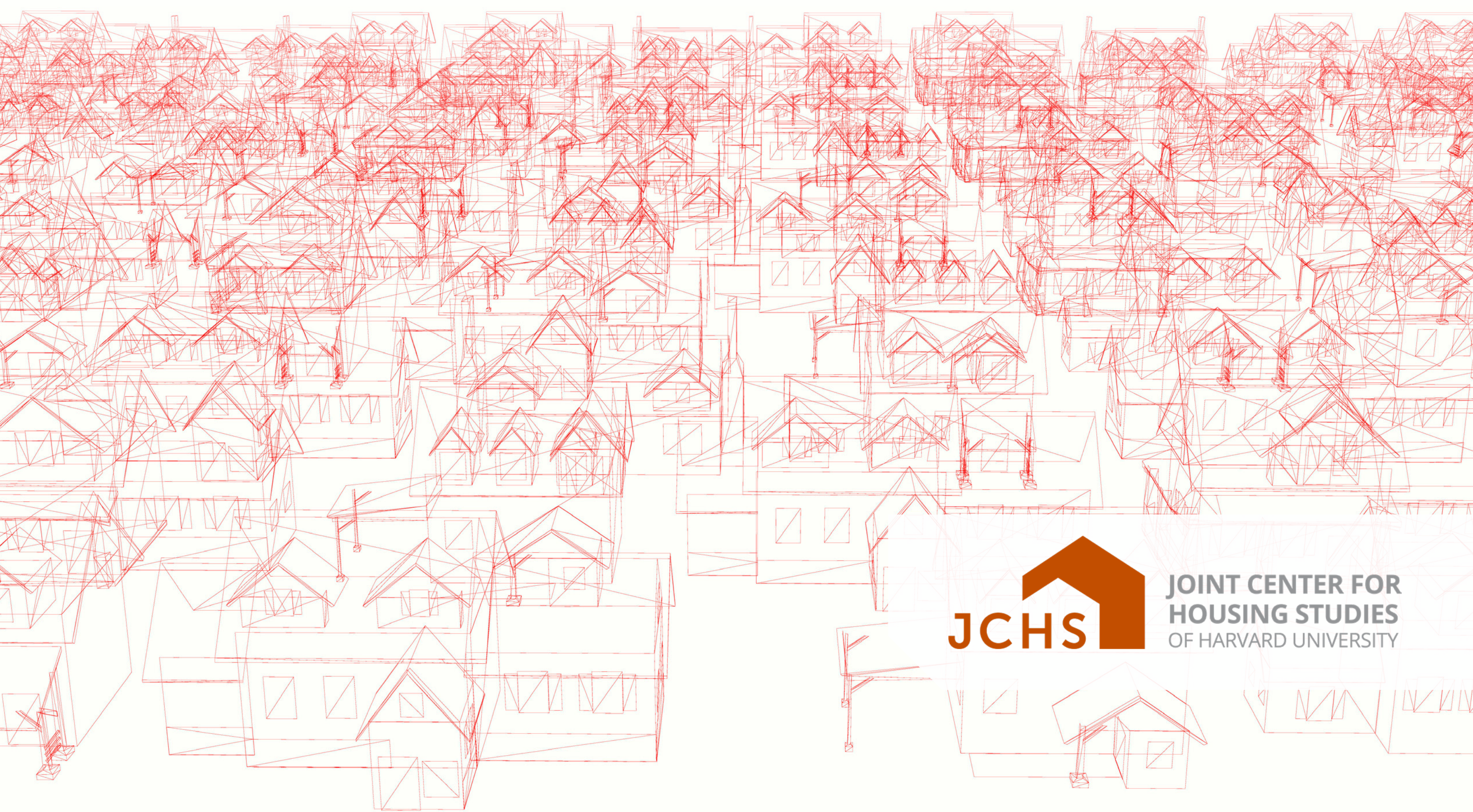
BRINGING DIGITALIZATION HOME SYMPOSIUM

Algorithms for All

Has Digitalization in the Mortgage Market Expanded Access to Homeownership?

MARCH 2023 | VANESSA G. PERRY, KIRSTEN MARTIN



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Algorithms for All: Has Digitalization in the Mortgage Market Expanded Access to Homeownership?

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This paper was presented as part of "Panel 3: How Is Digitalization Transforming How People Find & Finance Housing?" at the symposium "Bringing Digitalization Home: How Can Technology Address Housing Challenges?", hosted by the Harvard Joint Center for Housing Studies in March 2022 and funded by Qualcomm. Participants examined the changes that digitalization—the use of automated digital technologies to collect, process, analyze, distribute, use, and sell information—is spurring in the way housing is produced, marketed, sold, financed, managed, and lived in.

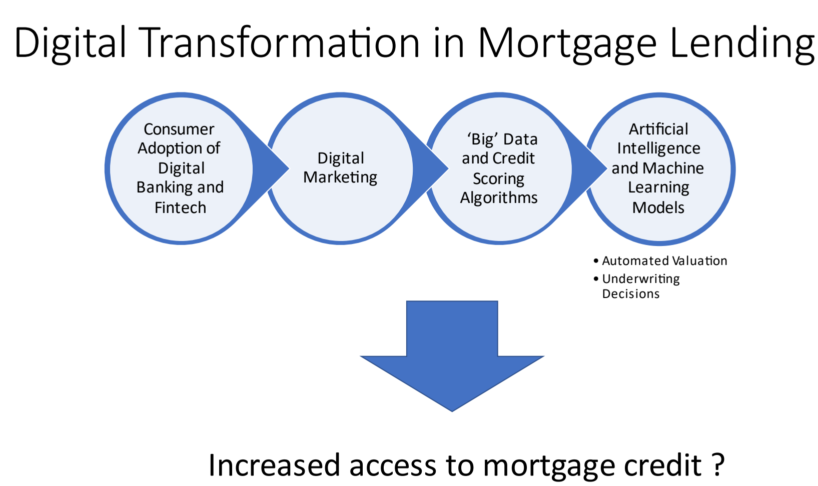
Abstract

Digitalization is transforming the mortgage market at every stage of the value chain. In this paper, we examine the potential for the mortgage industry to leverage digitalization to overcome historical and systemic barriers to homeownership for members of Black, Brown, and lower-income communities. We begin by proposing societal, ethical, legal, and practical criteria that should be considered in the development and implementation of a digitalization strategy. Based on this framework, we discuss four types of digitalization that are transforming the mortgage market, including digitalized banking and fintech, digital marketing, the inclusion of non-traditional "big data" in credit scoring algorithms, and the use of artificial intelligence and machine learning in automated property valuation and underwriting models. We conclude that although current digitalized tools may reflect the same biases that have existed historically in the mortgage market, opportunities exist for proactive, responsible digital transformation to remove systemic barriers to mortgage credit access.

