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REPORT

Fairness and Accountability for Algorithms in Financial Services

Addressing Bias and Discrimination to Prevent Digital Redlining

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Overview

How can credit unions differentiate on trust? This report reviews a key area where trust is increasingly at a premium: the use of consumers' data in algorithmic credit scoring. With this change comes new questions and concerns, especially about the potential for bias and discrimination in algorithmic underwriting.

MEET THE AUTHORS

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Consumers have expressed distrust in the financial services industry while also indicating a high degree of trust in their own primary financial services provider. Given the rise in use of alternative data for credit scoring, credit unions have a responsibility to ensure that bias and discrimination do not occur while implementing algorithmic underwriting. With the rapid advancement of technology, the time to build authentic trustworthiness and consider the ethics of algorithmic decisionmaking is now.

What Is the Research About?

This report reviews a key area where trust is increasingly at a premium: the use of consumers' data in algorithmic credit scoring. The promise of new forms of data-driven credit scoring is that the risk of lending to whole segments of the population currently excluded from financial services because of a lack of a credit score will now be able to be priced. This has the potential to vastly expand access to financial services. It also poses new challenges. While the use of algorithms to assess credit risk is not new, it has changed dramatically with the increase in the amount and diversity of personal data, the emergence of new algorithmic systems (sometimes based on machine learning techniques), and the growth in the importance of household debt to people's financial lives.

Algorithmic credit scoring presents new questions and concerns, especially about the potential for bias and discrimination in algorithmic underwriting. There is growing evidence that automating credit and other kinds of financial decisions may perpetuate long-standing kinds of inequality and exclusion, despite efforts to the contrary. Yet there is hope, as researchers have begun to devise methods to tackle the challenge of holding algorithmic systems to shared standards of fairness and accountability.

What Are the Credit Union Implications?

Credit unions are only just beginning to assess the opportunity to use their members' data in algorithmic systems of all kinds, from fraud protection to underwriting to service interactions through chatbots and the like. Many credit union leaders feel that the implementation of any such algorithmic system is years away. But the time to consider the ethics of algorithmic decisionmaking is now. This is because building authentic trustworthiness is a long-term process. When it comes to trust in the uses of personal data, it has to start from the beginning, in the creation of data governance and management systems. The opportunity to differentiate on trust will not wait.

It is important to remember that credit unions have always provided services to consumers otherwise excluded from the financial system. They have done so through traditional underwriting and bold, mission-driven decisions like no-credit-check, small-dollar loans for members in good standing.

Because of the high risks of alternative credit scoring contributing to "technological redlining," credit unions must acknowledge this history in the United States and take steps to ensure that there is equity in their lending practices whether or not they use alternative data.

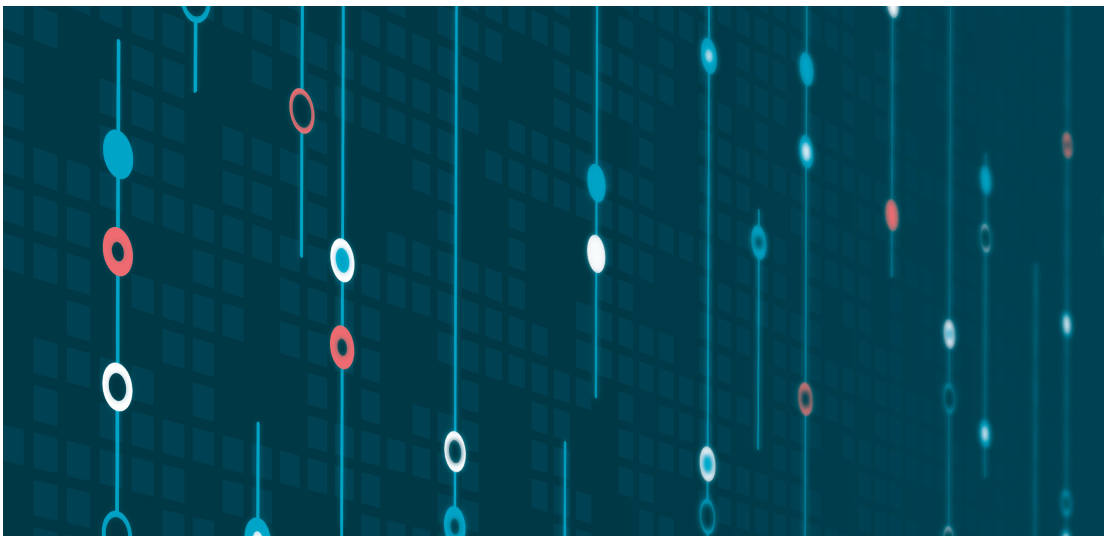
Credit unions are in a unique position to establish industry standards for algorithmic audits. First, as financial services become more explicitly driven by the use of consumer data, the security, transparency, and accountability of the organizations that have access to that data become paramount. Second, there will be a regulatory push at some time, in some form, to protect consumer data; credit unions must get out ahead of this curve to help shape the regulatory landscape, rather than be shaped by it.

In evaluating data governance plans and algorithmic financial services, credit unions need to address the following challenge areas:

- **Explanatory Power.** Maintain a clear sense of the gaps and limitations in these analytics.
- **Social Discrimination.** Machine learning systems must be designed to actively seek out, identify, and eliminate social inequalities.
- **Privacy.** Members must be given a choice about how their data is collected, used, and potentially exposed. To be meaningful, choice requires two things: consent and transparency.
- **Auditing.** Establish industry standards that shift the burden of proof from those claiming harm from artificial intelligence (AI) systems to those who own and operate these systems.
- **Entrenching Inequality.** Exercise caution: alternative scores risk reinforcing social discrimination by perpetuating bias and can further entrench social inequality because of the perceived objectivity of algorithmic processes.

Fairness and Accountability for Algorithms in Financial Services

Addressing Bias and Discrimination to Prevent Digital Redlining



CHAPTER 1

Introduction

Coercion is essential to the manner in which the "gift" is created. People must compel others to enter into debt: an object in the regard of one actor must be made to become an object in the regard of another. The magic of the gift economy, then, lies in successful persuasion. —MARILYN STRATHERN, "QUALIFIED VALUE: THE PERSPECTIVE OF GIFT EXCHANGE," 1992: 177

Trust is central to our relationships with friends, neighbors, distant strangers, organizations, institutions, governments, markets, and technology. Almost everything we do involves an implicit act of trust—from drinking a glass of water from a bottle or a faucet, to crossing a street, to using the Internet. While trust was always important in consumer finance, it has seemingly become even more significant in recent years. We seem to live in a world of increasing distrust. Equipment fails, databases are breached, misinformation spreads.

There is no shortage of proclamations about the disappearance of trust. The Edelman Trust Barometer, an annual survey of more than 30,000 respondents around the world, argues that only 1 in 5 people "believe that the system is working for them."[1] Financial services is the least trusted sector measured by Edelman, and new financial services innovations designed to expand access and meet evolving consumer technology expectations—like robo-advisers, peer-to-peer transactions, and mobile wallets—are among the least trusted areas.[2]

Trust, some say, is therefore a business frontier. It is also at the center of credit unions' mission and their value proposition.

Even as many consumers express distrust in the financial services *industry*, they also indicate high degrees of trust in their own primary financial services provider. One reason for this "trust paradox," as Ernst & Young (EY) calls it, is the growing importance of data in financial services.[3] That is, while consumers remain attached to financial institutions in terms of those institutions' banking capacity, they are growing increasingly—and rightfully—concerned about data security, data sharing, and the unethical uses and misuses of data by technology companies and other organizations that impinge on their financial lives.

This presents both a social challenge and a business opportunity. Consumers are not averse to sharing their data to be used by their bank or credit union—but they expect to see something of value in return. There is increasing consumer demand for financial services providers that offer not simply data security and privacy protections but comprehensive transparency and control over how consumer data is collected, shared, and used.
In fact, EY estimates that the emergence of new services with clear features of data trustworthiness—the ability to decide who uses personal data, guarantees not to share personal data beyond what is consented to, and so on—will result in the movement of $11.3 trillion in assets over the next five years.

How can credit unions differentiate on trust?

