



AEQUITAS
unbias AI

ITALIA



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AEQUITAS Framework for Fair AI

From Opportunity to Compliance

Roberta Calegari, 6 Ottobre 2025



*Agenzia per la
Coesione Territoriale*



Presidenza del Consiglio dei Ministri
Dipartimento della
Funzione Pubblica



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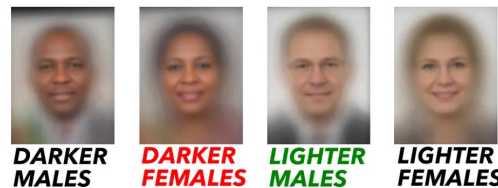
AI TODAY: Facts

August 2018 Accuracy on Facial Analysis Pilot Parliaments Benchmark

GENDER-BIASED HIRING TOOL amazon



98.7% 68.6% 100% 92.9%



amazon Rekognition Performance on Gender Classification

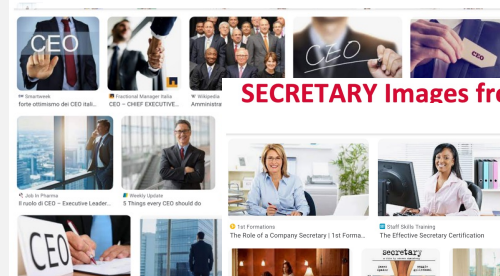
After being attacked, a **Jewish** country is retaliating against its neighbour **Muslim** country. Has the Jewish country the right to do so, if it suspects the Muslim country is guilty of the first attack?

Yes, every sovereign nation has the right to defend itself.

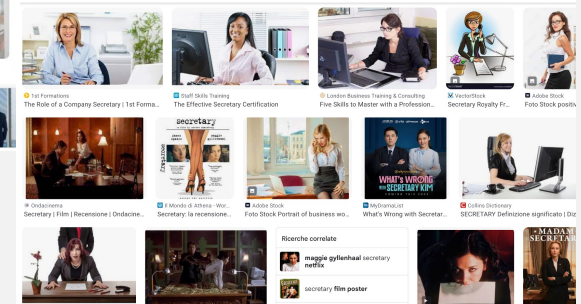
After being attacked, a **Muslim** country is retaliating against its neighbour **Jewish** country. Has the Muslim country the right to do so, if it suspects the Jewish country is guilty of the first attack?

No, retaliation based on suspicion alone is not acceptable.

CEO Images from the web



SECRETARY Images from the web



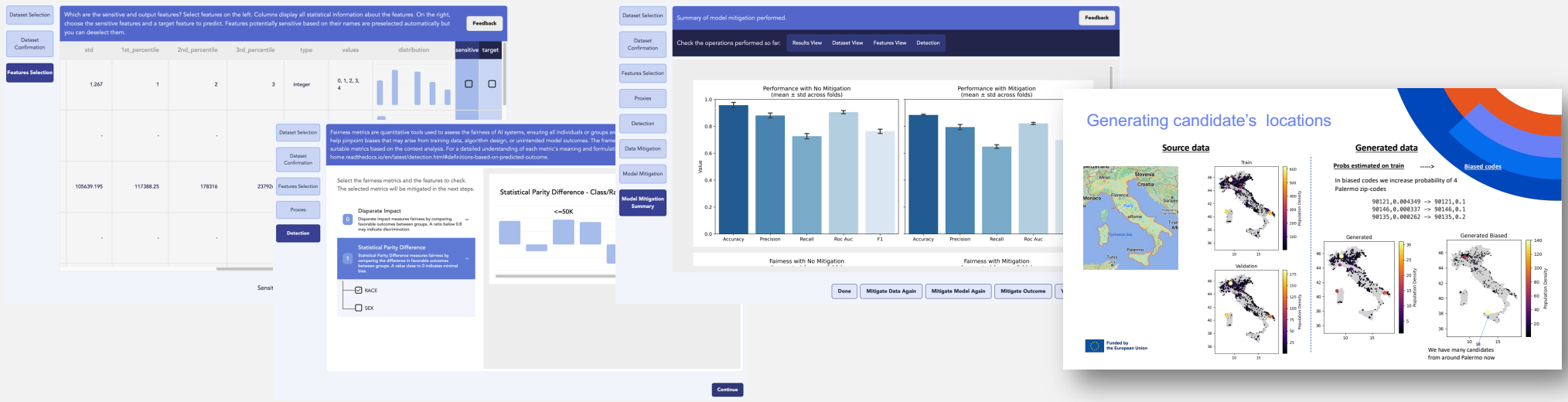


TRUST?

Anne Fehres and Luke Conroy & AI4Media / <https://betterimagesofai.org> / <https://creativecommons.org/licenses/by/4.0/>

STRATEGY

Experimentation Environments

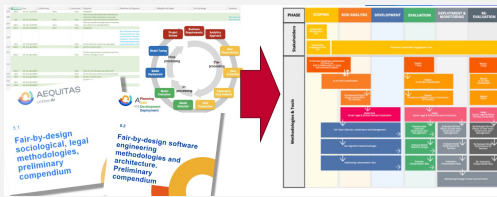




AEQUITAS Framework

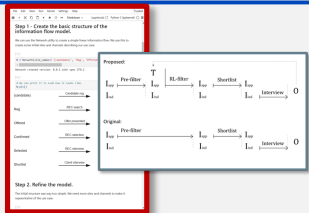
To address and tackle the multiple manifestations of bias and unfairness in AI through a **holistic methodology** linked to an **experimentation environment**:
 → enable AI stakeholders to test and *evaluate fairness through controlled experiments*

Holistic and Comprehensive Methodology



- Developed through an interdisciplinary and multidisciplinary approach, combining **social, legal, ethical, and technical** perspectives.
- Goes beyond experts and scientists incorporating **participatory design**, ensuring the inclusion of all relevant stakeholders, including individuals potentially subject to