Introduction

In the mortgage market, digitalization, "the use of digital technologies to change a business model and provide new revenue and value-producing opportunities," is already embedded and expanding throughout the mortgage value chain.[1] For example, mortgage lenders use sophisticated digital marketing techniques to target prospective borrowers and artificially intelligent bots to communicate with customers. Credit scoring companies are using machine learning processes to evaluate credit risk. Property valuation algorithms integrate large amounts of data on land titles, sales, market trends, and aspects of local infrastructure to produce digital appraisals. Digitized processes are replacing manual, paper-based workflows used for loan servicing and loss mitigation. Industry participants are experimenting with blockchain implementations to manage the origination process. Despite several potential benefits of digital transformation, including increased efficiency and accuracy and lower costs, institutions and regulators are finding it difficult to keep up with the rate of technological innovation. At the same time, evidence regarding the impact of digitalization processes on opportunities to expand mortgage credit to underserved communities, including lower-income and minority households, is lacking and inconclusive at best. In this article, we offer a framework to examine the effectiveness of digitalization in the mortgage industry.

Figure 1: Examples of Digitalized Processes in Mortgage Lending



[1] Gartner Information Technology Glossary, s.v. "Digitalization," https://www.gartner.com/en/information-technology/glossary/digitalization, accessed February 2, 2022.

The purpose of this paper is to examine the ways in which the mortgage industry is leveraging digitalization to help overcome historical and systemic barriers to homeownership for members of Black, Brown, and lower-income communities. As shown in **Figure 1**, we examine four types of digitalization that are transforming the mortgage market: consumer adoption of digitalized banking and fintech offerings, digital marketing, the inclusion of non-traditional "big data" in credit scoring algorithms, and the use of artificial intelligence and machine learning in automated property valuation and underwriting models. Building on prior research, we examine evidence of the potential of digitalization to transform market systems and outcomes. Based on this overview, we then describe how proactive, responsible digital transformation can be used to help overcome systemic barriers to mortgage credit for historically underserved households.

A Framework for Evaluating the Impact of Digitalization on Access to Homeownership for Underserved Communities

In subsequent sections, we provide an overview of key advancements toward the digitalization of the mortgage market and their potential for expanding access to credit for lower-income and minority households. We begin by establishing criteria for evaluating the extent to which these tools and processes serve this goal. Drawing on the SCALE framework developed by Perry and Schnare, we propose five factors summarizing the societal, ethical, legal, and practical issues that should be considered in the development and implementation of a digitalization strategy.[2]

- **Societal values.** A digitalized tool or process should be considered in light of similar decisions, the larger context, and historical factors, and should align with prevailing legal and ethical paradigms.[3] Recent political and social priorities in the US have focused on racial equity and social justice, and the Biden administration has directed regulatory agencies to increase fair access to homeownership. According to Kroll, credit scoring companies must "consider the context and impacts of their credit system and in particular … consider what outcomes are desired, how they might be reached, and how the deployment of a new system or changes to an existing system will alter the world."[4] New tools could be used to implement fair machine

[2] Vanessa G. Perry and Ann B. Schnare, "Tipping the SCALE: Will Alternative Data in Credit Scoring Promote or Impede Fair Lending Goals?"
[3] Kirsten Martin, "Ethical Implications and Accountability of Algorithms," 835.
[4] Joshua A. Kroll, "The Fallacy of Inscrutability," 3.

learning (FML) by deploying statistical algorithms to identify and correct for unjust or biased outcomes.[5]

- **Contextual integrity.** The appropriateness of a digital innovation depends on whether it conforms to contextual norms.[6] Regardless of its accuracy, a particular tool must be appropriate for the mortgage lending or housing domain. Walzer describes "spheres of justice" to underscore the importance of context in evaluating the fairness of outcomes by arguing that someone who excels in one sphere (e.g., education) should not be granted unmerited advantages in another sphere (e.g., mortgage loan access).[7] Certain social media advertising tactics, while appropriate for less consequential product categories, may result in unfair informational asymmetries in the mortgage lending context.
- **Accuracy.** It is also important to evaluate the extent to which a tool is reliable, error-free, and widely available across all major demographic and economic groups and macroeconomic conditions. One advantage of digitalization is rapid, systematic, and consistent data collection and modeling. However, inaccuracies can result when certain types of data are systematically omitted, or when biases are built into algorithms. For example, in property valuation models, due to varying assumptions about comparable property selection and historical racial disparities in property values, can models produce the "accurate" measurements necessary to predict risk? What types of errors are acceptable? "Accuracy" also refers to the absence of bias,[8] including representation bias, when the sample upon which a model is based differs significantly from the characteristics of the population; historical bias, when factors such as past discrimination are reflected in models; or systematic errors in estimation due to historical events, omitted variables, selection, aggregation,[9] or measurement.[10]
- **Legality.** It is also important to assess whether adopting a specific digital technology will have a negative and disparate impact on protected classes. The disparate impact standard prohibits any practice, including the use of a statistical algorithm, that has a negative, disparate impact on a particular racial/ethnic group when implemented. If a disparate impact occurs, the lender must provide a legitimate business justification and be able to rule out any less discriminatory

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[5] Jenny L. Davis, Apryl Williams, and Michael W. Yang, "Algorithmic Reparation," 1.
[6] Helen Nissenbaum, *Privacy in Context: Technology, Policy, and the Integrity of Social Life,* 1; Kirsten Martin and Helen Nissenbaum, "What Is It About Location?", 251.
[7] Michael Walzer, *Spheres of Justice: A Defense of Pluralism and Equality*, 1.
[8] FinRegLab, "The Use of Machine Learning for Credit Underwriting," 76.
[9] Laura Blattner and Scott Nelson, "How Costly Is Noise? Data and Disparities in Consumer Credit," 29.
[10] Will Douglas Heaven, "Bias Isn't the Only Problem with Credit Scores—and No, AI Can't Help."

alternative. Data and algorithms used for credit scoring, mortgage underwriting, and property valuation may run afoul of this standard.

