Appendix: Supplementary Material for Paper titled "Software Fairness: An Analysis and Survey"

EZEKIEL SOREMEKUN, Singapore University of Technology and Design, Singapore
MIKE PAPADAKIS, MAXIME CORDY, and YVES LE TRAON, SnT, University of Luxembourg, Luxembourg

Summary

This document is the appendix (or supplementary material) for the paper titled "Software Fairness: An Analysis and Survey". It provides additional or more detailed tables and figures to support the reported findings in the original paper.

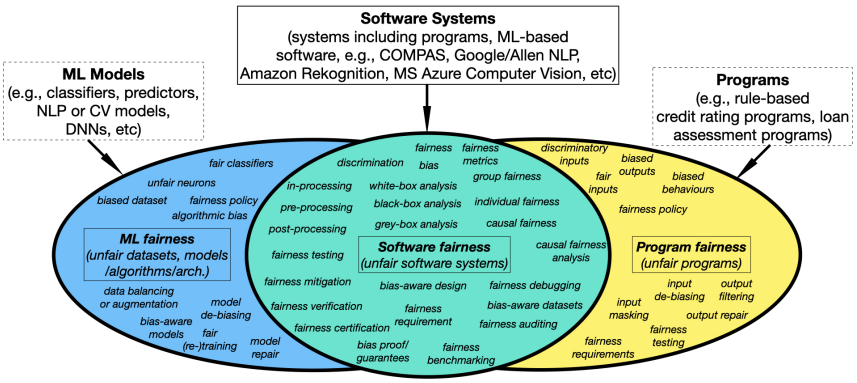


Fig. 1. Taxonomy and interplay of ML fairness and Software Fairness

Authors' addresses: Ezekiel Soremekun, ezekiel_soremekun@sutd.edu.sg, Singapore University of Technology and Design, 8 Somapah Rd, Singapore, Singapore, Singapore, 487372; Mike Papadakis, michail.papadakis@uni.lu; Maxime Cordy, maxime.cordy@uni.lu; Yves Le Traon, Yves.LeTraon@uni.lu, SnT, University of Luxembourg, 6, rue Richard Coudenhove-Kalergi, Luxembourg, Luxembourg, Luxembourg, L-1359.

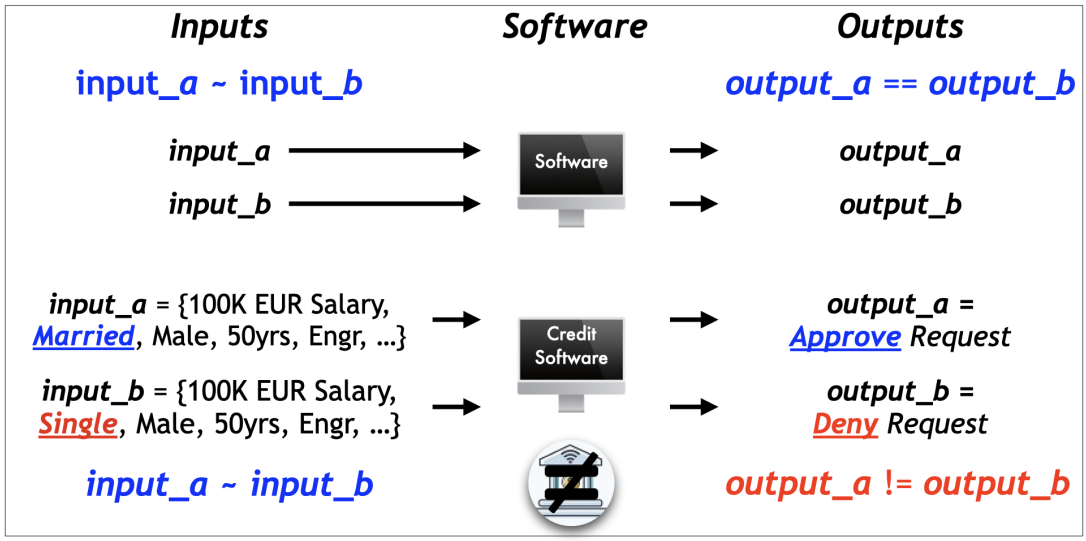


Fig. 2. Program fairness property showing fair program behavior (`output_a == output_b`) and unfair program behavior (`output_a != output_b`) using a (credit approval) software

