occupations [60].

Study 3: Stereotype-violating errors can be perceived as harmful too, but for system-justifying reasons

In this study, we first test the generalizability of the previous findings by using a popular dataset in object recognition tasks which is much larger: OpenImages [54]. We then explore a new hypothesis about gender presentation-aligned objects, e.g., clothing, to dive deeper into our findings. OpenImages has 600 objects, annotated with perceived binary genders of people present in the image if applicable [77]. Following the same procedure as in the COCO dataset with new online participants ($N = 120$), we find 249 of the 600 objects are marked as stereotypes by more than half participants, replicating the finding that not all objects are perceived as stereotypes (see more in Supplementary Materials). We then compile a list of 40 stereotypical objects (20 about men: e.g., `football`, `tool`; 20 about women: e.g., `doll`, `lipstick`), and 20 neutral objects (e.g., `balloon`, `goldfish`) for this study.

To test whether participants experience more experiential harm when they are exposed to stereotype-reinforcing (e.g., `skirt` on women), stereotype-violating (e.g., `skirt` on men), and neutral (e.g., `toothbrush` on women) errors, we use a similar procedure as in Study 2b. Rather than asking simply about "personal harm" as we did in Study 2b, here we draw from the Positive and Negative Affect Schedule (PANAS; [18, 90]) and provide more details by asking about if they experience harm such as feeling upset, irritated, ashamed, or distressed. We conduct a within-subjects study and ask participants ($N = 300$) to report their subjective experiences on a Likert scale from 0 to 9 for a variety of errors (see more in Methods). The analysis uses a mixed-effects regression with experimental conditions as the independent variable, a composite score of experiential harm as the dependent variable, participants' gender as the covariate variable, and error terms clustered at the individual level.

Replicating Study 2b, we find that participants experience stereotype-reinforcing errors to be more harmful than neutral ones ($b = .50$, 95% $CI[.42, .59]$, $p < .001$).

Again, this pattern is more pronounced among women participants (b = .67, 95% CI [.55, .79], $p < .001$), with now a small effect among men participants (b = .33, 95% CI [.21, .45], $p < .001$). Different from Study 2b, we do not see differences in experiential harm between stereotype-reinforcing and stereotype-violating conditions (b = -.04, 95% CI [-.13, .05], p = .338). The effect is canceled out by the opposite effects for women (b = .25, 95% CI [.13, .38], $p < .001$) and men (b = -.34, 95% CI [-.46, -.22], $p < .001$) participants. In other words, while women participants feel upset, irritated, ashamed, and distressed when they see stereotype-reinforcing errors (e.g., skirt on women), men participants feel that way when they see stereotype-violating errors (e.g., skirt on men). Results are in Fig. 4.

To better understand this finding, we conduct an exploratory analysis that digs deeper into the 40 stereotypical objects to understand why stereotype-violating errors are sometimes perceived to be more experientially harmful than stereotype-reinforcing ones. According to the gender trouble framework, costume (i.e., body and appearance) and script (i.e., behavior, traits, and preferences) are two aspects of gender performance, and reactions to androgynous or conventionally contradictory components can differ depending on which of the two it manifests in [15, 40, 63, 84]. We thus hypothesize that in our study, conventionally contradictory costume objects may be evoking a more negative reaction compared to conventionally contradictory script objects [74]. So, we add an additional independent variable we call "wearable." We determined the value of this variable by manually marking 13 of the 40 stereotypical objects to be conventionally wearable by a person. These include objects like `football helmet` and `lipstick`, and exclude those like `truck` or `wine glass`. After introducing this independent variable, we find that overall participants do rate stereotype-reinforcing errors to be more harmful than stereotype-violating ones (b = .23 95% CI [.12, .34], $p < .001$), though again this is true of women participants (b = .49, 95% CI [.34, .64], $p < .001$) rather than men participants (b = -.03, 95% CI [-.18, .12], p = .726).