- **Expanded opportunity.** A digitalized solution also should significantly increase access to credit in addition to cost, efficiency, or risk assessment benefits. Whereas digitalization has facilitated access to credit scores for previously unscoreable or "credit invisible" households, it is unclear whether it increases financing opportunities for a larger group of consumers with poor credit histories.[11]

Table 1 provides examples of how the SCALE criteria apply to digitalized processes in mortgage lending, and how these may affect access to mortgage credit to support minority homeownership. In the following sections, we apply these factors to understand the effects of digital technologies and fintech access, digital marketing, big data, artificial intelligence, and machine learning on minority households. We conclude with a discussion of implications for ethical and socially responsible digitalization and of opportunities to alleviate existing barriers to mortgage access.

[11] Ann B. Schnare, "Alternative Credit Scores and the Mortgage Market: Opportunities and Limitations," 24.

Table 1: SCALE Framework, Mortgage Digitalization, and Impact on Minority Homeownership[12]

Criteria	Digitalized Tool/Process	Impact on Minority Homeownership
Societal values	Including cash-flow data in credit scoring models	These data may magnify income and wealth disparities that have resulted from historical racism and discrimination.
Contextual integrity	Targeted digital advertising that filters content based on demographic or psychographic profiles	Although these tactics work well in the context of apparel or automobiles, digital advertising may be less appropriate for mortgage lending.
Accuracy	Property valuation algorithms	On average, Black and Hispanic borrowers pay higher rates and fees, and are more likely to have received high-cost subprime loans, faced foreclosure, or sustained significant equity losses during the 2008 crisis. Models that capture current home values may unfairly penalize minority communities, and may not be reliable predictors of default risk or losses.
Legality	AI/ML mortgage underwriting algorithms	AI models may have negative, disparate impacts on certain racial/ethnic groups; due to model complexity, sources of bias may be difficult to detect.
Expanded opportunity	AI/ML using non-financial data in credit scoring algorithms	Expanded data used for credit scoring may reduce the population of unscoreable households by increasing the number of households with high-risk (i.e., low) credit scores.

Have Digital/Mobile Technologies Expanded Opportunities for Minority Homeownership?

Digital solutions in the mortgage industry have promised to increase access to mortgage credit for underserved consumers and to do so at lower costs and increased efficiency. The term "fintech" has

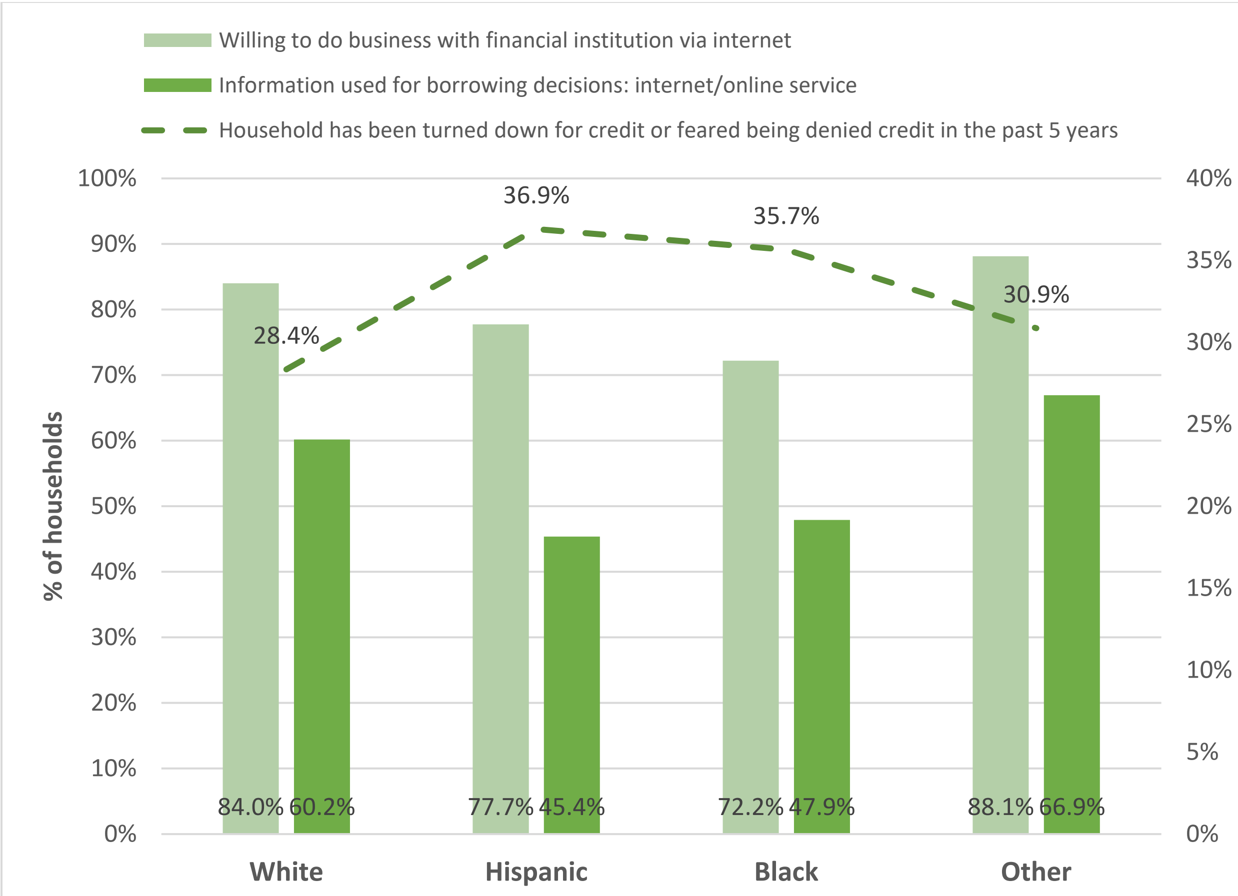
[12] Perry and Schnare, "Tipping the SCALE."

