Operationalizing Critical Data Approaches in Fraud Detection in Latin America

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Abstract

This study investigates the challenges and sociotechnical dimensions of cross-border AI deployment, focusing on fraud detection products entering Latin American markets. Through semi-structured interviews with 18 industry practitioners, we examine how AI systems trained primarily on Global North data can reproduce and amplify existing inequalities when deployed in diverse cultural contexts from the one it was originally designed. By analyzing these dynamics through lenses of algorithmic fairness, critical data studies, and science and technology studies, we identify three key sociotechnical challenges: technical-cultural misalignment, socioeconomic stratification effects, and problematic model behavior assumptions. Our findings reveal how standardized approaches to fraud detection can systematically disadvantage certain populations, particularly those with limited digital footprints. We translate these theoretical insights into practical recommendations for industry practitioners, contributing to ongoing conversations about responsible AI deployment across diverse contexts. This work bridges the gap between abstract fairness principles and concrete implementation challenges, advocating for a contextual approach to AI governance that prioritizes local knowledge and inclusive design.

Introduction

Financial fraud presents a significant challenge for companies operating in Latin America and the Caribbean (LAC), a region with a unique socioeconomic and technological landscape. Despite growing adoption of digital financial services and advanced fraud detection systems, these technologies often underperform in LAC markets. This performance gap reveals a critical disconnect between fraud detection product design and the region's specific cultural, infrastructural, and socioeconomic conditions. Drawing on Science and Technology Studies (STS), we frame fraud detection as a sociotechnical challenge requiring more than purely technical solutions. To examine this phenomenon, we conducted an ethnographic study embedded within industry, involving months of fieldwork, multiple interviews with practitioners, and qualitative data analysis. Through this immersive approach, we developed a framework that enabled us to translate STS insights into industry-relevant language and solutions that proved acceptable to corporate stakeholders.

This paper aims to: (1) analyze the challenges facing fraud detection systems in LAC markets, (2) present findings from our industry ethnography and demonstrate how STS perspectives can be effectively translated for industry application, and (3) propose actionable solutions for improving system performance in the region. Through ethnographic embedding, we identify key issues including data gaps, socioeconomic bias, and cultural misalignment in existing fraud detection products. We conclude by providing strategic recommendations for creating fraud detection systems better aligned with LAC realities.

We position our research as a contribution to understanding the importance of the problem formulation phase of AI/ML system development, where foundational decisions about what to build, for whom, and why are established. We recognize that problem formulation is not merely a technical translation of real-world needs, but a sociotechnical process shaped by organizational priorities, stakeholder negotiations, and informal reasoning. As such, we argue that fairness considerations must begin upstream (Passi and Barocas 2019), during problem definition, rather than being retrofitted during later stages such as model training or evaluation. This research bridges academic and industry perspectives, connecting theoretical analysis with operational implementation to advance a context-sensitive (Selbst et al. 2019) and practice-aware approach to fairness (Kennedy and Campos 2025; Brown et al. 2025).

The following sections provide an overview of the LAC region's fraud detection landscape, detail our research methodology, present our findings on product performance challenges, discuss broader implications, and conclude with actionable recommendations for improving fraud detection effectiveness in the region.

Financial Fraud in LAC

Latin America faces severe financial fraud challenges, with the highest global rates of credit card fraud—20% of ecommerce revenue lost to fraud and 3.7% of orders being fraudulent (Mastercard 2024). Each fraudulent transaction costs 3.68 times the value lost, including fees, penalties, labor, and recovery costs (LexisNexis 2021). The region's rapid financial transformation has created both opportunities and vulnerabilities. Brazil's Pix payment system, handling 36% of electronic transactions (de Andrade and da Cruz 2025), exemplifies successful digital adoption but has seen rising authorized-push payment (APP) scams, with Brazilians losing nearly $247 million in 2022 (ACI Worldwide 2023). Meanwhile, fragmented identity systems complicate verification efforts—Brazilians may hold multiple identification documents across different states, creating openings for identity theft (Peirano 2009; Arner et al. 2019; LoPucki 2001; Torres et al. 2016).

