

Article

# Analysis of Access to Emergency Funds in Sub-Saharan Countries— A Human Rights-Based Approach

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**Simple Summary:** A Simple summary goes here.

**Abstract:** Having access to emergency funds is a valuable resource that many people end up needing at least once in their lives. Those who have access to emergency funding and other financial services have the capacity to remain afloat when unexpected predicaments arise, while those who are without this privilege have no choice but to endure crises and simply hope for the best. The purpose of our project is to analyze the access adults have to emergency funds and financial services in Sub-Saharan countries using a 2017 dataset from the Global Findex Database. Additionally, an important goal of our project is to employ a variety of different approaches in an attempt to minimize bias and maximize fairness, particularly when examining the performance for males and females. We also aim to determine how adults in the Sub-Saharan African region access financial services as well as establish the amount of bias we have within our models using exploratory data analysis, a baseline model, and a variety of fairness metrics. We hope to implement our findings in a Jupyter notebook where this information can be made accessible to a broader undergraduate audience.

**Keywords:** keyword 1; keyword 2; keyword 3 (list three to ten pertinent keywords specific to the article, yet reasonably common within the subject discipline.).

## 1. Version

This Rmd-skeleton uses the mdpi Latex template published 2019/02. However, the official template gets more frequently updated than the ‘rticles’ package. Therefore, please make sure prior to paper submission, that you’re using the most recent .cls, .tex and .bst files (available [here](#)).

## 2. Introduction

Science is often viewed as a way to offer trustworthy research backed solutions and answers. A lot of that research involves statistical methods performed on data however, what happens when the data and statistical methods are not as objective and trustworthy as is so often assumed? The conclusions drawn from the data are biased and unfair, most often towards minorities and protected classes of people. To contribute to a human rights based approach to data analysis, we evaluate fairness metrics on a machine learning algorithm to measure bias. We use a Global Findex data set which contains financial information about 35 Sub Saharan countries. Specifically, we create models to predict access to emergency funds, then analyze the fairness of those models. We focus on group and individual fairness metrics for the protected attribute sex. In addition we investigate the data set itself to understand where potential biases might have been implanted.

Data sets and algorithms have real world impacts on real people. The inherent bias in data sets can carry over into machine learning algorithms that are used to profile and categorize people [1,2]. Since data set's are not collected in a vacuum and often represent the discriminatory environments in which they are collected [3], we must find ways to make data sets and statistical methods more equitable. In this study we explore fairness methods that can be used to evaluate machine learning models. The "impossibility theorem" is the idea that not all fairness metrics can be satisfied at the same time[4]. Although fairness is complex and there are multiple approaches to make a model fair [5,6], it's important to continue to question how data and algorithms can be biased and how to mitigate that bias.

While there have been previous studies implementing fairness techniques in different contexts[7,8], we implement them in an exploratory context meant to teach how and when to use these techniques thus giving us more freedom to branch beyond a specific question while supporting previous work about the importance of these fairness metrics[3,9]. We analyse the data, data collection methods, prediction models, and the fairness metrics to assess how biased our data is and understand how we can de-bias when possible.

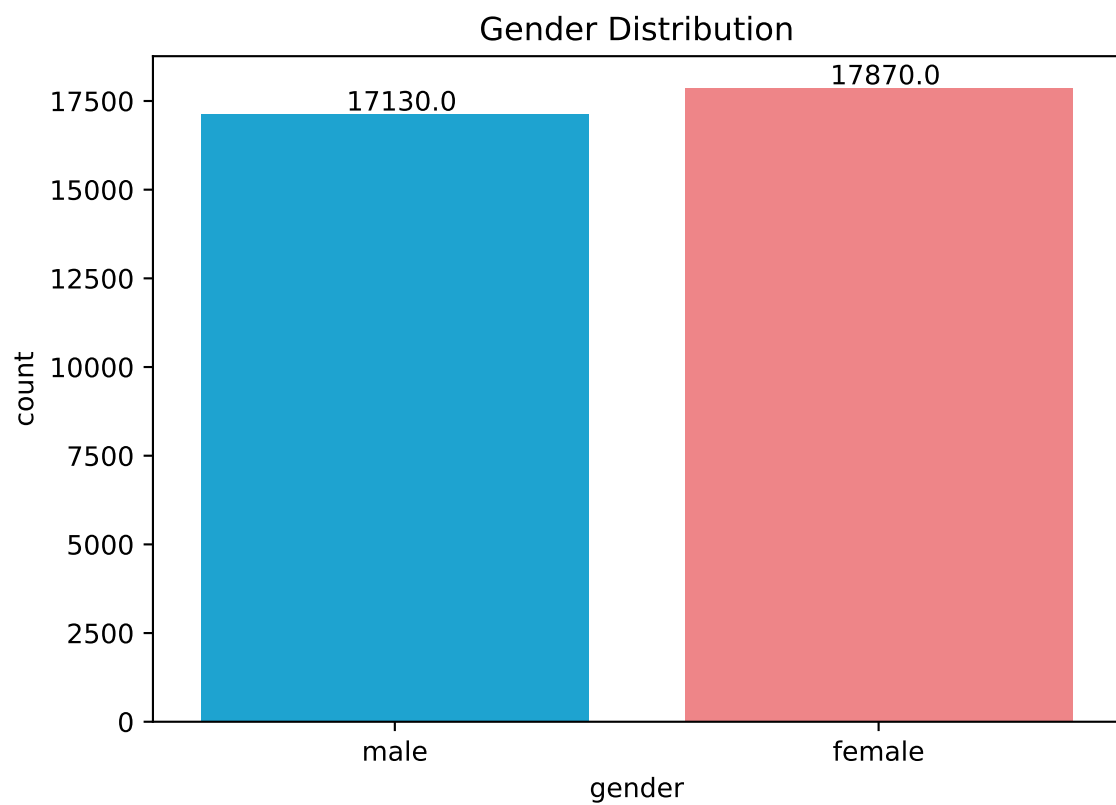
### 3. Data

Our data is derived from The World Bank in The Global Findex Database, comprising the most comprehensive data sets on how adults save, borrow, make payments, and manage risk in more than 140 economies around the world. The data set was created to record various measures of financial equity and inclusion, with the intention that such information could reveal opportunities to expand access to financial services and to promote greater use of digital financial services for individuals who do not have a bank account. Conducted by Gallup, Inc for the annual Gallup World Poll, the participants responded to the questionnaire either on the phone or in-person. There were several variables of interest in this dataset when creating models to predict access to emergency funds, including demographic and financial information. For this analysis, we are using only a subset of the data including countries in the Sub-Saharan region (35 countries total). Our data set includes 35000 observations and 105 variables in total.

#### 3.1. Demographics

##### 3.1.1. gender

The variable *gender* distinguishes gender. There are 16,716 males in this dataset and 17,388 females. This is a fairly equal distribution that we can see in the graph below.