been defined as “technology innovations used to support or enable banking or financial services” such as smartphone applications, wi-fi, online and mobile banking, electronic payment transactions, and direct deposits, as well as transactions on peer-to-peer platforms and access to blockchain and cryptocurrencies.[13] Friedline and colleagues noted that the proliferation of fintech has coincided with a decline in banking activities at brick-and-mortar institutions, and that “these trends have the potential to replicate and reinforce redlining by amplifying the existing racialized geography of financial services and exacerbating consumers' marginalization from the financial marketplace.”[14] They found that fintech rates among high-poverty communities are generally low, and are even lower in areas with larger shares of Black, Latinx, and American Indian/Alaska Native populations. Controlling for high-speed internet access, smartphone ownership, and checking account ownership, fintech usage is higher in areas with Hispanic and Asian residents; this is not the case in high-poverty areas with higher proportions of Black residents.

The fintech divide can also be seen in **Figure 2**. Based on analyses of the 2019 Survey of Consumer Finances, these charts compare the share of renter households willing to do business with financial institutions online and the share who rely on online sources to inform borrowing decisions by racial/ethnic category. Also shown is the share of renter households that had either been turned down for credit or feared being denied credit in the past five years. Black and Hispanic households were less willing to engage in online banking transactions and less reliant on online information for borrowing decisions relative to white and other households. Black and Hispanic households also were more likely to have been denied credit or to have feared being denied credit in the past five years. Those who had been turned down or feared being turned down were significantly less likely to access online financial services regardless of race or ethnicity; this relationship was significantly more acute for Black and Hispanic households.[15]

[13] nLIFT, “Fulfulling the Promise of Fintech: The Case for a Nonprofit Vision and Leadership,” 8; Johannes Ehrentraud, Denise Garcia Ocampo, and Camila Quevedo Vega, “Regulating Fintech Financing: Digital Banks and Fintech Platforms,” 3.
[14] Terri Friedline and Zibei Chen, “Digital Redlining and the Fintech Marketplace: Evidence from US Zip Codes,” 381.
[15] Findings are based on a binary logistic regression of willingness to conduct online transactions with a financial institution as a function of racial/ethnic category, a dummy variable for having been turned down for credit or fear thereof, and interaction terms between these variables using a sample of renters.

Figure 2: Renters' Digital Financial Services Activity and Expectations of Credit Denial



Source: Analysis of the 2019 Survey of Consumer Finances

These data were collected before the COVID-19 pandemic, which brought about accelerated investments in mortgage market digitalization. According to Fannie Mae, the use of digital mortgage services has increased significantly during the pandemic, but less so among certain groups of homebuyers.[16] In a 2020 Pew Research survey, higher-income, Asian, and Black recent homebuyers indicated a slightly higher preference for online mortgage-related activities, while lower-income and Hispanic consumers showed a stronger preference for in-person or telephone interactions. Thus, it appears that some of the same racial and ethnic indicators of a digital divide in financial services documented before the pandemic persist today.[17]

[16] Fannie Mae, "Q1 Special Topic: COVID-19, Mortgage Digitization, and Borrower Satisfaction."
[17] Sara Atske and Andrew Perrin, "Home Broadband Adoption, Computer Ownership Vary by Race, Ethnicity in the US"; Emily A. Vogels, "Digital Divide Persists Even as Americans with Lower Incomes Make Gains in Tech Adoption."

Haupert found evidence of small but significant racial disparities in loan approvals between similarly qualified white and non-white applicants, and fewer disparities in approvals from fintech lenders versus traditional lenders. However, relative to similarly qualified white applicants, non-white applicants are more likely to receive subprime terms from both types of lenders, and disparities in subprime lending between Black and white applicants are greater among fintech lenders than traditional lenders. Haupert thus recommended more careful regulation of fintech lending.[18]

In terms of the SCALE framework, these digital technologies and fintech services have the potential to expand opportunities for minority homeownership but have had limited impact due to significant racial and ethnic gaps in access and adoption.

Has Digital Marketing Expanded Opportunities for Minority Homeownership?

Anecdotal evidence and recent legal activity suggest that targeted digital advertising practices may contribute to a less inclusive informational environment for members of traditionally underserved groups. These practices have raised concerns about algorithms designed to optimize user acceptance in the context of social media.[19] Evans and Miller argued that digital marketing techniques based on AI and machine learning (AI/ML) can increase the incidence of bias and consumer exploitation due to a lack of transparency in how they identify potential customers.[20] These strategies could easily evade regulatory oversight. Another concern related to targeted digital advertising by mortgage lenders is that advertisements may steer consumers toward particular products.[21]

Specifically, digital marketers purchase data from third-party vendors which track users and their browsing behaviors across websites. Lenders also rely on third-party lead generators who provide lists of potential customers based on data collected from website users who have shown interest in a particular product or category—e.g., people searching for homes or real estate agents. Additionally, lenders' digital marketing teams apply algorithms using data extracted from various sources to estimate "e-scores" used to predict future usage behavior. Each of these techniques could exclude certain groups of borrowers from the market—particularly those who are currently underrepresented.[22]

[18] Tyler Haupert, "The Racial Landscape of Fintech Mortgage Lending," 339.
[19] Muhammad Ali, Piotr Sapiezynski, Miranda Bogen, Alexandra Korolova, Alan Mislove, and Aaron Rieke, "Discrimination through Optimization: How Facebook's Ad Delivery Can Lead to Biased Outcomes," 1.
[20] Carol Evans and Westra Miller, "From Catalogs to Clicks: The Fair Lending Implications of Targeted Internet Marketing."
[21] Ibid.
[22] Ibid.

