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Effort-aware Fairness: Incorporating a Philosophy-informed, Human-centered Notion of Effort into Algorithmic Fairness Metrics

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Abstract

Although popularized AI fairness metrics, e.g., demographic parity, have uncovered bias in AI-assisted decision-making outcomes, they do not consider how much effort one has spent to get to where one is today in the input feature space. However, the notion of effort is important in how Philosophy and humans understand fairness. We propose a philosophy-informed approach to conceptualize and evaluate Effort-aware Fairness (EaF), grounded in the concept of Force, which represents the temporal trajectory of predictive features coupled with inertia. Besides theoretical formulation, our empirical contributions include: (1) a pre-registered human subjects experiment, which shows that for both stages of the (individual) fairness evaluation process, people consider the temporal trajectory of a predictive feature more than its aggregate value; (2) pipelines to compute Effort-aware Individual/Group Fairness in the criminal justice and personal finance contexts. Our work may enable AI model auditors to uncover and potentially correct unfair decisions against individuals who have spent significant efforts to improve but are still stuck with systemic disadvantages outside their control.

Introduction

AI has assisted humans in making high-stakes decisions such as recidivism risk assessment (e.g., Bao et al. 2021) and loan approval (e.g., Mayer, Strich, and Fiedler 2020), leading to potentially increased efficiency.[1] However, the growing deployment of AI in critical decision-making contexts has also raised serious concerns about algorithmic bias, which can disproportionately impact individuals and communities. In response, the AI literature has deeply explored two notions of fairness: group fairness (ensuring that a quantity of interest, such as accuracy, is equalized across demographic groups like race/sex) (e.g., Pedreshi, Ruggieri, and Turini 2008) and individual fairness (ensuring that similar individuals get similar outcomes) (e.g., Dwork et al. 2012).

Typical applications of group and individual fairness treat similarly situated individuals as deserving similar treatment despite potential differences in demographic features (e.g., race, sex, and age). However, similarly situated individuals, e.g., those with the same income or arrest history, are often similarly situated for very different reasons. This leads to a hypothetical "identical CVs" problem: two people from very different backgrounds may have the same CV—and, therefore, are treated equivalently per group or individual fairness—but one of them may have had to work a lot harder to achieve that. The notion that Effort is an essential factor in fairness has been well studied in philosophy (e.g., the free rider problem Hardin and Cullity 2003) but has been largely, though not completely (see related work below), absent from the AI fairness literature. One key ingredient of Efforts is the temporal dimension: How an individual has changed over time. Liu et al. (2018) show that in an optimization problem, imposing a static fairness constraint, which often ignores the temporal dimension, may harm long-term improvement.

We first conceptualize a new measure of *Effort-aware Fairness (EaF)*, grounded in philosophical literature (De Tracy 1803; Massin 2017; Maine de Biran 2002), based on two key ideas: (1) acceleration, or more broadly the temporal trajectory of how an individual's task-relevant feature has changed over time; (2) inertia, or how much historical disadvantage each individual may have experienced outside their controls. We then conduct a human subjects experiment to validate whether our trajectory-based formulation of Effort is more relevant to laypeople's fairness perception than traditional formulations based solely on the feature's aggregate value (Romano, Bates, and Candes 2020; Ni et al. 2024). Finally, we demonstrate how to compute our EaF metric to audit AI models on two datasets, CLUE (criminal justice) and SHED (personal finance).[2]

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[1]By 2023, 42% of enterprises have actively deployed AI, while another 40% are experimenting with the technology. Among those using or exploring AI, 59% have accelerated their investments and implementation Efforts over the past two years (IBM 2024).

[2]Our **supplementary materials** (e.g., data, code) are uploaded to a Google Drive folder: https://drive.google.com/drive/folders/1RsSE1dUHDkn41iKCkIhY5QRdAVKVcrtB?usp=sharing

Background and Related Work

Traditional Metrics for AI Fairness

In the technical CS/AI fairness literature, two main approaches mathematically formulate "fairness" based on the outcome of human/AI-assisted decision-making systems: group fairness and individual fairness. Group fairness, or group parity, is achieved when a statistical metric of interest (such as positive outcome rate or false positive rate) is equalized across different groups with respect to a sensitive feature, e.g., race or sex (Pedreshi, Ruggieri, and Turini 2008; Barocas, Hardt, and Narayanan 2019). Individual fairness, introduced formally by Dwork et al. (2012), is based on the intuition that similar individuals should get similar outcomes. Formally, for a pair of individuals, given an input-space distance metric to measure how differently situated they are and an output-space distance metric to measure how different the distributions of their possible outcomes are, individual fairness requires (as a constraint in an optimization problem) that their output-space distance should be upper-bounded by their input-space distance. The more similarly situated two persons are (e.g., same demographics and criminal histories), the more likely that they should receive similar outcomes (e.g., risk scores). [3]

Counterfactual "Effort" in AI Fairness Literature

Recent AI fairness works attempt to incorporate some notion of "Effort" into fairness metrics by equalizing "Effort" across groups. They conceptualize "Effort" as the relationship between changes in mutable input features (e.g., prior arrests) and the probability predicted by a model of receiving a favorable outcome (e.g., granting bail). Approaches differ in terms of whether they take outcome parity as a requirement and attempt to equalize "Effort" across groups (Heidari, Nanda, and Gummadi 2019; Guldogan et al. 2023) or whether they take equalized "Effort" as a requirement and attempt to equalize outcome parity (Gupta et al. 2019; Huang et al. 2020; Von Kügelgen et al. 2022). These dual styles of approach are closely related to work on algorithmic recourse (Ustun, Spangher, and Liu 2019), in that they ask how much effort" an individual *would have to put in* to achieve a favorable outcome. Both approaches can be loosely considered to be in the space of counterfactual "Effort" and in contrast to our approach—we are interested in how much "Effort" an individual *has already put in* and use that as the value against which we seek parity.

Formally, existing approaches focus on counterfactual changes in input features ($\Delta \mathbf{x}$), which may lead to changes in the probability of receiving a favorable output label, e.g., from $f(\mathbf{x}) < \gamma$ to $f(\mathbf{x} + \Delta \mathbf{x}) \geq \gamma$ where γ is a probability threshold. On the one hand, Heidari, Nanda, and Gummadi (2019) and Guldogan et al. (2023) set an upper threshold δ for the norm function μ of "Efforts", i.e. $\mu(\Delta \mathbf{x}) \leq \delta$, and seeks to equalize across groups the maximized favorable output rate. On the other hand, Gupta et al. (2019), Huang et al. (2020), and Von Kügelgen et al. (2022) set a lower threshold for the desirable output rate and seek to equalize across groups the minimized norm of "Efforts". However, these works do not use actual changes over time, but they compare an individual with all others within the same group at only one time step to estimate $\Delta \mathbf{x}$ and $f(\mathbf{x} + \Delta \mathbf{x})$. [4]

In summary, the recourse-based formulation of "Effort" in the CS/AI literature, though practically informative, has theoretical shortcomings and may not be rooted in more fundamental theories of Effort that philosophers have proposed, debated, and refined over centuries—a gap we seek to fill.

How Philosophy Defines "Effort"

As reviewed by Massin (2017), the philosophy literature has used four main approaches to characterize Effort, of which two are directly related to Effort itself (rather than the perception of Effort): (1) Force-based account (how much force would it take to "move" an object; introduced by De Tracy (1803) and later formalized/advocated for by, i.a., Maine de Biran (2002)) and (2) Resource- or Energy-based account (spending Effort towards a goal means allocating part of a finite amount of resources, or energy tank, up until the energy tank is depleted; introduced by Arai (1912) and later formalized/advocated for by, i.a., Gendolla, Wright, and Richter (2012)).