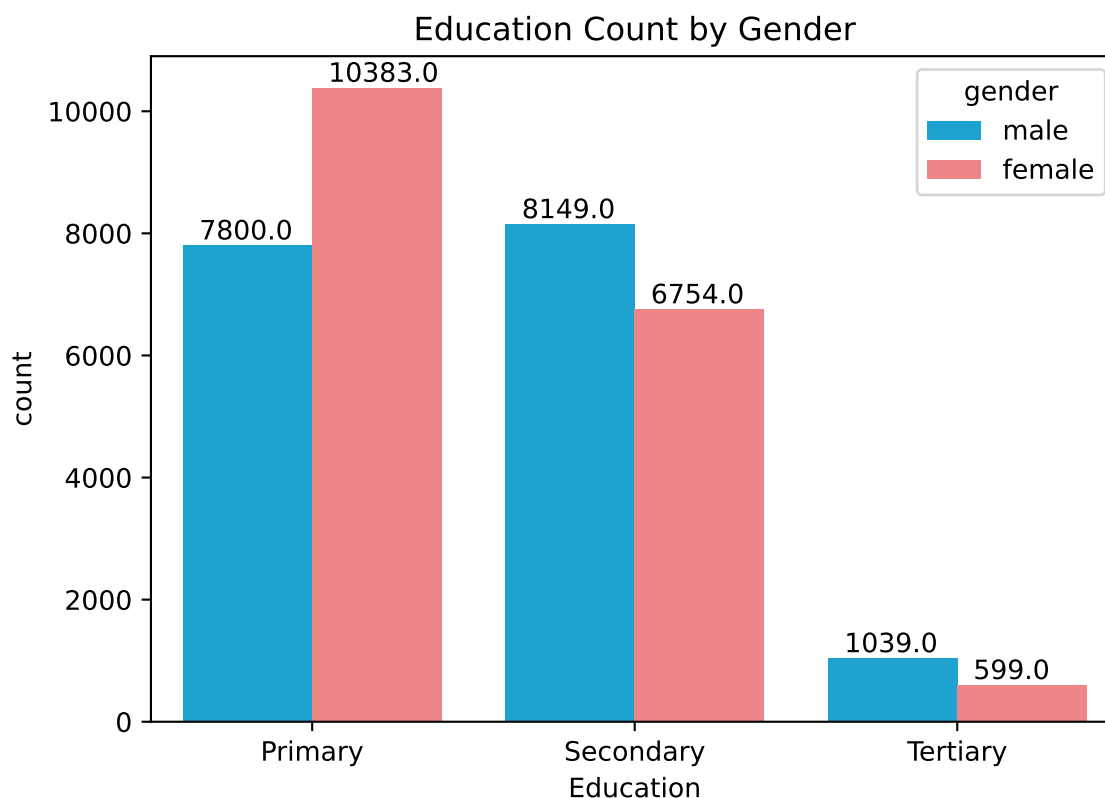


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### 3.1.2. Education

64 The *Education* variable corresponds to the highest level of education attained with 'Primary',  
65 'Secondary' and 'Tertiary' being the three options. Here is the distribution of education by gender:



The bar plot above shows us that there are more women with primary education, but more men with secondary or tertiary education. Overall, we can see that there are more men with higher education than women. About 1,000 more men have received a secondary education and there is about double the amount of men with tertiary education compared to women showing a clear disparity.

### 3.1.3. *economy*

The final demographic variable of interest is the *economy* variable that separates respondents by which country they live in. There are 35 different countries from Sub-Saharan Africa with exactly 1000 respondents from each.

```
df2['economy'].unique()
```

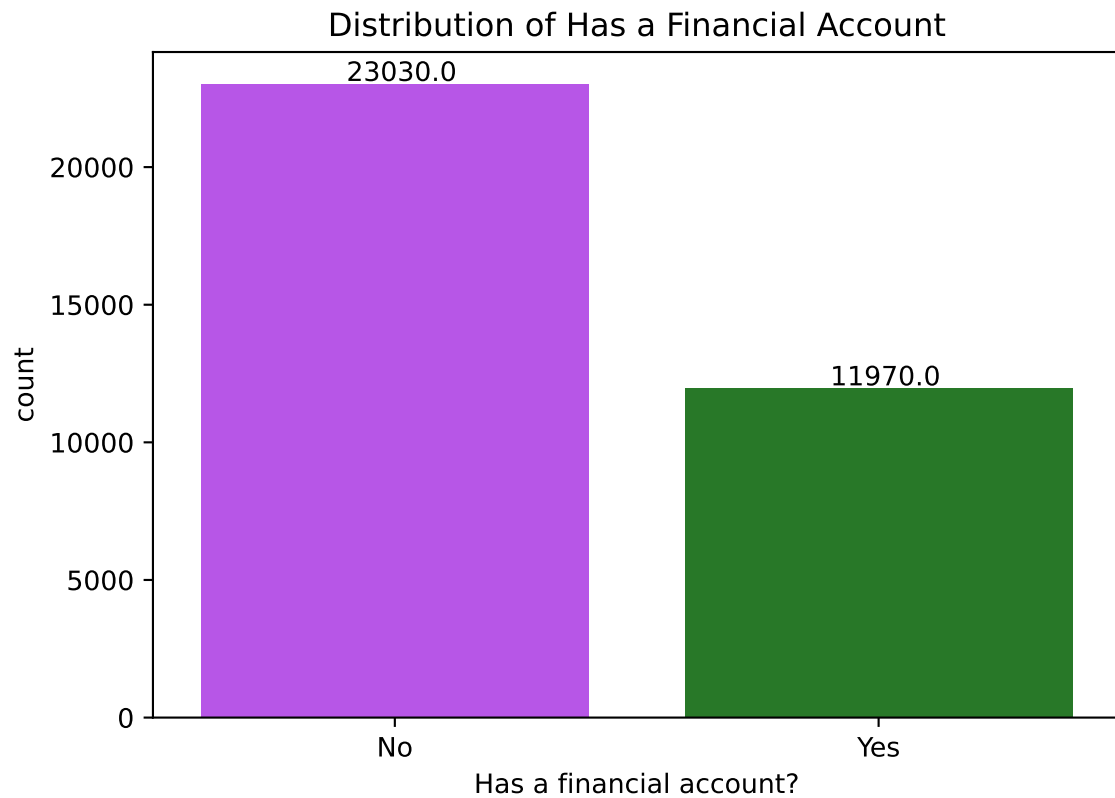
```
## array(['Benin', 'Botswana', 'Burkina Faso', 'Cameroon',
##        'Central African Republic', 'Chad', 'Congo, Dem. Rep.',
##        'Congo, Rep.', 'Cote d'Ivoire', 'Ethiopia', 'Gabon', 'Ghana',
##        'Guinea', 'Kenya', 'Lesotho', 'Liberia', 'Madagascar', 'Malawi',
##        'Mali', 'Mauritania', 'Mauritius', 'Mozambique', 'Namibia',
##        'Niger', 'Nigeria', 'Rwanda', 'Senegal', 'Sierra Leone',
##        'South Africa', 'South Sudan', 'Tanzania', 'Togo', 'Uganda',
##        'Zambia', 'Zimbabwe'], dtype=object)
```

### 3.2. *Financial*

From the financial related variables, we were most interested in a few specific financial variables that we thought would have an impact on access to emergency funds.