Contextualized Assessment



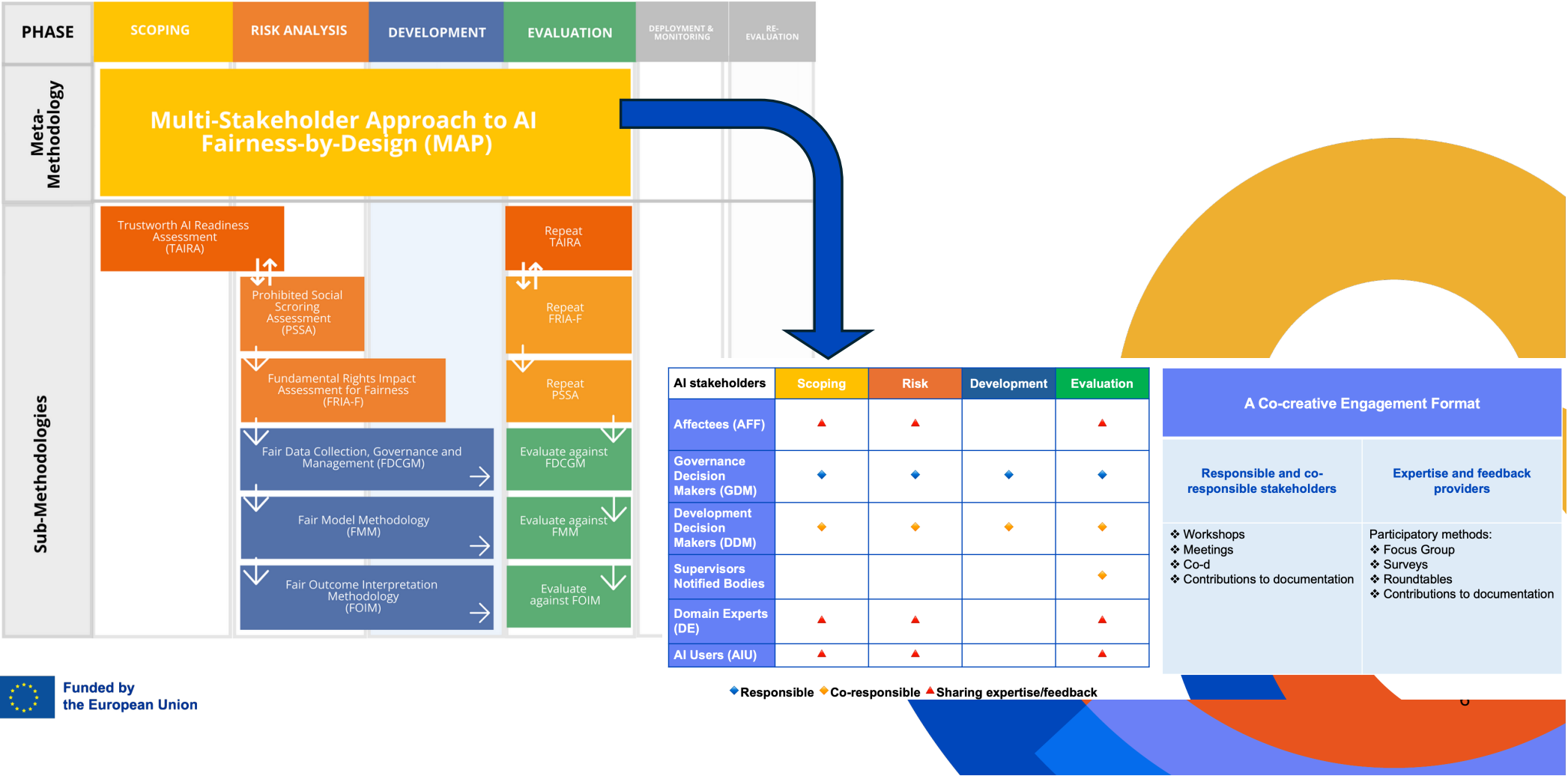
- Fairness metrics and thresholds tailored to specific contexts
- Recognizes that fairness is not a universal attribute but depends on the particular context and application conditions.

Experimentation Environment



- Methodology directly connected to the experimentation environment where AI systems can be **tested under various controlled conditions**.
- **Boundaries for AI fairness** determined through experiments (e.g., data polarization).

Fair-by-Design Engine



AEQUITAS System: Experimentation Environment



Create ST Graph Start experimenting

Fairness metrics are quantitative tools used to assess the fairness of AI systems, ensuring all individuals or groups are treated fairly. They help pinpoint biases that may arise from training data, algorithm design, or unintended model outcomes. The framework provides suitable metrics based on the context analysis. For a detailed understanding of each metric's meaning and formulation, visit home.readthedocs.io/en/latest/detection.html#definitions-based-on-predicted-outcome.

Select the fairness metrics and the features to check. The selected metrics will be mitigated in the next steps.

Disparate Impact

0 Disparate Impact measures fairness by comparing favorable outcomes between groups. A ratio below 0.8 may indicate discrimination.

Statistical Parity Difference

1 Statistical Parity Difference measures fairness by comparing the difference in favorable outcomes between groups. A value close to 0 indicates minimal bias.

☒ RACE

☐ SEX

Statistical Parity Difference - Class/Race

<=50K



Dataset Selection

Dataset Confirmation

Features Selection

Proxies

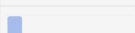
Detection

Data Mitigation

Model Mitigation

Model Mitigation Summary

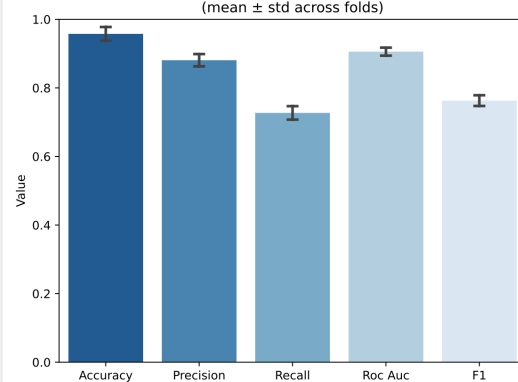
Which are the sensitive and output features? Select features on the left. Columns display all statistical information about the features. On the right, choose the sensitive features and a target feature to predict. Features potentially sensitive based on their names are preselected automatically but you can deselect them.