The Force-based account addresses several problems unresolved by the Energy-based account, such as capturing the concept of "resistance" to Effort, distinguishing between "fatigue" and "Effort", and explaining why Effort is unpleasant but praiseworthy. Massin (2017) informedly concludes that the Force-based account is "more fundamental".

The three main Philosophy arguments by Massin (2017) in support of the force-based account are highly applicable to our AI fairness contexts: (1) As "only force-based accounts properly capture the idea of a resistance to our Effort," these accounts can capture issues such as systemic discrimination that resists individual-level progress (Bohren, Hull, and Imas 2022). (2) As "force-based accounts, by contrast [to energy/resource-based accounts], stay clear of any substantive commitment about the relationship between fatigue and Effort," it is compatible with our AI-assisted decision-making contexts where a decision subject with better Effort (e.g., fewer arrests or higher income after each year) does not necessarily suffer from more fatigue. (3) As "force-based accounts neatly explain the apparently paradoxical facts that we seem to praise and enjoy Efforts partly in virtue of their unpleasantness," it is compatible with the later introduced inertia and acceleration terms in our force-based formulation of Effort because having grown up in childhood poverty but still managing to work harder for better income (or desistance) might be unpleasant but indicating of virtue and thus praiseworthy (McNeill and Farrall 2013). Bermúdez and Massin (2023) later expand this force-based conceptualization of Effort to conceptualize the "feeling of Effort": "Among the possible Effort-first accounts, a force-based approach seems most promising, partly because

[3] We discuss the legal relevance of group fairness and individual fairness under U.S. law in Appendix A.

[4] Shortcomings of the counterfactual Effort fairness literature and how our formulation overcomes them are in Appendix B.

it allows for a direct explanation of why the feeling of Effort involves the experience of countering a resistance."

Therefore, we will operationalize this philosophical force-based approach to formulate an individual-level "Effort" metric and incorporate it into existing algorithmic fairness metrics. Our force-based formulation of "Effort" will overcome both shortcomings of the recourse-based (counterfactual) formulation of "Effort" in the CS/AI literature: our approach is model-agnostic (as our force-based Effort metric is defined in a non-causal, output-independent sense) and we can loop force-based Effort into the individual distance function to define Effort-aware Individual Fairness (EaIF). Furthermore, real-world fairness audits may necessitate quantification of past Efforts to inform current/future decisions.

Formulating Effort-aware Fairness (EaF)

To estimate "Effort" as an individual-level metric, we formulate the "more fundamental" Force-based account of "Effort" from philosophy (Massin 2017) by using Newton's Second Law of Motion from Physics to develop an Effort-as-Force metric. Building on this idea, we formulate Effort-aware Fairness metrics to evaluate on real-world datasets.

Effort

As Massin (2017) does not give specific mathematical formulae to compute Force or Effort, we turn to the Physics literature for the well-known Newton's Second Law of Motion: $\mathbf{F}_{\text{net}} = m \cdot \mathbf{a}$ where $\mathbf{F}_{\text{net}}$ is the net force applied on an object of inertia m to give it an acceleration $\mathbf{a}$ (second-order time derivative of position $\mathbf{x}^i$) (Young, Freedman, and Ford 2014).[5] We look for analogies to model the two quantities m and $\mathbf{a}$ to compute our Effort-as-Force metric $E \propto \mathbf{F}_{\text{net}}$. Assuming no friction, a person with inertia m (characterized by systemic disadvantages or societal "holding-back" effects that are beyond their control) has to apply Effort E to make their features (e.g., number of arrests or income) move in a desirable direction with an (observable) acceleration $\mathbf{a}$.

Our first quantity to model is inertia m. We conceptualize m as the societal "holding-back" effect and/or historical disadvantage against an individual beyond their control/agency. One example metric for inertia is hereditary disability, i.e., a disability passed down to a person by their parents. However, this feature might be hard to obtain (due to health privacy concerns) and difficult to quantify. Another example metric for inertia is the socio-economic background of a person's family during their childhood, e.g., whether, back when the person was still a child, their family had to live below the federal poverty line, which is beyond the child's control. In our criminal justice and personal finance contexts, childhood poverty was found to be associated with significantly higher "hazard rate of being convicted of violent criminality" (Sariaslan et al. 2014) and to have "quantitatively large detrimental effects" on adult earnings (Duncan, Ziol-Guest, and Kalil 2010).

Next, acceleration $\mathbf{a}$ can be modelled as the second-order time derivative of task-relevant input features (e.g., number of past arrests in criminal justice, or income in personal finance). However, at first sight, there seems to be a problem with the second-order derivative. Suppose over a three-year period with equidistant time intervals (Δt = one year = 1), a person's annual income increases from $x_0 = 60k$ USD (first year) to $x_1 = 90k$ USD (second year) to $x_2 = 100k$ USD (third year). Our intuition suggests that they demonstrate positive Effort overall, as their annual income continued to increase, albeit at a slower velocity ($v_0 = 90k - 60k = 30k$ USD/year, followed by $v_1 = 10k$ USD/year). However, the slowing speed would result in a negative second-order derivative of $a_0 = 10k - 30k = -20k$ (USD/year^2), counterintuitively implying negative Efforts. Does this counterintuitive result mean the Force-based approach for Effort is wrong? Not necessarily. The underlying issue is that we should have modeled the temporal input feature (income) in a **cumulative** view: $X_0 = 60k$ USD, $X_1 = 60k + 90k = 150k$ USD, and $X_2 = 150k + 100k = 250k$ USD. In this cumulative formulation of income, velocity terms are $V_0 = 90k$ (USD/year) and $V_1 = 100k$ (USD/year); acceleration is $A_0 = 10k$ (USD/year^2), intuitively implying positive Efforts. We use lowercase letters (x, v, a) to signal a non-cumulative view and uppercase letters (X, V, A) to signal a cumulative view. This example highlights the importance of transforming a non-cumulative feature into a cumulative feature before computing its acceleration to quantify Effort.

We justify formally our choice of a cumulative formulation of the Effort-related feature to compute acceleration. A non-cumulative version of a feature can be obtained by differentiating (taking the derivative of) the cumulative version of that same feature. Therefore, acceleration (second-order derivative, i.e., derivative of the first-order derivative) in the cumulative version corresponds to velocity (first-order derivative) in the non-cumulative version, e.g., $A_0 = v_1$. If we took the second-order derivative in the non-cumulative version, it would correspond to the third-order derivative in the cumulative version, which is theoretically at odds with force and hard to compute in practice.

Since Effort and AI-assisted decision making are social phenomena, we explain the social science relevance of our force-based formulation of Effort in Appendix C.