Financial inclusion has improved significantly, with unbanked populations decreasing from 45% to 21% between 2020-2023 (Mastercard and Americas Market Intelligence 2023), driven by government initiatives including digital assistance programs and social savings accounts (Rousset et al. 2021; de Olloqui, Andrade, and Herrera 2015). However, this digitalization intensifies fraud challenges, requiring continuous innovation in detection technologies and regulatory frameworks (Gandhi and Gajjar 2024). Current academic literature predominantly focuses on technical aspects like algorithm optimization and model performance (Santiago, Pereira, and Hirata 2015; Torres and Ladeira 2020; Lima and Pereira 2015). Research has examined algorithmic unfairness in machine learning models, categorizing data bias types and fairness-accuracy trade-offs (Pombal et al. 2022; Pagano et al. 2023). However, few studies address regional fraud challenges from a sociotechnical perspective—considering how technological systems interact with social, cultural, and economic contexts.

Methodology

Research Questions

The investigation of this problem is driven by two critical research questions (RQs) that address both the practical and theoretical dimensions of deploying fraud detection systems in the Latin American (LAC) market:

RQ1: How can we improve product performance as we enter the LAC market? This question focuses on understanding and overcoming the challenges that fraud detection products face when entering the LAC market. Latin America represents a unique and diverse landscape with distinct socioeconomic, cultural, and technological characteristics that significantly influence the effectiveness of fraud detection systems. Addressing this question is essential for identifying actionable strategies to enhance product adaptability, efficiency, and relevance in this region.

RQ2: How can we address issues related to socioeconomic bias, data coverage, and model training? This question focuses on the systemic and structural challenges that underlie the performance of fraud detection models in the LAC market. The presence of socioeconomic bias in data, insufficient local data coverage, and inadequate model training are critical barriers that limit the effectiveness and equity of these systems. Investigating these issues through this research question allows us to explore solutions that prioritize fairness, inclusivity, and accuracy, ensuring that fraud detection systems work effectively for most demographics within the region.

Positionality Statement

This research was enabled by a large multinational corporation that creates fraud models and is committed to improving its fraud detection products in underserved markets. Recognizing the critical need to address challenges unique to diverse regions, the company funded this research and embedded an academic ethnographer.

Collection Method

Pilot Interviews

At the outset of this research, we explored the fraud landscape in Latin America and the performance of fraud detection products in the region. We conducted 10 pilot interviews with colleagues based in or actively engaged with the region to identify relevant products for our study, map research topics, and identify key stakeholders for subsequent structured interviews. These conversations provided qualitative data through shared experiences and narratives about fraud in Latin America. Analysis revealed recurring themes including product and model performance, data quality challenges, and regional client needs differences.

To enable in-depth analysis, we narrowed our focus to two products: one using identity verification with personal data for decision-making, and another utilizing transaction data. This selection allowed us to compare different data structures and approaches in the Latin American market and identify potential challenges each product might face. These preliminary findings informed our structured questionnaire for subsequent investigation.

Structured Interviews

We developed a ten-question questionnaire, as shown in Table 1, that was meant to be conducted semi-structured during a one-hour-long interview. We adapted the focus of the discussions based on the person being interviewed, so if someone were on the data strategy team, we would focus more on data-related issues; if someone were on a products team, we would focus more on product-related issues, and so forth.