Recent cases against Facebook for Fair Housing Act (FHA) violations focused on ads for housing, but also apply to ads for mortgages.[23] Cases filed by the National Fair Housing Alliance, other civil rights groups, and HUD found that Facebook enabled housing advertisers to screen viewers based on protected characteristics, such as race, sex, and disability, and to exclude parents, foreign-born individuals, and those seeking accessible units. In response, Facebook created a separate advertising platform that allows users to view all housing ads. The company also agreed to require advertisers to certify compliance with fair housing laws.[24] This example has prompted mortgage lenders to assess fair lending risk in their digital marketing strategies and to carefully examine the criteria used to exclude groups based on prohibited characteristics.[25]

In another example, the DOJ and CFPB settled a suit against Trustmark Bank in 2021 for using a digital marketing strategy designed for businesses in majority-white neighborhoods to generate mortgage business from majority Black and Hispanic neighborhoods in the Memphis area.[26] The legal implications of digital targeting practices by mortgage lenders under the FHA and the Equal Credit Opportunity Act raise important questions about fair access to information about mortgage loans.[27] Digital marketing tools are essential for reaching consumers in today's marketplace. Based on the SCALE framework criteria, targeted advertisements based on demographic categories or correlated attributes may not align with societal priorities aimed at increasing racial equity and inclusion, and it is unclear whether these practices contribute to expanded opportunity. These practices may exacerbate information gaps and steering activities, reduce competition, and exacerbate the "dual" mortgage market in which minority homebuyers pay more for mortgage credit.[28]

Have Non-traditional Credit Scoring Algorithms Expanded Opportunities for Minority Homeownership?

Policymakers and credit experts have touted the potential for the inclusion of alternative data sources to expand access to credit scores (which are necessary to access the mortgage market) for those who

[23] National Fair Housing Alliance, "Fair Housing Groups Settle Lawsuit with Facebook: Transforms Facebook's Ad Platform Impacting Millions of Users."
[24] Tracy Jan and Elizabeth Dwoskin, "Facebook Agrees to Overhaul Targeted Advertising System for Job, Housing and Loan Ads After Discrimination Complaints."
[25] Austin K. Brown, "Fair Lending—Digital Marketing and HMDA 2018."
[26] Ballard Spahr LLP, "DOJ/CFPB/OCC Settle Redlining Lawsuit Against Mississippi-based National Bank."
[27] Nadiyah J. Humber and James Matthews, "Fair Housing Enforcement in the Age of Digital Advertising: A Closer Look at Facebook's Marketing," 5.
[28] Michelle Aronowitz, Edward Golding, and Jung Choi, "The Unequal Costs of Homeownership," 2.

currently have sparse or missing credit files.[29] Proponents believe that using alternative data such as utility payments, online transactions, and social media activity in credit scoring models will expand opportunities to consumers who are currently “credit invisible” or unscoreable.[30] Such factors can be considered only because digitalization has enabled these data to be collected and modeled.

Perry and Schnare suggested that credit proxies could expand opportunities for minority homebuyers,[31] and other proponents have argued that utility, telecommunications, and rental (UTR) payment histories can improve credit underwriting models.[32] One study estimated that the inclusion of telecommunications and utility payment data in traditional scoring models would increase acceptance rates by about 10 percent for the overall population, and by more than 20 percent for Black and Latinx individuals and consumers making less than $20,000 a year.[33] Another analysis showed that the inclusion of rent and utility payments in credit scoring had a positive impact on consumers’ access to credit, although the opposite was true for remittance payments.[34]

A recent study conducted by FinRegLab and the Urban Institute examined the use of UTR payment data for mortgage underwriting made possible by new digital platforms that collect and transfer these data to lenders.[35] Critics suggest that UTR payment history data could inadvertently increase financial challenges for families who are struggling to recover from the pandemic downturn or seasonal fluctuations in energy costs. In addition, there is evidence that Black, Hispanic, and low-income households pay more not only in energy costs as a share of their incomes but also per square foot of their residences,[36] and that these households are particularly susceptible to negative effects of extreme weather events and global warming.[37] Another concern is that the impact of the COVID-19 pandemic on UTR reporting, particularly “full-files” of all UTR payments, would disproportionately disadvantage lower-income consumers and minority communities.[38] A recent study found that 25 to 50 percent of consumers who experienced delinquencies did so on utility or telecom tradelines, but not on credit

[29] FTC, “Big Data: A Tool for Inclusion or Exclusion? Understanding the Issues,” 5.
[30] Brian Kreiswirth, Peter Schoenrock, and Pavneet Singh, “Using Alternative Data to Evaluate Creditworthiness.”
[31] Perry and Schnare, “Tipping the SCALE.”
[32] Kelly Thompson Cochran, Michael Stegman, and Colin Foos, “Utility, Telecommunications, and Rental Data in Underwriting Credit,” 10.
[33] Michael A. Turner, Alyssa Stewart Lee, Ann Schnare, Robin Varghese, and Patrick D. Walker, “Give Credit Where Credit Is Due: Increasing Access to Affordable Mainstream Credit using Alternative Data,” 32.
[34] CFPB, “Report on the Use of Remittance Histories in Credit Scoring,” 24.
[35] Cochran, Stegman, and Foos, “Utility, Telecommunications, and Rental Data.”
[36] Ariel Drehobl and Lauren Ross, “Lifting the High Energy Burden in America’s Largest Cities: How Energy Efficiency Can Improve Low-Income and Underserved Communities,” 4.
[37] Jason Byrne and Chloe Portanger, “Climate Change, Energy Policy, and Justice: A Systematic Review,” 331; Sanya Carley and David M. Konisky, “The Justice and Energy Implications of the Clean Energy Transition,” 571.
[38] National Consumer Law Center, “The Credit Score Pandemic Paradox.”

tradelines.[39] Thus, adding these data to consumers' credit files could simply expand the population of consumers with lower credit scores.