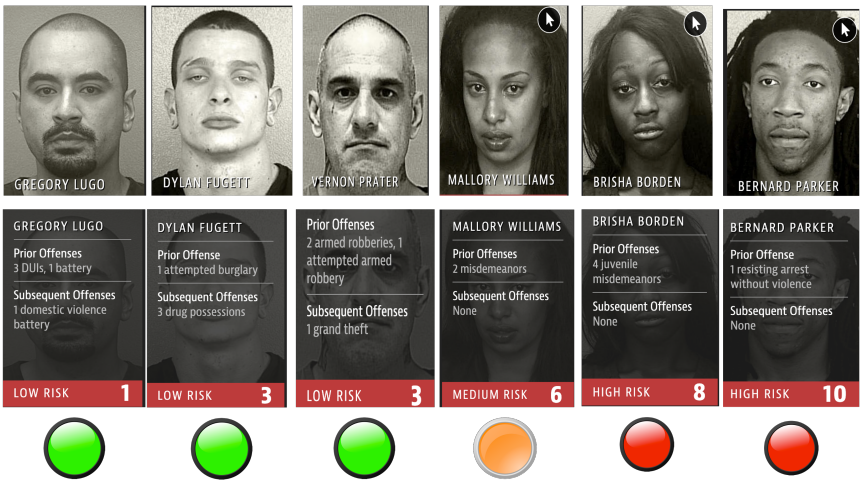


Fig. 3. An illustrative example of real-world discrimination (unfair software behavior) in the COMPAS software, a program that predicts recidivism – the likelihood of committing a future crime (adapted from Angwin et al. [12, 13])

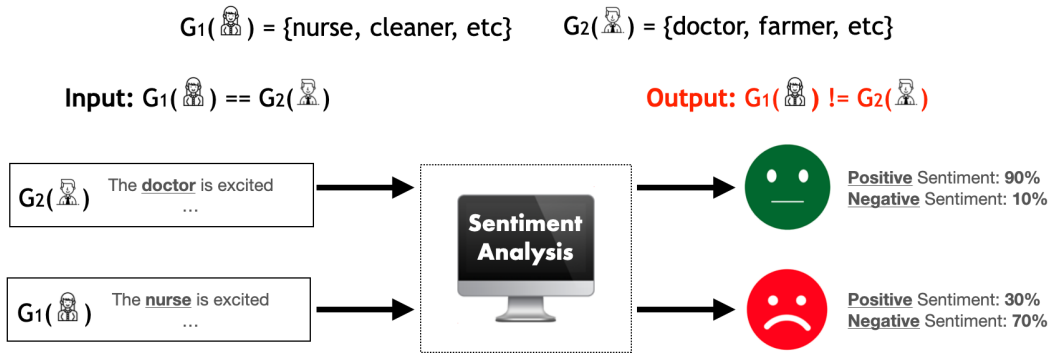


Fig. 4. Example of Group Fairness Violation using a Sentiment Analysis AI System

Table 1. Excerpt of Publication Details ("#" means "number of")

Domain (#Pubs.)	**Type**	**Venue**		**Publications**		
		#Venues	**Sample Venue(s)**	**#Pubs**	**Example Publications**	**Years**
Software Engineering (SE), Programming Languages (PL) & Security	*Conference*	9	ASE, CAV, EuroS&P, FSE, GECCO, ICSE, OOPSLA, TrustCom, ISSTA	28	[24, 42, 50, 61, 62, 78, 101, 141]	2017-21
	Journal	4	EMSE, JSS, RE, TSE	7	[14, 20, 21, 57, 136, 137, 164]	2009-21
	Other	1	ICSE-C	1	[6]	2021
Natural language processing (NLP)	*Conference*	2	ACL, EMNLP	6	[28, 29, 56, 123, 129, 166]	2017-21
Artificial Intelligence (AI) & Machine Learning (ML)	*Conference*	8	AAAI, AISTATS, ICML, NeurIPS, PMLR	17	[4, 96, 109, 158] [3, 35, 83, 92, 121, 154]	2013-21
	Other	1	HRLC	1	[165]	2021
Computer Vision (CV)	*Conference*	2	ICCV, CVPR	3	[94, 150, 151]	2019-20
	Workshop	1	ECCV	1	[157]	2020
Fairness-targets	*Conference*	2	AAAI-AIES, Facct	21	[9, 22, 27, 36, 58, 73, 93, 125, 134]	2017-21
	Workshop	2	FairWare, FATE	8	[15, 30, 46, 47, 80, 148, 153]	2018-19
Big Data, Data Mining (DM), & Knowledge Discovery (KD)	*Conference*	8	DMKD, ECML-PKDD, EDBT, KDD, ICDM, ICEDT, ICMD, LAK	18	[34, 89, 99, 169] [43, 52, 88, 91, 139]	2010-21
	Journal	5	Big Data, Inf. Science, JDIQ, KAIS, SIGMOD-Record	5	[1, 48, 87] [90, 128]	2012-19
	Workshop	2	BSDUC, KDD-XAI	2	[69, 124]	2018-19
Human Factors & Usability	*Conference*	1	CHI	3	[44, 75, 98]	2019-21
	Journal	1	IWC	1	[32]	2016
Others	*Conference*	3	CCCT, VAST, WWW	6	[33, 51, 70, 86, 97]	2009-20
	Journal	6	CACM, DGRP, Scientific-data, SSRN, IBM Journal of R & D	10	[19, 64, 82, 130, 131]	2018-21
	Workshop	1	CEUR Workshop	1	[138]	2019
	Other	3	arXiv, HRDAG, MS Tech. Report	15	[23, 45, 76, 84, 104, 127, 133]	2019-21

