DEV DAY 4 Women | NOVARTIS

BEGINI AS A CASE STUDY IN AI-BASED PSYCHOMETRIC CREDIT SCORING

Ethics and Algorithmic Bias from a Gender Perspective

CONTENTS

What we'll cover today

PART 1 · THE GENDERED LENDING DILEMMA

"A model that cannot see gender can still discriminate by gender—because our world has encoded inequality into every behavioral signal it measures."

GENEVIEVE SMITH · "THE GENDERED ALGORITHM" · ARXIV:2504.07312 (2025)

PART 1 · THE GENDERED LENDING DILEMMA

Creditworthy, but invisible

María is 34. For four years, she has run a textile workshop in Mexico City. She earns in cash, saves in a *tanda*, supports her family, and has never missed a payment to anyone.

The financial system has never seen her.

Her story is the story of millions of women across Latin America.

Why the system cannot see María

María's real financial life

- ✓ Steady cash income from the workshop.
- ✓ Disciplined savings — in a tanda, not a bank.
- ✓ Supplier credit, repaid on time for four years.
- ✓ Head of household through caregiving pauses.
- ✓ A growing business — but no property title in her name.

What the credit bureau sees

- No income record.
- No savings record.
- No repayment history.
- An employment gap → coded as a risk signal.
- No collateral.

Every signal of her reliability lives outside the formal system — so the system concludes she has none.

PART 1 · THE GENDERED LENDING DILEMMA

María is not an exception — she is the pattern

Women save formally far less than men

9.4pp

gap in formal savings accounts: 68.0% of men vs. 58.6% of women

ENIF 2024 · CNBV / INEGI · 2025

Credit pays off most for women — when it comes

+42%

sales growth of women-led Mexican firms two years after a fintech loan, vs. similar rejected firms

IDB INVEST · 2023

Most Mexican women have no credit file

63%

of women lack formal credit history, vs. 47% of men

CNBV · 2022

And the whole region mirrors it

73%

of women entrepreneurs across LatAm can't access financial-institution support

FAIR CENTER / PRO MUJER · 2023

Half of Mexico's microenterprises are women-owned or women-led. Behind each number: informal work bureaus can't see, unpaid care ≈ 21% of regional GDP, and property titled to men. · WWB / ILO / UNDP

Even when the system sees women, it discriminates

Less likely to be approved — identical loan requests, despite women's higher repayment rates

IDB · CHILE · 2020

14.8%

Of expected bank profits forgone because of taste-based discrimination

IDB · CHILE · 2020

9.9%

Higher annual interest paid by women on business loans in Honduras

WORLD BANK · 2022

+5.8pp

In Mexico specifically

Lenders offer women smaller amounts, shorter tenors, and higher rates and collateral requirements — even though half of Mexico's microenterprises are women-led.

IDB INVEST · 2023

It isn't ignorance — it's taste

In the Chilean experiment, showing loan officers women's actual (higher) repayment rates did not close the gap — the discrimination is taste-based, not statistical.

IDB · CHILE · 2020

Sources: Montoya, Parrado, Solís & Undurraga (2020), "Bad Taste: Gender Discrimination in the Consumer Credit Market", IDB Working Paper — field experiment, Chile ·World Bank Gender Data Portal (2022), Honduras ·IDB Invest (2023), Eliminating Gender Bias from Lending in Mexico

The bureau algorithm scores María

ILLUSTRATIVE EXAMPLE — NOT REAL DATA

Miguel — hardware shop

Mexico City · Age 34

Income: MXN 18,500 / mo

Debt: MXN 3,200

Credit bureau: thin credit history

Work record: continuous

Sector: Hardware, 4 yrs

Score: 674
APPROVED — MXN 50,000

María — textile workshop

Mexico City · Age 34

Income: MXN 18,500 / mo

Debt: MXN 3,200

Credit bureau: thin credit history

Work record: caregiving pause

Sector: Textile, 4 yrs

Score: 601
DECLINED

Where did her 73 points go?

−73 pts

Occupation code −31
Textile — a feminized sector — is classified "higher-risk" than hardware

Employment gap −24
Her caregiving pause is read as instability, not as life

Informal record −18
Her tanda savings and supplier credit are invisible to the bureau

None of these fields is gender — but sector codes, career gaps, and informality all track gender in Mexico.