Very interestingly, for the interaction effect of a "wearable" object with the condition type, we find that wearable stereotype-violating errors have higher experiential harm than wearable stereotype-reinforcing errors (b=.80, 95% CI [.62, .99], $p < .001$), which is higher for men participants (b=.94, 95% CI [.67, 1.12], $p < .001$) than women participants (b=.69, 95% CI [.43, .94], $p < .001$).

In addition to this result being a consequence of backlash effects [75], we raise two more possible mechanisms. First, it could be seen as an expression of precarious manhood; a concept that suggests manhood is precarious and needs continuous social validation such that threats to traditional masculinity can provoke anxiety in men [85]. Second, these results may reflect elements of transphobia, which involves a negative reaction to the apparent incongruity between a person's perceived gender and a wearable gender presentation item [15, 63]. The divergent effect between men and women participants aligns with research indicating that transphobia is higher amongst cisgender men when judging transgender women due to the perceived threat to masculinity [59, 64]. This analysis pushes us to reevaluate how we should think about reducing experiential harm, as it may encompass intolerances we do not wish to support.

Study 4: Plurality of stereotypes and harms with image recognition objects

Finally, we report qualitative analyses on open-ended responses from participants' annotations, where they explain why certain objects are seen as stereotypes and harmful or not. While prior work in gender stereotypes has often focused on social roles and traits [28, 38], our data provides insights as to how objects (e.g., `oven`, `hair dryer`) can also be associated with stereotypes. This is an important departure because it expands the scope of machine learning tasks for which stereotypes are relevant beyond its current more narrow framing. Specifically, when a participant from Study 1 responds that

an object is a stereotype, we follow up and ask: "Please describe in 1-2 sentences a) why you marked the above as a stereotype, and b) why you found it to be harmful or not."

One of the authors coded the responses for why an object is a stereotype into roughly six categories. The most prevalent reasons were: descriptive (45%), e.g., for `handbag` and women: "women are often seen wearing handbags and buying them"; occupation/role (22%), e.g., for `oven` and women: "women are stereotyped to always be in the kitchen cooking while the men go out and work"; trait (11%), e.g., for `chair` and men: "sometimes men would be seen as coming home and just being lazy and lounging in their chair." The full analysis is in the Supplementary Material. It is interesting to note that an object's association to a stereotype is frequently mediated by its connection to a role or trait, which are the more common sites of inquiry when it comes to stereotypes. We also found that associations between a group and an object can exist through a number of paths. For example, explanations for stereotypical associations between cats and women include: "cat lady," "women are called *kitten*," "women like cats more than dogs," "cats are a feminine animal," and "women are called *cougars*."

When asked why a stereotype was harmful or not, many respondents simply reiterated that the object was a stereotype. Dropping those responses, one of the authors coded the free responses of why a stereotype was marked to be harmful into seven categories, with the top three being: proscriptive (40%), e.g., for `dining table` and women: "it makes it looked down upon if a man cooks dinner"; prescriptive (26%), e.g., for `dining table` and women: "I think it puts women in a box that says they must prepare dinner"; negative trait (13%), e.g., for `handbag` and women: "it is harmful because it implies that women cares more about looks and their appearance." The remaining response categories are in the Supplementary Material. There seems to be a disparity in responses based on the participant's gender regarding whom they believe

is harmed. When women specify which of the men group or women group are harmed, they say it is the women group 79% (95% CI [.67, 88]) of the time, while men say it is the women group only 67% (95% CI [.51, .80]) of the time.