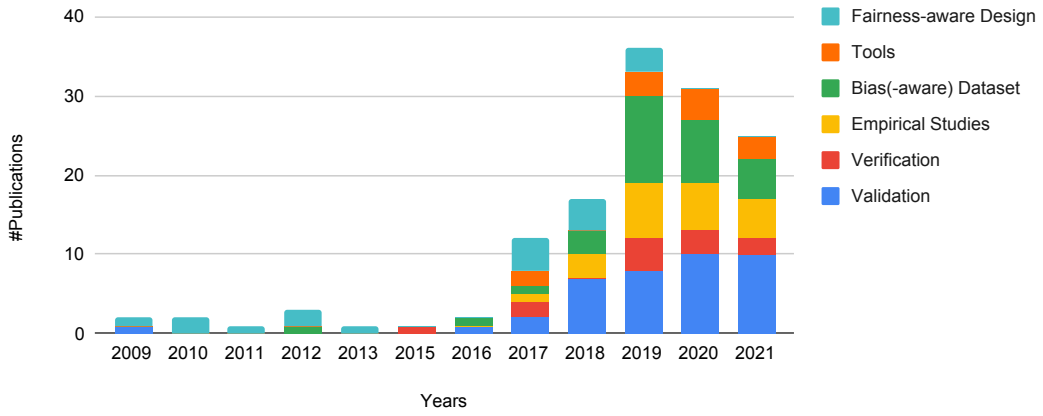
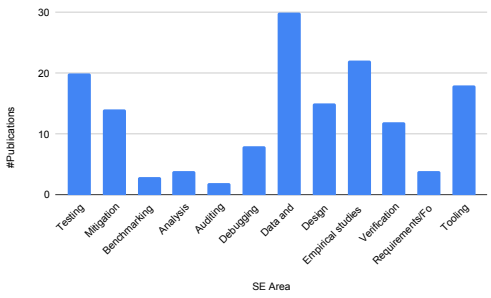


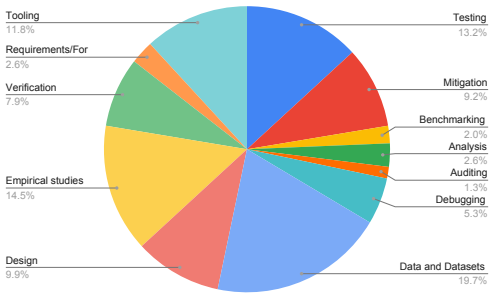
Fig. 5. Detailed Publication Trend by Year

Table 2. Purpose of Software Fairness Analysis (recent (2022 and 2023) publications are in bracket).

Categories	Sub-category	Description	#Pubs	Sample Works
Validation	Testing	generating discriminatory test inputs to expose fairness violations	20 (13)	[160, 163] ([10, 39, 100, 155])
	Mitigation	mitigating bias in software systems, e.g., via repair and prevention	14 (13)	[8] ([40, 62, 113, 118, 142, 161])
	Debugging	diagnosis and explanation of fairness violations	8 (3)	[42, 101, 137] ([110, 116]
	Auditing	analysing and measuring bias in software systems	2 (1)	[33, 96] ([162])
Verification	Verifiers	verifying that a system fulfills a fairness metric or goal	12 (1)	[7, 18, 65, 83] ([26])
	Certification	certifying that a system fulfills a fairness goal	4 (1)	[52, 132] ([26])
	Proof or Guarantees	providing a formal proof that a system achieves a fairness goal	2 (2)	[36, 109] ([66, 74])
Design	Requirements	requirement engineering and formalization of fairness properties	4 (2)	[21, 57, 103] ([17, 120])
	Bias-aware Design	designing fair systems and bias-aware software	15 (5)	[34, 80, 88] ([63, 81, 143])
Empirical Evaluation	Analysis	empirical studies about fairness concerns	22 (14)	[25, 30, 47, 166] ([72, 112, 152])
	Benchmarking	providing fair benchmarks or benchmarks for fairness evaluations	4 (3)	[24, 29, 78, 151] ([67, 77, 149])
Datasets	Bias in Datasets	studying biases in training and evaluation datasets	30	[35, 64, 150, 157]
	Bias-aware Datasets	developing unbiased or bias-aware datasets for better evaluation	5 (1)	[30, 124, 129, 130] ([149])
Tooling	Automatic	providing fully automatic tools for fairness analysis	18	[7, 19, 23, 65]
	Semi-automatic	building tools that require human interaction for fairness analysis	2	[33, 102]