Thematic Category	Question	Preliminary Codes
Product Experience & Outcomes	How do you perceive the fraud detection, prevention, or protection products you have worked on? Can you provide specific examples of successful outcomes?	-Positive experiences (POS) -Negative experiences (NEG) -Success examples (SUCCESS) -Failure examples (FAILURE)
Company Action Steps	What do you think are the most important steps the company should take regarding the issues with data/products in LAC?	-Product improvement (PROD_IMP) -Data-related improvements (DATA_IMP) -Process improvements (PROC_IMP)
Challenges with Models/Data	Can you describe any challenges or limitations you've encountered with models or datasets when working with Latin American clients?	-Data limitations (DATA_LIM) -Model limitations (MODEL_LIM) -Client-specific issue (CLIENT_ISSUE)
Success/Failure Factors	In your experience, what are the key factors that contribute to the success or failure of fraud detection and prevention efforts in Latin America?	-Key success factors (KSF) -Failure factors (FAIL_FACTORS) -Regional differences (REG_DIFF)
Cultural/Regional Differences	Have you observed any cultural or regional differences in the effectiveness of the products you have worked on? If yes, do you have any ideas or suggestions on how this can be improved?	-Cultural challenges (CULT_CHALL) -Regional adjustments (REG_ADJ) -Improvement suggestions (SUGG_IMP)
Bias	Have you collaborated with other departments or external partners to enhance fraud detection and prevention capabilities in Latin America?	-Bias in models (MODEL_BIAS) -Bias in data (DATA_BIAS) -Mitigating Bias (MITIGATE_BIAS)
Insights/Feedback	Can you share any insights or feedback gathered when dealing with Latin America regarding fraud protection/detection products?	-Specific feedback (SPEC_FEED) -Specific insight (SPEC_INSIGHT)
AI, Technology and Regulation	How do you envision the future of fraud detection in Latin America, considering evolving technologies and regulatory landscapes? Do you think AI plays an important role in this future?	-Role of AI (AI_ROLE) - Technology advancements (TECH_ADV) -Regulatory influence (REG_INF)
Inclusivity, Diversity, and Fairness	What strategies do you think would be effective in ensuring the inclusivity and fairness of fraud protection, detection, and prevention measures across the diverse populations of Latin America?	- Fairness strategies (FAIR_STRAT) - Inclusivity concerns (INC_CONC) - Diverse populations (DIVERSE_POP)

Table 1: Preliminary questions and codes for interviews

Coding Method

The interviews were recorded and transcribed. We analyzed transcripts of the interviews using Atlas.ti software, employing open coding within a grounded theory framework (Hwang 2007; Nanez Silva et al. 2024). This approach al- ˜ lowed us to break down qualitative data into discrete parts and identify emergent concepts without predefined structures. We then conducted thematic analysis (Clarke and Braun 2016; Herzog, Handke, and Hitters 2019) to systematically identify patterns across the data. Both methodologies leverage inductive reasoning to derive insights directly from the data (Fereday and Muir-Cochrane 2006). This analytical foundation informs our findings on challenges, opportunities, and contextual factors affecting product performance in the LAC region.

Additional Information on Participants

The participants in these conversations were employees of a large technology company that develops fraud products who had experience in product development, deployment, and ongoing operation. These participants were selected for their position as operators of fraud systems as boundary objects (Gal et al. 2008).

Findings

Product Selection

This study analyzes two widely deployed fraud detection products developed by a major financial service company. Both products operate across multiple Latin American markets, despite being initially designed and trained primarily on North American transaction patterns.

Product A provides identity verification through APIs, focusing on preventing fake accounts and transaction fraud. It analyzes patterns across four domains: device signatures, personal information, behavioral patterns, and payment data. The system leverages anonymized data from millions of monthly queries across over 200 countries to construct predictive models distinguishing fraudulent from legitimate interactions.

Product B specializes in real-time transaction authorization, employing machine learning models trained on global transaction data. These models evaluate thousands of data points per transaction—including contextual information, customer history, and geographic patterns—to generate risk scores guiding authorization decisions.