### 3.2.1. *account\_fin*

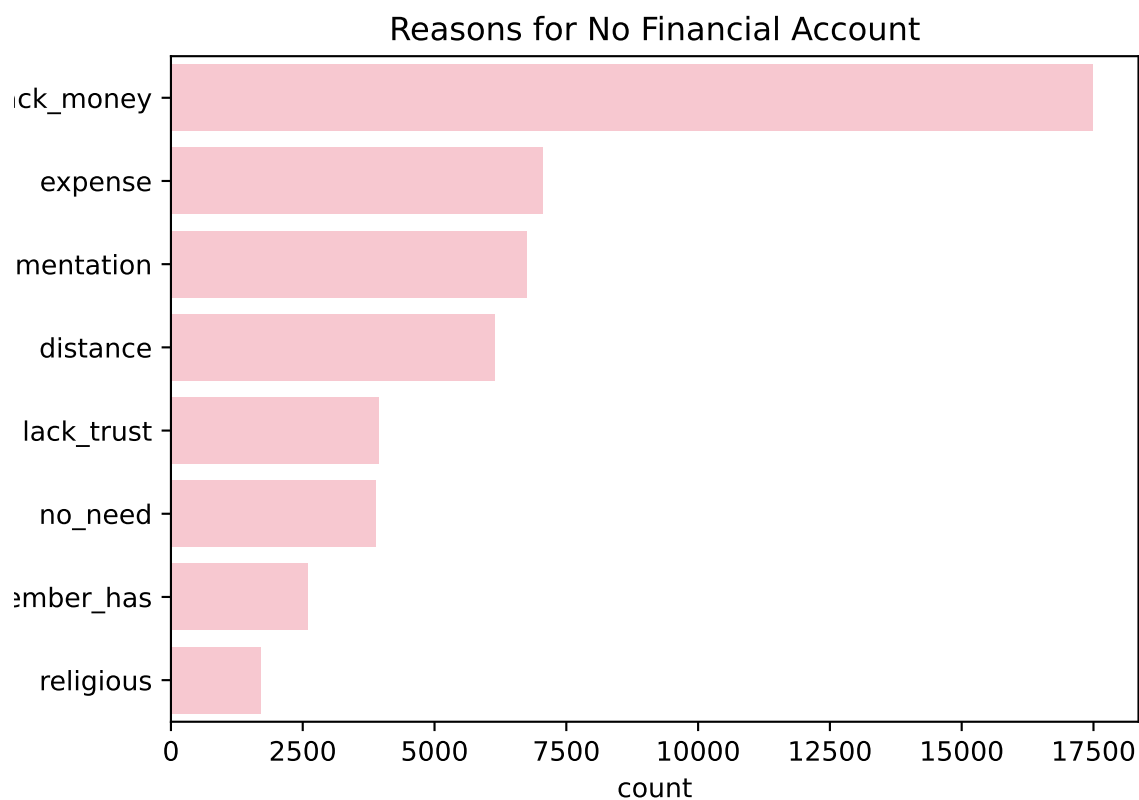
The first variable being *account\_fin* which distinguishes those who have a financial account from those who don't:



We can see that about two thirds of individuals do not have an account. This is likely connected to the lack of access to emergency funds displayed above given that if an individual does not have a financial account, we would expect they are less likely to have a source of emergency funds, as emergency funds are generally stored in an account.

### 3.2.2. *reason*

Those who do not have a financial account were asked why in the *reason* variable, that provides a list of possible reasons for not having a financial account:

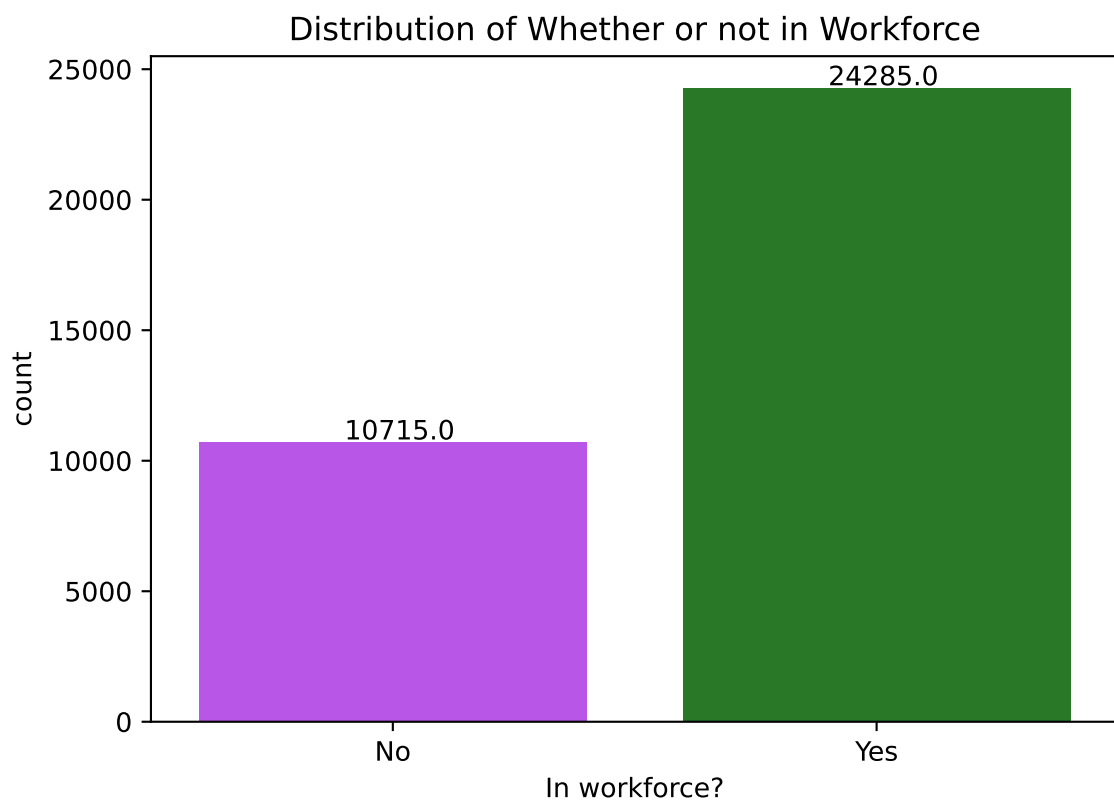


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### 3.2.3. *emp\_in*

99 Employment status was another financial variable of interest represented by *emp\_in*, which asks  
100 whether or not the participant is in the workforce. It appears that about three-fourths of individuals  
101 are in the workforce:



102

103 3.2.4. *inc\_q*

104 And lastly, we evaluated *inc\_q*, which represents income quantile. Income quantile is separated  
 105 into 5 quantiles with 1 being the poorest and 5 being the richest. The mean for all of the countries in  
 106 the dataset is 3.241. This means that all the countries average out to be about middle class.

107 ## 3.241085714285714

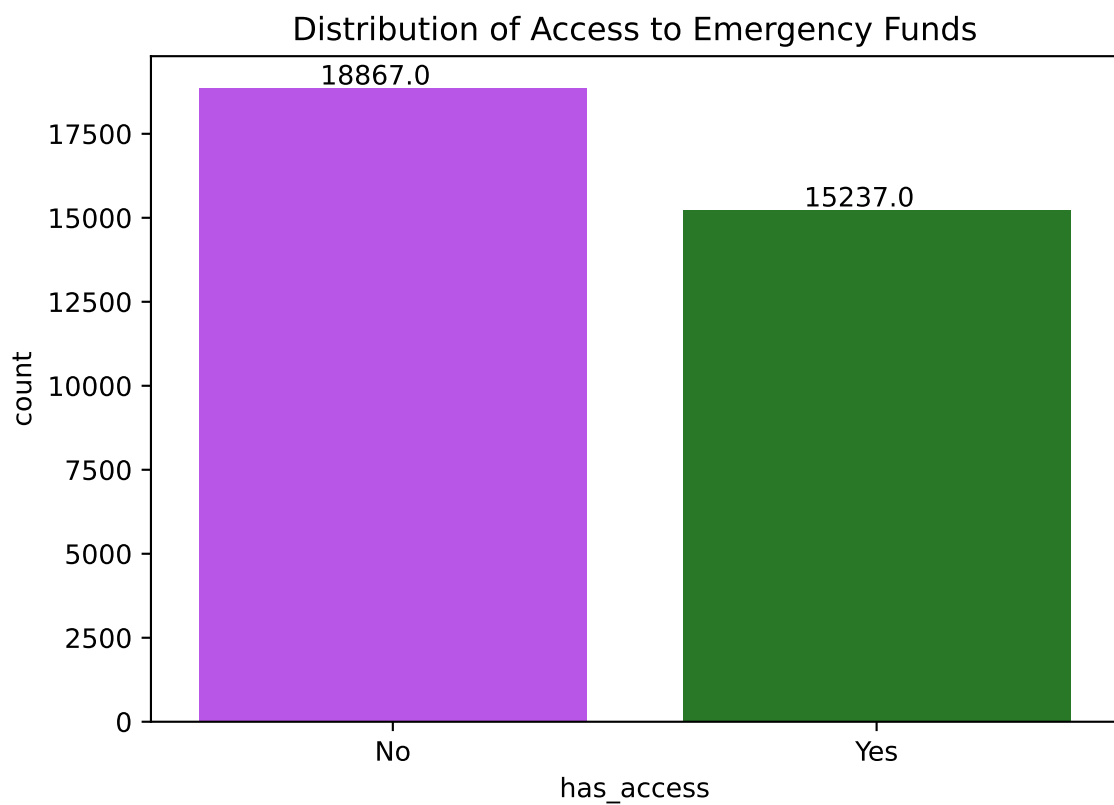
108 The majority of the data set has individuals within the richest quantile, Quantile 5.