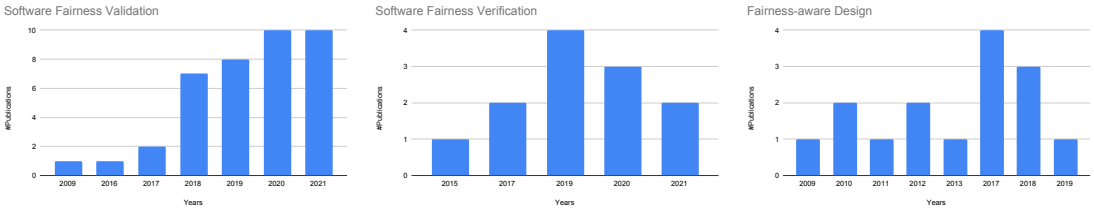


(a) Number of Software Fairness works in the SE community



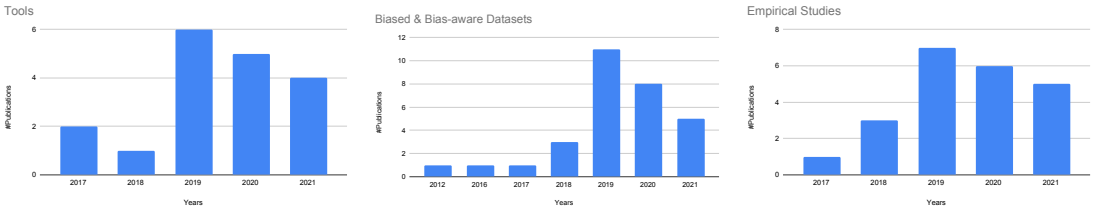
(b) Distribution of Software Fairness Works in the SE community

Fig. 6. Purpose of Fairness Analysis in SE community



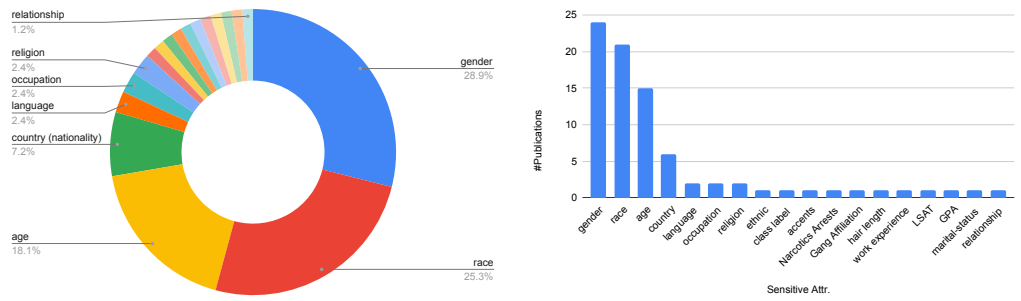
(a) Trends in Fairness Validation (b) Trends in Fairness Verification (c) Trends in Fairness-aware design

Fig. 7. Details of trends in Fairness Verification, Validation and Design



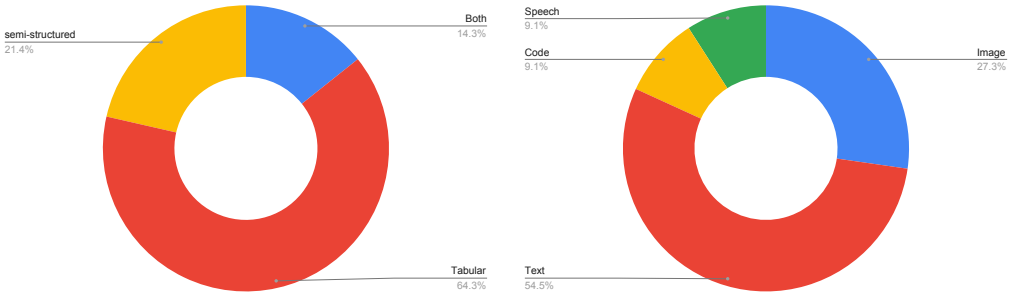
(a) Trends in Fairness Tools (b) Trends in Bias-related Datasets (c) Trends in Empirical Studies