Both products share a common architectural approach: they use machine learning models trained on large-scale datasets to generate risk scores, which are then used by financial institutions to make authorization decisions. However, this approach raises important questions about the transferability of fraud detection systems across different cultural and economic contexts. For instance, what constitutes "suspicious" behavior in one region may reflect common legitimate practices in another. This standardized approach to fraud detection, while technically sophisticated, provides an important case study for examining how cultural assumptions become embedded in algorithmic systems and the challenges that arise when deploying these systems in regions with different financial practices and social norms.

Product Findings

Our investigation of two fraud detection products in LAC revealed how technical systems designed for global markets can systematically fail to account for local realities. The findings reveal patterns of misalignment that transcend individual product limitations, pointing to broader structural challenges in adapting financial security technologies across diverse regions. We present these findings through excerpts of the interviews and divide them into three interconnected themes: technical-cultural misalignment, socioeconomic stratification effects, and problematic model behavior assumptions. Each theme represents a distinct dimension of the sociotechnical gap between product design and regional context, collectively explaining the observed performance disparities in LAC markets.

Technical-Cultural Misalignment

Both products demonstrated how technical architectures can encode cultural assumptions that create friction in new contexts. The first product, despite being well-established in the region, struggled with update cycles that didn't match local fraud patterns. As one product team member explained about Product B:

> "This transaction score is updated recurrently. And here, adding a bit of my opinion, my perception is that it's not recurrently enough, because we see clients complaining about a drop in the performance of the (transaction) score. Only after we notice this drop do we take action to try to improve it. There could also be a bit of bias associated with it. We typically use standard models for the market. (…) However, we see that this is not always ideal in Brazil, and we need to bring in specific modelling for some clients."

Product A's challenges stemmed from assumptions about data standardization. A team member highlighted how even basic data normalization encoded cultural assumptions:

> "But it's not just about culture; it's also about the technical aspects of the product. For example, with Product A, a key part of the process is data normalization. I might receive an address that I need to normalize so it becomes a kind of unique entity within our system. However, the way addresses are formatted in Brazil is different from how they're formatted in Argentina, which is very different from how they're formatted, for instance, in the United States."

Socioeconomic Stratification Effects

Our research revealed how fraud detection systems can systematically exclude lower-income populations. This was particularly evident in the second product's deployment, where initial data collection focused on internationally active users. As one team member noted:

> "Our data acquisition up until now seems to have had a significant bias toward people from higher economic brackets—people who are more digitalized, perhaps. This creates a strong correlation with socioeconomic status. When I start talking to local clients, for instance, about the unbanked population, or small business owners like the MEI (Brazil's Individual Micro-Entrepreneurs), these individuals don't exist in our database because we've been looking at a completely different population."

This exclusion had concrete impacts on product effectiveness. A particularly striking example came from a client-facing team member describing experiences in the city of Fortaleza, Brazil:

> "The population served by this client, which is in the city of Fortaleza, state of Ceará, is of very low socioeconomic status, extremely low. They are unbanked. Their information is not available from most providers... And what kind of data do they have? It's data that isn't compatible with the majority of the global population. They don't have a frequently used email. Their names are often misspelled, or they change their names—sometimes using a social name (…). They don't have a phone number—or if they do, the phones are prepaid, and they change their SIM cards all the time."

Model Behavior Assumptions

Both products encoded assumptions about "normal" versus "suspicious" behavior that didn't align with local realities. This was evident in how Product B struggled with sophisticated regional fraud patterns:

> "You would see like an extensive like high volume attack across the basket of merchants... So, you would see like a huge attack and then hours of dormancy, and then those cards would just show up like all over the country in card present transactions like on actual plastic... those kinds of patterns are super interesting and they're very difficult to stop."

Product A's global model architecture created systematic bias against Brazilian users:

> "In Brazil, the model was basically incrementing Brazilian IP's. So even though Ana may have connected to that Brazilian IP multiple times, just the fact that it was in a Brazil geolocation and fraud is higher in Brazil, the model was elevating it as part of the distribution to put it higher... we don't create regional models, we create global models."