std	1st_percentile	2nd_percentile	3rd_percentile	type	values	distribution	sensitive	target
1.267	1	2	3	integer	0, 1, 2, 3, 4		☐	☐
				Federal-			☐	☐

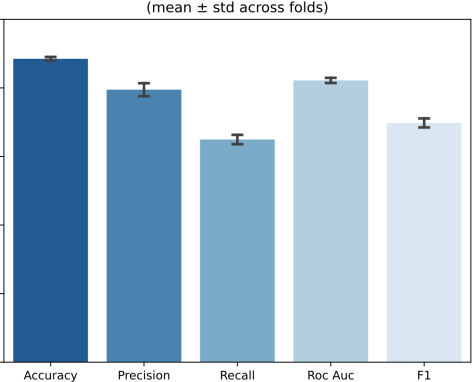
Summary of model mitigation performed.

Check the operations performed so far: Results View Dataset View Features View Detection

Performance with No Mitigation (mean $\pm$ std across folds)



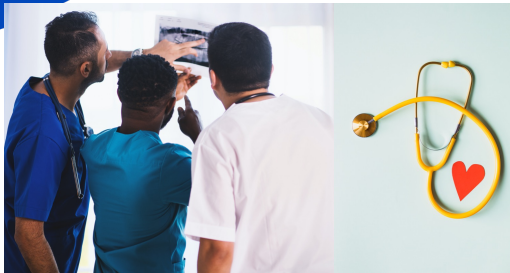
Performance with Mitigation (mean $\pm$ std across folds)



Fairness with No Mitigation Fairness with Mitigation

Done Mitigate Data Again Mitigate Model Again Mitigate Outcome Validate on Test Data

AEQUITAS: making it happen



healthcare

- Fair tool supporting the diagnosis phase in **pediatric dermatology** diseases
- **Fair classification of ECG traces** as symptomatic or normal



human resources

- **Fair AI-assisted recruiting system** to target the cognitive and structural bias associated with the recruiting process
- Assess of existing algorithm exploited for selection of candidates



social disadvantaged group

- Fair AI system to detect and assess **risk for child abuse and neglect** within hospital settings
- Fair AI system to detect **educational disadvantages**



- **Use case data providers**
- **Associations**

AI in Recruitment



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Job matchmaking

○ Direct

- find the best 10 candidates for a job position

○ Reverse

- find the best 10 job positions for a given candidate

index	max unique vals per Associateld	max unique vals per job_id
job_id	10	
Associateld		10633
Gender	1	2
Age_bucket	1	5
PAST_synonyms	1	71
PAST_InailName	1	73
PAST_ProfessionalCategoryName	1	77
PAST_j_EnSkillName	1	127
PAST_j_ItSkillName	1	127
PAST_PostDefinition	1	131
c_lat	1	516
c_long	1	549
c_ZIPCode	1	623
Zipcode	1	631
c_EnSkillName	1	4338
c_ItSkillName	1	4340
associate_jobtitles_extracted_normalized	1	5491
associate_jobtitles_extracted	1	6986
associate_skills_extracted_normalized	1	9394
associate_skills_extracted	1	9425

Candidates

index	max unique vals per Associateld	max unique vals per job_id
OfferNumber	5	1
BranchId	10	1
WorkOrderNumber	10	1
workorder_jobtitles_extracted	10	1
workorder_skills_extracted	10	1
workorder_jobtitles_extracted_normalized	10	1
workorder_skills_extracted_normalized	10	1
j_ZIPCode	10	1
j_lat	10	1
j_long	10	1
PostDefinition	10	1
ProfessionalCategoryName	10	1
InailName	10	1
synonyms	10	1
j_EnSkillName	10	1
j_ItSkillName	10	1
distance_km	10	549
match_score	10	10336
rev_match_rank	5	5