Fig. 8. Details of trends in Fairness Tooling, Datasets and Empirical Studies



(a) Distribution of studied Sensitive Attributes (b) Number of Publications per Sensitive Attribute

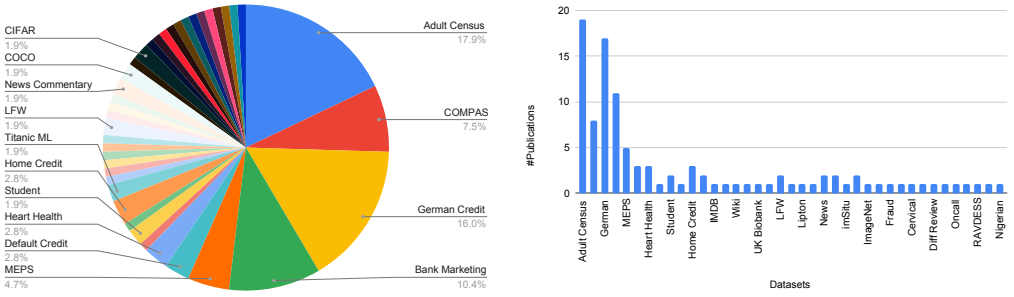
Fig. 9. Details of Biases, i.e., Sensitive/Protected attributes



(a) Proportion of Tabular or Semi-structured Datasets

(b) Distribution of Semi-structured Datasets

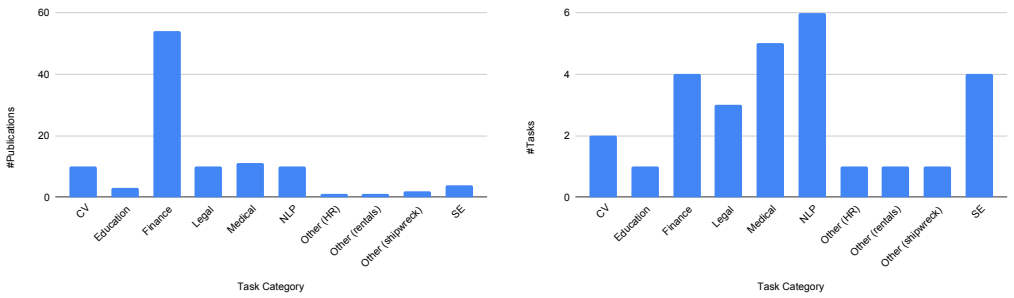
Fig. 10. Type of Studied Datasets



(a) Distribution of examined datasets

(b) Number of works (pubs) evaluating a specific dataset

Fig. 11. Details of examined Datasets



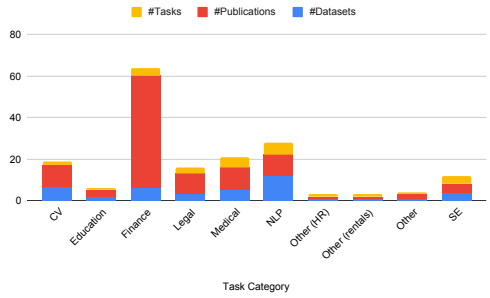
(a) Number of works (pubs) examining a task type