Analysis and Discussion

This section synthesizes our empirical findings within broader theoretical frameworks to illuminate the sociotechnical challenges of deploying global fraud detection systems in Latin America and the Caribbean. Our analysis bridges theoretical perspectives with practical implications, revealing how standardized approaches to fraud detection can systematically fail when confronting regional complexities. By integrating these frameworks, we aim to develop a more nuanced understanding of fraud detection as a sociotechnical process shaped by cultural contexts, economic structures, and institutional power relations.

Conceptual framework

Legibility and Data Standardization

We understand data standardization as a matter of legibility (Levine and Scott 1999; Lee and Zhang 2017; Yoffee 2001) and the way companies render individuals "legible" is through data collection and algorithmic systems. In contemporary data economies, data gaps create systematic invisibility for certain demographics—often marginalized communities with limited digital footprints or from historically deprioritized markets. This invisibility has profound consequences: machine learning models trained primarily on data from "legible" populations inherently reproduce these gaps, reinforcing existing disparities and limiting access to financial services and opportunities. This perspective moves beyond technical discussions of algorithmic bias to examine structural forces determining which populations are seen and served by data systems, suggesting that addressing fairness requires not just gathering more data, but critically examining what kinds of data or features are considered relevant when working with "illegible" populations.

Building on this framework, our findings reveal multiple complex manifestations of this legibility process in practice. The standardization of identity verification, exemplified by Product A's attempts to normalize address formats across countries, demonstrates how corporate systems impose uniformity on local variations. As one interviewee noted, "the way addresses are formatted in Brazil is different from how they're formatted in Argentina," highlighting the friction between global standardization and local practice.

The implications of legibility become particularly stark in our Fortaleza case study, where populations remain fundamentally "illegible" to corporate fraud detection systems. Local financial practices, such as frequent SIM card changes or shared utility bills, fall outside the standardized frameworks of global fraud detection, resulting in dramatic exclusion, with "only 5% of them [being captured] through the API." This illegibility extends to sophisticated regional fraud patterns, as evidenced by the "card present" attacks described in our interviews.

Model Accuracy and Localized Deployment

The statement, “This product doesn’t work in Brazil,” emerged early in the research, even before formal interviews, and became a critical point of inquiry: why was the product underperforming in Latin America (LAC)? Initial assumptions about data quality failed to fully explain the gap between the model’s reported high-performance metrics and client dissatisfaction. Interviews with key stakeholders, including data scientists, revealed that while accuracy metrics indicated strong performance, client feedback consistently contradicted these findings, highlighting a disconnect between technical metrics and real-world outcomes. This emphasizes the importance of the problem formulation phase as explained by (Selbst et al. 2019; Passi and Barocas 2019) and reflects challenges where mismatches between user-focused and model-focused metrics and communication gaps often hinder industrial ML teams.

An incident during the launch of the product in LAC further underscored these issues. The model initially flagged nearly all IPs (Internet Protocol Address) from Latin America as high-risk, a sweeping and implausible categorization. Though quickly resolved, this anomaly highlighted the need for robust data frameworks that account for regional nuances, aligning models with localized realities and client expectations. Research supports this, with (Nogare et al. 2024) emphasizing continuous monitoring and risk management frameworks, and (Mancilla-Caceres and EstradaVillalta 2022) discussing ethical considerations in Latin America, such as power imbalances. Similarly, (Oluka 2024) highlights the importance of incorporating local values to mitigate bias and enhance effectiveness in diverse global contexts and (Okolo, Dell, and Vashistha 2022) advocate for robust data frameworks and human-centered approaches to ensure AI aligns with localized realities in the Global South.

Adopting comprehensive data quality frameworks, such as the one developed by (Wang and Strong 1996), which emphasizes intrinsic, contextual, representational, and accessibility dimensions of data quality, can help address these challenges effectively during the AI lifecycle as suggested by (Priestley, O’donnell, and Simperl 2023).