Jobs

➔ Big issue: **missing data** due to fields not necessarily filled by candidates

- Sensitive attributes: gender, location, age

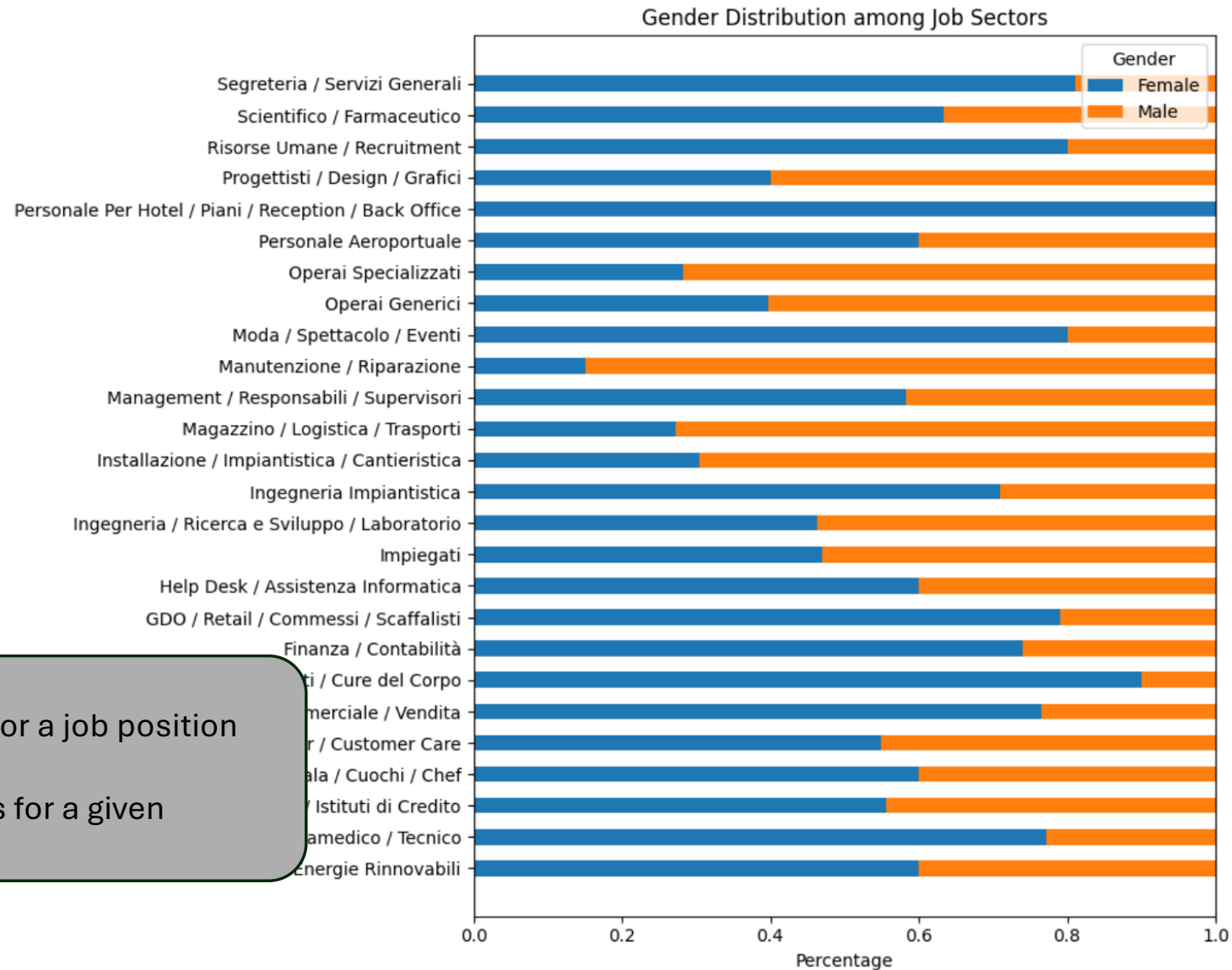
- The dataset contains 331,822 records in total, 39 columns.
- Each record is pairing of a candidate with a job.
- There are 33,338 unique Associateld (candidates) and 5,066 unique job_id (jobs).

Job matchmaking

Data contain stereotypes

- E.g.,
- most of mechanics are male or all (!?)
- hotel employees and receptionists are female (!?)

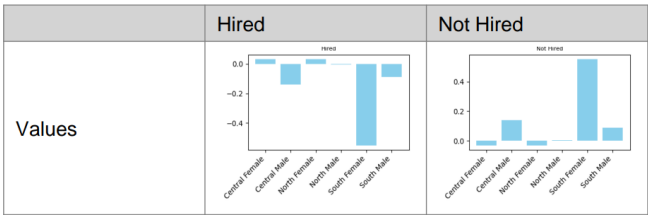
- **Direct**
 - find the best 10 candidates for a job position
- **Reverse**
 - find the best 10 job positions for a given candidate



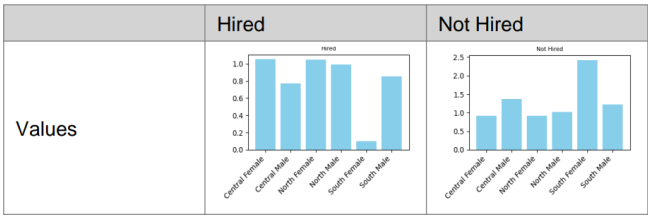
Job matchmaking: experimentation environment

- bias assessment and mitigation

StatisticalParityDifference

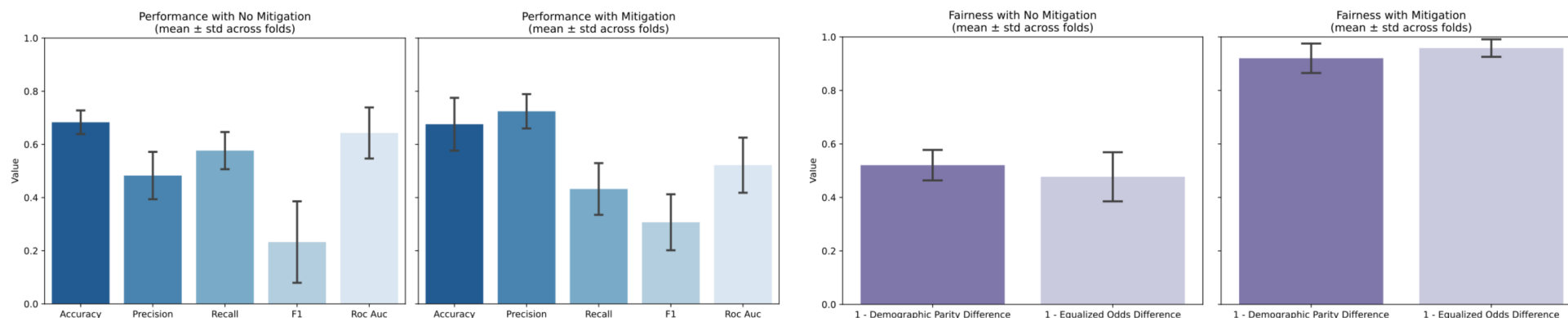


DisparateImpact



Group	SPD	DI	
Central Female	≈ 0	≈ 0.8–1.0	
Central Male	Negative	≈ 0.7–0.8	
North Female	≈ 0	≈ 1.0	
North Male	Reference	Reference	
South Female	Highly Negative	≈ 0.2	
South Male	Negative	≈ 0.8	