The model never saw gender. It learned it anyway. *Identical income · debt · city · age · business tenure — using bureau data only.*

Three risks to watch in any “gender-blind” model

This talk is not about whether the new scoring works. It works. ***It is about whether it works fairly.***

1

Proxy Features

Historical credit data encodes gender — and models reproduce it through correlated features.

María's sector code and career gap did exactly this

2

Skewed Training Data

If 70%+ of training data is male, female patterns are systematically underfit.

e.g., a portfolio built when most borrowers were men

3

Construct Validity

Does the model measure repayment — or conformity to male norms?

e.g., “confidence” scores that penalize women’s realistic self-assessment

What if we could score ***who María is*** — not what her credit history says?

NEXT: PART 2
THE NOVEL DATA SOURCE →

PART 2 · THE NOVEL DATA SOURCE: TRAITS FROM THE PSYCHOMETRIC TESTS

A New Epistemology of Creditworthiness

Instead of asking what María has — psychometric scoring asks who she is.

A genuinely new class of data: behavioral and cognitive signals that exist even where files do not.

Two theories of creditworthiness: the file vs. the person

Traditional scoring — the file

- What you have — assets, history, collateral.
- Backward-looking — punishes past exclusion.
- Requires a formal financial footprint.
- Encodes historical inequality as “objective” risk.
- Data type: transactional records

★ Psychometric scoring — the person

- ✓ Who you are — stable personality & cognitive traits.
- ✓ Forward-looking — measures future behavior capacity.
- ✓ Works with zero bureau history (thin-file, unbanked).
- ✓ Breaks the circularity trap: score without prior credit.
- ✓ Data type: behavioral/psychological signals.

The novelty: measuring willingness and ability to repay independently of prior access to the financial system.

PART 2 · THE NOVEL DATA SOURCE: TRAITS FROM THE PSYCHOMETRIC TESTS

Six traits María already lives — now measurable

Conscientiousness

planning · reliability · follow-through

María: *four years of on-time supplier payments*

Self-control

resists impulse · avoids over-debt

María: *she has never missed a tanda contribution*

Locus of Control

"outcomes depend on my own actions"

María: *she rebuilt the workshop after every setback*

MARÍA'S CHARACTER

measured in a 10-minute game

Delayed Gratification

invest now for future payoff

María: *she reinvests every profit into fabric stock*

Fluid Intelligence

problem-solving · learning from feedback

María: *she adapts her designs to what sells each season*

Confidence / Self-efficacy

realistic sense of what you can execute

María: *she knows exactly how much she can repay*

She has been passing this test her whole life — no one was scoring it.

Begini: the company that could score María

How it works

Gamified mobile assessment

Short, adaptive tests via smartphone — optimized for emerging markets

Privacy-by-design

No name, age, or gender collected — only trait responses feed the ML pipeline

ML risk model

Traits → features → machine-learning model → a single risk score that complements underwriting

Who it serves

Thin-file borrowers in emerging markets

Entrepreneurs with limited bureau history across Latin America, Africa, and Asia

Lenders seeking safe growth

Banks, MFIs, fintechs expanding into new segments without increasing portfolio risk

A new 4-dimension evaluation standard

AUC is necessary — but no longer sufficient. Credit AI must be evaluated on four dimensions simultaneously.

Accuracy

AUC, Gini, KS — predictive power

Necessary but not sufficient

Fairness

Demographic parity + equal opportunity across gender

Declared + audited

Transparency

SHAP explainability — every decision is contestable

No black boxes in credit

Gender Awareness

Gender-blind ≠ gender-fair. Structural inequality must be actively countered

Design choice, not a gap

WHY HOLD ALL FOUR AT ONCE?

Because a credit model is not just a prediction engine. It is a gate to economic participation — and gates are held to a higher standard.

Maria was always creditworthy.

The question was never whether she could repay; it was whether our models could see it.
Psychometric scoring finally sees her. Built gender-aware, it also scores her fairly.

Judge credit AI not only on whether it predicts defaults, but on who it sees, who it excludes, and whether that exclusion is just.

Accuracy is a metric; fairness is a decision.

HORA DE PREGUNTAS

- Medium: MFrancys

Linkedin: Maria Francys Lanza Garcia

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