



PIPL TRUST · CUSTOMER CASE STUDY

Adding identity clarity to account onboarding

How a financial services provider used a calibrated Trust Score to tell genuine customers apart from fraudulent applications at signup, without adding friction for the customers it wanted to win.

USE CASE	PRODUCT	METHOD	COVERAGE
Account onboarding	Pipl Trust	Calibrated Trust Score	20+ markets

The provider scored tens of thousands of real account openings with Pipl Trust, then calibrated the score on its own fraud. The calibrated model separated genuine customers from fraud with an ROC-AUC of **0.93**, identifying the large majority of fraud while clearing most good customers instantly.

ROC-AUC, AFTER CALIBRATION

0.93

Excellent separation of good customers from fraud, up from 0.80 before calibration.

HOW THE SCORE WORKS

Identity resolved. Each signup is matched to the real person behind it, across a global identity graph.

Calibrated to the provider's fraud. The score is tuned on the provider's own labelled outcomes.

One clear number. A single score from 0 to 1000, with the signals that explain it.

94%

GOOD CUSTOMERS CLEARED
AT THE ACCEPT THRESHOLD

69%

OF ALL FRAUD IN THE
LOWEST 25% OF SCORES

91%

FRAUD RATE IN THE
LOWEST SCORE BAND

76%

SMALLER MANUAL
REVIEW QUEUE

Figures from a proof of concept on real signups in a European portfolio. See the closing note for scope.

The challenge

Account onboarding is one of the hardest moments to de-risk. Every applicant is unknown, and the controls meant to stop fraud tend to punish good customers first.

A blind decision at signup. A real customer or a synthetic identity, mule or bot, judged in less than a second with no account history to go on.

Evolving fraud and attack waves. Tactics changed week to week and defeated static rules that needed constant manual tuning.

Rising review cost. Every tightening pushed more applicants into manual review and document checks.

Friction on good customers. Blunt rules produced false declines that sent genuine customers to a competitor.

Every rule added to catch fraud also stood in the way of a genuine customer. The team was trading conversion for safety, with no way to have both.

What the provider needed. A signal that read the real identity behind each applicant: strong enough to automate the easy calls at scale, and precise enough to stop making good customers pay for the behavior of fraud.

The solution

Pipl Trust scored every signup against the identity behind it and returned one number, plus the signals that explained it, calibrated to the provider's own fraud.

The score resolved the email, phone, name, address and device against a global identity graph and returned a single value from 0 to 1000, where higher meant more trustworthy. Calibrating on the provider's labelled outcomes polarized the score: genuine customers rose toward the top, fraud collapsed to the bottom, and the two groups barely overlapped.



Share of each group at each score. Grey shows genuine customers, near the top of the range. Blue shows fraud, at the bottom. Strongest identity signals: a name matched to its email was about 12x more likely to belong to a genuine customer, a name matched to its phone about 11x, and an email with a long history about 9x.

0.93

ROC-AUC
AFTER CALIBRATION

0.80

ROC-AUC
BEFORE CALIBRATION

900+

MEDIAN SCORE
GOOD CUSTOMERS

<100

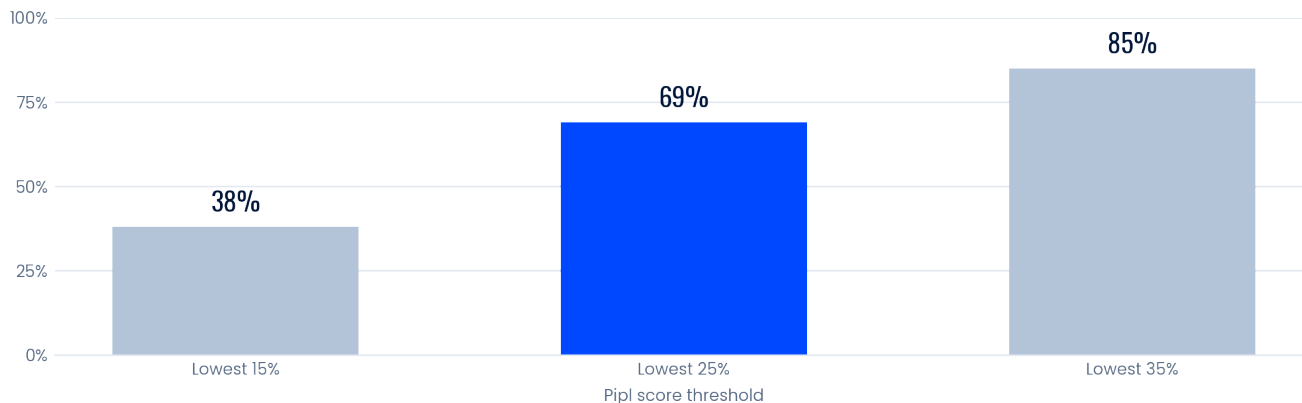
MEDIAN SCORE
FRAUD

One calibrated score, two clean populations. Performance held across every market tested, with ROC-AUC from 0.88 to 0.98.

The impact

Clean separation let the provider act on most signups automatically: fraud stopped at the front door, good customers moved straight through, and review shrank to the cases that needed a person.

Share of all fraud captured, by score cutoff



Fraud concentrates at the bottom of the score. Holding back the lowest-scoring applicants captures a large share of all fraud, so the team could set an accept threshold that stopped most fraud while clearing good customers.

BUSINESS OUTCOMES

94%

GOOD CUSTOMERS CLEARED
AT THE ACCEPT THRESHOLD

69%

OF ALL FRAUD IN THE
LOWEST 25% OF SCORES

91%

FRAUD RATE IN THE
LOWEST SCORE BAND

76%

SMALLER MANUAL
REVIEW QUEUE

GAINS FROM CALIBRATION

+73%

FRAUD DETECTION LIFT
FROM CALIBRATION

4.2x

REDUCTION IN FALSE
POSITIVES AFTER CALIBRATION

Typical Pipl calibration results, shown for context. Tuning the score to a provider's own fraud lifts detection and cuts false declines at the same time.

Scope. Figures come from a proof of concept on real signups in a European portfolio, with accounts labelled by the provider. Score separation, ROC-AUC and fraud concentration figures are independent of the fraud mix in the sample. Approval and precision figures reflect this portfolio and will differ on another book of business. The +73% and 4.2x calibration gains are typical Pipl results, not measured outcomes for this portfolio.