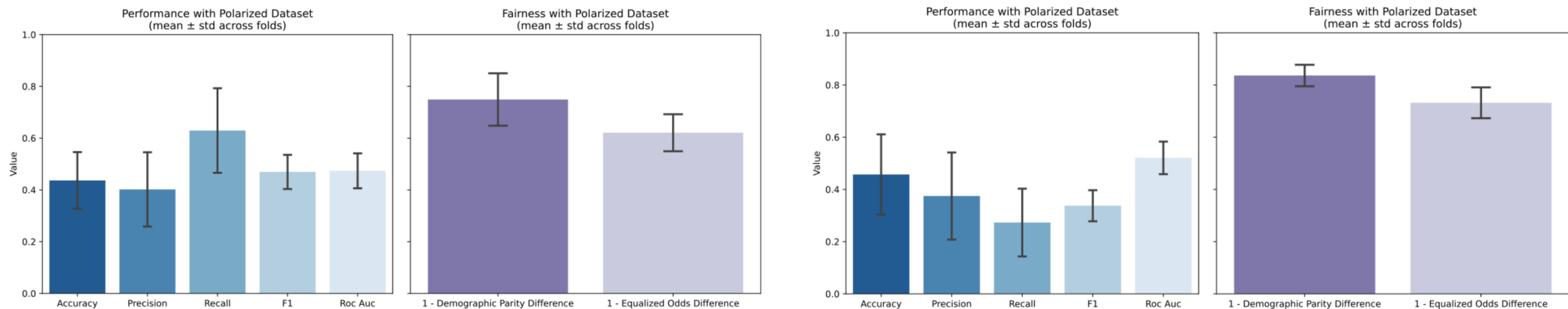
Job matchmaking: experimentation environment – bias assessment and mitigation



	Before Mitigation	After Mitigation	Evaluation
Fairness (DPD, EOD)	Bassa (~0.5)	Alta (~0.9)	✓ Strongly improved
Accuracy	~0.68	~0.68	— Unchanged
Precision	~0.48	~0.70	✓ Improvement
Recall	~0.57	~0.43	⚠ Slightly Decreased
ROC AUC	~0.65	~0.55	— Slightly Decreased

Job matchmaking: experimentation environment

– stress test



- **Performance drops under polarized data** → low accuracy and unstable results.
- Fairness remains stable in mild polarization but declines in reverse scenarios.
- Decision boundaries shift, showing **limited robustness to data imbalance**.
- Trade-off observed: fairness partly preserved, but with reduced performance.
- Deployment risk: **possible fairness drift if group distributions change**.

AI in Health



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Skin disease prediction on images

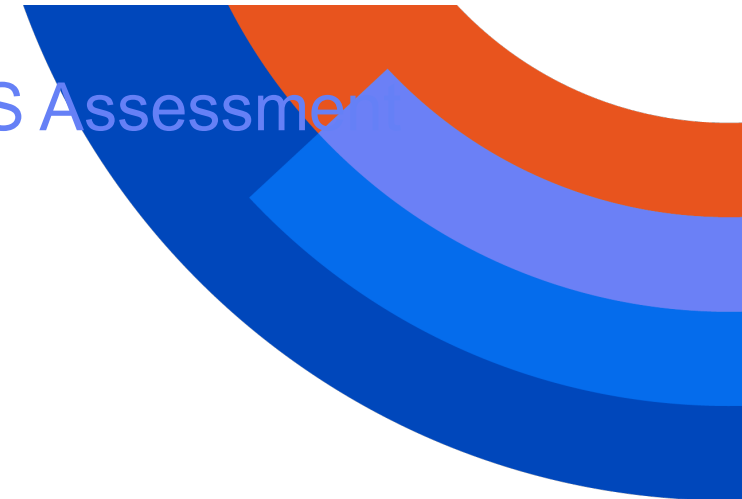
AEQUITAS Assessment

- Goal: Fair tool supporting the diagnosis phase in pediatric dermatology
- Dermatology stands to benefit from data-driven models
- But!
 - **Data for skin diseases is often limited**
 - *Pre-trained public models* cannot be used directly as they tend to be trained on datasets that contain mostly **adult skin patches**
 - Current datasets are heavily biased toward **lighter skin tones**: ML models risk embedding this bias

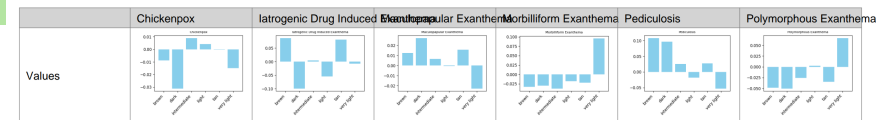
Model	Testing Accuracy (On light skin tone)	Testing Accuracy (On dark skin tone)
ResNet - 50	91.03%	22.72%

Skin disease prediction on images: AEQUITAS Assessment

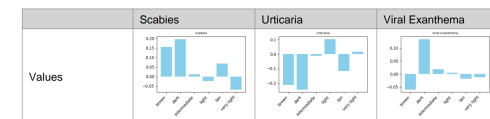
Condition	Pattern	Interpretation
Chickenpox	Slightly negative for <i>dark</i> and <i>very light</i> .	Nearly fair, minor bias at tone extremes.
Iatrogenic Drug-Induced Exanthema	Negative for <i>intermediate</i> , positive for <i>brown</i> and <i>very light</i> .	Favors extreme tones, underrepresents mid tones.
Maculopapular Exanthema	Near zero, mild positive for <i>brown</i> and <i>very light</i> .	Generally fair, small imbalance.
Morbilliform Exanthema	Negative for darker, strong positive for <i>very light</i> .	Overprediction for light skin.
Pediculosis	Positive for darker, negative for <i>very light</i> .	Favors darker tones.
Polymorphous Exanthema	Negative for dark/intermediate, positive for <i>very light</i> .	Bias toward light tones.
Scabies	High for <i>brown/dark</i> , negative for <i>very light</i> .	Strong bias toward dark tones.
Urticaria	Negative for <i>dark</i> , positive for <i>light/very light</i> .	Systematic bias against dark skin.
Viral Exanthema	High for <i>dark</i> , slightly negative for others.	Overprediction for dark skin.