How can credit unions differentiate on trust? In this report, we review a key area where trust is increasingly at a premium: the use of consumers' data in algorithmic credit scoring. The promise of new forms of data-driven credit scoring is that the risk of lending to whole segments of the population currently excluded from financial services because of a lack of a credit score will now be able to be priced. This has the potential to vastly expand access to financial services. It also poses new challenges, however. We show, in particular, that while the use of algorithms to assess credit risk is not new, it has changed dramatically with the increase in amount and diversity of personal data, the emergence of new algorithmic systems (sometimes based on machine learning techniques), and the growth in the importance of household debt to people's financial lives. We are still in the wake of the 2008 financial crisis, which has shaped a generation's financial perspectives and habits as well as altered people's visions of the good life and their planning of their own personal futures. We are also in the middle of a tech boom (or bubble), in which machine learning and AI promise fantastic leaps forward in everything from health care to transportation to financial services. Fintech and alternative credit scoring are part of this new world.

With this change comes new questions and concerns, especially about the potential for bias and discrimination in algorithmic underwriting. There is growing evidence that automating credit and other kinds of financial decisions may perpetuate long-standing forms of inequality and exclusion, despite efforts to the contrary. Yet there is hope, as researchers have begun to devise methods to tackle the challenges in holding algorithmic systems to shared standards of fairness and accountability. These challenges include:

- Explanatory power.
- Social discrimination.
- Privacy.
- Auditing.
- Entrenching inequality.

There is growing evidence that automating credit and other kinds of financial decisions may perpetuate long-standing forms of inequality and exclusion, despite efforts to the contrary.

It is important to remember that credit unions have always provided services to consumers otherwise excluded from the financial system. They have done so through traditional underwriting and bold, mission-driven decisions like no-credit-check, small-dollar loans for members in good standing. In this sense, credit unions compete with alternative financial services providers. Historically, this has meant payday lenders and the like, but with the rise of data-driven fintech, there's a lot more, and much different, competition.

It is important to remember that credit unions have always provided services to consumers otherwise excluded from the financial system.

Credit unions are only just beginning to assess the opportunity to use their members' data in algorithmic systems of all kinds, from fraud protection to underwriting to service interactions through chatbots and the like. Many credit union leaders feel that the implementation of any such algorithmic system is years away. But the time to consider the ethics of algorithmic decisionmaking is now. This is because building authentic trustworthiness is a long-term process. When it comes to trust in the uses of personal data, it has to start from the beginning, in the creation of data governance and management systems. The opportunity to differentiate on trust will not wait.

The time to consider the ethics of algorithmic decisionmaking is now. This is because building authentic trustworthiness is a long-term process.

CHAPTER 2

Credit and Crisis: Three Historical Moments

Credit scoring is a way of managing risk. How likely is an applicant to default on a loan? Is that a risk a lender is willing to take? A "traditional" credit score is comprised of the following:

- Payment history.
- Accounts owned.
- Length of credit history.
- Credit mix (or type of credit in use).
- New credit.

Though this seems simple enough, it took centuries for people to conceptualize the risk of lending this way. And it happened not only because of new recording technologies, new financial products, and changing societal norms, but also in response to various crises. In US history, efforts toward instituting a more systematic means of assessing risk and managing the uncertainty of repayment developed in response to financial crises. We review three periods in US history to illustrate. This schematic history will help situate contemporary moves to further automate the credit scoring process through the use of artificial intelligence.

The Panic of 1837: Capital, Capacity, and Character

In 1837, the United States experienced a financial crisis, commonly referred to as the Panic of 1837, that led to a long recession. In part because of speculative lending practices that reduced monetary reserves,[4] the Panic led to what some have termed the United States' "first Great Depression."[5] In the wake of the crisis, legislation was passed to allow debtors to voluntarily file for bankruptcy and have their debts discharged. This sent many creditors themselves into a panic about the prospect of universal debt pardon and prompted lenders to ask a new question: Which borrowers could they trust?[6]

In 1841, a silk wholesaler in New York City named Lewis Tappan capitalized on creditors' fears by establishing the Mercantile Agency, an organization that centralized information about potential customers and sold it to subscribers. The Mercantile Agency relied on a network of attorneys who, in exchange for referrals on local debt collections they could prosecute, would file reports on what became known as the "three Cs": capital (or assets), capacity (or profitability), and character (or reputation). The anecdotes, hearsay, and local rumors that attorneys scooped up were transcribed by hand into massive ledgers that then became an "independent" point of reference for assessing potential customers. In seeking to institute a national system of credit checking, the Mercantile Agency (and competitors that followed, like Bradstreet) made not just a system of recordation, therefore, but created a new form of abstracted financial identity that could be represented by those three Cs.[7]

FIGURE 1

MERCANTILE RATINGS: "INDISPENSABLE TO BUSINESS"

The Mercantile Agencies.

They Have Grown Indispensable to Business.

WITHOUT the mercantile agency the modern wholesale merchant would not know how to do business. It is true the wholesale merchant's ıdfather did very nicely without the

be kept. It was seen that one man his entire time to the work of lookin the standing of dealers seeking credi accomplish more with greater econon thoroughness than was possible fo small number of merchants to do. Th

Source: "The Mercantile Agencies: They Have Grown Indispensable to Business," *Chicago Tribune*, March 15, 1896, p. 6 (no author attributed).

FIGURE 2

EXPLANATORY KEY AND LISTINGS FROM A MERCANTILE AGENCY REFERENCE BOOK, 1877

EXPLANATORY KEY

TO THE

LEFT-HAND COLUMN.	ESTIMATED PECUNIARY STRENGTH.	RIGHT-HAND COLUMN.	GENERAL CREDIT.
AA	$1,000,000 or over.	A1	Very High.
A+	750,000 or over.		
A	500,000 to $750,000		
B+	300,000 to 500,000	1	High.
B	150,000 to 300,000	1½	High.
C	75,000 to 150,000		
D	40,000 to 75,000		
E	20,000 to 40,000	2	Good.
F	10,000 to 20,000	2½	Good.
G	5,000 to 10,000		
H	2,000 to 5,000		
K	1,000 to 2,000	3	Fair.
L	—— to 1,000	3½	Fair.

The absence of a Rating indicates those whose business and investments render it difficult to rate them satisfactorily to ourselves. We therefore prefer, in justice to these, to give our detailed report on record at our offices.

BELOIT, Rock Co.

Abbott J. W. & Co.	D. G.	E	2
Ackley Geo. F.	Marble.	L	
Adams A. M.	Wagons.	H	3
Aldrich & Parker	Foundry.	K	3½
Alexander D.	Saloon.	K	3½
Allen E. C.	Real Estate, &c.	E	2
Allen A. B. & Son	Livery.	G	2½
Austin H. S.	Contec.	L	
Bagley Mrs. M. I.	Hair Goods.	L	
Bailey T. B.	Grain.	F	2½
Barnes L. N.	Meat Market.	K	
Barritt Joel	Oil, &c.	K	3
Bartlett C. M.	Gro.	K	3
Bell S.	Physician.	G	2½
Beloit Gang Plow Co.			
Beloit Gas Works		D	2
Beloit Strawboard Manufactory		D	2½
Bennett A.	Grain.	L	3½
Bentley & Son	D. G.	F	2½
Berger John	Butcher.	L	
Bittlo A.	Blacksmith.	K	3
Blodgett & Nelson	Flour.	E	2
Booth, Hinman & Co.	Paper Bag Mnfy.	C	1½

Source: Mercantile Agency Reference Book. 1877 (2nd ed.). New York: Dun, Barlow. archive.org/details/mercantileagency1877merc/page/n3.

The Great Depression: New Statistical Methods and Racial Discrimination in Creditworthiness

The second crisis was the Great Depression, exactly a century after the Panic. Interestingly, throughout the Depression there were only small losses in the area of consumer loans. After weathering the Great Depression, the National Bureau of Economic Research (NBER) led a study into standards around "consumer installment financing." Consumer lending grew increasingly competitive post-Depression, and pressure mounted to relax some of the more stringent credit assessment procedures that were instated after the crash. This prompted the NBER to investigate and aggregate best practices for setting credit standards.