109 3.3. *Emergency Funds*

110 To explore access to emergency funds in our dataset, we were interested 3 variables we thought  
 111 could be related:

112 3.3.1. *has\_access*

113 The variable *has\_access* directly asks participants if they have access to emergency funds, with  
 114 “emergency funds” defined as 1/20th of the GNI (gross national income) per capita for the country.  
 115 GNI per capita is the country’s total income in a year/ the country’s population size. For context, in  
 116 the United States, “emergency funds” would be defined as about \$3,000.

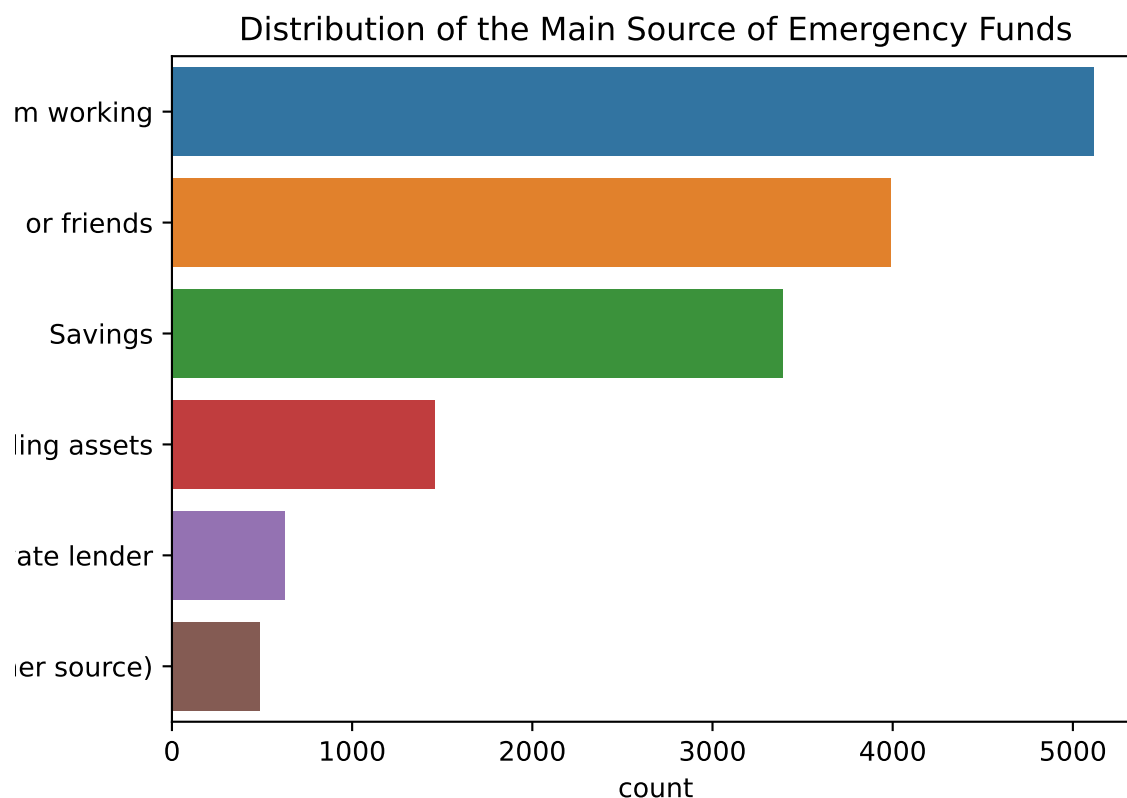


The barchart above displays the overall distribution of access to emergency funds. We can see that over half of individuals represented in the data do not have access.

### 3.3.2. *main\_source\_funds*

We proceeded to explore the source of emergency funds using the *main\_source\_funds* variable, which provides a list of options for where participants receive their main source of emergency funds:

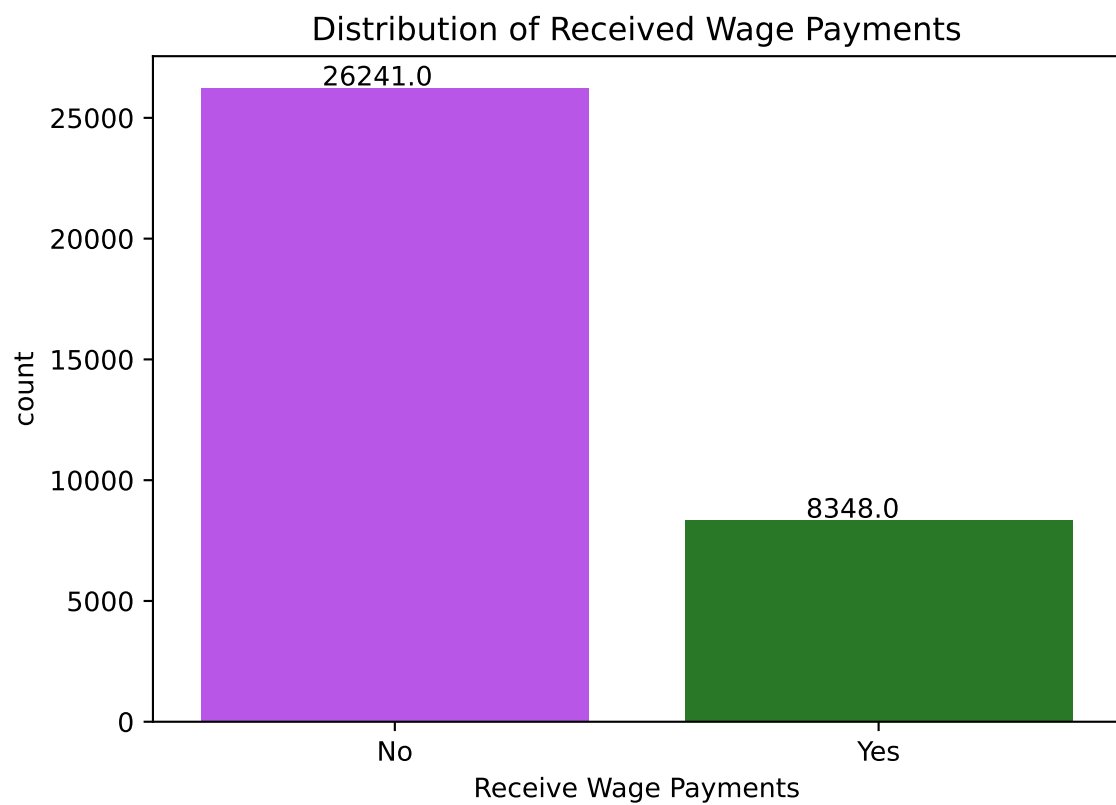




The barchart above displays the overall distribution of the main source of emergency funds. Most of the individuals with access to emergency funds receive their funding from work, their family and friends, or their savings.