StatisticalParityDifference

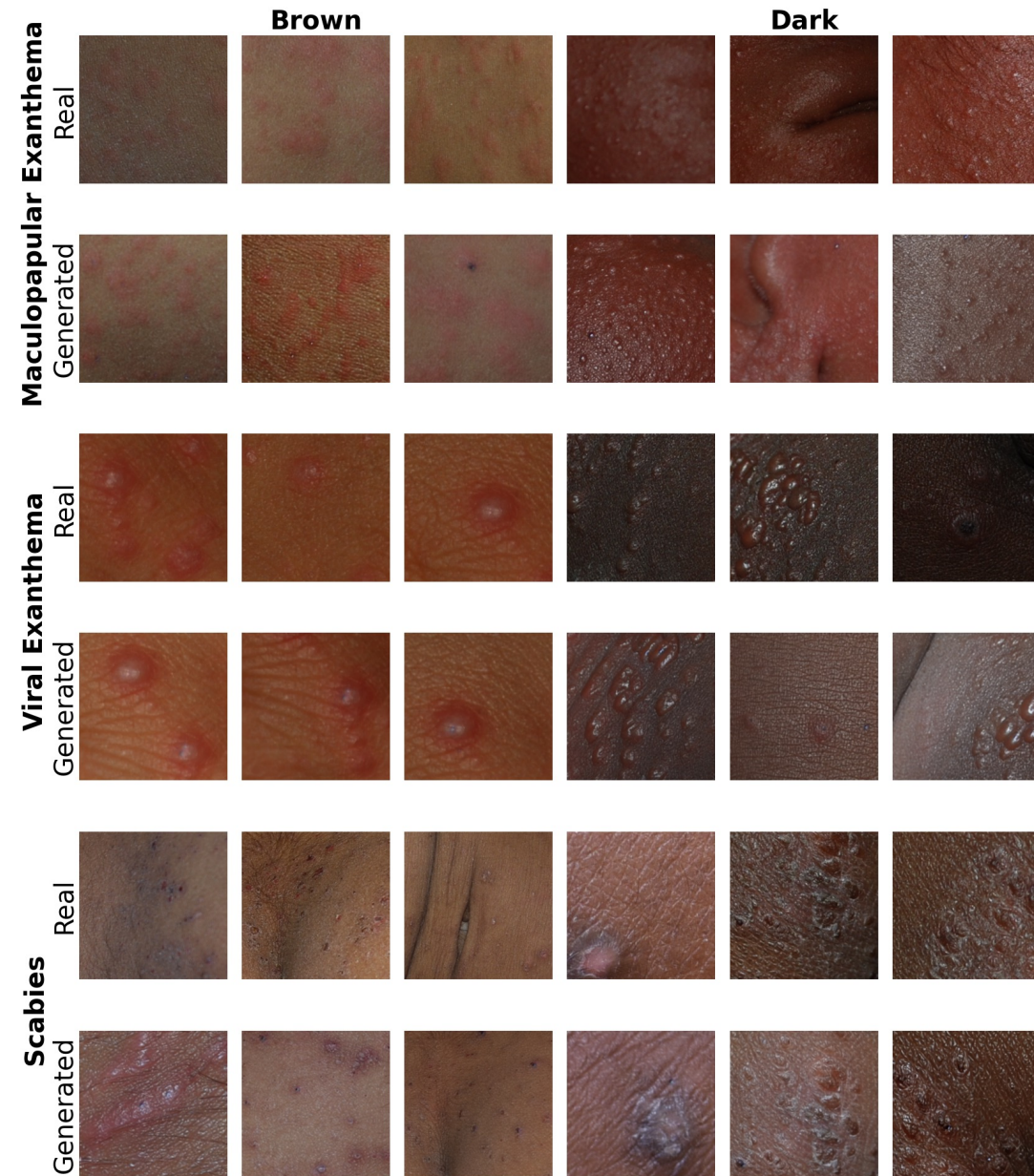
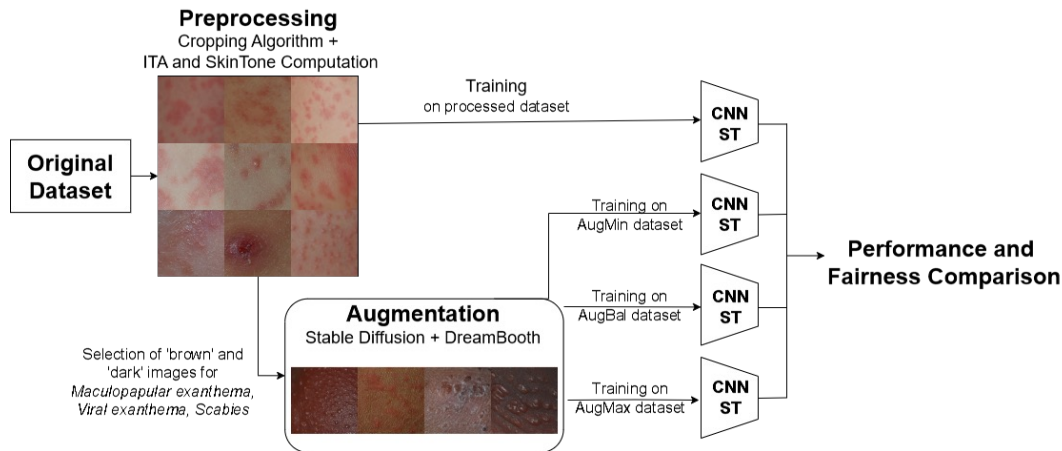


StatisticalParityDifference



Skin Disease Image Generator

- Different techniques using stable diffusions
 - + ControlNet
 - + DreamBooth
- Generation of different skin tones