Building on Study 1's finding that participants do not even all agree on whether an object is a stereotype or not (and if it is, whether it is harmful), this analysis further shows that even when participants are in agreement that an object is a stereotype, they are not necessarily in agreement about why. The same holds true for whether a stereotype is harmful. One potential implication of this is considering whether different reasonings should lead to different bias mitigation. For example, if the reason an object is a stereotype is descriptive, then mitigation should aim to change the cognitive representations of people. To change these descriptive statistics, while we can work to alter the model outputs, we should also work to change society, the burden of which falls on a much larger group than just machine learning practitioners, e.g., policymakers. On the other hand, if particular stereotypes are deemed harmful because they are proscriptive and seem to restrict people from various avenues, we can consider ways to break free of gender norms.

Discussion

In summary, our studies have three key findings regarding our three conceptual contributions: a meaningful distinction between machine learning errors is whether they are stereotype-reinforcing, stereotype-violating, or neutral; harm formulated as pragmatic or experiential; and showcasing how harm annotations can stem from a diversity of reasons that require critical engagement. First, we find that harm is different depending on a machine learning error's relation to a stereotype. Second, while stereotype-reinforcing errors do not lead to more pragmatic harm in the lab setting we use, we do find that stereotype-reinforcing errors are consistently found to be more experientially harmful. Such experiential harm is unequally distributed, impacting more participants who

are women than who are men. Formulating concrete notions of harm as we have done has implications beyond just machine learning: legal documents like the European AI Act is beginning to incorporate notions of psychological harm but lacking definitions to ground regulation in [7, 70]. Third, we find stereotype-violating errors are also experientially harmful, especially when these errors pertain to wearable items associated with gender presentation. This effect is stronger for participants who identify as men compared to those who identify as women. This final point warrants an especially nuanced discussion, as we find ourselves qualifying a prior claim that we should take people's words at face value when they indicate something is personally harmful. To navigate this complexity, we turn to the notions of epistemic injustice [35] and standpoint epistemology [31, 67, 93]. If we interpret the negative reactions to misclassifications of stereotypically feminine clothing items on men as a manifestation of precarious manhood [85] or transphobia [15], then we should down weight these concerns in designing mitigation algorithms. Respecting people's experiential harms may not be as simple as accepting them at face value for direct measurement, but rather involves understanding which groups are likely to be harmed by what kinds of errors and why.

Our findings call for reconsidering fairness measurement in supervised machine learning tasks. This involves considering how we can leverage human-driven insights to inform model training and evaluation [13]. Traditionally, fairness evaluations tend to focus on stereotypes only in relation to occupations or traits. However our work expands this idea by showing that labels such as objects can also give rise to such harms. Additionally, most prior work has only considered the implications of errors that reinforce stereotypes, which is relatively more intuitive to think of as harmful. However, both practically and normatively, it is important to understand the implications of stereotype-violating errors. Practically, strategies aimed at mitigating stereotype-reinforcing errors which act upon the target label will inevitably impact

the occurence of stereotype-violating errors as well. And normatively, there are also questions about whether stereotype-violating errors may even play a role in reducing stereotypical associations by counteracting them. This finding that not only are certain labels more liable to cause harm than others, but that it matters for *which* demographic group that label is misclassified, suggests that generic approaches like having a higher threshold for the classification of certain labels are insufficient. Instead, more nuanced fairness-through-awareness approaches [27] will need to be taken. While adopting simply a cost-sensitive framework [53] (e.g., different costs are associated with false positives and false negatives) is a simplified interpretation of our findings, it could be a starting point as one grapples with the questions of whose levels of harms we would prioritize reducing in a bias mitigation framework.

Understanding whose levels of harms we should prioritize, and why, will come from stronger understandings of the psychological basis and reasoning of different harms. Our finding from Study 4 that stereotypical associations between a single group and object can emerge from many paths (e.g., the many reasonings behind the association between cat and women), each with different normative valences, illustrates what an oversimplification it is to only label an association as "good" or "bad," and the limitations of mitigations simply aiming to sever the associations deemed "bad." This underscores the importance of work about diversity in annotators' perspectives [22, 23, 26, 50, 65, 89], and how much complexity is reduced by the use of discrete labels. Qualitative follow-up questions supplemented our annotations, where a lack of consensus is not a weakness or artifact to be averaged out, but rather a point for deeper inquiry on how to prioritize differential experiences of harm. This also indicates that even if the growing power of large language models enables us to predict with higher accuracy which objects are stereotypes, we likely still may want to ensure these annotations come from people themselves [3, 46, 94], thus allowing room for positionality, explanation, and critical reflection.