### 3.3.3. Recieve Wage Payments

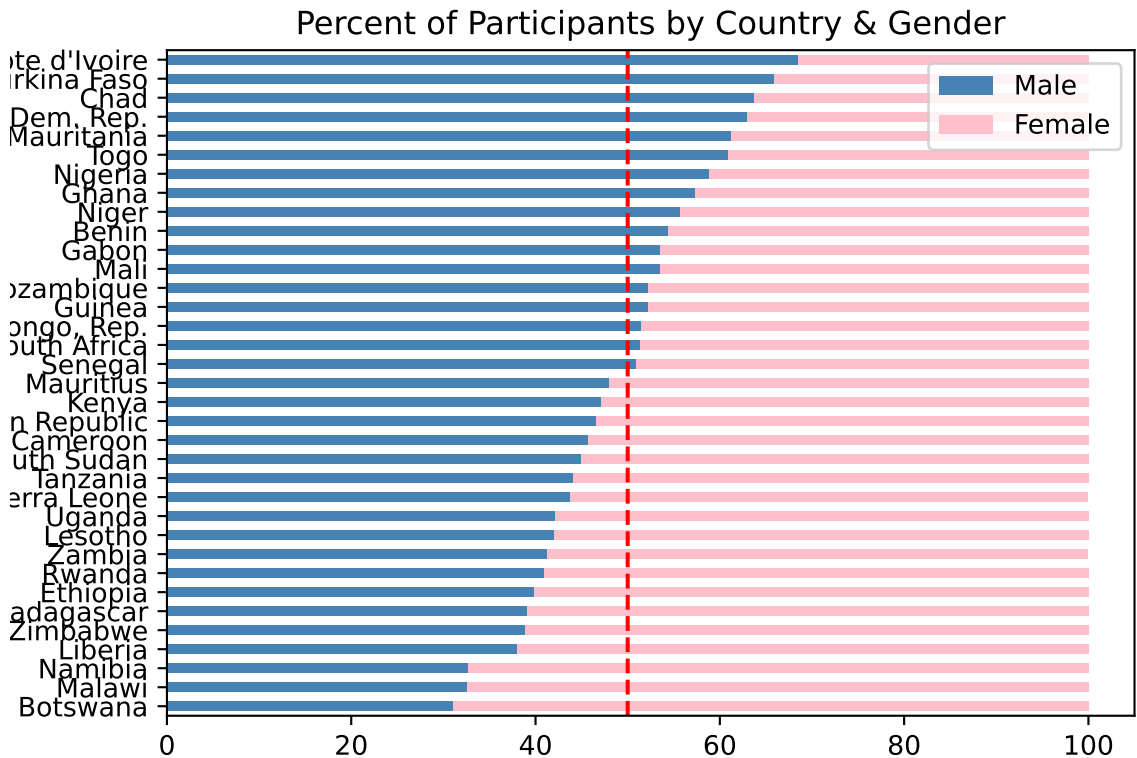
Diving further into the “Money from Working” category, we can see that only 8196 individuals receive wage payments from the *Receive Wage Payments* variable. This analysis suggests that receiving wage payments may be a key factor in determining access to emergency funds.



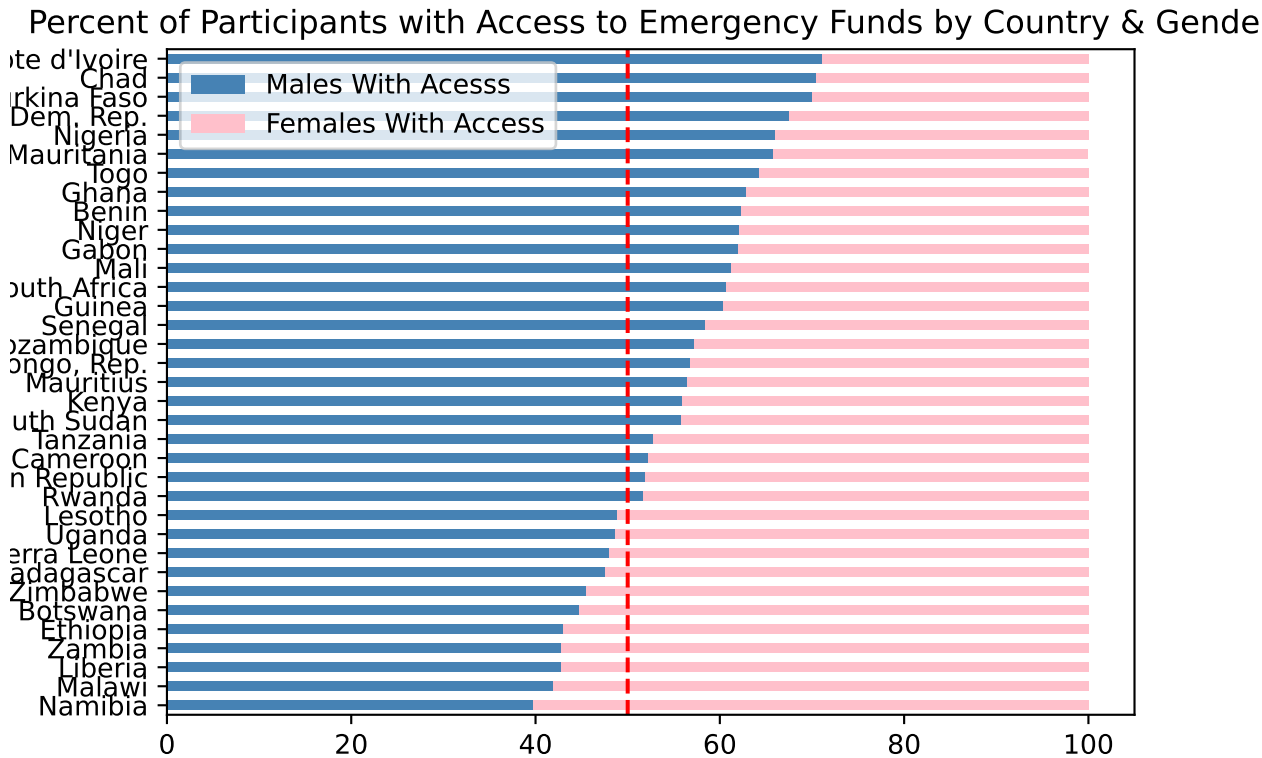
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132 3.3.4. *gender, economy* and *Education* in relation to Emergency Funds

133 Finally, we sought to find if there were disparities in access to emergency funds by *gender, economy,*  
134 and *Education*.