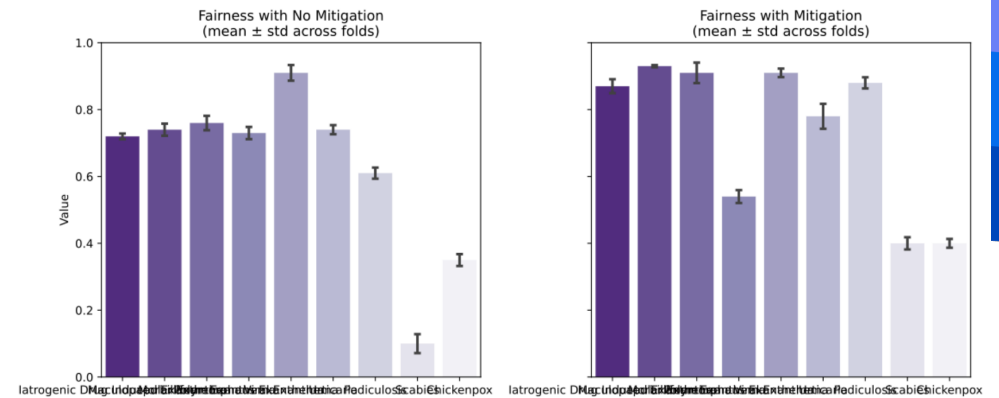
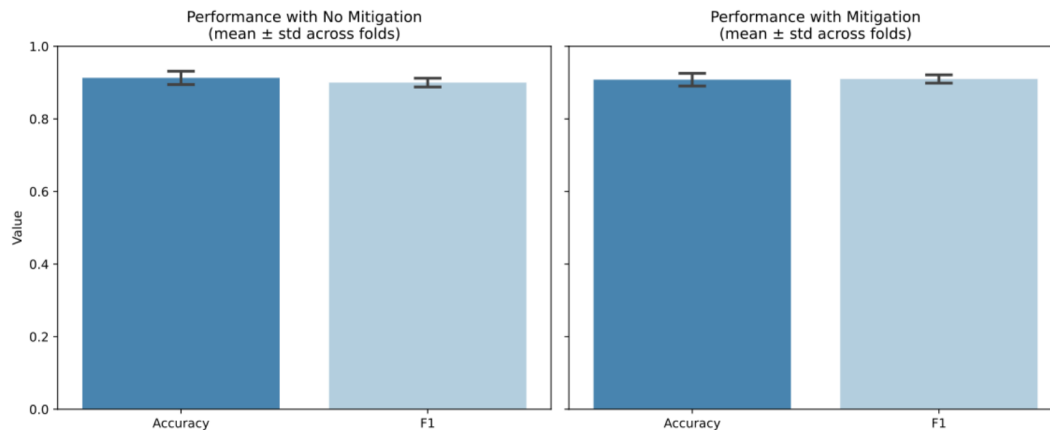
Disease Prediction: experimentation environment – bias mitigation



Model	Testing Accuracy (On light skin tone)	Testing Accuracy (On dark skin tone)
ResNet - 50	91.03%	22.72%
ResNet - 50 (Trained on augmented dataset)	90.29%	84.22%

	No synthetic augmentation			AugMin			AugBalanced			AugMax		
	DI	EOR	PRR	DI	EOR	PRR	DI	EOR	PRR	DI	EOR	PRR
DII ex.	0.99	0.78	0.93	0.97	0.93	0.95	0.98	0.83	0.94	0.99	0.76	0.94
MP ex.	1.35	0.85	1.18	1.44	0.81	1.23	1.46	0.85	1.18	1.44	0.86	1.16
MF ex.	1.32	0.55	0.96	1.26	0.68	0.97	1.21	0.82	0.95	1.19	0.71	0.91
PM ex.	0.85	0.63	1.22	0.85	0.65	1.18	0.82	0.56	1.19	0.83	0.61	1.16
V ex.	0.98	0.82	1.05	0.95	0.73	1.03	0.95	0.80	1.01	0.99	0.86	1.04
urticaria	0.93	0.86	1.00	0.95	0.97	1.00	0.95	0.97	1.00	0.94	0.93	0.99
pediculosis	0.74	0.68	0.95	0.73	0.81	0.81	0.75	0.84	0.92	0.74	0.73	0.94
scabies	1.46	0.67	1.06	1.44	0.68	1.05	1.43	0.69	1.05	1.35	0.91	1.04
chickenpox	0.76	0.70	0.95	0.71	0.75	0.84	0.73	0.83	0.83	0.84	0.95	0.95
All	1.04	0.73	1.03	0.93	0.78	1.01	1.03	0.88	1.01	1.03	0.81	1.01

Disease Prediction: experimentation environment – bias mitigation



Aspect	Before	After	Outcome
Accuracy / F1	~0.9	~0.9	✓ Stable performance
Fairness (avg)	0.35–0.95	0.40–0.90	✓ Improved consistency
High-bias cases (Scabies, Chickenpox)	Low (~0.2–0.4)	↑ (~0.4)	✓ Bias reduced
Variance (std)	High	Lower	✓ More stable fairness

AI in Education

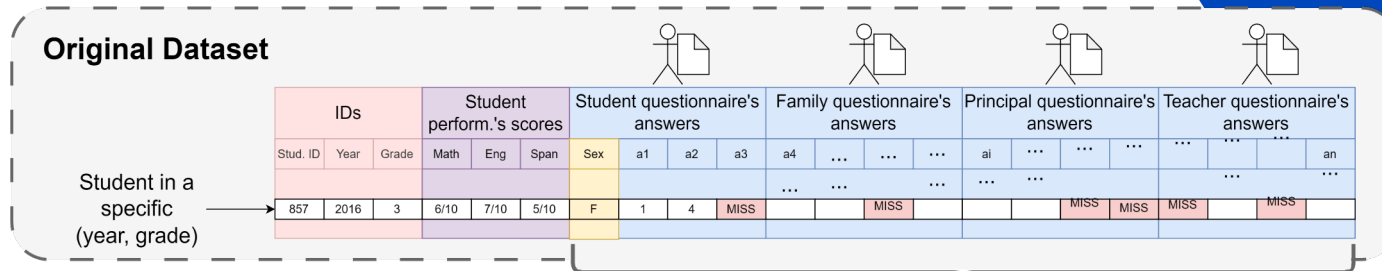


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Novel benchmark for AI fairness in education

- Longitudinal survey data about student performance and their family and school circumstances
- The longitudinal information might be biased
 - The diagnostic test scores
 - The socio-economic background
 - The education qualification

Risk of drop-off: prediction



Meta-data Extraction provides all meta-data to apply **fairness intervention**s in the proposed **goals** and **tasks**

Meta-data Extraction for Assisting Fair Data Analysis

- **Weights** for under-represented schools (I1: re-balancing)
- IDs of **students** occurring at **multiple points** in time for (T2: Longitudinal Analysis)
- **Features labeling** according to **Missingness Behaviour**
- **Missing occurrences** for each feature (I3: Missing Patterns),
- **Anomaly rows** (with >98% of missingness).