Effort-aware Individual Fairness (EaIF)

To develop an Effort-aware Individual Fairness (EaIF) metric, we stipulate that similar individuals who spent similar Efforts should get similar outcomes. We propose a pairwise individual similarity function as a weighted combination between the aggregate task-relevant feature and Effort E. We use Definition 2.1 (Lipschitz mapping) by Dwork et al. (2012) as the individual fairness condition. Let $\mathbf{x}^i$ and $\mathbf{x}^j$ denote task-relevant feature vectors for a pair of individuals. A risk predictor M maps individual $\mathbf{x}^i$ to a risk score, i.e., $M\mathbf{x}^i$. We define an Effort function $E(\cdot)$ that maps an individual $\mathbf{x}^i$ to an Effort score $E(\mathbf{x}^i)$ and an aggregate (summing) function $S(\cdot)$ (e.g., to sum all non-cumulative values of income or past arrests $S(\mathbf{x}^i)$ of individual $\mathbf{x}^i$). We also define an input-space individual distance function $d(\cdot, \cdot)$ over individuals' feature representations and an output-space dis-

[5] m is more commonly known as "mass" in everyday Physics. Inertia is a more generalizable understanding of this metric.

tance function $D(\cdot,\cdot)$ over their predicted risk scores. The predictor M achieves perfect Effort-aware individual fairness if for every pair of $(\mathbf{x}^i, \mathbf{x}^j)$, this constraint is satisfied:

$$D(M\mathbf{x}^i, M\mathbf{x}^j) \leq d(\mathbf{x}^i, \mathbf{x}^j). \quad (1)$$

Our EaIF formulation requires that the input-space individual distance function additionally takes into account the Efforts exerted by both individuals. With a scalar $0 \leq \alpha \leq 1$ to model the normative weight of Effort compared to aggregate features, we can give a simple formulation of d based on the weighted Euclidean distance:

$$\begin{aligned} &d(\mathbf{x}^i, \mathbf{x}^j) \\ =&\sqrt{\alpha[E(\mathbf{x}^i) - E(\mathbf{x}^j)]^2 + (1-\alpha)[S(\mathbf{x}^i) - S(\mathbf{x}^j)]^2}. \end{aligned} \quad (2)$$

However, the AI community has recognized that individual fairness is hard to operationalize across different real-world contexts because it is hard to formalize an application-agnostic individual distance metric (Lahoti, Gummadi, and Weikum 2019; Ilvento 2020, i.a.). We acknowledge that our formulation of $d(\mathbf{x}^i, \mathbf{x}^j)$ is just one among many options.

Effort-aware Group Fairness (EaGF)

We formulate Effort-aware Group Fairness (EaGF) as $\hat{Y} \perp G \mid E$, where $\hat{Y}$ is a predicted outcome (e.g., risk score) that predicts some ground-truth outcome Y (e.g. violent recidivism, payment failure), G is a protected demographic feature (e.g., race, sex, or age group, which defines the "groups" that we normatively expect parity), and E is Effort as force. Our intuition behind this formulation is that people who have exerted similar amounts of Effort historically should receive similar predicted outcomes, regardless of their demographics. Computationally, EaGF means

$$\begin{aligned} &\hat{Y} \perp G \mid E \\ \iff\; &\forall e_0 \in \mathbb{R},\ \forall g_i, g_j \in \mathcal{G}, \\ &\lim_{\epsilon \to 0} \mathbb{P}(\hat{Y} = 1 \mid E \in [e_0, e_0 + \epsilon], G = g_i) \\ =&\lim_{\epsilon \to 0} \mathbb{P}(\hat{Y} = 1 \mid E \in [e_0, e_0 + \epsilon], G = g_j), \end{aligned} \quad (3)$$

where $[e_0, e_0 + \epsilon]$ is a small range (bin) of Effort values, which can be computed from inertia m and acceleration $\mathbf{A}$ (from the cumulative formulation of Effort-related feature). The terms g_i and g_j are demographic groups (e.g., White and Black), and $\mathcal{G}$ denotes the set of all such groups.

Datasets and Predictive Models

For the following two empirical sections (human subjects experiment and metric demonstration pipelines), we use two real-world datasets that are relevant to two different AI-assisted decision-making contexts and have a temporal dimension. We also build simple predictive models to obtain AI predictions, on which Effort-aware Fairness can be evaluated.

CLUE (criminal justice)

We select defendants from a real dataset, Client Legal Utility Engine (CLUE), with over 4.4 million District Court and $700,000$ Circuit Court cases between 2012 and 2020 scraped by the Maryland Volunteer Lawyers Service (MVLS) from the Maryland Judiciary Case Search.[6] CLUE contains criminal history and demographic features, e.g., race, sex, and age (at the time of arrest).

For our analysis, the key Effort-related feature is the number of prior arrests that resulted in charges before the current charge. The outcome variable is a risk binary label of getting re-arrested for a violent offense, within one year of the current arrest. Due to the data licensing condition, we cannot publicly release our clean version of CLUE.

For every defendant who had an arrest between 2016 and 2018, we develop simple machine learning models (Random Forest classifier, whose predictions we use for the human subjects experiment, and three other models, LightGBM, Logistic Regression, and Decision Tree, whose predictions we use for the metric demonstration) with 5-fold cross-validation to predict their (violent) recidivism risk (on a scale of 0 to 1) within one year current their recent arrest.[7]

SHED (personal finance)

We use the "Survey of Household Economics and Decision-making" (SHED) published by the Federal Reserve since 2013.[8] To obtain the time dimension, we perform record linkage across four years (2019 to 2022). After selecting only the households that have data available across all four years, we obtain the final set of 704 households. Our Effort-related feature is the annual range of household income (I40). We turn this range-based feature into a number by taking the lower bound. Our outcome feature of interest is the respondent's frequency of unpaid credit card balance (C4A), which can be of real-world predictive interest for financial institutions to process credit/loan applications.

We implement multiple AI models, including XGBoost, Random Forest, and Logistic Regression, to predict whether a household missed a payment on a credit card balance at least once in the 12 months before the 2022 survey. [9]

Human Subjects Experiment: Trajectory (Acceleration) Impacts Fairness Perception

Experimental Design

We must first decide on an appropriate population. Several major works in the AI fairness literature have used laypeople's perception of fairness to decide on an appropriate fairness metric for a specific task, or even to construct new fairness metrics (Saxena et al. 2019; Harrison et al. 2020; Wang et al. 2019). We follow these precedents of informing our fairness metrics via laypeople's fairness perception, based on two rationales. In principle, laypeople's fairness judgment is vital for policy. Awad et al. (2020) argue that policymakers should be aware of and prepare for societal

[6]https://casesearch.courts.state.md.us/casesearch/

[7]We provide more details about the predictive models in Appendix D.

[8]www.federalreserve.gov/consumerscommunities/shed.htm

[9]Additional details about the predictive models are provided in Appendix D.

pushback of potentially beneficial but high-stakes decision-making AI tools. Liu, Du, and Li (2021) maintain that the discrepancy between a human-AI legal responsibility allocation framework from laws and the public's expectations may hinder the adoption of and trust in AI at large. In practice, to potentially achieve statistical significance, a human subjects experiment typically needs hundreds of participants. For example, the mean sample size for online human subjects experiments at CHI, a leading Human-Computer Interaction conference, was 224 participants (Caine 2016). It is both expensive and logistically impractical to recruit such a large sample of technical CS/philosophy domain experts.

Next, we must decide on a more convenient fairness metric (e.g., group or individual fairness) to elicit fairness judgements from laypeople and measure the impact of Effort-related features on such judgements. We choose individual fairness over group fairness because individual fairness evaluation minimizes the effect of participants' cognitive load and mathematical ability as potential confounders.[10]

Individual fairness is formulated as "similar individuals are treated similarly" (Dwork et al., 2012). To evaluate whether a decision-making process (with or without AI) satisfies the individual fairness criterion, the probabilistic formulation of individual fairness might be simplified into two simple, more deterministic steps: (1) (Overall) Input-space distance: evaluate pairwise distance (based on features in the input space) to find pairs of highly "similar" individuals; (2) Output-space distance: in each pair of two highly similar individuals, check if their two outcomes are similar enough.