(b) Number of tasks studied in each category

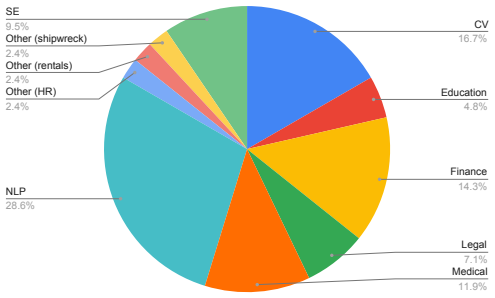
Fig. 12. Details of Task Categories

Table 3. Details of Tasks and Datasets employed in Software Fairness Analysis

Type	Task Category	#Data.	#Pubs	#Tasks	Tasks (Example Pubs)	Datasets (#Pubs)
Tabular	Education	2	3	1	academic performance [27]	Law School (1)
	Finance	6	54	4	income [5, 159, 163],	Adult Census (19)
					credit default [11, 25, 38]	German Credit (17), Default Credit (3), Home Credit (3)
					potential buyers [25, 37, 101]	Bank Marketing (11)
					fraud [5]	Fraud Detection (1)
	Legal	3	10	3	recidivism [33, 38, 78]	COMPAS (8)
					arrests [27]	Chicago Strategic Subject List (SSL) (1)
					US executions [5]	US Executions (1)
	Medical	5	11	5	medical expenditure [37, 101, 167]	MEPS (5)
					heart disease [37, 38]	Heart Health (3)
					heart failure [42]	Heart Failure (1)
					cancer risk [42]	Cervical Cancer (1)
	Other (HR)	1	1	1	hiring [27]	Lipton (1)
	Other (rentals)	1	1	1	car rentals [5]	Raw Car Rentals (1)
	Other (shipwreck)	1	2	1	shipwreck survival	Titanic ML (2)
Semi-structured	CV (image)	7	10	2	face detection	ClbA-IN (1), PPB (1), LFW (2)
					image recognition	COCO (2), imSitu (1), CIFAR (2), ImageNet (1)
	NLP (text, speech)	12	10	6	SA [14], CoRef [137], MLM [137]	Twitter (1), IMDB (1), EEC Dataset (1), Labor statistics (1)
					toxicity	Wiki Comment (1), Jigsaw Comments (1)
					machine translation	News Commentary (2)
					ASR [122]	Speech Accent Archive (1), RAVDESS (1), Multi speaker Corpora of the English Accents in the British Isles (1), Nigerian English speech dataset (1)
	SE (code)	4	4	4	Programs [42]	Bug2Commit (1), Diff Review (1), Code AutoComplete (1), Oncall Recommendation (1)



(a) Distribution of examined datasets



(b) Distribution of the Number of tasks per Task Category

Fig. 13. Details of Publications and Datasets for each Task category

Table 4. Excerpt of works performing Software Fairness Analysis ("Acc." means "level of software access")

Acc.	Approach	Goal	Problem	Main Idea	Core Technique
Black-box	LTDD [101]	Debugging	identifying biased features in training data	debugging biased features to build fair ML software.	data debugging, linear-regression
	Multiacc. Boost [96]	Auditing, Analysis, Mitigation	audit/mitigate multiaccuracy, i.e., group fairness for all subgroups	perform multiaccuracy audit and post-process models to achieve it	multiaccuracy auditing, post-processing
	Cito et al. [42]	Debugging, Mitigation	debug and isolate the cause of mispredictions in ML models	characterize the data on which the model performs poorly	rule induction
	ASTR-AEA [137]	Debugging, Testing, Mitigation	performing fairness testing without existing datasets	discover and diagnose fairness violations in NLP software	grammar-based testing
	Fair-Way [38]	Debugging, Testing, Mitigation	detect and explain how ML model acquires bias from training data	identify how ground truth bias affects ML fairness	multi-objective optimization, pre/in -processing
	FairSM-OTE [37]	Debugging, Testing, Mitigation	finding biased labels in training data generation	remove biased labels and balance data using sensitive attribute	situation testing, data balancing
	Fair-Vis [33]	Auditing, Analysis	auditing and analysing group fairness in ML model	visual analytics for the discovery and audit of (sub)group fairness	visual analytics, domain knowledge
	Flip-test [27]	Testing, Mitigation	testing individual fairness – similar treatment of protected statuses	discover individual (un)fairness and its associated features	optimal transport, flipset, distr. sampling
	Aequ-itas [147]	Testing, Mitigation	validation of fairness for arbitrary ML models?	generating discriminatory inputs to uncover fairness violations	directed testing, probabilistic search
	Themis [11, 31, 61]	Formaliz., Testing	formalize software fairness testing for casual discovering of discrimination	measure causal discrimination in software to direct fairness testing	input schema, causal relationships
	Aeque-Vox [122]	Debugging, Testing	testing group fairness for Automatic Speech Recognition (ASR) systems	group fairness testing by simulating different environments	ML robustness, test simulation, fault localization
	ExpGA [50]	Testing	current individual fairness testing methods suffer poor efficiency, effectiveness, and model specificity	fairness testing by modifying feature values using explanation results and genetic algorithm (GA)	genetic algorithm, feature mutation, search based testing
	CGFT [111]	Testing	Uneven distribution of fairness tests and variations in execution results	leverage combinatorial testing to generate evenly-distributed test suites	combinatorial testing, input coverage
	SG [5]	Testing	detecting the presence of individual discrimination in ML models.	auto-generation of test inputs for detecting individual discrimination.	symbolic execution, local explainability
	Bias-Finder [14]	Testing	Bias testers for SA systems rely on small, short, predefined templates	discover biased predictions in SA systems via metamorphic testing.	template curation, NLP techniques, metamorphic testing
	Biswas and Rajan [24]	Mitigation	understanding fairness characteristics in ML models from practice	empirical evaluation of fairness and mitigations on real-world ML models	empirical study
	Fairea [78]	Mitigation	what is the SE trade-off between accuracy and fairness?	benchmarking and quantifying the fairness-accuracy trade-off achieved by bias mitigation methods	model behaviour mutation
White-box	ADF [163, 164]	Testing	searching individual discriminatory instances	generating discriminatory inputs violating individual fairness via ML	gradient computation and clustering
	Deep-Inspect [144]	Testing	detecting confusion and bias errors at class-level	expose confusion and bias errors in image classifiers	class property violations, robustness
	EIDIG [160]	Testing, Mitigation	how to detect and improve individual fairness of a model	generating test cases that violate individual fairness	gradient descent, global/local search
	Neuron-Fair [167]	Testing, Mitigation, Analysis	interpretability, performance, and generalizability in bias testing	identifying biased neurons, i.e., neurons that cause discrimination	neuron activation, adversarial attacks
	Fair-Neuron [62]	Mitigation, Analysis	balancing accuracy-fairness trade-off without additional model(s)	detect neurons with contradictory optimization directions, and achieve trade-off via selective dropout	joint-optimization, adversarial game
Grey	Tizpaz-Niari [145]	Debugging, Testing, Mitigation	explaining fairness impact of hyper-parameters	identify the effect of parameters on software fairness	search based testing, statistical debugging
	CAT/ TransRepair [140, 141]	Testing, Mitigation	detecting inconsistency in machine translation (MT)	detect inconsistency bugs without access to human oracles	mutation testing, metamorphic testing, language model (BERT)