Our findings are limited by the methodological choices we made: First, we focused on gender stereotypes as a case study. We do not know to what extent this finding generalizes to other groups such as race and age. Second, we recruited online participants who identify as men and women and who speak English without an extensive inclusion of non-binary participants or who come from a different cultural background. Given that stereotypes are culture-sensitive, and our work also shows that the harm perception is identity-sensitive, future work needs to study the interaction between participants' identity, culture, and harm perceptions. Third, by setting a threshold of 50% for respondents indicating an object is a stereotype, we are in some senses privileging the majority opinion which may further reify marked stereotypes to be those for the majority subset [37, 61]. Fourth, the survey experiment does not capture harms beyond the two we measure (e.g., stereotype-threat [82, 83]), nor the longitudinal effects of machine learning effects. Future work needs to capture not only the plurality in harm of machine learning errors but also how its' effect emerges and endures over time.

Overall, our work offers a rigorous empirical study connecting machine learning outputs to concrete harms by understanding the impact of stereotypical misclassifications. Rather than gesturing at harm as a justification for fairness measurement, we are very concrete in our analysis of the effects on people. Our finding that stereotype-reinforcing errors are experientially harmful for women underscores the importance for machine learning fairness interventions to be more rooted in social contexts, moving beyond objectives like just achieving equal prediction performance across groups. The diversity of responses we've presented, each influenced by participants' unique rationales, suggests the need for greater exploration of human psychological experiences in understanding how machine learning can cause harm.

Methods

Analysis

We use a mixture of qualitative and regression analyses to report our findings. For our within-subjects surveys, we regress with a mixed-effect model whose parameter estimations are adjusted by the group random effects for each individual. We report the coefficients from our regression analyses, which represent the effect size of that independent variable.

Participants

While men and women generally tend to hold the same gender stereotypes [29, 44, 58, 92], we still collect equal numbers of participants who identify as men and women, and use this variable as a covariate throughout. Due to limitations in the survey platform which only allow us to specify gender as "male" or "female," this formulation excludes people who identify as non-binary, which is a harmful limitation. Because we do not control for race in the recruitment of participants, our sample diverges from a nationally representative sample. For the gender stereotype scope of our current work, we find this to be an acceptable limitation, especially given that one defining feature of stereotypes is they are largely shared through a cultural consensus [51].

We did not use quality check questions in any of our surveys, because our pilot studies showed high quality responses. Instead, we used filters on Cloud Research to only recruit participants who have had at least 50 HITs approved, and have a HIT approval rate of 98%.

Studies 1, 3: Distinguishing Errors by Stereotype

When asking about which machine learning errors are stereotypes, we make sure to ask participants about their perception of stereotypes held by Americans, rather than for their personal beliefs [24].

Table 1 The time, pay, and reported races of the participants for each of our five studies. The full column names of races from left to right are: American Indian or Alaska Native, Asian, Black or African American, Hispanic or Latinx, Native Hawaiian or Other Pacific Islander, White, Multi-Racial / Other, and Prefer not to say.