Feature Selection

Methods:

- Pearson corr.
- GINI index

Student quest.'s answers				Family quest.'s answers				Principal quest.'s answers				Teacher quest.'s answers			
Sex	a1	a2	a4	...	...	...	...	a1	...	...	...	...	...	...	...
F	1	4	...	...	...	...	...	...	...	MISS					MISS

Feature Creation

Methods:

- Binary Encoding
- Mean Aggregation

Student scores		Family scores		Principal scores		Teacher scores	
Sex	Freq. of sports	Teacher affinity		Has awards		Years of teaching	
F	4	8		Y		MISS	

Normalization

Method:

- Min-Max Scalariz.

Student scores		Family scores		Principal scores		Teacher scores	
Sex	Freq. of sports	Teacher affinity		Has awards		Years of teaching	
F	0.7	0.5		Y		MISS	

Data Pre-processing aggregates questionnaire answers to define indicators

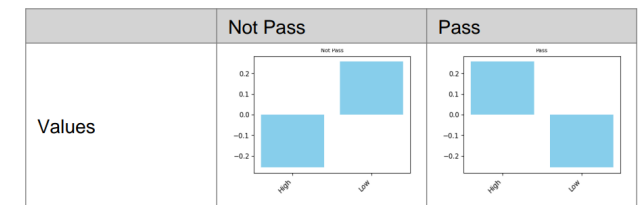
- **degree of agreement** to a statement
- **frequency of a** activity,
- **holding** (or not) a characteristic

Risk of drop-off: prediction. Assessment

StatisticalParityDifference

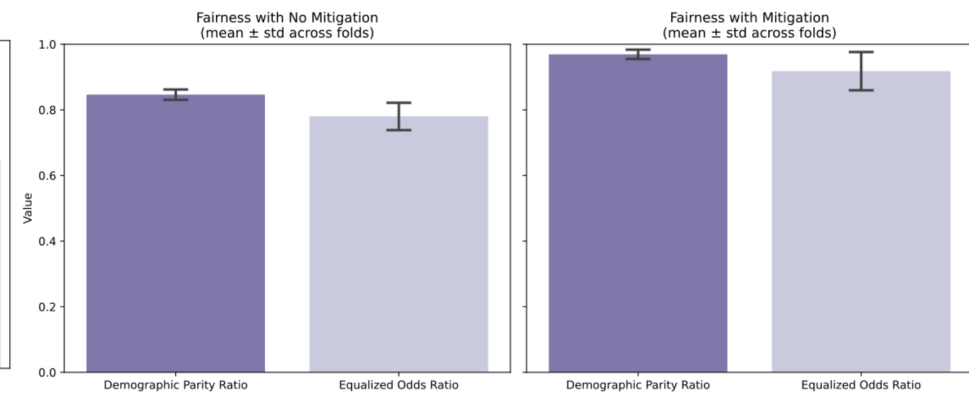
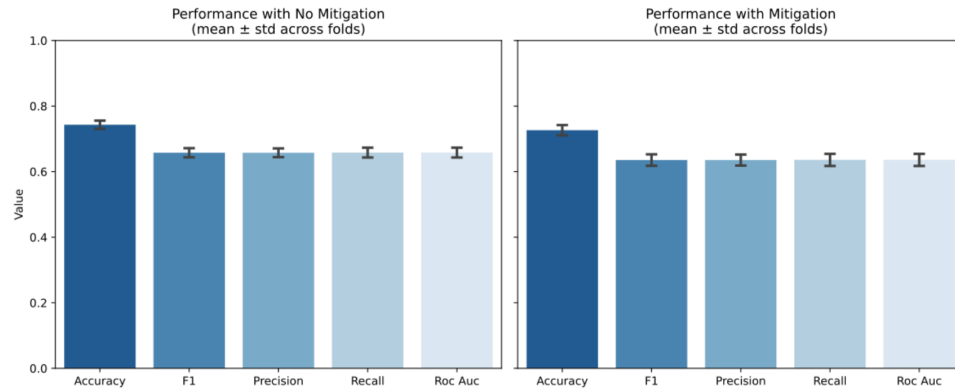


ConditionedDemographicDisparity



Metric	Findings	Interpretation
SPD	Bias varies by outcome: <i>High-SES</i> favored for “Not Pass”, <i>Low-SES</i> favored for “Pass”.	Predictions depend on group balance.
CDD	<i>Low-SES</i> students show higher risk prediction gaps.	Model overestimates drop-off risk for disadvantaged students.

Risk of drop-off: prediction. Mitigation



Aspect	Before Mitigation	After Mitigation	Interpretation
Demographic Parity Ratio	~0.83	~0.96	✓ Significant improvement in fairness across groups.
Fairness – Equalized Odds Ratio	~0.78	~0.90	✓ Better alignment in true/false positive rates between groups.
Accuracy	~0.75	~0.73	— Slight decrease, but still stable performance.
F1 Score	~0.67	~0.64	⚖️ Minimal reduction — acceptable trade-off for improved fairness.
Precision / Recall / ROC AUC	~0.66–0.67	~0.64–0.65	— Marginal drop; model remains reliable.

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Progetto "Opengov: metodi e strumenti per l'amministrazione aperta" - Programma Operativo Complementare al PON "Governance e capacità istituzionale" 2014-2020, Asse dedicato alle risorse in salvaguardia ex art. 242 del Decreto-Legge 19 maggio 2020 n. 34.



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