The inclusion of rental payments to expand access to credit scores with absent or sparse credit files has garnered a great deal of recent attention. The FHFA recently approved the use of rental payments to bolster credit files used in GSE underwriting models. California, Colorado, and the District of Columbia have enacted laws to require government-subsidized landlords to report rental payments to credit bureaus, who are developing reporting standards. However, the inclusion of rental payments poses significant potential challenges. There is wide variation in the timing, consistency, and quality of rental payment and eviction data. Rental payment data are more likely to be collected from large-scale property management companies, yet Black and Latinx renters reside in only 35 percent of the units in buildings with 50 or more units and 44 percent of all units in two-to-four-unit buildings.[40]

Several fintech initiatives to provide digital cash-flow data have been implemented to overcome these challenges. FinRegLab analyzed data from several non-bank financial companies that have adopted cash-flow variables in credit decisions instead of traditional indicators and found that cash-flow variables improve predictiveness when used in tandem with traditional credit history information, and, in some cases, can predict default risk with similar effectiveness.[41] Data and models reflect value judgments that may include certain biases.[42] For example, in existing scoring models, mortgage payments are weighted more heavily than other forms of credit. Blattner and Nelson found that credit scores are less predictive of default for racial and ethnic minority and low-income mortgage loan applicants and that these errors have a significant negative impact on mortgage approvals. The authors linked these disparities to differences in the underlying credit files rather than biases embedded in the model specification.[43]

Other potential predictors of credit risk include a consumer's GPS location, social media activity, health records, club memberships, educational history, academic performance, and digital footprint. Critics of these approaches have raised concerns that alternative factors are proxies for demographic characteristics (e.g., race, ethnicity, gender, and family status) that bias credit decisions, and thus are

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[39] Cochran, Stegman, and Foos, "Utility, Telecommunications, and Rental Data," 20.
[40] Jung Hyun Choi and Caitlin Young, "Owners and Renters of 6.2 Million Units in Small Buildings Are Particularly Vulnerable During the Pandemic."
[41] FinRegLab, "The Use of Cash-Flow Data," 27.
[42] Batya Friedman and Helen Nissenbaum, "Bias in Computer Systems," 330; Martin and Nissenbaum, "What Is It About Location?" 251.
[43] Blattner and Nelson, "How Costly Is Noise?" 29.

likely to exacerbate the effects of past marketplace discrimination.[44] Moreover, research suggests that the inclusion of non-financial personal data in lending decisions can pose several ethical and legal risks.[45] Models that rely on these data may do little more than digitalize historical discriminatory practices in mortgage markets, harkening back to the days when FHA guidelines explicitly advised underwriters to consider whether a borrower intends to reside "in a location inhabited by a class or race of people that may impair his interest in the property and thereby affect his motivation [to repay the loan]."[46]

Digitalization in the mortgage industry has introduced opportunities to expand the types of data used in underwriting models, thereby expanding opportunities for homeownership to historically underserved households. However, the use of UTR payment data, cash-flow (i.e., aggregated banking) data, and non-financial personal data in underwriting raises important ethical and legal questions for those who develop and apply credit scoring algorithms. While potentially predictive of repayment and default, these data raise questions of contextual integrity, accuracy, and perhaps even legality. Although there is overwhelming evidence that these new data sources will expand access to credit scores, it remains to be seen whether this will simply produce a larger pool of consumers with high-risk credit profiles who are more likely to be denied mortgage credit or targeted by subprime lenders.[47]

Has the Use of AI/ML in Automated Property Valuation and Underwriting Models Expanded Opportunities for Minority Homeownership?

Artificial intelligence (AI) is a technological advancement whereby a computer or computerized actor (e.g., a robot) mimics human decision processes. Traditionally, humans program computers to perform specific computational or predictive functions, and then programmers update and improve these programs.[48] AI systems perform complex tasks in ways that are similar to how humans solve problems. Machine learning (ML) is a form of AI in which the computer program optimizes its performance based on information gathered during previous tasks.[49] AI and ML are important digital transformation tools because of their ability to analyze much larger amounts of data and to discover complex relationships that transcend traditional statistical assumptions and analyses. These tools have been increasingly

[44] Haupert, "The Racial Landscape of Fintech Mortgage Lending," 340; Christopher K. Odinet, "Predatory Fintech and the Politics of Banking," 1757.
[45] Perry and Schnare, "Tipping the SCALE."
[46] FHA, *Underwriting Manual: Underwriting and Valuation Procedure Under Title II of the National Housing Act*, 137.
[47] Schnare, "Alternative Credit Scores," 24.
[48] IBM Cloud Education, "What Is Artificial Intelligence (AI)?"
[49] Sara Brown, "Machine Learning Explained."

applied in the private and public sectors.[50] Complex, multivariate algorithms have been in place for mortgage underwriting and pricing for more than two decades, and AI and ML are being used to enhance these models. AI and ML techniques have also been applied to marketing, customer relationship management, and servicing activities.[51]

One supposed advantage of AI models is that they are not subject to human biases and errors; they are thus viewed as possibly producing more accurate, consistent, and efficient decisions. Depending on how AI models are designed and developed, these enhanced capabilities could potentially expand access to credit for groups currently underserved by extant credit systems, particularly Black, Hispanic, and low-income consumers. However, it is unclear how well these models can adapt to changes in the market or how much they could magnify the effects of past discrimination.[52]

Because these models rely on historical data, critics in the academic and policy communities have raised concerns about the potential for these models to perpetuate historical discrimination and inequality.[53] In terms of the SCALE criteria, these models have raised concerns about sociopolitical priorities to advance racial equity. Beyond the mortgage context, these tools have already embedded or exacerbated some of the biases that plague human decision-makers. For example, Microsoft's AI chatbot "learned" to respond using racist language gathered from social media users,[54] and reports claim that a Twitter algorithm automatically edited out images of Black faces.[55] Racial bias also has been found in popular facial recognition programs and tenant screening algorithms adopted by landlords.[56] According to a recent paper published by the Brookings Institution, these systems embed "biased feedback loops" whereby consumers who previously encountered barriers to traditional forms of credit and obtained financing via higher-risk and more expensive subprime loans have lower credit scores, thereby capturing these circumstances in models for future credit decisions and pricing.[57] Based on the SCALE framework, these approaches also raise concerns in terms of accuracy due to the potential for