Study	Time (min)	Pay ($)	Gender	AI/AN	Asian	Black	H/L	NHOPI	White	MR/O	PNTS	**Total**
1 and 4	7	1.75	Women	0	3	5	0	0	25	6	1	40
			Men	1	4	2	2	0	30	1	0	40
2a	10	2.50	Women	1	11	32	8	0	229	19	0	300
			Men	0	19	35	10	1	211	22	2	300
2b	5	1.25	Women	0	4	7	3	1	35	5	0	50
			Men	0	4	2	3	1	35	5	0	50
3	4	1	Women	0	5	8	0	0	42	4	1	60
(Labeling)			Men	0	2	6	5	1	44	2	0	60
3	5	1.25	Women	0	5	15	1	0	120	7	2	150
(Harms)			Men	1	9	17	6	1	107	9	0	150

Study 2a: Measuring Pragmatic Harm

We conduct a between-subjects survey experiment on participants who are exposed to an image search result page that contain one of three types of errors: stereotype-reinforcing, stereotype-violating, or neutral (Fig. 5).[2] To have the participants engage with these results we ask them to describe it in 3-4 sentences. Next, we ask them the behavior questions, then re-expose them to the stimulus before asking them the cognitive belief and attitude questions. We analyze changes in cognitive beliefs, attitudes, and behaviors as pragamatic harms resulting from stereotype-reinforcing errors compared to the two other conditions as controls. In this section when describing our method, we will use as examples `oven` and women for the stereotype-reinforcing error, `oven` and men for the stereotype-violating error, and `bowl` and women for the neutral one. Each question we ask is carefully grounded in the social psychology literature.

The stimuli take the form of an image search result and are pictured in Fig. 5 with teal and orange colored boxes around the component of the image that changes between conditions. The search bar contains the search query, and then eight images

[2]The people pictured in our search results pages are predominantly White, which is the majority group in the dataset we employ.

that may or may not be correctly retrieved are shown. Each of the eight images is annotated with either "In image" or "Not in image" to make it clear to the participant which images are correct or not. The stereotype-reinforcing condition on the left contains the search query of "oven" with five correctly identified ovens, and three false positive images that all contain women. In other words, this classifier erroneously (and stereotypically) assumes there are ovens in images of women. The stereotype-violating condition contains the same search query, but the mistakes are replaced with false positive images that all contain men. The neutral condition contains all of the exact same images as the stereotype-reinforcing condition, with the only change being that the search query is now "bowl" instead of "oven." This is because the five correct images were deliberately chosen to contain both bowls and ovens, which allows us to control for the variance between the different search conditions. All false positive images were selected from the actual errors of a Vision Transformer (ViT) model [25] trained on COCO so that they are as realistic as possible to a computer vision model's errors, and not completely egregious, e.g., a picture of a woman in a sports field as a false positive for "oven" or "bowl."

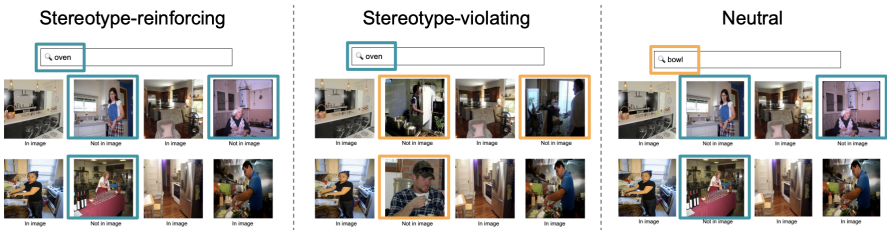

Fig. 5 Study 2 Stimuli. Our three different stimuli are shown for the conditions: stereotype-reinforcing, stereotype-violating, and neutral. They are all image search results containing minimal changes from each other, each of which indicates whether the search query is pictured in the image, i.e., if the image search retrieval was correct or not. The teal and orange squares indicate that the only difference between the stimuli, as all images which contain an oven also contain a bowl, and all which do not contain an oven also do not contain a bowl. This was a deliberate choice to control for all potential confounding factors from the images in the study.