A 1941 study, *Risk Elements in Consumer Instalment Financing* [*sic*], used questionnaires to survey commercial bankers and retail merchants, ultimately compiling data on 7,200 loans to statistically identify the two criteria most indicative of "good risk." Of primary importance was an applicant's "moral character," based on past payment record, general reputation, and stability of employment. Of secondary importance were assets and obligations to other creditors. (One repeatedly referenced result of the analysis was that women were seemingly less risky to lend to than men—"a fact that seems puzzling to a number of credit executives"[8]). In addition to generating an "efficiency" index to rank the importance of various factors in creditworthiness, the NBER study also developed several "credit-rating formulae." These NBER formulas were among the first to differentiate between "good" and "bad" loans using the new statistical techniques.[9] Interestingly, these formulas were not intended for practitioners; they were meant for "students of statistical theory."[10] Statistics was a relatively new field in the 1920s and 1930s. R. A. Fisher's *Statistical Methods for Research Workers* (1925), for example, and other classic texts were just being published. Yet in identifying forms of "good risk," the NBER study also contributed to normalizing lending as a potential source of profit, a risk to be probabilistically assessed rather than avoided wholesale.

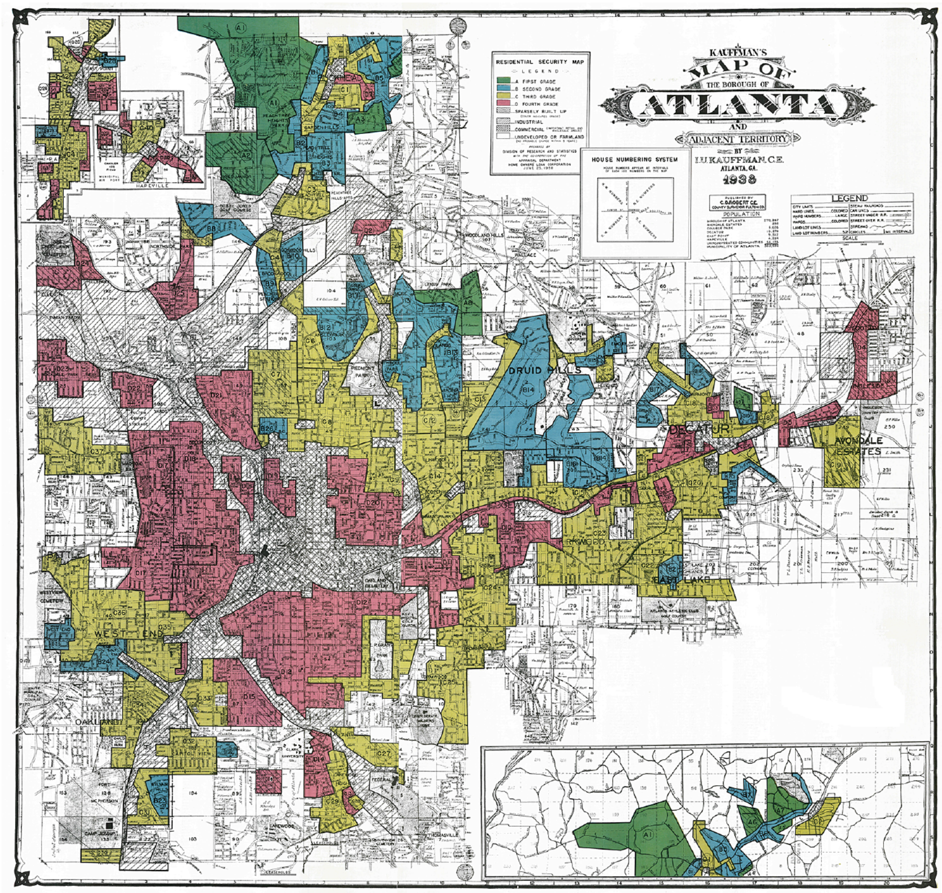
Assessments of "moral character" and creditworthiness in the United States have been highly racialized. On the heels of the Great Depression in particular, New Deal policies like the National Housing Act of 1934, which established the Federal Housing Administration (FHA), created the possibility for millions of Americans to access financing for home building and buying for the first time. However, "confidential" city surveys generated by the FHA largely funneled funding for loans to white communities and away from people of color. In the racially diverse community of Boyle Heights in Los Angeles, for example, appraisers from the FHA denied homebuyers federally supported loans because it was a "'melting pot' area literally honeycombed with diverse and subversive racial elements."[11]

This perception of risk was visualized in the notorious color-coded Home Owner's Loan Corporation (HOLC) maps, which represented neighborhoods with a high proportion of African Americans as red: hazardous (see Figure 3). These maps, along with racially restrictive agreements ("covenants") on government-insured housing, not only helped to nationally systematize racial segregation[12] but also seeded generations of white families with the capital for future financial stability and upward mobility while effectively denying the same to Black families. As Mehrsa Baradaran has shown, such home-lending policies were one of many examples of racial discrimination via credit: "The New Deal created a separate and unequal credit market—high-interest, non-bank, installment lenders in Black ghettos, and low-cost, securitized, and revolving credit card market in the white suburbs."[13] This history is important to recall as we consider the emergence, or perhaps re-emergence, of bias in algorithmic processes.

Although historically consumer credit was only available to a very select proportion of the American population, access gradually expanded throughout the twentieth century, and with it expanded the use of credit scoring systems. In the early 1950s, Bill Fair and Earl Isaac formed the first consultancy for statistically derived lending decision models. Fair Isaac's FICO score remains essential to consumer lending today. With the advent of credit cards in the late 1950s, a more widespread appreciation for the usefulness of a scoring system emerged. Firms relying on direct marketing also became early adopters of credit scoring methods. Sears, for example, used scores to target where to send its catalogs.[14] With the rise in computing power in the latter half of the twentieth century, it increasingly became possible to automate certain aspects of the credit decisioning process, leading to a greater reliance on inferences from consumer data sets.[15] And yet, even by the late 1990s, many still relied on traditional credit assessment methods, trusting "gut feel" and

FIGURE 3

1938 HOLC "RESIDENTIAL SECURITY" MAP OF ATLANTA WITH NEIGHBORHOODS COLOR-CODED BY RISK LEVEL



Source: Mapping Inequality Project at the University of Richmond, s3.amazonaws.com/holc/tiles/GA/Atlanta/1938/holc-scan.jpg, accessed December 16, 2019.

subjective judgments about a borrower's character rather than depending on scoring analytics.[16] Even the NBER study suggests that the very credit rating formulas it developed should be used to supplement judgment and experience, not as a substitute.[17]

Later, two key pieces of legislation were enacted that crucially shaped the formation of traditional credit scores as we know them today. The Fair Credit Reporting Act (FCRA) regulates how reporting agencies' collect consumer information and requires them to allow consumers to access their credit reports; the Equal Credit Opportunity Act (ECOA) gives every consumer the equal opportunity to apply for loans by prohibiting discrimination based on factors not related to creditworthiness.

Despite these legal efforts, biases in traditional lending processes, which have historically centered on heteronormative, nuclear family, white notions of respectability, remain

- Fair Credit Reporting Act
  - *Enacted 1970.*
  - *Regulates consumer reporting agencies.*
  - *Promotes accuracy, fairness, and privacy of information in files.*
  - *Entitles consumers to know what is in their files and to dispute inaccurate information, which must be corrected by reporting agencies.*[18]
- Equal Credit Opportunity Act
  - *Enacted 1974.*
  - *Outlawed discrimination on the basis of "race, color, religion, national origin, sex or marital status, or age" in lending unless it is "empirically derived" and "statistically sound."*
  - *Entitled denied applicants to a statement of reasons for the creditor's actions.*[19]

important. To take one illustrative example from the auto lending industry, in 2018 a National Fair Housing Association investigative report revealed that "more than half the time white borrowers with weaker credit profiles received less expensive financing options and more favorable treatment than their non-white counterparts who were more financially qualified."[20] This is not an isolated case study. Others include:

- *Discrimination in Lending Markets: Status and the Intersections of Gender and Race*[21]
  - In 2016, sociologist Sarah K. Harkness published an experimental study into mechanisms of discrimination in peer-to-peer (P2P) lending.
  - Harkness drew a sample of 225 participants using Amazon.com's Mechanical Turk service to rate a random series of P2P loan applications.
  - The study demonstrated that cultural stereotypes about the borrowers' status, particularly related to gender and race, significantly affected lenders' funding decisions.
- *Discrimination in Mortgage Lending: Evidence from a Correspondence Experiment*[22]
  - In 2016 economists used an experimental email correspondence test to analyze differential treatment by mortgage loan originators (MLOs) based on applicant race and credit score.

