The Double-Edged Sword of Big Data and AI for the Disadvantaged: A Cautionary Tale from Open Banking

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Outline

- Motivation: expansion of Big Data and AI
- Hidden dangers, e.g. amplified algorithmic bias/unfair outcomes
- Open Banking (OB) as an example of Big Data
- Data description
- Regulatory context, protected and sensitive attributes
- Power of OB data: Financial Vulnerability (FV) profiling
  - Indicators and specification
  - What if someone wants to target a vulnerable group? Predicting FV – machine-learning wins
- Associations with protected and sensitive attributes:
  - What it means for the probability of being accepted for credit
  - What it means for customer segmentation (clustering)
- Conclusions and recommendations: It is essential to recognise and address hidden patterns to prevent inadvertently disadvantaging protected groups.

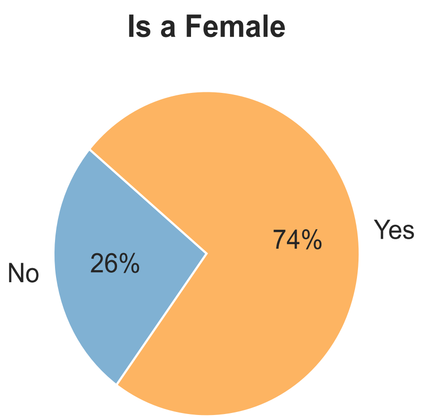
Open Banking/ transactional data

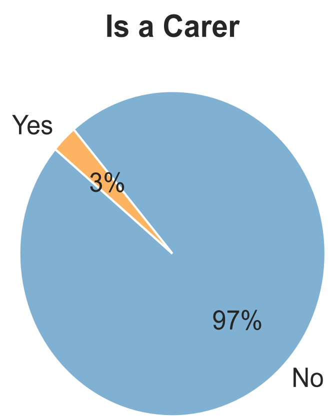
- The second Payment Services Directive (PSD2 or Open Banking in the UK) is a game changer in retail finance. It enables easier access to dynamic, real-time consumer data in practice, with bank transaction data being of particular interest.
- The research uses a new, proprietary dataset provided by a UK social lender, offering small loans (£500 to £1,000) to financially challenged public sector workers. The lender assesses applicants via Open Banking during the affordability check procedure, excluding the need for a bureau credit score.
- The data was collected in February 2022 and focuses on approximately 100,000 applicants who have applied for a loan in the previous two years, yielding a dataset of over 180 million transactions.

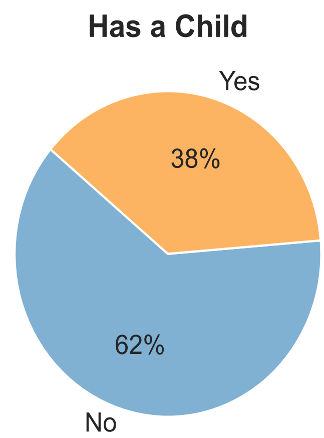
Financial Vulnerability indicators/ binary target variables

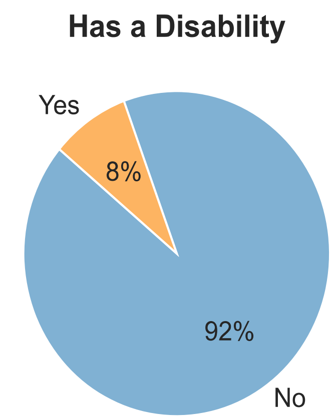
1. *Financial shock withstanding* (48.3% of applicants): average median monthly balance below £100.
2. *Insolvent* (4.0%): payments to *debt management and insolvency companies*.
3. *Insufficient disposable income* (11.6%): average monthly disposable income is less than £100.
4. *Overdraft* (67.4%): one or more days in overdraft (OD) per month for more than 50% of the months throughout their account history.
5. *Returned direct debits* (28.3%): When an applicant has at least one or more returned direct debits (RDD), insufficient funds resulting in a rejection of a pre-arranged payment by the bank.
6. *Gambler* (20.2%): £100 or more on average per month spent on gambling.