Our main question is whether people consider pairwise distance in terms of a feature's aggregate value ("aggregate distance") more or in terms of its trajectory ("trajectory distance") more during each of the two aforementioned steps in the individual fairness evaluation pipeline. We design two types of trajectory: increasing vs. decreasing, which means positive vs. negative velocity in a non-cumulative formulation (e.g., annual income) as shown in Figure 1, and is mathematically equivalent to positive vs. negative acceleration in a cumulative formulation (e.g., cumulative income since the first year). We show participants a non-cumulative (annual) feature view because many laypeople would not be able to distinguish positive vs. negative second-order derivative (convex vs. concave curvature) in a cumulative view. Therefore, "trajectory" in this experiment corresponds to the cumulative-view "acceleration" term, a cornerstone in our philosophy-informed formulation of Effort. We draw real-world (anonymized) samples of defendants/households from CLUE (with past arrests as an Effort feature) and SHED (with income as an Effort feature). Our research questions:

RQ1: Does trajectory distance correlate with overall input-space distance? If so, does it correlate more strongly than aggregate distance?

RQ2: Does trajectory distance correlate with output-space distance? If so, does it correlate more strongly than aggregate distance?

RQ3: Do answers to RQ1 and RQ2 depend on the nature of the Effort feature, our between-subjects variable? (desirable "income" in SHED vs. undesirable "arrests" in CLUE)

The two main independent variables are trajectory distance and aggregate distance with respect to an Effort-related feature (e.g., number of arrests or income). We measure these variables by directly asking people to rate, on a Likert scale, the difference between two pairwise decision subjects in terms of their trajectories and in terms of their aggregate feature values (income/arrests summed across four years).

The two main dependent variables are overall input-space distance and output-space distance. Overall input-space distance is measured by asking participants, after they have rated the trajectory distance and aggregate distance for a pair, to rate, on the same Likert scale, how different the two decision subjects are overall. Regarding output-space distance, in each set of 5 decision subjects, 1 of them is the reference subject (K) and the other 4 are comparison subjects (A, B, C, D).

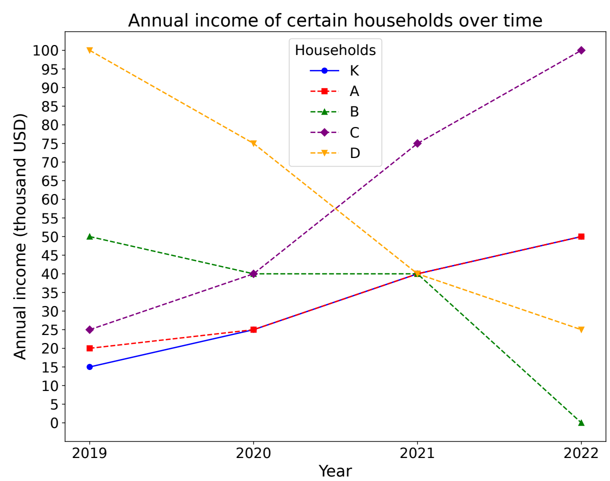


Figure 1: Example SHED set of 1 reference subject (K) and four subjects to be compared to K. A: similar trajectory/aggregate; B: different trajectory, similar aggregate; C: similar trajectory, different aggregate; D: different trajectory/aggregate. All households' incomes are real SHED records, except that we slightly perturb the first time step of K to get A.

The output-space distance for a given pair is then calculated as the absolute difference between the participant-assigned risk scores for the two subjects in the pair. For example, we calculate the output-space distance D for the pair (K, A) as:

$$D(\tilde{M}\mathbf{x}^K, \tilde{M}\mathbf{x}^A) = \left|\tilde{M}\mathbf{x}^K - \tilde{M}\mathbf{x}^A\right|, \quad (4)$$

[10]If we validated the role of Effort in people's group fairness perception instead, we could not simply ask people to make fair decisions for two individuals, but for many individuals simultaneously from varying demographics to compute group parity metrics, increasing their cognitive load and making their fairness judgement more sensitive to non-substantive factors like visualization techniques (Van Berkel et al. 2021). A group fairness setting also assumes that people can compute group statistics (percentages) in their heads if they want to make group-wise fair decisions, which is not true even for college-level laypeople (Jacobs Danan and Gelman 2018).

where $\tilde{M}$ presents participants' mental predictive model of the risk scores.

To test if our findings will be robust across different AI application contexts and different Effort-related features, each participant will be randomly assigned to one of the two between-subjects conditions: CLUE (where the Effort-related, input-space feature is defendants' number of previous arrests, and the output-space feature is defendants' risk of committing a violent crime if released on bail) vs. SHED (where the Effort-related, input-space feature is households' income, and the output-space feature is households' risk of not paying back a monthly credit balance).

Experimental Set-up

We show interfaces for the main types of questions in the experiment in Figure 2 (SHED condition) and Figure 4 (CLUE condition, Appendix E). Since the answers to these questions are highly subjective, to incentivize participants to think carefully and give informedly truthful opinions, we apply the Bayesian Truth Serum (BTS) method introduced by Prelec (2004) (details in Appendix E). The BTS method was validated and applied in fields ranging from Psychology (John, Loewenstein, and Prelec 2012) and Marketing (Weaver and Prelec 2013) to AI (Witkowski and Parkes 2012) and HCI (Miller, Bailey, and Kirlik 2014). Therefore, we use a simplified version of BTS on our most subjective type of MCQ: overall input-space distance, with a \$5 "Honesty bonus" for the top 10% participants in BTS score.

For the other type of dependent variable question (output-space distance), since this question asks people to estimate a numeric "fair" risk score, BTS (designed for MCQ) is not suited. Our alternative incentive mechanism is a \$5 "Rationale bonus" for the top 10% participants who write the most detailed and persuasive rationales to justify their risk scores. As people write down justifications, they have more time to think and potentially recalibrate their risk scores.

We apply the following filters when recruiting Prolific participants: approval rate of at least 99%, Bachelor's degree, U.S. residency, and English fluency. Considering the median study completion time of approximately. 42 minutes, we pay each participant \$8.45, corresponding to a median pay rate of \$12 per hour. After excluding 6 participants who failed 2 out of 3 attention checks under Prolific's policy, our final data include 149 samples.[11]

This experiment has been approved by our Institutional Review Board (IRB). We also pre-registered our experimental hypotheses and analyses on Jan 10, 2025 before recruiting Prolific subjects on Jan 11, 2025 to collect data.[12]