- MLOs were found to be more likely to send follow-up correspondences to whites and responded to emails from African Americans at a rate equivalent to those with a credit score 71 points lower.

⇢ *Kept Out: For People of Color, Banks Are Shutting the Door to Homeownership*[23]

- A yearlong analysis was done of 31 million records from 61 metro areas in the United States by Reveal from the Center for Investigative Reporting.
- The 2018 Reveal study, which was independently reviewed by the Associated Press, determined that African American and Latino applicants are denied conventional mortgage loans at rates far higher than white applicants.

These old biases may be taking new forms with the development of novel analytics capabilities. "Stability," for instance, is a fairly nebulous term used by Experian, among others in the alternative credit scoring space. It includes elements such as housing, employment, and financial stability. Scholars have found that such factors closely correlate to race and class.[24] It is important to note that "residence/stability" is also a factor assessed by Northpointe's predictive policing analytics system known as Correctional Offender Management Profiling for Alternative Sanctions (COMPAS). ProPublica has demonstrated that COMPAS's algorithmic system differentially rates African Americans as being at a greater risk for recidivism and criminal behavior than whites.[25,26]

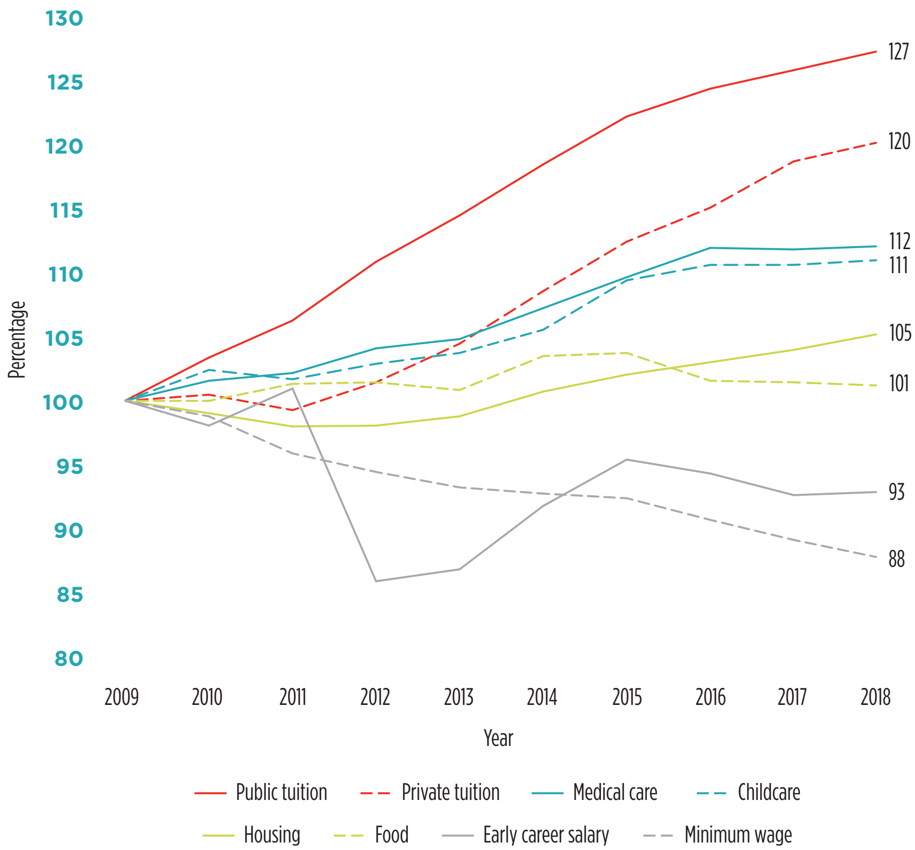
The Global Financial Crisis and Great Recession: New Financial Challenges and New Financial Technologies

This brings us to the third crisis in this brief history: the 2008 Great Recession. Given its origins in the 2007 subprime mortgage crisis, it is unsurprising that the global financial crisis, and new regulations that followed, led to a withdrawal (or at least greater caution) around serving the nonprime market. A wave of financial technology innovations (hereafter "fintech") has emerged in the last decade to fill this void, offering new channels and sources of credit to consumers. Fintech promises reduced loan approval times and greater objectivity through the use of new data sources, analyzed using machine learning algorithms and AI.

Contemporary Americans' financial lives are dramatically different from those that were the basis for developing traditional credit scores. Key differences can be found in income and savings rates, levels of consumer debt, and a more heterogeneous lending landscape, peppered by new entrants from the fintech sector. Over the past 10 years since the recession, inflation-adjusted expenses such as higher education have continued to soar, closely followed by medical care and childcare while early career salaries and the minimum wage have dipped (Figure 4). Rising higher education costs have resulted in

FIGURE 4

10-YEAR CUMULATIVE CHANGES IN PRICES OR AMOUNTS (ADJUSTED FOR OVERALL INFLATION, 2009–2018)



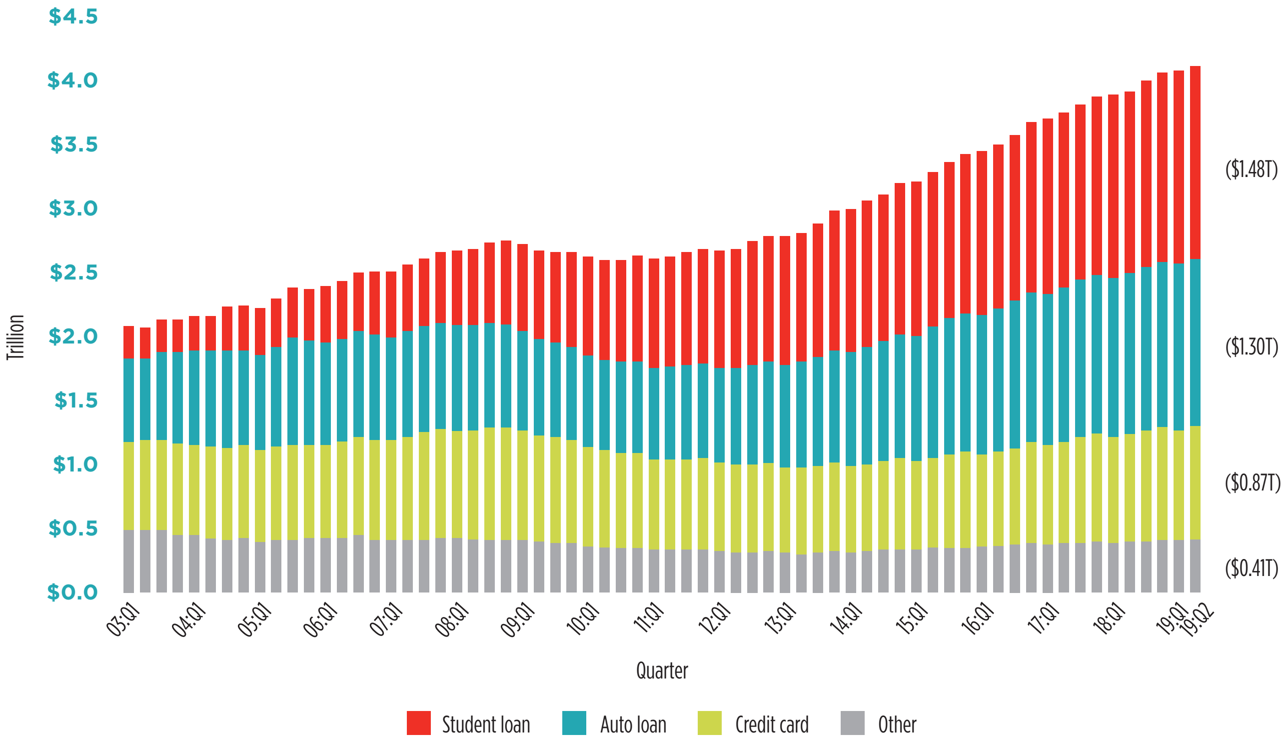
Sources: Bureau of Labor Statistics, National Center for Education Statistics, National Association of Colleges and Employers, and Department of Labor.

ballooning student debt, which now represents the largest share of nonhousing debt (Figure 5). Nearly 37 million Americans are saddled with student loan debt—approaching 10% of the US population.[27] As the amount of nonhousing debt grows postrecession, so has the proliferation of nonbank lending companies.