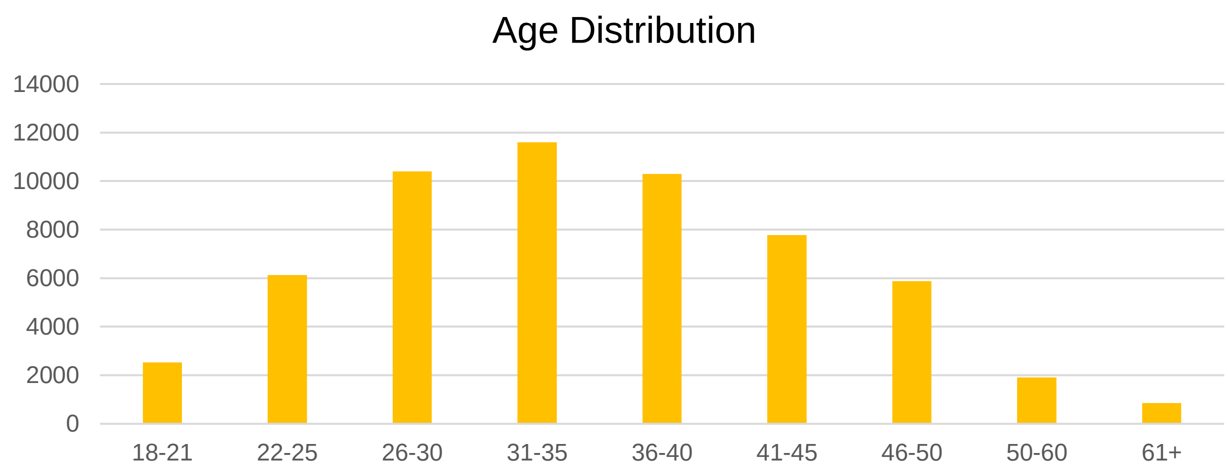
Protected and sensitive attributes











Legal position

The Law makes the distinction between direct and indirect discrimination.

It is concerned with procedural fairness or ‘**equal treatment**’ or ‘direct discrimination’ which is strictly prohibited → certain variables cannot be used as inputs into a model (be it a regression or a machine-learning algorithm).

The public and media seem to be more concerned about outcome fairness or ‘**equal outcome**’. However, unequal outcomes can arise from ‘indirect discrimination’, where an apparently neutral criterion would put persons of a particular group (e.g. gender) at a disadvantage compared with other persons. This can be justified by a legitimate aim, given the means of achieving that aim are appropriate and necessary.

Financial behaviours/predictors

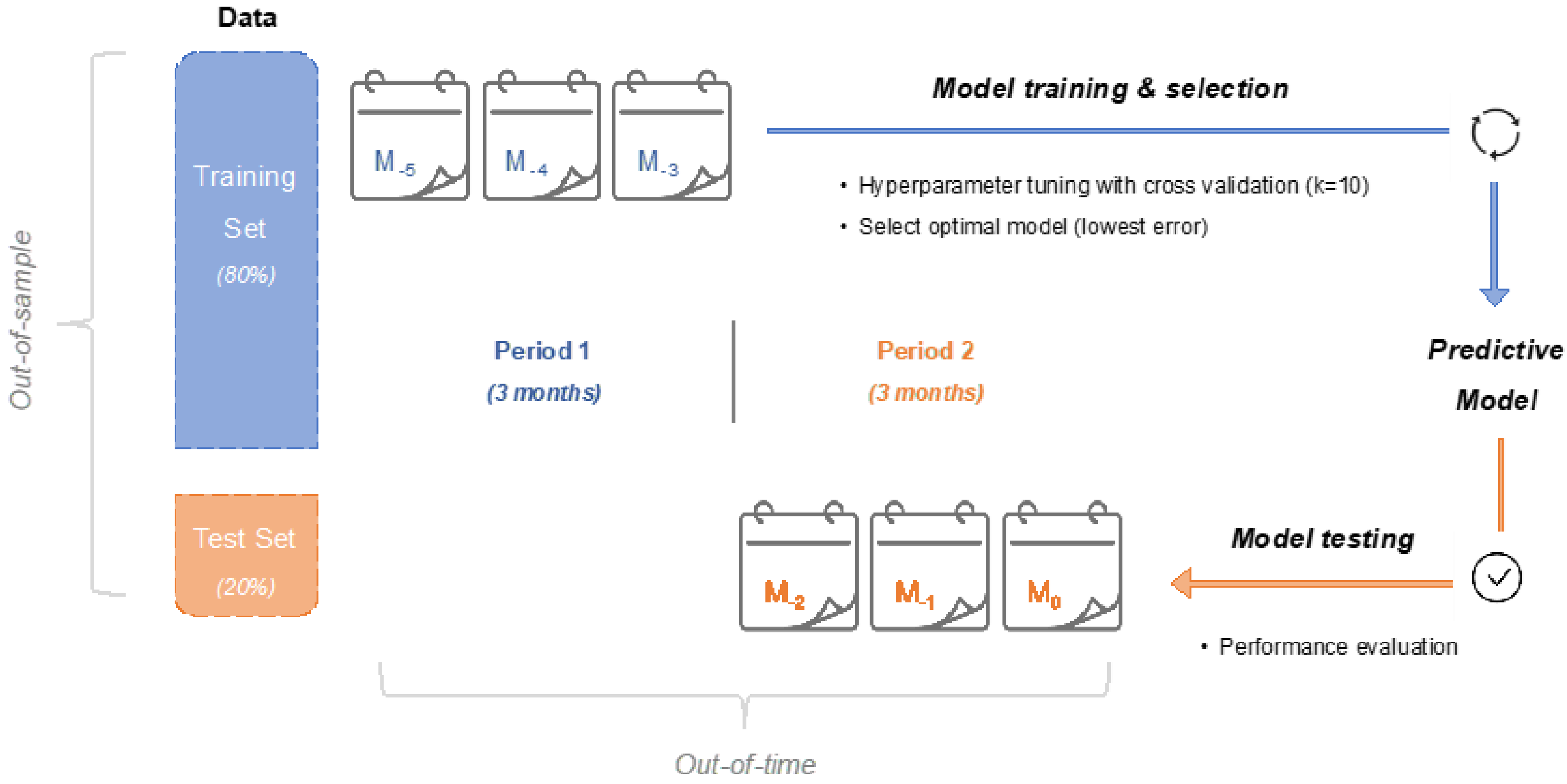
Over 100 variables, examples include:

- Financial Management:
  - Inflow (e.g. Total Income, # of income sources, consistency)
  - Outflow (Expenditure by category: housing, groceries, health, gambling)
  - Volatility (Burstiness in spending)
- Financial Distress (Debt management payments, overdraft, RDD)
- Financial Resilience (Account Balance, Disposable Income)
- Financial Planning (Insurance, Savings)
- Financial Aid (Total Benefits, Amount by Benefit Types, Pensions)
- Financial Inclusion (# credit providers, # cards, loans, payday loans).

Correlations

		Profile			*Benefits Received*			*Financial Vulnerability Indicators*				
		Age	Employment Length	Female	Carer	Child	Disability	Financial shock	Gambling expenditur e	Insolvency & DM	Disposabl e income	Over-draft
Profile	Employment Length	0.269**										
	Female	0.043	-0.014									
Benefits Received	Carer	-0.001	-0.030	0.038								
	Child	-0.010	0.028	0.362**	0.095**							
	Disability	0.073**	0.011	0.078	0.334**	0.131**						
Financial Vulnerability Indicators	Financial shock withstanding (% of months)	0.182**	0.089**	0.033	0.007	0.053**	0.060**					
	Gambling expenditure (£)	-0.004	0.036	-0.116**	0.008	-0.045**	0.001	0.101				
	Insolvency & debt management expenditure (£)	0.096	0.072	0.008	-0.017	0.022	-0.003	0.103	0.001			
	Disposable income (£)	0.015*	0.027	-0.006	0.043	0.053**	0.051	0.059	0.403**	0.031		
	Overdraft (% of months)	-0.077	-0.014	-0.004	-0.019	0.024	-0.014*	-0.586**	-0.009	-0.026	-0.030	
	No. of returned direct debits	-0.025	-0.043	0.041	0.031	0.088**	0.047	-0.163**	0.025	0.049	0.059	0.332**

Modelling


Data
Training Set
(80%)
Test Set
(20%)
Out-of-sample
M -5
M -4
M -3
Model training & selection
• Hyperparameter tuning with cross validation (k=10)
• Select optimal model (lowest error)
Period 1
(3 months)
Period 2
(3 months)
Predictive Model
Model testing
M 2
M 1
M 0
• Performance evaluation
Out-of-time

Predictive accuracy

		AUROC	
		Mean	*Std*
Withstand financial shock	*LR*	0.756	0.007
	RF	0.903	0.004
	XGB	0.895	0.004
Gambler	*LR*	0.875	0.006
	RF	0.893	0.006
	XGB	0.911	0.006
Returned Direct Debits	*LR*	0.775	0.005
	RF	0.870	0.004
	XGB	0.884	0.004