Analysis Methods

To address RQ1, we compute Spearman correlation coefficients to examine the relationships between trajectory distance and overall input-space distance, as well as between aggregate distance and overall input-space distance. Spearman correlation is appropriate here because it does not assume linearity and is robust to non-normal distributions and outliers, which are suitable for ordinal data. We then perform one-sample t-tests to determine if these correlations are significantly different from 0. If both correlations are significant, we use Hotelling's t-test (May and Hittner 1997) and Steiger's Z-test (Meng, Rosenthal, and Rubin 1992) to compare the strengths of these correlations. Hotelling's t-test is well-suited for assessing differences in dependent correlations, as it accounts for the shared dependent variable. However, it is known to be overly powerful, which can come at the expense of a higher Type I error rate in some scenarios (May and Hittner 1997). Steiger's Z-test, on the other hand, provides a more generalizable framework and is less sensitive to deviations from normality by implementing Fisher's z transformation of sample correlation coefficients. This makes Steiger's Z-test particularly valuable for larger datasets where the normality assumption may not hold perfectly. By using both tests, we can balance the strengths and limitations of each approach, providing more reliable comparisons of correlation coefficients. To address concerns related to multiple testing and reduce the likelihood of Type I errors, we apply the Bonferroni correction to adjust the p-values. To further validate these findings, we employ a bootstrapping procedure to estimate the confidence intervals of the differences between the two correlation coefficients. Moreover, we estimate a linear regression model:

$$d = \alpha_0 + \alpha_1 \cdot d_{\mathrm{S}} + \alpha_2 \cdot d_{\mathrm{E}} + \epsilon, \tag{5}$$

where d_S and d_E represent the aggregate distance and the trajectory distance, respectively, and d denotes the overall input-space distance. We conduct a Wald test with H_0 : $\alpha_1 = \alpha_2 = 0$. If both α_1 and α_2 are significantly different from 0 and their effects are statistically significant, we can conclude that aggregate distance and trajectory distance have significantly different impacts on overall input distance. The rationale for including the linear regression model is that it allows us to examine the effects of aggregate distance and trajectory distance on overall input-space distance simultaneously. While Hotelling's t-test and Steiger's Z-test provide direct comparisons of the correlations, the linear regression offers additional insight into the magnitude and statistical significance of the individual contributions of aggregate and trajectory distances.

For RQ2, we follow a similar approach as our aforementioned statistical tests in RQ1, simply replacing (pairwise) overall input-space distance d with (pairwise) output space distance D. The corresponding regression model is:

$$D = \beta_0 + \beta_1 \cdot d_{\mathrm{S}} + \beta_2 \cdot d_{\mathrm{E}} + \epsilon, \tag{6}$$

For RQ3, we perform a regression analysis to test if the between-subjects variable moderates the relationships examined in RQ1 and RQ2. We estimate the following models:

$$\begin{aligned} d = {} & \alpha_0 + \alpha_1 \cdot d_{\mathrm{S}} + \alpha_2 \cdot d_{\mathrm{E}} + \alpha_3 \cdot C_{\mathrm{CLUE}} \\ & + \alpha_4 \cdot d_{\mathrm{S}} \times C_{\mathrm{CLUE}} + \alpha_5 \cdot d_{\mathrm{E}} \times C_{\mathrm{CLUE}} + \epsilon, \end{aligned} \tag{7}$$

$$\begin{aligned} D = {} & \beta_0 + \beta_1 \cdot d_{\mathrm{S}} + \beta_2 \cdot d_{\mathrm{E}} + \beta_3 \cdot C_{\mathrm{CLUE}} \\ & + \beta_4 \cdot d_{\mathrm{S}} \times C_{\mathrm{CLUE}} + \beta_5 \cdot d_{\mathrm{E}} \times C_{\mathrm{CLUE}} + \epsilon, \end{aligned} \tag{8}$$

[11] 144 regular participants and 5 timed-out participants, who exceeded the maximum time allowed by Prolific but still finished the survey on Qualtrics

[12] Pre-registration proof: https://aspredicted.org/4qg6-zpfm.pdf

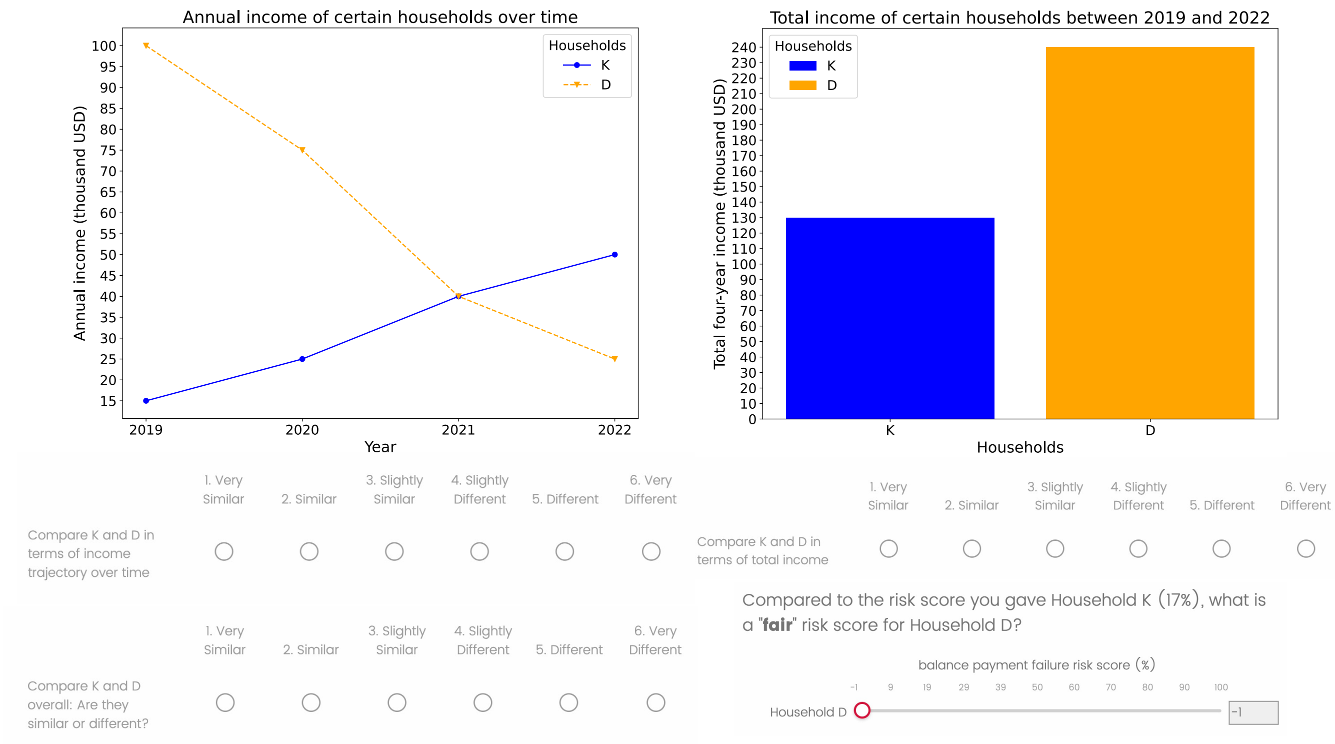


Figure 2: Example human subjects experiment interfaces to measure: (1) trajectory distance (upper left); (2) aggregate distance (upper right); (3) overall input-space distance (lower left); (4) output-space distance (lower right).

where C_{CLUE} represents the between-subject variable, indicating the experimental condition in which participants were randomized to the criminal justice context. Here, significant values for α_4 and α_5 (or β_4 and β_5) indicate a moderation effect. These coefficients provide insights into whether respondents treat the relationships between aggregate or trajectory distances and overall input/output distances differently when evaluating criminal history versus income. For instance, if α_4 (β_4) is positive and significant, this suggests that respondents place greater weight on aggregate differences when evaluating criminal history compared to income. Similarly, if α_5 (β_5) is positive and significant, this indicates that respondents attribute more weight to trajectory differences when evaluating criminal history compared to income.