Socioeconomic Bias in Technical Systems

Our analysis reveals the multifaceted ways socioeconomic bias (Herzog 2021) becomes embedded in fraud detection systems through technical design choices. The data collection process itself introduces systematic bias, with our interviews revealing a persistent skew toward “higher economic brackets—people who are more digitalized.” This initial bias creates a feedback loop where models continually improve their performance for privileged populations while failing to serve others.

This bias manifests deeper in the technical architecture through feature engineering decisions, where the selection of fraud indicators implicitly encodes assumptions about financial stability. The reliance on stable addresses and consistent phone numbers as signals of legitimacy systematically disadvantages populations experiencing economic precarity. Furthermore, the global risk scoring system’s tendency to penalize Brazilian IPs demonstrates how technical architectures can amplify regional inequalities.

This aligns with findings in (Olteanu et al. 2019) and (Shahbazi et al. 2023), which emphasize how unrepresentative datasets and representation bias can lead to AI solutions that fail diverse populations. The product could reliably verify high-income individuals but struggled with lower income demographics, which mirrors (Singh et al. 2024) observation that AI systems often reinforce inequalities by failing to address the needs of disadvantaged groups. Addressing such biases requires a socio-technical approach that goes beyond performance metrics to consider real-world impacts and structural discrimination (Clavell, Aumaitre, and Calders 2024).

A major contributing factor is the limited availability and quality of outcome data from clients; an issue particularly pronounced in Latin America. Outcome data is often incomplete or infrequent, making it unreliable for retraining models to reflect regional realities. This exacerbates performance issues and underscores systemic inequalities, as noted by (Hargittai 2015). Furthermore, (Arora 2016) cautions that big data in the Global South often risks being framed as a tool for empowerment while failing to address critical perspectives needed for meaningful societal impact.

Critical Data Studies and Power Dynamics in Fraud Detection

Through the lens of critical data studies (Iliadis and Russo 2016; Neff et al. 2017), our research demonstrates the complex power dynamics inherent in global fraud detection systems. The privileging of international transaction data over local financial behaviors reflects broader Global North-South power relations, embedding colonial patterns of knowledge validation into technical systems. This asymmetry manifests in the fundamental assumptions about what constitutes “normal” versus “suspicious” behavior, where global standards derived from Northern contexts become the implicit benchmark against which all financial activities are judged.

These power dynamics extend into the data infrastructure itself, as evidenced by the systematic challenges in obtaining quality outcome data from LAC clients. This infrastructure gap reveals how global inequities in technical capacity and data collection capabilities reproduce existing power imbalances, creating a self-reinforcing cycle where Northern technical standards continue to dominate global fraud detection practices.

Addressing Regional Challenges Through Inclusive AI Practices

To address the challenges faced by the product in the Latin American market, the organization formed a dedicated work group focused on regional issues. The composition of the work group reflected the company's commitment to fostering diversity, comprising professionals based in Latin America alongside members of the global team. This diversity brought invaluable cultural insights, as interviews revealed the importance of understanding context and the cultural nuances from different countries within the LAC region.

Studies support the importance of diversity and inclusion (D&I) in AI system design to address fairness, trust, bias, and transparency issues (Constantinides et al. 2024; Hagendorff 2020), with neglect leading to risks like digital redlining and algorithmic discrimination (Singh and Park 2022).

This effort aligns with responsible AI (RAI) frameworks, for example, (Constantinides et al. 2024) propose dynamic guidelines to enhance collaboration, while (Lu, Raji, and Mitchell 2022) advocate for sociotechnical approaches, and (Mancilla-Caceres and Estrada-Villalta 2022) emphasize addressing ethical and power dynamics, especially in structurally unequal regions like Latin America. Achieving fairness also requires overcoming barriers to interdisciplinary collaboration. Practitioners often perform "bridging work" to address fairness within constraints, relying on existing practices like privacy assessments, though these approaches have limitations (Deng et al. 2023). Supporting this labor is essential for sustainable fairness in AI.