		AUROC	
		Mean	*Std*
Has a Child	LR	0.824	0.006
	RF	0.917	0.003
	XGB	0.917	0.004
Has a Disability	LR	0.796	0.018
	RF	0.885	0.010
	XGB	0.864	0.010
Female	LR	0.832	0.004
	RF	0.896	0.003
	XGB	0.917	0.002

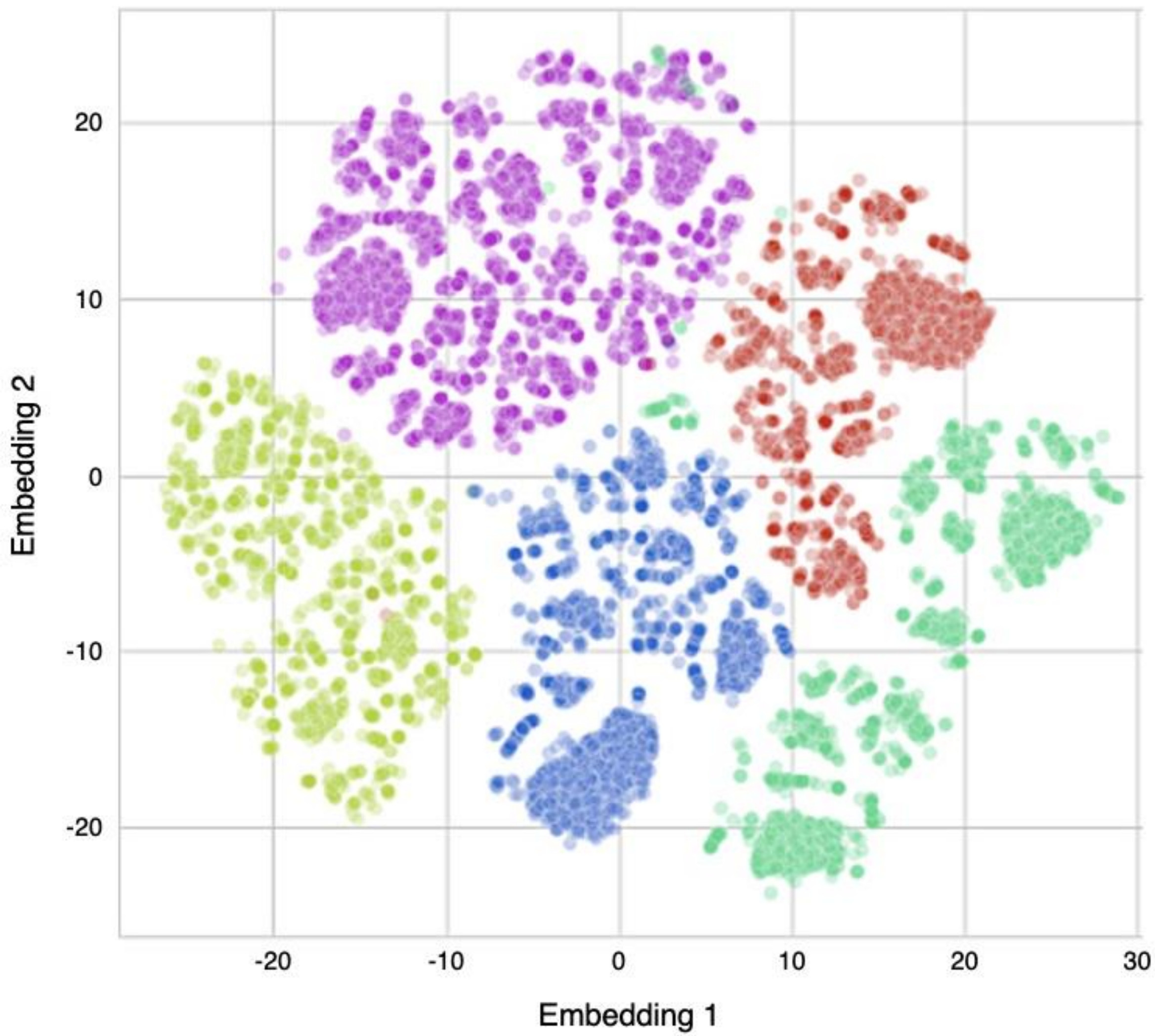
Machine learning models performance
(LR=Logistic regression, RF = Random Forest, XGB = eXtreme Gradient Boosting)
evaluated with the Area Under the Receiver Operating Characteristic Curve (AUROC), higher values → better predictions.