Quantitative Results and Analysis

Our responses to RQ1 and RQ2 are affirmative. In both the CLUE and SHED conditions, trajectory distance exhibits stronger correlations with overall input-space and output-space distances compared to aggregate distance, as shown in Table 2 (Appendix F). Under the CLUE condition, trajectory distance shows a strong correlation with overall input distance ($r_{\text{traj,input}} = 0.7056$) and a moderate correlation with output distance ($r_{\text{traj,output}} = 0.4218$). In contrast, aggregate distance has weaker correlations ($r_{\text{aggr,input}} = 0.5022$ for input and $r_{\text{aggr,output}} = 0.2089$ for output). In the SHED condition, trajectory distance strongly correlates with overall input distance ($r_{\text{traj,input}} = 0.7881$) and moderately with output distance ($r_{\text{traj,output}} = 0.4986$), while aggregate distance shows mixed correlations with a moderate correlation with input distance ($r_{\text{aggr,input}} = 0.6547$) and a weak output correlation ($r_{\text{aggr,output}} = 0.2507$).

Table 3 (Appendix F) shows Hotelling's t-test and Steiger's Z-test to compare these correlations' strengths. Across conditions, trajectory distance consistently shows significantly stronger correlations with overall input and output distances than aggregate distance.[13] To further validate our findings, we implement a bootstrapping procedure in Table 4 (Appendix F) to estimate the confidence interval of the difference between the two correlation coefficients. [14]

As shown in Table 5 (Appendix F), after controlling

[13]In the CLUE condition, the differences in correlations are highly significant, with Hotelling's t-test yielding statistics of 7.9758 for input-space and 5.5161 for output-space distances (p-value < 0.001). Steiger's Z-test further supports these results with statistics of 6.9077 for input and 5.3461 for output (p-value < 0.001). In the SHED condition, the differences are statistically robust, with Hotelling's t-test statistics of 7.3360 (input) and 7.9612 (output), and Steiger's Z-test statistics of 6.5541 (input) and 7.6466 (output), all significant at p-value < 0.001 after Bonferroni correction.

[14]The 95% confidence interval of the differences between $r_{\text{traj,input}}$ and $r_{\text{aggr,input}}$ and is $[-0.2780, -0.1280]$ for CLUE and $[-0.1950, -0.0730]$ for SHED, with neither interval containing 0. The 95% confidence interval of the differences between $r_{\text{traj,output}}$ and $r_{\text{aggr,output}}$ is $[-0.3000, -0.1280]$ for CLUE and $[-0.3330, -0.1610]$ for SHED. Both intervals also exclude 0.

for aggregate distance, trajectory distance remains significantly correlated with overall input-space distance[15] and with output-space distance[16].

Regarding RQ3, while the CLUE vs. SHED condition itself does not have a direct impact on overall input distance (p-value $= 0.442$), it significantly moderates the impact of aggregate distance and trajectory distance. [17]

Qualitative Results and Analysis

After each input-space distance question, we have an optional question where participants select factor(s) that influence their assigned input-space distance: trajectory, aggregate, and "Other (please specify)". Participants select trajectory more often than aggregate in both CLUE ($80.6\% > 71.4\%$) and SHED ($75.2\% > 60.0\%$) conditions, reaffirming our quantitative result that trajectory distance has a stronger impact than aggregate distance on overall input-space distance. We perform thematic coding inductively on the 55 free-text responses (rationales) that follow the third choice, "Other (please specify below)" (1.9% in CLUE, 4.6% in SHED), and come up with 9 themes (after filtering out 4 vague rationales). Although we expect people to specify "Other" factors, most rationales are still about: (1) Both trajectory and aggregate (23 rationales); (2) Only trajectory (12 rationales); (3) Only aggregate (3 rationales).

New themes that influence how people evaluate overall input-space distance include: (4) Concern about unobserved factors (4 rationales, e.g., "Possible retirement or loss of job by B"); (5) First time step (3 rationales, e.g., "Similar/near equal high amount of arrest to start with."); (6) Last time step (2 rationales, e.g., "In addition to the vastly different trajectories, it is important to consider the endpoint of the graph, as it is at this time that the decision will be made, such as by a bank."); (7) Magnitude of acceleration (2 rationales, e.g., "Jumps in increased or decreased crimes."). Two other rationales are unique enough to each define its own theme: (8) Comparing to an average person: "Although the total arrest times have a significant different, the number of total arrests for both people is quite a bit and more than an average person"; (9) Intersection: "The intersection of their trajectories".

[15]In CLUE, our regression model estimates α_1 and α_2 as 0.3580 and 0.5454, respectively, both significant at the 1% level. The Wald test yields a chi-square statistic of 48.3438 (p-value < 0.001). In SHED, α_1 and α_2 are estimated as 0.3182 and 0.6114, respectively, both also significant at the 1% level, with a Wald test chi-square statistic of 111.5533 (p-value < 0.001).

[16]In CLUE, our regression model estimates β_1 and β_2 as 0.0070 and 0.0403, respectively, both significant at the 1% level, with a Wald test chi-square statistic of 39.4285 (p-value < 0.001). In SHED, β_1 and β_2 are estimated as -0.0132 and 0.0565, respectively, again both significant at the 1% level, with a Wald test chi-square statistic of 116.2329 (p-value < 0.001).

[17]The interaction terms $\alpha_4 = 0.0399$ (p-value $= 0.091$) and $\alpha_5 = -0.0661$ (p-value < 0.001) show that the effect of aggregate distance (and trajectory distance) on overall input-space distance becomes stronger (and weaker, respectively) in the CLUE (criminal history) condition than in the SHED (income) condition. A similar finding applies to output-space distance, considering $\beta_4 = 0.0201$ (p-value < 0.001) and $\beta_5 = -0.0163$ (p-value < 0.001).

After each output-space distance question, participants may optionally explain their rationales, e.g., "How did you decide on this 'fair' risk score for A (compared to K)?". We manually code rationales for the first set (out of three defendant/household sets) to minimize the impacts of survey fatigue (Porter, Whitcomb, and Weitzer 2004). After excluding vague, data-inconsistent, or AI-generated rationales, we have 243 rationales (CLUE) and 194 rationales (SHED).

Among those rationales, our "Only trajectory" code appears most often, assigned to 42.8% of rationales in CLUE and 41.8% in SHED (e.g., "They both are trending upward which makes me think they are similar. I gave them both the risk of 28% regardless of the number of arrests."). In contrast, our "Only aggregate" code is assigned to merely 21.0% of rationales in CLUE and 15.5% in SHED (e.g., "The graph shows that Household D has a significantly higher total income compared to Household K. Therefore, a fair risk score for Household D should be lower than 15%. [...]"). This qualitative comparison reaffirms our quantitative finding that trajectory distance influences output-space distance more strongly than aggregate distance does, with the caveat that many rationales still factor in both trajectory and aggregate distances (21.4% in CLUE and 30.4% in SHED), e.g., "Defendant D has been arrested a lot more than Defendant K, but he is trending down. That being said, I think it balances out and their likelihood of reoffending is probably similar."

Demonstrating Effort-aware Fairness

Our human subjects experiment shows that the key component in our force-based formulation of "Effort" – the cumulative-view acceleration term (increasing vs. decreasing trajectories of non-cumulative, annual arrests/income) – impacts laypeople's individual fairness evaluation process. We now demonstrate how to compute "Effort" and Effort-aware Individual Fairness (EaIF) on real-world datasets.

Since the CLUE term of use does not allow us to release data, we will first compute our Effort, EaGF, and EaIF metrics on the published SHED dataset and release our record-linked version of SHED (2019-2022) for reproducibility. An analogous demonstration on CLUE data is in Appendix G.