Though home-buying statistics have not flagged, more people are deferring purchasing a home to a later age: 41% of millennial college and grad school students live with their parents.[28] With the casualization of labor, more and more Americans are employed on short-term contracts (1 in 5, according to a recent Marist/NPR poll), which means greater instability in employment.[29] For those age 60 and older, 13% have no retirement savings or pension, and 55% do not think their savings are on track.[30] Forty percent of American households lack a basic level of savings. If their income was interrupted, these “liquid asset poor” households would not have enough savings to subsist at the poverty level for three months, and 12.0% of Americans have less than one week of living expenses saved in 2019.[31]

FIGURE 5

NONHOUSING DEBT BALANCE AND ITS COMPOSITION, 2003–2019



Sources: New York Fed Consumer Credit Panel/Equifax.

For many Americans, therefore, nonbank lenders may present an opportunity to gain access to credit instruments at a rate more indicative of their ability and willingness to pay. With the rise of fintech and the return of alternative financial services after the 2008 financial crisis, we are arguably seeing a return to a diverse, competitive lending landscape. This poses challenges for credit unions in competing with new entrants. Moreover, this shifting landscape changes how consumers navigate financial services and piece together their own financial lives. It also makes tracking and evaluating responsible lending all the more difficult. This is fertile ground for credit decisioning systems fueled by alternative data.

The Growth of Nonbank Credit Providers

The number of loan brokers continues to grow, with 2019 totals topping 12,000 businesses.[32] Over the past few years, in keeping with the growth in debt loads, the share of loans originated by nonbank providers has grown rapidly. Nonbank credit providers offer credit cards, mortgages, student loans, consolidation, and other products. Alternative credit providers often provide consumers with easier access to credit and relaxed eligibility criteria.[33] Mortgages issued by nonbank lenders reached 53% in 2016, up from 9% in 2009.[34] This share grew in part because of banks pulling back from the mortgage market after the financial crisis, but also because nonbanks have taken advantage of technological innovations such as algorithmic underwriting.[35] Nonbank lenders such as SoFi and Quicken Loans have become industry leaders in an abbreviated amount of time.

With the rise of fintech and the return of alternative financial services after the 2008 financial crisis, we are arguably seeing a return to a diverse, competitive lending landscape.

This brief history shows that innovation follows crisis: each new technique for understanding and scoring risk—the three Cs, the statistically generated credit score, and alternative credit scoring through data analytics—followed major economic downturns, even ones not caused primarily by bad lending decisions.

Next, we explore some of the perceived shortcomings of traditional credit scores, as well as the promise of alternative data analytics.

CHAPTER 3

Closing the Information Gap

Despite being entrenched as an industry standard for assessing borrowers, traditional credit scores are no longer reflective of contemporary financial obligations for many consumers. This is reflected in efforts by both the credit bureaus and a wide range of new companies to build scores intended to supplement or supplant traditional credit histories.

There are two types of "unscoreable" consumers: people who are "un-estimated" (so-called thin-file or no-file consumers) and those who are underestimated (scored as marginal or subprime, or otherwise scored below their true ability to pay). Some studies have suggested that 20% of adult Americans (45 million people) do not have a traditional credit bureau score (although others put the estimate closer to 35 million to 70 million[36]), while 32% who are scoreable have a poor credit score.[37] Marginalized groups are particularly vulnerable to being un(der)estimated. African American, Hispanic, and low-income consumers are more likely to have no or thin credit histories.[38] Moreover, one-third of millennials are unable to receive a score from a national consumer reporting agency.[39] People with poor traditional credit scores, or no score at all, struggle to access affordable credit from the mainstream financial system.[40] Yet, there is a growing recognition that an "un-scoreable" person is not inherently risky but rather is an unknown risk.

There is a growing recognition that an "un-scoreable" person is not inherently risky but rather is an unknown risk.

Mainstream financial institutions and fintechs alike are turning to "alternative" data—that is, data not captured within the scores from traditional credit reporting agencies—to bridge this information gap. Alternative data for credit scoring can include metrics such as the following:

- Bill payment (from utilities, cable companies, and wireless providers).
- Rental history (duration of residence and record of payment).
- Online marketplace, payday, and subprime lending.
- Insurance claims.
- Bank account activity (bank balances, account transfers, electronic records of deposits and withdrawals).
- Personal credentials (occupation, education).
- Digital communication (social media networks, email, Internet usage).

Example: Amanda, a marginal consumer with a traditional bureau score of 656, approaches an online fintech lender that considers cell phone payment history. Analysis of this alternative data reveals that Amanda opened a cell phone account four years ago and has not missed any payments. This positive track record benefits Amanda in her loan application, and she is able to get a small-dollar loan at an affordable rate.

Example: Paul, who has a traditional credit bureau score of 627, is denied a loan from his bank because of a series of late credit card payments he incurred when a family member was sick. Paul then applies for a loan from a fintech that considers rental history; however, this data reveals that he also missed a few rent payments. Paul's loan application is denied again.

Though seemingly far-fetched, even things like email meta-data (e.g., a consumer's inbox structure, message-length, and the timing of their account creation) are being considered for use in fraud detection and credit scoring.[41] A number of recent studies suggest that alternative data are meaningfully predictive of risk[42] and are able to capture more abstract characteristics that are key in repayment (like "stability") by more holistically describing a person's life course. These data may be better able to capture individual behavior missed by credit bureaus and traditional credit scoring—for example, people who suffered from a financial or personal hardship but are on a path to recovery—closing the information gap with a more granular analysis of people's financial lives.

Extensive marketing by credit rating agencies and the growing availability of credit scores through dashboards provided by financial institutions and third parties have made people more cognizant of their credit score—that is, both aware that it exists and, increasingly, preoccupied with improving it. Those annoyingly catchy tunes from Freecreditreport.com, featuring a musician forever plagued by bad marriages, crappy cars, basement apartments, and more, all because of his ignorance of his credit score, were ubiquitous in the late 2000s. Credit Karma's commercials, presenting bizarre scenarios with "not great" odds (e.g., the odds of a doofus-y older man "dominating the skate park") compared to the odds of getting approved for a credit card on their app ("pretty great!"), are a contemporary, if less infectious, example.

The calculative instruments involved in credit scoring have not only helped to produce contemporary conditions of consumer credit consumption, but have also had the social effect of framing credit risk as a personal attribute, as social scientist Martha Poon argues.[43] This also has produced a backlash, with people not feeling like their credit scores reflect who they are as a person, thus making the idea of an alternative credit score attractive.

The use of alternative data is often narrated as a form of "empowerment" and financial inclusion for marginalized consumers. In 2018, at the Money 20/20 conference (a premier payments and fintech industry event), executives from FICO, Experian, and Finicity launched their Ultra FICO score collaboration, which enables customer-permissioned inclusion of banking data. "If you don't love your FICO score, why don't you come share a little bit of information with us and we can do better ... if you feel it doesn't reflect who you are," FICO CEO Will Lansing offered. The chairman of Finicity jumped in: "We're applying digital transformation and consumer empowerment in credit scoring," adding that Ultra FICO is a model of "the empowered consumer." Many studies analyzing the use of alternative data propose that significantly more consumers can be scored than with the use of traditional data alone. In a study by the software company ID Analytics, for example, 75% of "no-hit" and thin-file consumers could be predictively scored using alternative data.[44] This trend is not purely altruistic, of course. Expanding the pool of creditworthy borrowers also presents an area of future growth for lenders: 64% of lenders have said they have seen tangible benefits within the first year of using alternative data.[45] With the influx of fintech lenders, embracing new types of data may offer a route for mainstream institutions to "future proof" themselves and remain competitive.[46]

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Alternative data are one part of a growing economy of data-driven services that are now possible through increased computational power and new machine learning techniques and automation algorithms, often lumped together as "AI."[47] Though aggregating the vast amounts of data sets necessary for alternative scoring creates its own challenges for lenders, the use of machine learning techniques presents an efficient means of processing that data rapidly, and at scale. It can also facilitate searching for nonintuitive connections between data points. These types of functions would be impossible for human analysts to complete on their own, and some have suggested that the further automation of analysis is likely to lead to more rapid, time-efficient loan decisioning at what will perhaps be a lower cost.[48]

Trends in alternative credit scoring suggest that, in the future of lending, FICO scores may become just one data point among many. In keeping with broader trends toward the formation of collaborative ecosystems in finance, it seems likely that bank-fintech partnerships will emerge in response to innovations in data processing through machine learning, particularly given how vast and fragmented much of this data is. Alternative data adoption is highest among credit and debit card lenders, where the cost of customer acquisition is high; this is followed by the automotive and consumer finance sectors. Furthermore, according to the same benchmark lenders' survey, "While respondents from the credit union sector are far more likely than others to extend credit to thin-file or no-file customers (97% versus 84% overall), fewer than one in five (16%) currently uses alternative data, compared to one-third (34%) of all lenders."[49] This was the lowest adoption rate among the types of lenders profiled. Thus, as the American lending landscape may be on the precipice of yet another postcrisis evolution in the measurement and conceptualization of risk, it is vital that credit unions critically assess the ethical implications of alternative credit scores.