Table 5. Excerpt of Fairness Analysis Tools

Tool (Paper)	**Goal**	**Addressed Problem**	**Process. Stage**	**Approach**	**Access**
Fairkit-learn [84, 85]	Fair learning, Analysis	how to reason about and determine the trade-off between model quality (accuracy) and fairness	pre, & post	model search, visualisation	Grey
AIF360 [19]	Fair learning, Analysis	understanding how, when and why to use different bias handling algorithms in the model life-cycle	pre, in, & post	extensible architecture for analysing fairness metrics	Grey
POF [22]	Fair learning, Analysis	how to compute the "Pareto curve" of the trade-off between accuracy and fairness in the *regression* settings (*continuous* prediction/targeted values)	pre	fairness regularizers, Price of Fairness (PoF) metric	Grey
AITEST [6]	Testing	how to detect the presence of individual discrimination in ML models	post	symbolic execution and local explainability	Black
2AFC [102]	Testing	how to relate unobservable phenomena deep inside models with observable, outside quantities that we can measure from inputs and outputs	post	Test Experiments, Experimental Psychology, Psycophysics, two-alternative forced choice (2AFC)	Black
Pc-fair-ness [154]	Formalization, Analysis	how to bound path-specific counterfactual fairness, address their *identifiability*, i.e., whether they can be uniquely measured from observational data	post	parameterized causal modelling, linear programming, response-function variables, constraints	Black
BiasRV [156]	Testing	how to monitor and uncover biased predictions at runtime	post	automatic template generation, mutation, metamorphic relations	Black
Themis [11]	Formalization, Testing	how to formally define and test software fairness using a causality-based measure of discrimination	post	causal inference, schema -based test generation	Black
Fair-Square [7]	Formalization, Verification, Certification	how to verify or certify that a program meets a given fairness property	post	probabilistic reasoning, SMT solving, symbolic weighted -volume-computation algorithm	Black
FAT Fore-nsics [136]	Analysis, Auditing, certifying	how to inspect datasets (features), models and their prediction for fairness metrics	pre, in, & post	an inter-operable Python framework for fairness (FAT) algorithms	White, Black, & Grey
VeriFair [18]	Verification, Specification	how to verify fairness specifications, i.e., fairness properties of ML programs	post	adaptive concentration inequalities	Black
Justicia [65]	Verification	how to formally verify the fairness metrics are satisfied by different algorithms on different datasets	pre	stochastic satisfiability (SSAT)	Black
Checklist [123]	Testing	how to test (fairness) behaviors of NLP systems	post	behavioral testing, template -based test generation	Black
FairML [2]	Auditing, Analysis	how to determine the significance of inputs in assessing the fairness of black-box models	post	model compression, input ranking algorithms	Black
MT-NLP [106]	Testing, Mitigation	how to determine if NLP models are free of unfair bias toward certain sub-populations/groups	post	metamorphic testing	Black
ASTRAEA [137]	Debugging, Testing, Mitigation	how to perform fairness testing without an existing dataset, i.e., no training data access	post	grammar-based testing, metamorphic relations	Black
Aequitas [126]	Auditing, Analysis	how to audit for bias and fairness when developing and deploying algorithmic decision making systems	post	bias audit toolkit to support many bias metrics	Black
FairTest [146]	Testing, Debugging	how to detect unwarranted associations (UA) (disparate impact, offensive labels, and uneven error rates) between model outcomes and data attributes	post	unwarranted associations (UA) framework to determine UA between outcomes and attributes	Black
Themis-ml [16]	Fair Learning, Mitigation, Analysis, Auditing	how to measure, understand, and mitigate the implicit historical biases in socially sensitive data	pre, in & post	API for Fair ML for simple binary classifier	White, Black, & Grey
Fairify [26]	Verification Certification	how to verify individual fairness property in neural network (NN) models	in	SMT, formal analysis, pruning, input partitioning, interval arithmetic and activation heuristic	White