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[50] Michael Akinwumi, John Merrill, Lisa Rice, Kareem Saleh, and Maureen Yap, "An AI Fair Lending Policy Agenda for the Federal Financial Regulators," 4.
[51] Ibid.
[52] FinRegLab, "The Use of Machine Learning," 9.
[53] David Arnold, Will Dobbie, and Peter Hull, "Measuring Racial Discrimination in Machine Learning," 1; Kirsten Martin, "Designing Ethical Algorithms," 129.
[54] Oscar Schwartz, "in 2016, Microsoft's Racist Chatbot Revealed the Dangers of Online Conversation."
[55] Kevin Collier, "Twitter's Racist Algorithm Is Also Ageist, Ableist and Islamophobic, Researchers Find."
[56] Jessica Guynn, "Google Photos Labeled Black People 'Gorillas'"; Eva Rosen, Philip M. E. Garboden, and Jennifer E. Cossyleon, "Racial Discimination in Housing: How Landlords Use Algorithms and Home Visits to Screen Tenants."
[57] Michael Akinwumi, John Merrill, Lisa Rice, Kareem Saleh, and Maureen Yap, "An AI Fair Lending Policy Agenda for the Federal Financial Regulators," 2.

bias in the representation and selection of samples upon which models are based, in addition to omitted variables and historical factors which could also contribute to systematic errors.

The complexity of AI and ML tools makes it difficult but not impossible for non-developers to scrutinize and monitor their inputs. Kroll questioned the inscrutability of AI and argued that technological applications can and should be designed to facilitate auditing and validation processes.[58] Likewise, Johnson, Pasquale, and Chapman argued that ML-driven decision-making processes, such as credit underwriting models, should not simply be regulated to ensure fair results, but must be overseen in a manner that ensures ethical and transparent data collection and analysis methods.[59]

Digitalization in the appraisal process has improved efficiency in the loan origination process, and proponents argue that the accuracy of risk assessment has improved as well. Recent innovations include digitalized appraisal inspections whereby appraisers collect certain property data elements without in-person inspections in some cases. This information is then submitted to AI automated valuation models (AVMs) that replace traditional, more subjective procedures.

Meanwhile, appraisal bias has emerged as one of the most controversial issues in the mortgage industry, and several studies have documented systematic biases in traditional appraisals that result in lower values for Black and Hispanic homebuyers and neighborhoods.[60] One widely cited study, for example, revealed that homes owned by Black and Hispanic individuals are more likely to be appraised at a lower value than the sales price.[61] In another recent study, researchers compared traditional appraisals with those conducted by AVMs and found that homes owned by white borrowers are more likely to have an appraised value that is at least 10 percent higher than the AVM's estimated value compared to homes owned by Black borrowers; these overvaluations are also more likely to occur when white borrowers live in majority-Black neighborhoods.[62] Additional evidence suggests that AVM models are less likely to produce biased results, and as such, can be used to advance more equitable outcomes in appraisals for minority homebuyers and homeowners.[63]

[58] Kroll, "The Fallacy of Inscrutability," 8.
[59] Kristin N. Johnson, Frank A. Pasquale, and Jennifer Elisa Chapman, "Artificial Intelligence, Machine Learning, and Bias in Finance: Toward Responsible Innovation," 500.
[60] Jonathan Rothwell and Andre M. Perry, "Biased Appraisals and the Devaluation of Housing in Black Neighborhoods."
[61] Jennifer Folk and Kenon Chen, "Avoiding Overvaluation Risk and Appraisal Bias in Today's Uniquely Challenging Market Session."
[62] Jake Williamson and Mark Palim, "Appraising the Appraisal: A Closer Look at Divergent Appraisal Values for Black and White Borrowers Refinancing Their Home," 8.
[63] House Canary, "Reducing Racial Bias in Home Appraisals Using Automated Valuation Technology," 4.

Concerns that plague credit scoring and underwriting algorithms also apply in the case of AVMs—namely, the potential for these models to capture and amplify latent discrimination and redlining. Homes owned by Black and Hispanic families as well as homes located in minority neighborhoods have historically and consistently had lower values and rates of house price appreciation than homes owned by similarly situated white counterparts.[64] AI/ML models could be developed to remove barriers to equitable outcomes and offset the effects of bias and discrimination in AVMs by assimilating a wider range of data.

In another recent analysis, researchers argued that due to the complexity and dynamic nature of ML models, it would be difficult to identify the specific cause of disparities affecting underrepresented groups or to perform standard fair lending analyses.[65] The authors suggested that existing legal, policy and regulatory frameworks lag woefully behind in understanding these technologies or how best to oversee their application.[66] To increase transparency, some modelers develop "inherently interpretable" models, while others combine complex models with post hoc explainability methods, i.e., supplemental information. Kluttz et al. argued that in addition to transparency and explainability, AI models should be subjected to the higher standard of "contestability"—that is, the extent to which sufficient information is available to meaningfully challenge the model's outcomes.[67] In contexts involving AI/ML applications, contestability would be analogous to consumer protection laws that require, for example, disclosure of the reasons for a mortgage loan denial to the applicant.

Despite concerns about accuracy, potential bias, and legality, AI/ML applications have significant potential to expand homeownership opportunities. If calibrated to do so, ML models could be deployed to identify sources of bias and discrimination, as well as non-discriminatory alternatives.[68] Davis, Williams, and Yang recently proposed an "algorithmic reparation" approach whereby ML techniques are explicitly designed to minimize or eliminate the effects of historical disadvantages (e.g., structural racism), rather than to attempt to remove bias from existing algorithms.[69]

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[64] Vanessa G. Perry et al., "2020 State of Housing in Black America."
[65] FinRegLab, Laura Blattner, and Jann Spies, "Machine Learning Explainability & Fairness: Insights from Consumer Lending," 12.
[66] FinRegLab, "The Use of Machine Learning," 119.
[67] Daniel N. Kluttz, Nitin Kohli, and Deirdre K. Mulligan, "Shaping Our Tools: Contestability as a Means to Promote Responsible Algorithmic Decision Making in the Professions," 137.
[68] Akinwumi et al., "An AI Fair Lending Policy Agenda," 12.
[69] Davis, Williams, and Yang, "Algorithmic Reparation."