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Do alternative credit scores work? Yes—at least in the strict sense of producing actionable scores for people who would not otherwise have them. Are credit unions using them? Not as much as other financial institutions. Should they be? Yes. Alternative credit scores can help them serve their members—and, in particular, those who are underserved. Recall that in the first quarter 2019, the number of credit unions with low-income designation rose to 2,571.[50] But credit unions also have a proud history of guarding their members' interests and putting members first. This is core to their values. It is also core to their value proposition and their brand as a movement of "people helping people." Given their values orientation, the potential legal and regulatory implications, and most especially, their brand differentiation, credit unions *must* consider the ethical implications of alternative credit scores.

First, credit unions must protect and grow their reputation as a responsible and trustworthy provider of financial services. As the financial services industry becomes more explicitly driven by the use of consumer data, the security, transparency, and accountability of the companies with access to that data becomes paramount. Second, there will be a regulatory push at some time, in some form, to protect consumer data; credit unions must get out ahead of this curve to help shape the regulatory landscape, rather than be shaped by it.

Next, we survey the five most important issues in fairness and accountability in machine learning algorithms in financial services.

CHAPTER 4

Challenges to Fairness, Accountability, and Transparency in Alternative Credit Scoring

Challenges

- EXPLANATORY POWER
- SOCIAL DISCRIMINATION
- PRIVACY
- AUDITING
- ENTRENCHING INEQUALITY

Explanatory Power

If consumers are denied credit, according to the FCRA, lenders must explain to them the reason for this decision. Moreover, research suggests that increasing operational transparency can actually increase users' trust of institutions.[51] As lending institutions begin to make use of alternative data sources in credit decisioning, they must consider the implications that using data with a less conventionally obvious relationship to financial behavior will have for explainability. Often machine algorithms "learn" in a way that can't easily be explained by their human coders and "make decisions" on the basis of variables that are not always immediately identifiable. How will financial institutions connect the dots for consumers when they cannot always explain their own decisionmaking process to themselves?

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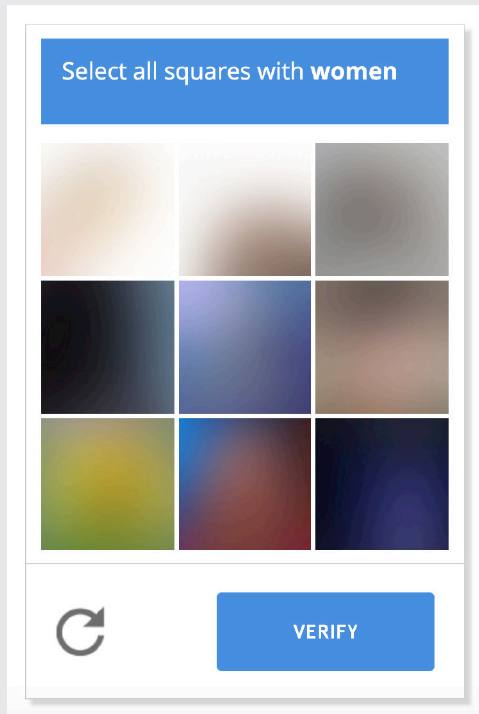
Furthermore, for many alternative sources it remains unclear how truly predictive they are of a person's likelihood to repay a loan. Some metrics are seemingly preferable to others. One's history of bill payment, for example, reflects actual payment performance and is fairly universal. The Center for Financial Services Innovation (now the Financial Health Network) found that utility bills and rent payments are some of the most reliable data sources for alternative credit scores.[52] (Although even with seemingly straightforward metrics like bill payment there are complications. Households often split bill payment for utilities, cable services, and the like, which presents difficulties for associating creditworthiness with an individual based on this data.)

How will financial institutions connect the dots for consumers when they cannot always explain their own decisionmaking process to themselves?

Internet artist Damjanski has toyed with the impenetrability of autonomous programs (or "bots") and machine learning through his Humans Not Invited project. Upon visiting humansnotinvited.com, one is presented with a CAPTCHA test with prompts like "Select all squares with dogs" or "Select all squares with memes" and nine inscrutably blurred squares. Only specially programmed bots are able to correctly complete the CAPTCHA, which itself has been blurred using an algorithm. Rogue humans trying to enter the site receive the message: "You're a human. You are not invited."



Even data sources that are directly related to financial transactions are fraught. Take rental payment history, for instance. In *The Predictive Value of Alternative Credit Scores*, the Financial Health Network reviewed an analysis of RentBureau, a consumer reporting agency with millions of rental payment histories (owned by Experian).[53] While touted as an innovative means of allowing consumers to build their credit history, the RentBureau case is illustrative of the challenges new data sources present to explainability. At the time of the study, RentBureau conducted an analysis of nearly 45,000 lease records to assess the relationship between past payment behavior and outstanding balances left on leases (known as "write-offs"). While the study determined that "past rental payment behavior is highly predictive of future behavior,"[54] nearly half (47%) of the write-offs were completely unpredictable (i.e., not preceded by late payments), so 53% is perhaps an improvement over some methods for predicting write-offs. But in the rush to pinpoint lucrative new data sources, credit unions must maintain a clear sense of the gaps and limitations of these analytics.

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Social media platforms provide other data sets that can be used to score risk. Given their ubiquity, these platforms are generating previously unfathomable amounts of data about users' behavior and preferences. Though much of this data is severely fragmented and not fit for this purpose, some fintech companies have begun to mine social media profiles for data not only to target new customers but also to make lending decisions. For example, Kreditech, a German fintech operating primarily in developing countries, is using social media (including blogs, wikis, social networking sites, and media-sharing sites) to help assess the creditworthiness of potential borrowers.

However, social media data is easily gamed. As Experian pointed out, someone could simply "like" a number of financial articles or begin following finance gurus and manipulate their profile to make themselves appear to be more fiscally responsible.[55] Social media could also present a problem of "creditworthiness by association,"[56] (mis)representing people within the same online social spheres as being similarly trustworthy and responsible—and punishing others. In the words of Malaysian Maybank's Mah Kim Lin, social media data is "unicorn data" in which anyone can aspirationally represent themselves as something they wish to be.[57]

Social Discrimination

New forms of alternative credit scoring present grave threats of social discrimination, particularly for historically marginalized groups. These can be categorized according to three types of problems:

- Biased data inputs.
- Algorithms that contain or acquire biases through the data sets on which they are "trained."
- Data that will facilitate intentionally biased and predatory decisioning.

All three risk contributing to "technological redlining," using data to profile would-be borrowers and create prejudicial access to lending, potentially re-creating in the digital space the kind of exclusion historically perpetuated by financial institutions in ways reflected in those old HOLC maps (Figure 3).[58]

Companies deploying machine learning are quick to tout the comparative "objectivity" of computing processes over subjective human assessment. Numbers don't lie, so the conventional wisdom goes. It is worth recalling at length what a traditional credit assessment, before the use of credit scores, entailed:

> *[A] prospective borrower did not approach a bank manager or building society manager until they had been saving or using other services for several years. Then, with some trepidation, an appointment would be made and, wearing Sunday best, the customer would ask to borrow some money. The manager would consider the proposition and, despite the length of relationship with the customer, would ponder the likelihood of repayment and assess the stability and honesty of the individual and their character. He—the manager was invariably male—would also assess the proposed use of the money, and then he might ask for an independent reference from a community leader or the applicant's employer. He might arrange for a further appointment with the customer and then perhaps reach a decision and inform the customer.*[59]

Narratives of this process are commonly invoked in support of decisioning that is further abstracted, ostensibly decoupled from the perils of individual subjective bias. In the words of CEO and founder of ZestFinance Douglas Merrill, "Back in the 1950s to get a loan you would go to a bank and sit across from a man, and it was always a man, sitting at a big wooden desk and he would give you a loan because he knows your kids from baseball. I didn't play baseball—I fenced! AI allows you to re-create the good part of that man behind the desk without the bias."[60] While surely rooting out this kind of bias in lending is positive, focusing on individual bias alone will miss the point. In many cases, there is a tendency to treat discrimination as the result of an individual person's biases in decisionmaking, or to treat it as the outcome of the harmed person's choices. The problem is that discrimination is not always so straightforward. More often, in fact, it is built into (or "implicit in") decisionmaking processes and policies.