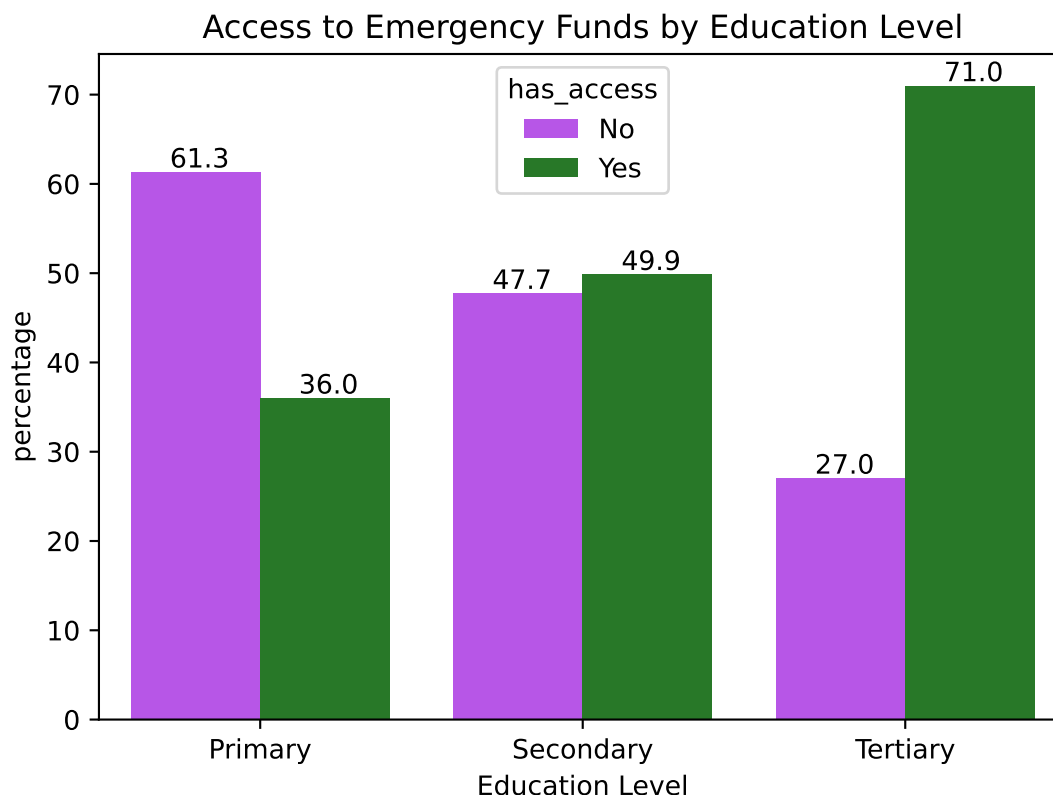


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In the side-by-side barplots above, we can see that although only about 50% of the countries have a higher percentage of men represented in the questionnaire (left bar plot), in 75% of the countries more men have access to emergency funds than women (right bar plot).



Additionally, in the barplot above we can see the distribution of funds based on an individual's highest education level. 63% of people with only a primary education do not have access to emergency funds compared to 37% of people who do. These numbers are more evenly distributed for those with secondary education, with about 49% of people not having access to emergency funds, while 51% of people do have access. Finally, for those with a tertiary level of education we can see that about 72% of people have access to emergency funds while only 28% of that group does not have access. Overall, we can make the assumption that people with a higher level of education are more likely to have access to emergency funds.

## 4. Methods

### 4.1. Software

We conducted our analysis in a Google Colab Notebook primarily employing the python libraries [pandas](#) and [numpy](#) for data cleaning and exploratory analysis, as well as [sklearn](#) and [aif360](#) for implementing machine learning methods, fairness metrics, and de-biasing techniques. The notebook detailing our [full analysis](#) is available via our public [GitHub repository](#).

### 4.2. Data Cleaning

Before fitting the model, we performed several pre-processing steps on the data in order to remove unnecessary or redundant information, address missing values, and ensure that the variables were coded such that they would be processed appropriately by the model. Some of these steps were

performed after fitting the initial model, and some choices were made based on the impacts of those choices on the performance of the model.

First, we removed the arbitrary variables *economycode* (country code) and *regionwb* (region); *economycode* is essentially a duplicate of *economy* (country name), and *regionwb* is the same for all rows (value is Sub-Saharan) since this is the variable that we initially filtered by. Next, we checked for variables with a high percentage of missing values. Several variables have many missing values because they are follow-up questions to a previous question that are only asked if the respondent gives a specific response for a previous question. We chose to drop all variables with more than 30% missing values (58 variables total) because we observed by running the model multiple times that variables with NA percentages above this threshold had no impact on the model accuracy or fairness. Thus, it made sense to remove them if their presence is negligible when included in the model. Next, we checked for variables with high levels of redundancy (i.e. little variation), defining a high level of redundancy as 95% or more of the values being the same. The only variable with a high level of redundancy was *pay\_online* (a binary variable indicating whether or not an individual has paid online for something), and we chose to remove it because removing it had no impact on the model accuracy and fairness.

Many of the questions in the survey were structured such that the potential responses were “yes”, “no”, “don’t know”, and “refuse”. Based on our exploratory data analysis, it seems that for most questions, the numbers of “don’t know” and “refuse” responses are very low. Furthermore, these responses would not give us much useful information when implementing a predictive model. Thus, we chose to replace all “don’t know” and “refuse” values with NA values. We then replaced all remaining missing values (including missing values not removed previously and “don’t know” and “refuse” values) with the column mean rounded to the nearest whole number (i.e. the most frequent value if the variable is categorical).

Next, we re-coded the country variable into a variable with five categories based on the percentage of sampled individuals in the country who have access to emergency funds (1 = < 20% have access, 2 = between 20% and 40% have access, etc.). All other variables in our data set were coded such that the model could appropriately interpret them, so we did not have to do any additional re-coding. The majority of the variables are binary with 0 = no, 1 = yes, and the rest are either categorical variables with hierarchical categories such as income quantile and education level or continuous numerical variables such as age.

Finally, we created a cartesian product to combine two variables – one indicating whether or not an individual has a financial account and the other indicating whether or not the individual has saved money in the past 12 months– in order to increase the accuracy of the model after fitting the initial model.

After this pre-processing, we have 42 predictor variables and 35,000 observations.

#### 4.3. Model Selection

Given that we are aiming to predict a binary outcome (possible or not possible to come up with emergency funds), our model needs to be a classification model. We tried two of the most common model types used for classification– logistic regression and decision tree classifier. We ultimately chose the decision tree classifier model over the logistic regression model because the baseline accuracy was higher (61% versus 55%). Furthermore, the decision tree model makes more intuitive sense given our data since most of our predictors are binary variables, and binary predictors fit well into the tree structure. We were able to further improve the accuracy of the decision tree model to 68% by using cross-validation to specify the max depth as 6. The decision tree model uses machine learning to predict outcomes by organizing the variables into a tree that branches off at each decision point based on the value of the variable at that point. The most influential variables are at the top, and the outcome variable is at the end of each branch. We split our data into 70% training, 30% testing because this is the standard train-test split used for machine learning algorithms.

#### 4.4. Metrics

Fairness metrics are a way to assess machine learning algorithms for unwanted bias. Algorithms can classify people unfairly using data collected in a biased environment. When classifying people, it's important to understand how these classifications can contribute to and reinforce discriminatory social systems. Accuracy shouldn't always be prioritized. It is useful to sacrifice accuracy in favor of fairness when using machine learning algorithms to make decisions impacting people. To assess fairness and accuracy in our model we explore 12 different metrics, 10 of which are fairness metrics. Fairness metrics can be split into group and individual metrics.