Computing Effort

One inertia metric that is relevant to both criminal justice and personal finance is childhood poverty, as explained earlier. However, for adults in our two real-world datasets, information on adults' childhood socio-economic background is not available, especially not at the individual level. Therefore, to quantify inertia empirically, we may use race as an individual-level but imperfect proxy for childhood poverty (or inertia) in the U.S. as the National Center for Education Statistics (NCES) found that childhood poverty rate differs substantially across races (e.g., White: 13%, Asian: 14%, Pacific Islander: 25%, American Indian: 36%, Black: 39%) in 2012.[18] To obtain m per race, we scale these poverty rates by the maximum rate (39%) so that m spreads across $[0, 1]$.

[18]https://nces.ed.gov/programs/coe/indicator/cce/family-characteristics—figure 4. Accessed Jan 19, 2025

Given four equidistant time steps $\{0, 1, 2, 3\}$ (assuming $\Delta t = 1$), we model cumulative arrests in CLUE (or cumulative income, in multiples of $\$10k$ in SHED) at each time step as X_0, X_1, X_2, X_3. Their velocities are V_0, V_1, V_2, where $V_i = \frac{X_{i+1}-X_i}{\Delta t} = X_{i+1}-X_i$. Their accelerations are A_0 and A_1, where $A_i = \frac{V_{i+1}-V_i}{\Delta t} = V_{i+1}-V_i$. We average these two acceleration terms to get $A_{\text{avg}} = \frac{1}{2}(A_0 + A_1) = \frac{1}{2}(v_1 + v_2)$. Noting that the Effort-related feature is desirable in SHED (income) but undesirable in CLUE (arrests), we compute the individual-level (good) Effort, E, with context adaptations:

$$\text{SHED: } E = m \cdot \sigma(A_{\text{avg}}), \tag{9}$$

$$\text{CLUE: } E = m \cdot \big[1 - \sigma(A_{\text{avg}})\big]. \tag{10}$$

The function $\sigma(z) = \frac{1}{1+e^{-z}}$ monotonically maps real values from $(-\infty, \infty)$ to the $(0, 1)$ range, serving two purposes. First, it allows $\sigma(A_{\text{avg}})$ to obtain only one possible sign. More specifically, considering the desirable Effort feature, income, in SHED. Note that m is always positive. When the average acceleration term is positive, $E = m \cdot A_{\text{avg}}$ will assign better (more positive) Effort to those with higher inertia (from more disadvantaged backgrounds). However, when the average acceleration term is negative, $E = m \cdot A_{\text{avg}}$ will assign worse (more negative) Effort to those with higher inertia, which contradicts our intention (given the same acceleration, more disadvantaged people should be credited for better Efforts). The sigmoid function eliminates the possibility of a negative sign and solves this problem. Second, the sigmoid function gathers extreme values closer together so that we have more data points to compute group parity even for subjects with extreme accelerations.

Computing Effort-aware Individual Fairness

We operationalize the pairwise individual distance function (Equation 2) by first setting the weights, α and $(1 - \alpha)$, between the Effort feature and the aggregate feature to be either an equal baseline (0.5 and 0.5) or our human subjects experiment's regression coefficients (0.6114 and 0.3182 in SHED condition, which we normalize to 0.6577 and 0.3423 in this EaIF pipeline), illustrating the relative impacts by trajectory distance d_E (proxy for difference in Efforts) and aggregate distance d_S on the overall input-space distance d.

To ensure the aggregate income feature stays in [0,1] like the Effort feature and reflect the intuition that the same income gap at lower income (e.g., $\$10k$ vs. $\$20k$) is more significant than at higher income (e.g., $\$110k$ vs. $\$120k$), we define an aggregate (sum) function $S(\mathbf{x})$ by applying a modified (scaled and translated) right-hand side of the sigmoid function σ on the whole four-year (non-negative) income $X_3 = \sum_{t=0}^{3} x_t$, scaled by $\lambda = \$200k$ so that this aggregate feature is empirically spread out across [0,1] range:

$$S(\mathbf{x}) = 2 \cdot \sigma\left(\frac{X_3}{\lambda}\right) - 1. \tag{11}$$

Noting that the output-space and input-space distances (D and d) take values in $[0, 1]$, to operationalize the individual fairness constraint (Equation 1), for each pair of individuals $\mathbf{x}^i$, $\mathbf{x}^j$ and predicted risks $M\mathbf{x}^i$, $M\mathbf{x}^j$ by an AI model M, we compute their pairwise fairness score:

$$F(\mathbf{x}^i, \mathbf{x}^j, M) = 1 - \max\{0, D(M\mathbf{x}^i, M\mathbf{x}^j) - d(\mathbf{x}^i, \mathbf{x}^j)\}, \tag{12}$$

which should be 1 if this constraint is satisfied, or otherwise be lower, i.e., in $[0, 1)$, depending on the degree of constraint violation. We get an overall EaIF score for model M by averaging pairwise fairness scores across all $\binom{|\mathcal{D}|}{2}$ pairs from $|\mathcal{D}|$ individuals in dataset $\mathcal{D}$ (SHED) with predictions by M:

$$\text{EaIF}(M) = \frac{1}{\binom{|\mathcal{D}|}{2}} \sum_{\mathbf{x_i}, \mathbf{x_j} \in \mathcal{D} \text{ and } i<j} F(\mathbf{x}^i, \mathbf{x}^j, M). \tag{13}$$

Table 1 shows that according to our EaIF metric, XGBoost is less fair than the other two models, and random forest is slightly more fair than logistic regression. This result is consistent across both sets of weights (between the Effort feature and the most recent cumulative feature).

	EaIF	
Model	Equal weights	Human study weights
XGBoost	0.80	0.79
Logistic regression	0.88	0.87
Random forest	0.91	0.90

Table 1: Effort-aware Individual Fairness Results on SHED

Computing Effort-aware Group Fairness

Binns (2020) found that group fairness and individual fairness are rooted in similar philosophical concepts ("consistency" and "egalitarianism"). Algorithms that satisfy both group fairness and individual fairness were developed, demonstrating the two metrics' compatibility (Zemel et al. 2013). Therefore, we will also demonstrate how to compute Effort-aware Group Fairness (EaGF) with our same force-based notion of "Effort", which was validated by our human subjects experiment in the individual fairness context.

Given an individual-level Effort feature, our goal is to compute Effort-aware group parity and observe this metric as a function of numeric Effort. Our main steps include (1) partitioning decision subjects into similar-effort bins; (2) computing a demographic group parity metric within each bin; (3) plotting this parity metric against the Effort bins. We used demographic features of each household representative who completed the SHED survey to compute group fairness metrics.