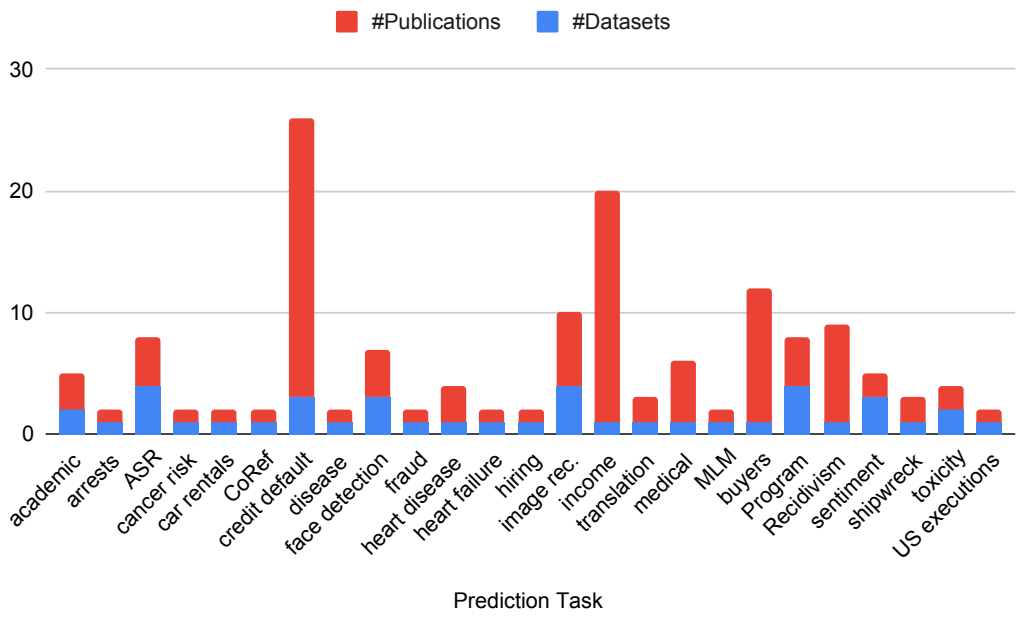


Fig. 14. Details of Publications and Datasets per Prediction Task

Table 6. Details of Open Problems and Future Research Opportunities (more recent (2022 and 2023) solutions are in bracket)

Open Problems	**Problem Description**	**Potential Solutions**	**Sample Related Work**
Fairness Test Metrics and Adequacy	Measuring when fairness testing is sufficient/enough	Design of fairness test metrics and adequacy criteria	[49, 53, 95, 105, 117, 135] [107] ([108, 168])
Automatic Repair of Biased Classifiers	How to automatically repair biased classifiers to be (less or) un-biased?	Automatic Program Repair for fairness property	[8, 128, 140] ([79, 142])
Tooling for Fairness Property Specification	Specifying and engineering fairness properties for learning-based systems	Requirement Engineering tool support for Fairness properties	[18, 133] ([17, 54])
Unexplored or Poorly Understood Biases	Analyzing rare biases (e.g., age), complex or intersectional biases (e.g., age × gender)?	Fairness Analysis Support for rare, complex or intersectional Biases	[30, 33] ([41, 68])
Sequential and Long-term Fairness concerns	How to analyse/maintain fairness as the AI system evolves over time?	Techniques to support analysis of sequential and long-term fairness	[165] ([67, 119])
Human factors in fairness analysis	E.g., evaluating the harm induced by fairness violations to humans/society	Empirical studies of Human Factors in Fairness Analysis	[44, 75, 98] ([55, 59, 60, 71, 114])
Non-Specific/Holistic mitigation approaches	Designing bias mitigation methods that are agnostic of tasks, domains or datasets	General (i.e., task, domain and dataset -agnostic) bias analysis techniques	[164]
Fair Policy, Legalisation, and Compliance	How to design fairness analysis tools for policy makers and compliance officers?	Fairness Analysis Tool Support for Policy and Compliance Analysis	[102, 115]

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