Group fairness metrics ensure parity between privileged and unprivileged groups of a protected class. For example, for the protected class sex, the privileged group is men and the unprivileged group is women. The model should work similarly for both of these groups and not favor the privileged group. Group fairness metrics measures how discriminatory the model classifies the unprivileged group [22]. The group metrics we explore include statistical parity difference, equal opportunity difference, disparate impact, precision score difference, general entropy difference, and conditional demographic parity. Not all group fairness metrics can be satisfied at the same time. For example equal opportunity difference and statistical parity difference cannot be simultaneously accounted for [5].

Individual fairness metrics measure how similarly the model predicts for similar observations. Will two very similar people receive the same classification? Individual fairness metrics contradict group fairness metrics. When accounting for imbalanced predictions between groups, the within group fairness can suffer [5]. In the process of satisfying group metrics, two similar subjects only differing by sex, may be classified differently [23]. The individual metrics we explore are general entropy error and consistency score. We can measure both individual and group fairness with the between group general entropy error metric.

One approach to fairness in machine learning is "fairness by unawareness" meaning a model is blind to the sensitive attributes. Although it may seem an intuitive approach to simply remove the protected attribute from the data in order to make the algorithm unbiased, this is often not an effective approach to reduce bias. There are often variables that remain in the data that act as pseudo substitutes for the protected attribute [24]. For example, if race was excluded from the model but the variable zip code remained. Zip code can act as a stand in for race in regions where people are segregated by race.

In our case we are focusing on the protected attribute gender. The other variables in this data set are education, age, and all the financial variables. If any of these variables are segregated by gender, by inheriting gender bias in society, then simply removing the gender variable will not solve anything.

##### 4.4.1. Accuracy.

Accuracy is a measure of how many classifications our model predicts correctly compared to all the predictions. The ratio of correctly predicted classifications to all the predictions. Accuracy cannot tell us if the predictions are equally correct across positives and negatives [25]. 55% of the people in our data set don't have access to emergency funds. As long as our model predicts negatives more than half the time, we can get a good accuracy. However, our model will lose the ability to accurately predict positives. It is important to consider accuracy along with precision and recall so we can more fully understand how our model is classifying people.

$$\text{Accuracy} = (\text{TruePositives} + \text{TrueNegatives}) / (\text{TruePositives} + \text{TrueNegatives} + \text{FalsePositives} + \text{FalseNegatives})$$

##### 4.4.2. Precision.

Precision is a measure of how accurately a model predicts positive outcomes. The ratio of correctly predicted positives to all predicted positives. With high precision rates, we have low false positive rates [26].

$$\text{Precision} = \text{truepositives} / (\text{truepositives} + \text{falsepositives})$$

#### 4.4.3. Recall.

Recall is a measure of how accurately a model predicts negative outcomes. The ratio of correctly predicted negatives to all predicted negatives[? ]

$$\text{Recall} = \text{truenegatives} / \text{allnegatives}$$

#### 4.4.4. Statistical Parity Difference.

This metric computes the difference in percentages between the “privileged” and “non-privileged” group of individuals who were predicted to have the desired outcome. In this case, it is essentially (% of females who were predicted to have access to emergency funds) - (% of males who were predicted to have access to emergency funds)

The “ideal” value is 0 because if we define fairness as statistical parity, the goal would be for the percentages to be equal for both groups. If the value is negative, that means that the percentage of individuals with the positive outcome is higher for the privileged group (males), implying that the model is biased in favor of the privileged group. Conversely, if the value is positive, the model is biased in favor of the unprivileged group. The acceptable range in which the model is considered fair is between -0.1 to 0.1 (with percentages expressed as decimals, e.g. 0.1 = 10%). It is important to note that this metric is solely focused on making the percentage of *predicted* favorable outcomes equal across groups and does not take into account the accuracy of the predictions at all.[5? ]

Relating to our data, this metric will tell us if our model predicts that men have more access to emergency funds than women. In our data, men in fact do have more access to emergency funds than women. 51% of men have access to emergency funds while only 38.2% of women have access to emergency funds. When using this metric to assess our model the interpretation depends on the context. If this model is being used to decide how to allocate emergency funds, we might not want to prioritize satisfying this metric. We are using this model in an educational and exploratory manner, so we will use techniques to account for this metric.

#### 4.4.5. Equal Opportunity Difference.

This metric is similar to statistical parity in that it is also a group fairness metric, but it is different in that it takes into account accuracy of the model in addition to equalizing outcomes across groups. Instead of measuring the simple differences in percentages between groups of individuals with the (predicted) positive outcome, it measures the difference in percentages of *accurately identified* individuals with positive outcomes (i.e. true positives). Essentially, the calculation is the same as for statistical parity, but only taking into account true positives for each group. Again, the “ideal” value is 0 with negative values indicating bias in favor of the privileged group, and the fairness range is -0.1 to 0.1 [? ].

This metric helps us answer if our model predicts positives with more accuracy for men than women. Are men more accurately predicted to have access to emergency funds than women?

#### 4.4.6. Disparate Impact.

The disparate impact metric measures the proportion of positive outcomes between an unprivileged group and a privileged group. It is usually assessed when predicting an outcome that disproportionately affects a sub population. For example, hiring more men than women as construction workers on the basis of height and strength. For this case we want to know the proportion of females that are categorized as having access to emergency funds VS males who are categorized as having access to emergency funds. The standard for satisfying this metric is that the unprivileged group must receive a positive outcome at a ratio of 4:5 to the privileged group. As long as females are classified as having access to emergency funds no less than around 80% of the time males are categorized as having access to emergency funds, then our model satisfies this metric.[? ] This

metric is similar to statistical parity except it measures a ratio which can be useful for legal purposes.  
 $P(\hat{Y} = \text{unprivilegedPositivePredicted}) / P(\hat{Y} = \text{privilegedPositivePredicted})$

A similar problem arises when assessing this metric as statistical parity. In reality women have less access to emergency funds than men. If we manipulate our model to satisfy this metric, we will falsely predict that women have access to emergency funds when they don't. This could be more harmful than not satisfying this metric.

#### 4.4.7. Conditional Demographic Disparity.

Statistical parity difference and equal opportunity difference both measure positive outcomes. The conditional demographic disparity measures negative outcomes. Demographic Disparity is a metric that examines how disadvantaged groups compare to advantaged groups for negative outcomes from the model. This metric checks if a subpopulation is classified with a negative outcome more than a positive outcome. Are females classified as not having access to emergency funds more often than men? Looking at the entire data set, women have less access than men to emergency funds. Predicting more negative outcomes for women than men is not necessarily a bad thing. We want to know if someone doesn't have access to emergency funds so that they can potentially be helped.

Sometimes when we split data into categories we can find patterns that don't exist when the data is combined. This is called Simpson's paradox [? ]. We can see this in our confusion matrices. When our data is split by gender there are different prediction rates than the entire model. The true negative rates are heavily weighted by females, and the true positive rates are weighted towards males. Is this the Simpson's paradox or does gender split the data into different distributions? The Conditional Demographic Disparity metric accounts for the Simpson's paradox to confirm true differences or no differences in negative outcomes in the model.

The range of scores for this metric is from -1 to 1. In general a positive value means that the model is more unfair towards the unprivileged group. A value of zero is ideal. In our case, if our model were to predict an equal proportion of negative and positive outcomes for men and women, our model would realistically be unfair to women. Women do have less access to emergency funds and predicting that men and women equally don't have access to emergency funds might put women at a greater disadvantage if a relief program were to be put in place. However, if assessing financial stability between men and women we would be more concerned with satisfying this metric.