Impact on protected and sensitive groups

		Acceptance Rate			
		Withstanding financial shock always		No Returned Direct Debits	
		PA Excluded	*PA Included (delta)*	*PA Excluded*	*PA Included (delta)*
Gender	Female	21.4%	0.0%	20.4%	0.0%
	Male	16.1%	0.1%	18.9%	-0.1%
	Male & no benefits	14.4%	-0.3%	18.7%	-0.1%
Benefit	Is carer	25.5%	-0.1%	16.9%	-0.1%
	Has child	23.9%	0.0%	18.7%	0.0%
	Has disability	29.4%	-1.1%	17.7%	-0.1%
Intersectionality	Female & has child	23.5%	0.0%	18.5%	-0.1%
	Female & has disability	31.1%	0.1%	18.1%	0.3%
	Female & is carer	25.7%	-1.4%	16.7%	-0.1%
	Has child & disability	32.9%	-1.5%	16.3%	0.2%
	Has child & is carer	29.4%	0.0%	15.0%	0.2%
	Is carer & has disability	32.0%	0.5%	15.8%	0.2%
Age	Age: 18-21	5.1%	1.2%	16.9%	0.0%
	Age: 22-25	7.2%	0.9%	15.1%	-0.1%
	Age: 26-30	13.1%	1.1%	17.0%	0.3%
	Age: 31-35	18.6%	0.3%	18.1%	0.2%
	Age: 36-40	24.2%	-0.1%	20.1%	0.0%
	Age: 41-45	24.7%	-0.8%	22.2%	0.1%
	Age: 46-50	28.3%	-1.2%	23.3%	0.0%
	Age: 51-55	30.0%	-1.6%	27.2%	-0.8%
	Age: 56-60	32.6%	-1.3%	28.0%	-1.0%
	Age: 60+	30.4%	-0.2%	29.1%	-1.5%

Simulating a scenario, where a lender accepts 20% of applicants, based on the higher probability of e.g. No RDD. Equal outcome would mean 20% acceptance rate across all the subgroups.

Clustering



Cluster composition

	Cluster				
	1	2	3	4	5
Age range	3.4	4.4	4.4	3.1	3.6
Female	0.7	0.5	0.8	0.6	1.0
Council tenant (binary)	0.1	0.1	0.2	0.1	0.2
Gambling expenditure	134.4	233.3	254.6	205.8	135.2
Insolvency & debt management (DM)	29.6	28.2	39.2	17.3	27.7
No. of days in Overdraft (OD)	8.1	7.7	0.9	6.8	7.7
No. of Returned Direct Debits (RDD)	1.1	0.9	0.4	0.5	1.1
Account Balance: Mean	74.2	103.1	662.4	51.5	88.5
% of M can withstand financial shock	0.4	0.4	1.0	0.4	0.4
Disposable income	748.7	719.8	878.3	703.6	824.4
Savings	330.9	269.5	136.4	326.7	418.8
Total benefits	110.3	94.9	378.1	129.7	677.3
Carer benefits	1.8	2.3	7.3	2.6	8.2
Child benefits	0.0	0.4	94.6	1.2	187.1
Disability benefits	16.4	16.3	47.1	17.3	40.9
Pension income	5.8	11.8	7.8	4.2	2.4
CC payments	44.9	42.5	44.5	25.9	26.3
Loans received	229.6	208.4	202.1	176.7	167.6
Loan payments	403.3	301.4	379.5	239.9	284.9
No. of unique traditional loans	0.9	0.7	0.8	0.5	0.6
No. of unique non-traditional loans	3.5	0.9	2.7	1.9	2.6
Payday loan payments	69.5	60.8	48.9	55.1	44.7

Conclusions and recommendations

- Open Banking (OB) is a recent example of Big Data providing detailed insights into customer behaviour.
- We demonstrated the power of OB and AI/ML in profiling the vulnerable customers.
- Good use: e.g. to take early actions to improve the customer's situation.
- Bad use: e.g. targeting vulnerable consumers by predatory lenders.
- Recommendation 1: ensure that powerful data and technology benefits the customers.
- Need to be aware of hidden associations with protected and sensitive attributes.
- Recommendation 2: guidance on dealing with these associations.
- Intersectionality is another big topic that requires attention and research.

Credit Scoring & Credit Control conference

The 19th conference will be in Edinburgh 27-29 August 2025.

Last conference in 2023:

- 400 delegates (20% academics, 80% practitioners),
- 34 countries: US to Australia and Norway to Vietnam,
- 9 commercial sponsors,
- 111 competitively selected papers in 5 streams,
- Special Issue of ‘Annals of Operational Research’.

Call for abstracts