Critical race and feminist scholars in the social sciences have demonstrated that racism is a structurally articulated form of bias. This means that racism is not just the result of individual people's prejudiced beliefs. It is also built into all kinds of different elements of society that differentially shape people's access to power, privilege, and opportunities (like housing, jobs, medical care, and more). Like redlining maps, these structures have histories and durable, lasting impacts in the present. This is borne out in analyses of alternative credit scoring systems. In a landmark study, researchers at the University of California at Berkeley found that Latinx and African American borrowers were consistently charged higher interest rates in *both* face-to-face and fintech lending. This amounted to an aggregate $250 million to $500 million per year in extra mortgage interest for these borrowers.[61] The good news, however—if there was any—was that at least the fintechs did not reject applicants of color out of hand at the same rate as in-person lenders.

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Our society is only just beginning to grapple with how to handle algorithmic discrimination; enforcement and regulation have been spotty and ad hoc. To date, most of the regulation has emphasized issues of data privacy. Furthermore, with discrimination, the burden of proof has been placed on the one seeking redress, not the originator. In May 2018, the City of New York passed a law requiring the creation of a task force to examine city agency automated decisions and their potential harm. A report from the New York City Automated Decision Systems Task Force "recommending procedures for reviewing and assessing city algorithmic tools to ensure equity and opportunity" is expected in December 2019.[62] However, this bold step is a rare example.

In considering the implications of racial categories for machine learning, Sebastian Benthall and Bruce D. Haynes have powerfully articulated the double bind facing those who would design and implement AI systems.[63] Either directly account for protected class labels (like race) in computational analyses and reify or reinforce them (not to mention risk violating the ECOA and create the opportunity for intentionally biased outcomes), or disregard these categories (an approach sometimes referred to as "color-blind") and reproduce the status quo. For Benthall and Haynes, the only way out of this dilemma is to produce systems that are "designed with the objective of promoting social integration based on similar treatment of segregated populations."[64] In other words, one way to deal with existing bias and discrimination in lending would be to create an AI system that recognizes race. Doing so, however, runs afoul of ECOA. Another way would be to design it intentionally to disregard race. Doing that, however, risks perpetuating whatever discrimination in lending already exists (as was indeed discovered in the study from Berkeley referenced above[65]). Unless lending institutions can prove that machine learning systems are designed to actively seek out, identify, and eliminate social inequality, it is ethically questionable whether they should be making use of alternative data sources at all.

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Privacy

Alternative data sources, particularly those that rely on content scraping for collection, raise fairly conventional consumer privacy issues surrounding notice, consent, sharing, and storage. Ensuring that the use of alternative data requires consumer consent is an important step; yet, when linked with credit decisioning processes, credit unions must seriously consider the quality of that consent. First, it is disingenuous to suggest that customer-permissioned data obtained through digital user agreements constitutes a robust and meaningful form of engagement. Terms of service agreements are not, in practice, reliable indicators of consent (in fact, one study deemed them to be the "biggest lie on the Internet"[66]). Moreover, if access to credit is truly as vital to marginalized consumers' lives as most financial institutions and fintech start-ups suggest, then it is highly likely that permission will be given within a tacitly coercive context. The Center for Financial Inclusion at Accion found that people are more willing to provide consent in exchange for a valuable service. Experian similarly found that 70% of consumers are willing to share credit data if it increases their chances of approval. A serious analysis of the power dynamics at play in obtaining customer-permissioned data must take place before alternative data is collected and used in lending decisionmaking processes. The credit union system prides itself on people-to-people service and must challenge the tendency today to posit a necessary trade-off between privacy and quality financial services.

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There is some good news! In the Center for Emerging Technology's study of fintech budgeting and investing apps, *The Lessons of Fintech Apps*, study participants overwhelmingly expressed that they trusted their financial institution (credit union or bank) to protect their data and use it responsibly.[67] This finding is echoed by A.T. Kearney's 2017 *Consumer Digital Behavior Study* of more than 7,000 US-banked consumers, which found that "consumers view their primary bank as the service provider with whom they are most comfortable sharing personal data."[68]

So how can credit unions do better with respect to privacy to honor this trust? At its core, privacy is about choice. Members must be given a choice about how their data is collected, used, and potentially exposed. To be meaningful, choice requires two things: consent and transparency. At every stage possible, credit unions must seek to obtain affirmative consent from their members to collect, store, share, and otherwise make use of their data. Honoring that consent means guarding against "creep" in use; that is, data collected for a particular purpose should not be used for other purposes or exposed for use by other businesses or persons. Transparency means clearly communicating to members in a way that is understandable how data is being collected and used, and giving members the ability to control, or curtail, these processes, particularly with respect to third-party vendors and analytics services.

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Auditing

In further automating evaluative processes, alternative credit scoring has the potential to make seeking access to credit even more opaque for members. This is no coincidence. Credit bureaus were among the first institutions to originate what legal scholar Frank Pasquale terms "black box" scoring techniques, concealing the methods by which data was collected and analyzed.[69] But those "black boxes" are becoming as difficult for those on the other side of the loan to peer into. As machine learning becomes increasingly dynamic and unsupervised, humans often struggle to explain particular outcomes. And even when they are explainable, that does not always mean the system is getting things right. In a hilarious but telling example, researchers at the University of California created an AI system that would "learn" the difference between wolves and huskies.[70,71] It worked. But when they opened up the black box they had created to understand how the AI had learned to complete this task, they were surprised to discover that the system had learned to detect the presence of white areas in the pictures. In other words, they hadn't created a system capable of identifying huskies; they created a snow-detector.

Algorithmic Audits: Some Possibilities[72]

Code Audit

- The Approach: Copying an algorithm and testing if it creates discriminatory outcomes more than would be expected at random.
- Challenges:
  - *Platform companies are under no obligation to share their proprietary algorithms.*
  - *Auditing algorithms might not reveal anything if it is the underlying data set that the algorithm was trained on that was biased.*

Normative User Audit

- The Approach: Users report on what they input into an algorithmic process and what happens next. Researchers can look for correlations based on race, gender, and other things reported by the users to determine if the process was biased.
- Challenges:
  - *The sample population that responds to your request to report on their activity might not reflect the broader population or exhibit enough variation demographically to draw any meaningful conclusions (sampling bias).*
  - *When people are asked to report what happened after the fact, this data is often biased by faulty memories, the desire to provide the researchers what the user thinks they are looking for, or just plain error (self-report bias).*

Sock-Puppet Audit

- The Approach: Researchers write code to impersonate users, creating false accounts and then seeing what happens when decisions are made by the algorithm about the sock-puppet.
- Challenges:
  - *In accessing a platform in an unauthorized way, this technique runs afoul of the Computer Fraud and Abuse Act.*

Crowdsourced Audit

- The Approach: Researchers use a crowdsourcing platform to recruit humans to test a system.
- Challenges:
  - *There could be self-report bias, but this could be mitigated by automating some of the data collection through the crowdsourcing platform.*

Alternative credit scores are not only opaque because of the technical complexity of machine learning. They are also becoming increasingly inaccessible to credit unions because of basic governance issues. Credit unions, like many other financial institutions, often lack the capacity and the expertise to implement alternative data analytics themselves. Alternative scoring mechanisms purveyed by third-party analytics services treat their algorithms as proprietary. This disempowers credit unions to be able to fully harness their members' data and dictate the terms under which the data are analyzed and used. Relatedly, the mechanism by which credit unions would hold third parties accountable in the case of misuse is unclear.