After computing a (good) Effort value for every individual, we partition all individuals and their Effort values into equidistant bins (intervals) of Effort length = 0.1. Within each bin, which represents individuals with similar Efforts, we compute the demographic group parity in terms of the mean predicted risk by the same model for each demographic group (G is race, sex, or age). For statistical stability, we only consider a demographic group if the group has at least 10 data points in the respective Effort bin. We define (within-bin) group parity (scale: 0-1) as the ratio of the demographic group with the lowest average risk score $\hat{Y}$ divided by the demographic group with the highest average risk score $\hat{Y}$, formally derived from Equation 14 as follows:

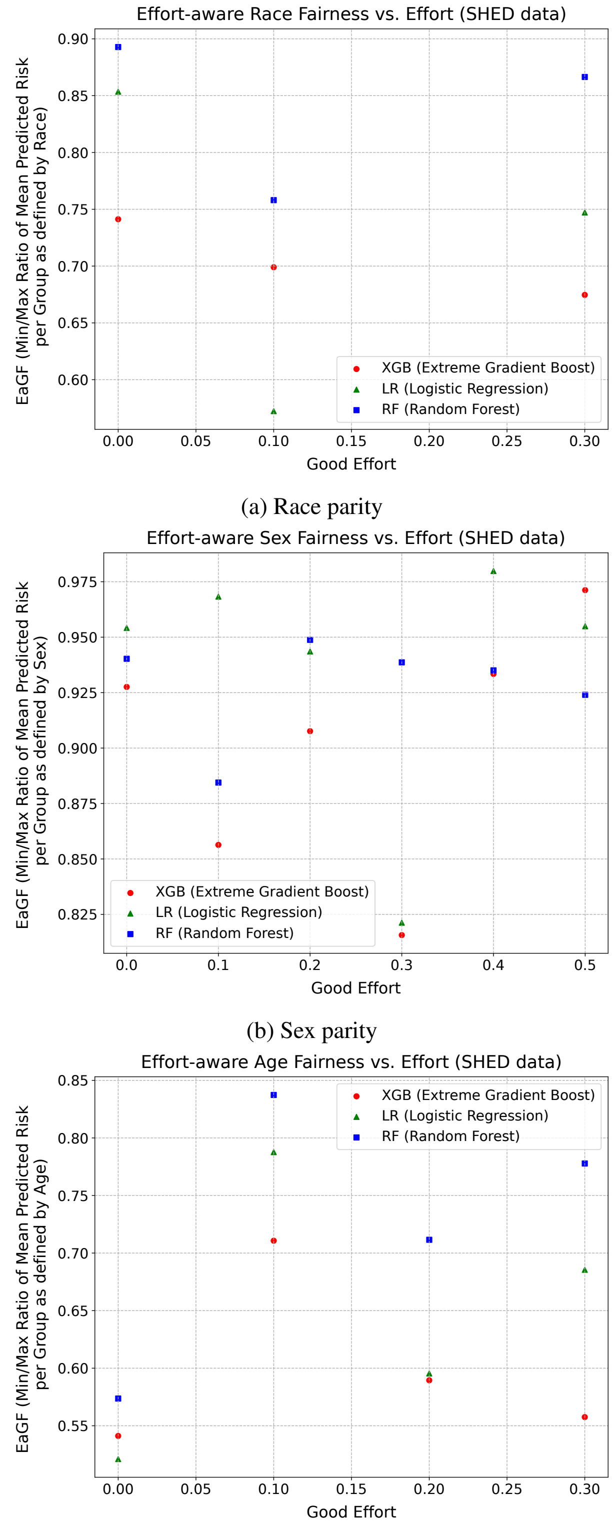
$$\text{Parity}_{G,e_0} = \frac{\min_i \mathbb{P}(\hat{Y}=1 \mid E \in [e_0, e_0+\epsilon],\ G=g_i)}{\max_j \mathbb{P}(\hat{Y}=1 \mid E \in [e_0, e_0+\epsilon],\ G=g_j)}. \quad (14)$$

Figure 3 shows Effort-aware, i.e., within-bin, demographic group parity as a function of Effort.[19] To illustrate why EaGF information is helpful, we first look at Table 6 (Appendix F) on overall demographic parity, i.e., not conditioned on similar Efforts, showing random forest to be among the most group-wise fair models in terms of race, sex, or age group. Figures 3a and 3c reassure us that, conditioned on similar Efforts, random forest remains the fairest model among racial and age groups. However, Figure 3b cautions us that when conditioned on higher-effort bins (0.4-0.5 and 0.5-0.6), random forest is among the least fair models in terms of sex. This pattern might be concerning since we do not want to disincentivize people from exerting more Effort. If sex parity is a legal/policy priority in our context, our EaGF audit might suggest using XGBoost instead of random forest because XGBoost achieves roughly the same best overall sex parity as random forest (Table 6) and XGBoost achieves the best EaGF score when conditioned on the highest-Effort bin (Figure 3b), thereby incentivizing people to exert more effort. Our demonstration highlights a key strength of EaGF over traditional group fairness, as it provides a more granular view of any concerning trend in parity vs. Effort when evaluating AI models.

Conclusion

We identify a gap between how the CS/AI literature has attempted to formalize the notion of "Effort" into existing fairness metrics and how philosophers/legal scholars understand "Efforts". We seek to fill this gap by operationalizing the Force-based account of Effort from philosophy, formulating an "Effort" metric as the product of inertia (systemic disadvantage beyond an individual's control, such as childhood poverty) and accelerations (temporal changes in a task-related input-space feature), which can be looped into existing fairness metrics to formulate Effort-aware Group/Individual Fairness (EaGF/EaIF). As we can conceptualize acceleration more broadly as trajectory, we conduct a human subjects experiment and successfully validate that the acceleration/trajectory component of our Effort-aware Fairness formulation aligns with laypeople's perception of fairness across two distinct AI-assisted decision-making contexts, namely criminal justice and personal finance. Finally, we develop practical pipelines to compute EaIF and EaGF on real-world datasets (SHED and CLUE), demonstrating how these metrics complement traditional fairness metrics.

[19]The subplots' x-axes might differ since not all Effort bins within the 0-1 range have enough data points to compute EaGF.



(a) Race parity

(b) Sex parity

(c) Age group parity

Figure 3: Effort-aware Group Parity (in terms of mean predicted risk) as a function of Effort (SHED data). Bin length is 0.1. Only demographic groups with at least 10 data points are considered. Random forest consistently achieves the best EaGF results in terms of race and age, but not sex.

Ethics Statement

We minimize privacy risks to our human subjects experiment participants by removing any identifiable information (such as Prolific ID) from any supplementary materials we publish, as well as complying with any related institutional (IRB) and federal human subjects protection policies. We commit to compensating our participants reasonably. For example, as our original estimation of 30 minutes for study completion time turns out to be an under-estimation compared to the median completion time (42 minutes), we have adjusted the pay rate from $\$6$ to $\$8.45$ to maintain a median hourly compensation rate of $\$12$, which is considered a "Good" rate in Prolific standard. We also carefully comply with the CLUE dataset's terms of use to protect defendants' privacy, such as by storing the dataset on a password-secured server and only using non-personally identifiable features in our simple AI models development and fairness evaluation.

We acknowledge two core limitations of our proposed metrics. First, in our formulation of both EaIF and EaGF, by using efforts to find pairs of similar individuals or by conditioning on similar-effort bins when computing group parity metrics, we normatively prescribe the ideal outcomes of similar-effort individuals. Still, we leave open the more complex normative question of how the outcomes of individuals with different levels of Effort should be. We have not incorporated a notion of directionality for the relationship between Effort and outcome. In other words, we do not necessarily stipulate that people who exert more Effort should always receive more favorable outcomes, as this involves more unsettled philosophical debates on meritocracy, e.g., whether resources should be allocated based on one's efforts or one's natural talents (such as a basketball athlete's height), which are often due to luck and beyond one's control (Sandel 2021). Second, the risk of fairwashing, i.e., generating posthoc explanations to make predictions by an otherwise unfair black-box AI models score well on specific fairness metrics (Aïvodji et al. 2019, 2021), might extend to our EaF metrics because bad actors might manipulate the particular time steps when computing our acceleration term as well as the feature(s) from which our inertia term or the societal holding back effect is approximated. Therefore, we welcome future research on how to guard the quantification of Efforts against fairwashing, as well as more AI-assisted decision-making data collection initiatives to include more individual-level features that might reflect disadvantages beyond one's control, such as disability or childhood poverty.

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