By embedding these principles, the work group moved beyond technical metrics to address broader sociotechnical factors crucial for AI fairness and effectiveness. Reviews of D&I in AI systems stress aligning fairness and accountability with practical frameworks, such as ethics checklists (Okolo, Dell, and Vashistha 2022), and offer strategies for integrating inclusivity into AI processes (Shahbazi et al. 2023). This initiative underscores the value of inclusive, culturally informed strategies in global AI deployment and offers a roadmap for incorporating sociotechnical considerations into practical, adaptable frameworks.

Recommendations and Future Work

Recommendations for Product Teams

Our findings and theoretical analysis suggest several key interventions for fraud detection product teams operating in LAC markets. The systematic exclusion of certain populations calls for a fundamental restructuring of data collection practices. Product teams should develop partnerships with local data providers who specifically serve underbanked populations, while implementing regular demographic audits of their training data. These audits should examine not just technical performance metrics but also patterns of exclusion across different socioeconomic groups.

The challenge of corporate legibility demands changes to model development practices. Rather than attempting to impose global standardization, teams should create flexible architectures that can accommodate local variations in financial behavior. This includes developing region-specific performance benchmarks and incorporating cultural expertise early in the model development process. Teams should also establish formal processes for incorporating local market feedback, moving beyond traditional performance metrics to consider how models interact with local financial practices.

Organizations must also address structural barriers to equity in their fraud detection systems. This requires establishing dedicated cross-functional teams that combine regional expertise with technical knowledge. These teams should have the authority to modify global models when they create systematic disadvantages for specific populations. Additionally, organizations should invest in building stronger relationships with local financial institutions to better understand regional needs and fraud patterns.

Future Research Directions

Our investigation reveals several promising areas for future research at the intersection of technical systems and cultural context. Theoretical work is needed to further develop the concept of corporate legibility, particularly examining how private sector algorithmic systems differ from state standardization efforts. Researchers should investigate how power dynamics influence the transfer of financial technologies across borders, and how different cultural contexts interpret and adapt global technical standards. Empirical research is needed to track how fraud patterns evolve in response to detection systems, particularly in regions with significant informal economies. Comparative analyses of fraud detection system performance across different cultural contexts could help identify which technical approaches are most adaptable to local conditions. Additionally, detailed case studies of successful adaptations of fraud detection systems to local contexts would provide valuable insights for both practitioners and researchers.

Finally, interdisciplinary research is needed to bridge the gap between technical capability and cultural understanding. This includes developing new evaluation frameworks that can capture both technical performance and cultural appropriateness, as well as investigating how local financial practices could inform the design of more inclusive fraud detection systems. Such research would contribute to both the theoretical understanding of sociotechnical systems and the practical improvement of fraud detection in diverse cultural contexts.

Conclusion

This research demonstrates that improving fraud detection in Latin America requires more than technical optimization—it demands a fundamental rethinking of how cultural assumptions become embedded in algorithmic systems. Our findings reveal how standardized approaches to fraud detection can systematically disadvantage certain populations, particularly when systems trained on Global North data are deployed in Global South contexts.

The challenges we identified—from socioeconomic bias in data collection to the misalignment between model assumptions and local financial practices—highlight the importance of incorporating sociotechnical perspectives into fraud detection system development. By examining these challenges through the lenses of legibility, socioeconomic bias, and critical data studies, we provide both theoretical insights and practical guidance for improving system performance. Most importantly, our research shows that creating more equitable fraud detection systems requires sustained engagement with local contexts and communities. The path forward involves not just technical innovation, but a deeper commitment to understanding and respecting the diverse ways that people engage with financial systems across different cultural contexts.

As financial services continue to digitalize globally, the lessons learned from this study have broader implications for how we design and deploy algorithmic systems across cultural boundaries. Future work in this area must continue to bridge the gap between technical capability and cultural understanding, working toward fraud detection systems that are both effective and equitable.

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