Credit unions have the opportunity to take the lead on pressing for the burden of proof to be shifted from those claiming harm from AI systems to those who own and operate these systems. In order to do this, they must establish industry standards for algorithmic audits.

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Entrenching Inequality

Because alternative data can potentially allow lenders to include previously unscoreable, or poorly scored, individuals, it is often posited in terms of financial inclusion initiatives. However, alternative scores not only risk reinforcing social discrimination through perpetuating bias, but also can potentially further entrench social inequality because of the perceived objectivity of algorithmic processes. Humans are biased to believe that quantitative data are more neutral and objective. Again, "the numbers don't lie." Using alternative data sources means normalizing the acquisition of more and more facets of our personal lives and rendering them as a mere number. This is not simply a depressing reduction of the richness of human experience. It risks ossifying fluid and complex elements of a person's life into a fixed score. The more data included in these scoring processes, the more totalizing we may perceive the score to be. For already marginal consumers without a digital footprint, they will perhaps be further marginalized by perceptions of the alternative scoring's comprehensiveness. And for marginal consumers with personal circumstances that cast them as "unstable," they may be further locked out of a credit system that is increasingly essential for survival in the United States.

Humans are biased to believe that quantitative data are more neutral and objective.

Conclusion

In the last few years many academics, advocacy groups, and activists have sought to develop standards for fairness, accountability, and transparency in artificial intelligence. On the heels of a number of high-profile algorithmic blunders, primarily by big tech companies—recently, think of Amazon's sexist AI recruitment tool[73] or Facebook's racially discriminatory advertising[74]—a number of institutions have published matrices, tool kits, and all manner of guides for building, or holding to account, more ethical AI systems. In a project sponsored by the Open Society Foundation, for example, Allied Media Projects has published "A People's Guide to AI," which includes prompts such as the following:

- What problem are you trying to address?
- How can AI help solve this issue?
- What role will humans have in addressing this issue?
- What data do you need to create an AI to help you address your issue?
- How will you responsibly gather this data in a way that respects individuals' privacy and consent?[75]

The number of resources for building and auditing accountable AI systems has grown exponentially and has not yet coalesced. Review these guides, tool kits, and other resources to develop a deeper understanding of identified guardrails, processes, questions, and assessments to build accountable and more transparent AI.

- Filene Research Institute: Navigating AI Decisions in Financial Services.
- Allied Media Projects: A People's Guide to AI.
- G20: Ministerial Statement on Trade and Digital Economy.
- Vox: 10 Things We Should All Demand from Big Tech Right Now.
- AI Now: Algorithmic Accountability Policy Toolkit.
- Ethicstoolkit.ai: Ethics and Algorithms Toolkit.
- United Kingdom Department for Digital, Culture, Media, and Sport: UK Data Ethics Framework.
- ETH Zurich: A Moral Framework for Understanding Fair ML [Machine Learning] through Economic Models of Equality of Opportunity.
- AI4People: An Ethical Framework for a Good AI Society.
- Singapore: A Proposed Model Artificial Intelligence Governance Framework.
- PWC: Responsible AI Toolkit.
- Algorithm Watch: AI Ethics Guidelines Global Inventory.

In June 2019, the G20 adopted a nonbinding set of principles on what they call "human-centered AI" in order to promote "'inclusive growth, sustainable development and well-being,' 'human- centered values and fairness,' 'transparency and explainability,' 'robustness, security and safety,' and 'accountability.'"[76] The European Union has recently released its guidelines for trustworthy AI.[77] The news website Vox released a crowdsourced algorithmic bill of rights, which includes the following 10 rights:

- Transparency.
- Explanation.
- Consent.
- Freedom from bias.
- Feedback mechanism.
- Portability.
- Redress.
- Algorithmic literacy.
- Independent oversight.
- Federal and global governance.[78]

The list goes on and on. Some of these principles have clear implications for the development of alternative credit scoring processes and are also articulated in the FCRA and ECOA (explainability, freedom from bias, and redress, for instance). But others, like federal and global governance, are clearly beyond the remit of the credit union system. In this sea of stances and standards, what is the way forward for credit unions?

It seems there are two paths. One, don't use alternative credit scores. Perhaps don't try to capture alternative data. Imagine a credit union that actively works to help consumers reduce their data footprint, working to build trust and value rooted in interpersonal relationships. Though perhaps appealing to our inner-Luddite, this simply may not be viable. Alternative credit scoring through new data sources and algorithmic analytics is already in use. Though the "black box" may be increasingly opaque, Pandora's box is already open. This does not mean that there are not important lessons to be taken from critics of alternative scores—first and foremost among them making a commitment to asserting that individual members are the owners of their own data and ensuring rigorous standards for consent. Credit unions can also work to ensure that people who do opt out of new data acquisition strategies have access to the same quality of service as those who opt in. And they can ensure that, despite increasing automation, people remain involved in the process of assessing creditworthiness. Calls for regulation of the use and ownership of personal data and for specification of the rights around data will only grow. Credit unions are in a unique position to shape the regulatory conversation based on their historical commitment to serving all their members and the high degree of trust they command.

The second path is for credit unions to embrace the power of artificial intelligence in order to explicitly target and eliminate racial and economic bias in the US financial system. Credit unions have the capacity, and a mission and record of commitment to responsible financial services, to set an industry standard for the responsible use of this new technology. To reiterate: credit unions have always used innovative techniques to serve the underserved. This has pitted them against payday lenders and other fringe banking services in the past. Today, with the rise of algorithmically driven financial services, credit unions stand to shape the competitive marketplace while growing their reputation as responsible and trustworthy providers of financial services and now as responsible and trustworthy guardians and users of people's data to enhance not just financial access but financial justice.

Credit unions have the capacity, and a mission and record of commitment to responsible financial services, to set an industry standard for the responsible use of this new technology.

To this end, we conclude with a list of the most important questions credit unions can ask to critically interrogate the five key challenges to fairness, accountability, and transparency in alternative credit scoring.

1. *Explanatory Power*
   - Is there a meaningful, explainable relationship between data inputs and a members' financial behavior?
   - Are human beings actively engaged in the credit decisioning process in addition to AI systems?
   - How might the use of different types of alternative data play out in different communities? For instance, are there ways of capturing remittance data for immigrant communities sending money to relatives in their home countries that might meaningfully predict repayment reliability? Are there ways that social media data differentially predict risk among different racial and ethnic groups that would need to be guarded against in any credit scoring AI application using such data?
2. *Social Discrimination*
   - What qualitative and quantitative evidence of inequity exists around the financial product or service? Can credit union employees be trained to spot potentially biased outcomes in the use of new alternative data sets and processes?

- Do the AI system's language and behaviors reinforce discriminatory stereotypes and biases?
- Are there people involved in both developing and auditing AI systems from minoritized backgrounds (including people of color, women, and low-income communities)?
- Are there machine learning mechanisms built into AI systems to detect biased outcomes?

3. *Privacy*
   - Are data being collected with member's full knowledge and consent (i.e., not content scraping)?
   - Are the members being asked to share data being told the possible negative consequences of sharing it?
   - Can members retroactively withdraw permission to access their data?
   - Can members access the same quality of services and products without providing access to alternative data sources?
4. *Auditing*
   - Is it possible to easily edit, modify, and override outcomes when the AI system is wrong?
   - Is the member able to access an explanation of why the AI system behaved the way it did?
   - Is it possible for members to provide feedback indicating their preferences during interactions with the AI system?
   - Are members notified when the AI system upgrades or otherwise changes its functions and capabilities?
   - Has provision been made for community-based research that can assess the impact of AI systems? That is, aside from initiatives like that of the municipal government of New York City, can credit unions partner with community data activists and advocates—like those that have arisen in response to the use of algorithms in policing—to help monitor the impacts, positive and negative, of new data-driven products and services?
5. *Entrenching Inequality*
   - Have you made it clear to members what the system can (and can't) do and how well it can do it?

- What additional barriers might prevent members from experiencing potential benefits of an AI system?
  - Consider, for example, language, gender, socioeconomic status, digital inequality, LGBTQ status, (dis)ability, employment status, immigration status, education level, geography, environment, religious beliefs, culture, and history of incarceration.[79]
- Are specific individuals liable for the design, behavior, and effects of AI systems? Where does accountability lie?
- Are there enforceable procedures in place to hold them those individuals accountable?
- Is the process of accountability transparent? Is this information made available to members?

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