Conclusions, Implications, Recommendations for Public Policy and Future Research

Mortgage lenders, policymakers, and other industry stakeholders should consider the elements of the SCALE framework when designing, adapting, evaluating, and monitoring digitalized tools. These perspectives could help inform recently proposed legislation (e.g., HR 6580, the Algorithmic Accountability Bill of 2022 proposed by Senators Ron Wyden and Cory Booker and Representative Yvette Clarke) intended to expand FTC oversight of AI in housing, financial services, and other industries.[70] Trade publications and the blogosphere are replete with examples of digitalized solutions claiming to increase efficiency in marketing, operations, risk assessment, regulatory compliance, and servicing. However, there are far fewer frameworks for proactive responsible digital transformation that could provide solutions to systemic barriers to mortgage credit in current market structures.

The proposed Algorithmic Accountability Act would direct the FTC to require impact assessments of AI systems and "augmented critical decision processes." Although this proposal acknowledges the issues and would increase resources for the FTC and other agencies to evaluate AI models, it is unclear how audits would account for the iterative, dynamic, and rapidly changing nature of model development. How often should models be evaluated and at what stage of development or implementation? In addition to the concerns about transparency and interpretability described above, as well as the pervasiveness of AI modeling in these industries, it is hard to imagine that the government would ever have the resources to meaningfully evaluate these practices. In the case of AI, industry self-regulation might be a more viable, less costly alternative to traditional regulatory oversight. FinRegLab, Blattner, and Spiess compared ML credit decision models in terms of explainability and fairness and found that these models vary in the extent to which they can identify characteristics that have a negative and disparate impact on protected classes. These authors propose an approach for "evaluating the quality and usability of information produced about machine learning models' behavior" which could be adopted by lenders and regulators who are seeking transparency in the context of fair lending.[71]

Another policy recommendation is to revisit HUD's 2020 "disparate impact rule" that requires "a robust causal link between the challenged policy or practice and the adverse effect on members of a

[70] Kate Kaye, "This Senate Bill Woulf Force Companies to Audit AI Used for Housing and Loans"; Office of Senator Ron Wyden, "Wyden, Booker, and Clarke Introduce Algorithmic Accountability Act to Require New Transparency and Accountability for Automated Data Systems" (press release).

[71] FinRegLab, Blattner, and Spiess, "Machine Learning Explainability & Fairness," 11.

protected class." The "robust causal link" standard has been difficult to prove or enforce, and harkens back to a time when manual underwriting decisions based on a few discrete factors were the norm. Because of the large number of factors and combinations thereof in AI/ML models, causal links, including those that unduly harm disadvantaged groups, are difficult to uncover. New language and interpretation of this standard would foster more effective enforcement of the disparate impact legal standard.

As described above, digitalization in the mortgage market can help advance social and political goals of eradicating racism and discrimination, as captured in Davis's notion of digital reparation.[72] Digitalization strategies could improve accuracy and remove rather than introduce bias; however, such strategies require thoughtful design, development, and implementation. Theoretical and empirical research on the effects of AI and ML, for example, suggests that if designed to do so at the outset, these tools have the potential to identify and eradicate the effects of systemic discrimination while simultaneously increasing predictive accuracy and efficiency in the mortgage value chain. It is important, however, to ensure that tools and approaches adapted from other contexts are appropriate for mortgage lending. Developers of these tools should address potential legal and regulatory issues, such as the potential for discrimination in the form of disparate impact. Lastly, in addition to increased efficiency, lower transaction costs, and/or improved predictiveness, digitalization strategies should be designed to expand opportunities by reducing barriers associated with manual, more subjective, and biased processes used by many traditional brick-and-mortar institutions.

The Black-white homeownership gap persists due to economic and social disadvantages that have accumulated over generations. The effects of "color-blind" regulations are a subject of heated debate among scholars and policymakers, and some argue that to account for racial effects, race must be explicitly included in models that predict outcomes such as loan defaults. As described by Samuel Myers in his "Minnesota paradox," a reliance on race-neutral metrics of homeownership and other economic outcomes can obfuscate segregation, poverty, and other conditions that exist for Black communities.[73] Ifeoma Ajunwa more broadly described the paradox of automation where more automated decision making is positioned as an anti-bias intervention, yet "has served to replicate and amplify bias."[74] Recent research on ethics in AI and ML suggests that models need to include race at the design stage, rather than simply as a test for bias on the back end. Existing, well-intentioned public

[72] Davis, Williams, and Yang, "Algorithmic Reparation."
[73] Samuel Myers, "Prof. Samuel Myers Jr. on the Surprise of the Minnesota Paradox and Large Racial Disparities."
[74] Ifeoma Ajunwa, "The Paradox of Automation as Anti-bias Intervention," 1671.

policies prohibit the inclusion of race as a factor in credit or valuation models. This paradigm fails to acknowledge that race is an endogenous and recursive measure of systematic and institutional discrimination. To address societal goals of advancing equity and expanding homeownership opportunities, these same models could be used to measure and potentially offset the effects of race in estimates of credit costs and risks.

Several important unanswered questions remain. For example, what are the appropriate goals for adopting new digitalized tools, particularly those used to inform lending decisions? Replicating human decisions is one such goal. Should the outcomes of these models (i.e., the ability to assess and price risk) necessarily be superior to bias and other errors often associated with human decisions? We assume firms should use established criteria to assess whether digitalization projects and any new programs or projects in mortgage lending expand opportunities for minority ownership. More work should be done to translate established criteria of success so they can be applied to outcomes of digitalization projects. As Thomas and Uminsky noted, defining the outcomes or metrics of success (accuracy, effectiveness, etc.) narrowly and without regard to the context of the decision exacerbates underlying problems.[75] Metrics should be broad, multi-faceted, and informed by an understanding of those stakeholders most impacted by the program—in this case, minority mortgage applicants.

Another important issue is how digitalization tools can be used to *verify* fair and equitable treatment of individuals for each of these types of decisions, as prescribed by Davis, Williams, and Yang's notion of algorithmic reparation.[76] Rather than simply making the decisions, these tools could be used to support or validate decisions being made by humans and/or AI. This suggests a fifth responsible use of digitalization in the mortgage market: using novel data analytics techniques to monitor, assess, and verify the fair and equitable treatment of mortgage applicants.

[75] Rachel Thomas and David Uminsky, "The Problem with Metrics is a Fundamental Problem for AI," 1.
[76] Davis, Williams, and Yang, "Algorithmic Reparation."

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