#### 4.4.8. General Entropy Error.

This metric is an individual metric rather than a group metric, and it computes fairness by computing the level of unfair benefit being assigned by the model. The metric defines "benefit" as follows: for any individual in the testing data set, that individual has received a benefit if the model predicted the favorable outcome when the truth was that the individual did not have the favorable outcome (i.e. a false positive). Each individual in the data receives either a 2 (benefit, false positive), a 1 (no benefit, correct prediction), or 0 (no benefit, false negative). The metric then compares the benefit of each individual to the average accuracy and false positive level of the model. The "ideal" value is 0, and a higher number indicates a higher level of inequity in benefit among individuals. In other words, if many individuals have a benefit score that is far off from the average, that indicates that the model is unfairly benefiting some individuals and not others. This metric does not consider privileged versus unprivileged groups, and thus is not able to indicate whether or not the inequality in benefit is systematic in any particular way (i.e., it cannot tell whether males receive more benefit than females; it can only tell that some individuals receive higher benefits than others)[5? ].

This metric is important to our data because a false positive outcome (higher benefit) would mean that someone is predicted to having access to emergency funds when they don't. If there is a high general entropy error, there are many individuals who's need for emergency funds are being overlooked.



#### 4.4.9. General Entropy Error Difference.

The general entropy error cannot tell whether males receive more benefit than females so we calculate the general entropy error difference between males and females. Do men “benefit” from our model more i.e does our model predict more accurate and false positives for men than women? Again the interpretation of this metric will depend on the context. A higher score is given for false positives, but this means a group of people are being predicted to have emergency funds when they don’t. It is not necessarily a good thing for any group to “benefit” from our model. A value of 0 represents no difference.

#### 4.4.10. Between Group Generalized Entropy Error.

We explored generalized entropy error and how it differs for males and females. Using the between group generalized error metric we will be able to see if the between group unfairness or the individual unfairness dominates. Is there truly a difference in generalized entropy error between men and women or is the general entropy error not due to gender inequality. Is our model unfairly benefiting individuals based on sub populations or is the inequity equal between groups and differs at the individual level?

We don’t want generalized entropy error in our model, but it would be better to have it at the individual level than the group level. We don’t want either men or women to have more generalized entropy error than the other. If the error is equally within the groups, then both men and women are at a similar “benefit” to each other.

#### 4.4.11. Consistency Score.

Are similar people treated similarly. Is our model consistent in the way it classifies people as having access to emergency funds? This metric alone wont tell us if our model is fair but we can see how different groups of people are generally treated. We split the consistency score by gender and we can see if our model is more consistent for men or women. Are individuals within each group being treated similarly? With the other metrics in mind we can determine if they are being treated similarly unfairly or similarly fair. This metric is calculated on a scale from 0 to 1 where a value of 1 means completely consistent.

### 4.5. In and Post Processors

To account for any unfairness we find in the model we can use in and post processing techniques. These techniques restructure the data and reclassify observations in order to satisfy these metrics.

#### 4.5.1. Reweighting.

Reweighting is a pre-processing technique which assigns weights such that the protected attribute (gender) becomes statistically independent from the outcome variable (access to emergency funds). This means that after reweighting, knowing the gender of an individual does not provide any information about whether or not the individual has access. In mathematical terms,  $P(\text{gender} = \text{male and access} = \text{yes}) = P(\text{gender} = \text{male}) * P(\text{access} = \text{yes})$ , and this equality holds true for all gender-access combinations.

#### 4.5.2. Exponentiated Gradient Reduction.

The exponentiation gradient reduction is an in-processing optimization approach. This processor aims to optimize both accuracy and fairness focusing on demographic parity and equalized odds. The algorithm this processor uses considers randomized classifiers and cost restraints to find the optimal classifier that satisfies fairness restraints without losing too much accuracy [? ].

### 4.5.3. Grid search Reduction.

Grid search reduction uses the cost restraint lamda to find a balance between fairness and accuracy. This processor searches over a grid of lamda values until the best value is found. This value is used in the classifier to satisfy fairness and maximize accuracy. The grid search reduction is useful for binary sensitive attributes and fairness metrics with minimal constraints like demographic parity and equalized odds [? ? ]

### 4.5.4. Calibrated Equalized Odds.

Calibrated equalized odds uses a post-processing technique that re classifies values to satisfy the equalized odds metric while keeping the classifier calibrated. A classifier is calibrated if the proportions of positive and negative outcomes in the data match the probabilities produced by the model. We want the calibration to hold across groups such as male and female. This processor aims to satisfy an equalized cost constraint while maintaining calibration [? ].

### 4.5.5. Reject Option Classifier.

The reject option classifier is a post-processor that aims to reduce discriminatory classifications based on the sensitive attribute. In our case we aim to find a balance for predictions between males and females. This classifier will relabel observations in a way that reduces discrimination. More males will be relabeled with the unfavorable outcome and more females will be relabeled with the favorable outcome [? ].

### 4.5.6. Meta Fair Classifier.

The meta fair classifier creates a new estimator but includes a reweighing pre-processing step [? ]. This classifier should be used as part of a pipeline of steps. We must create a binary label data set. This means that the data includes either a 1 representing access to emergency funds or 0 for no access to emergency funds. This classifier aims to transform the data in a way that will satisfy as many fairness metrics as possible [? ]. ## Subsection Heading Here

Subsection text here.

### 4.5.7. Subsubsection Heading Here

Bulleted lists look like this:

- First bullet
- Second bullet
- Third bullet

Numbered lists can be added as follows:

1. First item
2. Second item
3. Third item

The text continues here.

All figures and tables should be cited in the main text as Figure 1, Table 1, etc.



**Figure 1.** This is a figure, Schemes follow the same formatting. If there are multiple panels, they should be listed as: (a) Description of what is contained in the first panel. (b) Description of what is contained in the second panel. Figures should be placed in the main text near to the first time they are cited. A caption on a single line should be centered.

**Table 1.** This is a table caption. Tables should be placed in the main text near to the first time they are cited.

Title 1	Title 2	Title 3
entry 1	data	data
entry 2	data	data

This is an example of an equation:

$$\S \quad (1)$$

Example of a theorem:

**Theorem 1.** *Example text of a theorem.*

The text continues here. Proofs must be formatted as follows:

Example of a proof:

**Proof of Theorem 1.** Text of the proof. Note that the phrase ‘of Theorem 1’ is optional if it is clear which theorem is being referred to.  $\square$

The text continues here.

## 5. Discussion

Authors should discuss the results and how they can be interpreted in perspective of previous studies and of the working hypotheses. The findings and their implications should be discussed in the broadest context possible. Future research directions may also be highlighted.

## 6. Conclusion

This section is not mandatory, but can be added to the manuscript if the discussion is unusually long or complex.

## 7. Patents

This section is not mandatory, but may be added if there are patents resulting from the work reported in this manuscript.

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## Abbreviations

The following abbreviations are used in this manuscript:

MDPI Multidisciplinary Digital Publishing Institute

DOAJ Directory of open access journals

TLA Three letter acronym

LD linear dichroism

## Appendix A

### Appendix A.1

The appendix is an optional section that can contain details and data supplemental to the main text. For example, explanations of experimental details that would disrupt the flow of the main text, but nonetheless remain crucial to understanding and reproducing the research shown; figures of replicates for experiments of which representative data is shown in the main text can be added here if brief, or as Supplementary data. Mathematical proofs of results not central to the paper can be added as an appendix.

## Appendix B

All appendix sections must be cited in the main text. In the appendixes, Figures, Tables, etc. should be labeled starting with 'A', e.g., Figure A1, Figure A2, etc.

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**Sample Availability:** Samples of the compounds ..... are available from the authors.

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