For *cognitive beliefs*, we ask three sets of questions which span the spectrum of stereotype-specific to more generically about gendered beliefs. Concretely, we ask

about: estimations of who uses ovens and bowls more between men and women; estimations of who tends to be the homemaker more between men and women; and perceived levels of warmth and competence [33] of women. To assess *attitude*, we ask two sets of questions. The first is about how participants feel about women in terms of four emotional components that are believed to mediate interactions between cognitive beliefs and behaviors: a) respect or admiration, b) pity or sympathy, c) disgust or sickening, and d) jealousy or envy [20, 32, 78]. The second asks about sexist attitudes via a shortened scale focused on benevolent sexism [38, 39, 73].[3] Finally, for *behavioral* measures, we ask participants to undertake a realistic task they are liable to encounter which can cause harm: data labeling [62]. We chose this behavior measure because online participants are often the source of training labels in large-scale machine learning datasets. We ask participants to perform two common types of labeling on image data: tagging and captioning (Fig. 6). In the tagging task, we ask participants to label the top three most relevant tags in an image which contains both the stereotype object (e.g., `oven`) and neutral object (e.g., `bowl`). We alter the perceived gender of the person to assess whether this changes what is tagged in the image. For the captioning task we show two people, one who looks masculine and another feminine, and swap whether there is a bowl or oven present in the image. This is to understand if the annotators will differently describe who is interacting with the object depending on whether it is stereotypically associated with women or not. All images are generated and/or manipulated by DALL-E 2.

Dependent Variables

For most of our measurements, we simply use the measure directly (e.g., the value for competence of women) as the dependent variable to regress on. For the measurements that we do something more complicated, we describe below.

[3] We ask questions from the Ambivalent Sexism Inventory [38] about benevolent sexism, as opposed to hostile sexism, because the latter is believed to suffer heavily from social desirability bias.

Fig. 6 To measure behavioral tendencies, we ask participants to complete a realistic data annotation task on images which are created and manipulated by DALL-E2. The left pair is for the annotation of image tags, and the right pair is for image captions. Each participant is shown one image from each pair, and then we perform a between-subjects analysis to understand whether perceived gender expression affects the tags, and whether object shown influences how people of different perceived genders are described.

Behavior - Tags. Each participant produces a set of three ordered tags associated with an image of a feminine-presenting person and a set associated with a counterfactual image of a masculine-presenting person. We convert this set of tags by scoring the presence of the object in question, e.g., "hair dryer" (along with common misspellings such as "hair drier") based on its position in the ordered list of tags. When the word is present in the first spot it is given 3 points, second spot 2 points, third spot 1 point, otherwise no points. The dependent variable is the score of both the stereotypical and neutral object on the feminine-presenting person. This is intended to capture whether the stereotype-reinforcing condition is able to increase the presence of the stereotype tag more than just the priming effect captured by the neutral object.

Behavior - Captions. We offer some descriptive statistics about the captions in the Supplementary Material. This analysis was mostly exploratory, and we do not find any statistically significant differences. We first ran Study 2a looking at pragmatic harms on the stereotype of women and `oven` (with `bowl` as the control). In this iteration, we asked that respondents please describe each person in the image in separate sentences. However, there was too much noise in how respondents interpreted this set of instructions, such that the data became hard to interpret. Thus, in our second iteration of this study using the stereotype of women and hair dryer (with `toothbrush` as the control), we have two separate text entry boxes to caption each person in the

image. We only present the results of this iteration in the table, as we were unable to parse anything differentiating in the first iteration.

Cognitive - Object Use. In this measurement, we have a value from -10 (mostly men) to 10 (mostly women) for both the stereotypical and neutral object. The dependent variable is the summation of both values. Again, this is intended to capture whether the stereotype-reinforcing condition is able to change the value of its associated object more than the control condition is able to.

Study 2b, 3: Measuring Experimental Harm

In Study 2b, in addition to personal discomfort, we also ask about societal harm. This way, even if the participant does not personally feel harmed, they may feel it on behalf of the stereotyped group. However, we find that participants' responses to both personal and societal harm are extremely correlated, and leave the results for the latter in the Supplementary Material.

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