

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

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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.

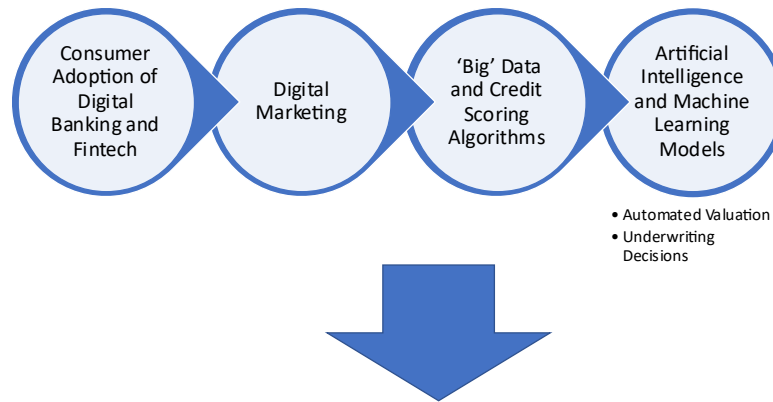
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In the mortgage market, digitalization, i.e., “the use of digital technologies to change a business model and provide new revenue and value-producing opportunities,”¹ is already embedded and expanding throughout the mortgage value chain. For example, 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.

¹ Gartner.

Figure 1: Examples of Digitalized Processes in Mortgage Lending [Decorative]

Digital Transformation in Mortgage Lending



Increased access to mortgage credit ?

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, including 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 on 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 S.C.A.L.E. framework developed by Perry and Schnare,² 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.

- **Societal values.** A digitalized tool or process should be considered from the perspective 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 U.S. 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 to 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 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 with contextual norms.⁶ Regardless of its accuracy, a particular tool must be appropriate for the mortgage lending or housing domain. Walzer described “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 advantages without merit 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 biases are built into algorithms. For example, in property valuation models, due to varying assumptions about comparable

² Perry and Schnare.

³ Martin, “Ethical Implications,” p. 835

⁴ Kroll, p. 3

⁵ Davis, Williams, and Yang, p. 1.

⁶ Nissenbaum, p. 1; Martin and Nissenbaum, p. 251.

⁷ Walzer, p. 1.

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 bias⁸ 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 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 unscorable 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 opportunities to alleviate existing barriers to mortgage access.

⁸ FinRegLab, “The Use of Machine Learning,” p. 76.

⁹ Blattner and Nelson, p. 29.

¹⁰ Heaven.

¹¹ Schnare, “Alternative Credit Scores,” p. 24.

Table 1: SCALE Framework, Mortgage Digitalization, and Impact on Minority Homeownership¹²

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 unscorable 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.

been defined as “technology innovations used to support or enable banking or financial services”¹³ such as smartphone applications, wi-fi, online and mobile banking, electronic payment transactions, direct deposits, as well as transactions on peer-to-peer platforms and access to blockchain and cryptocurrencies. 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 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 5 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 feared being denied credit in the past 5 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

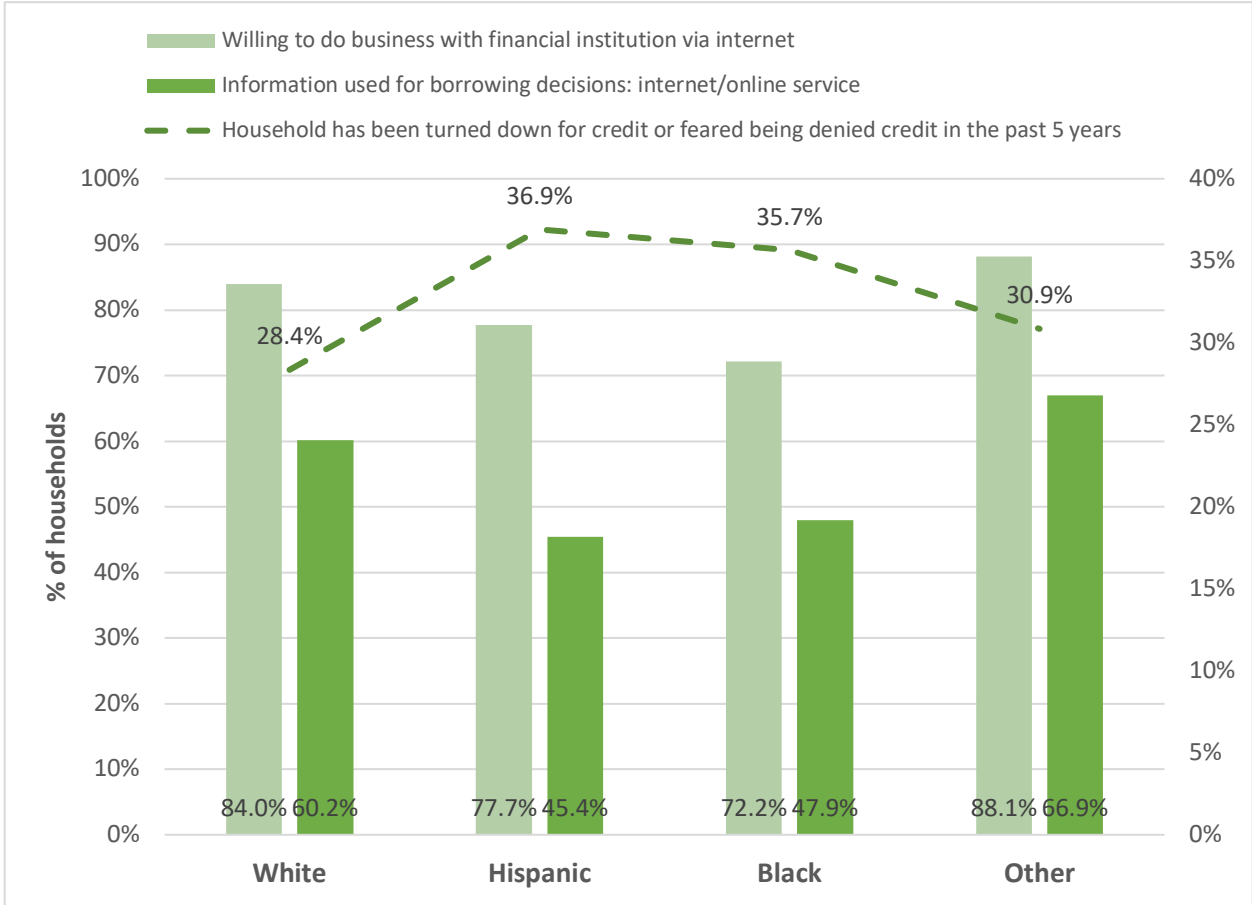
¹³ nLIFT, p. 8; Ehrentraud, Ocampo, and Vega, p. 3.

¹⁴ Friedline and Chen, p. 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

[Digital financial services activity varies by race and ethnicity of renters. For example, 72% of Black and 78% of Hispanic renters reported a willingness to do business with financial institutions via internet, compared to 84% of White and 88% of other (including Asian) renters. Black and Hispanic renters were also less likely to use online information for borrowing decisions relative to White or Other (including Asian) renters. At the same time, Black and Hispanic renters were more likely to have been turned down or denied credit in the past 5 years.]



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,¹⁶ the use of digital mortgage services has increased significantly during the pandemic, but less so among certain groups of homebuyers. 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

¹⁶ Fannie Mae.

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

Hauptert 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. The author 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 tracks 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"

¹⁷ Atske and Perrin; Vogels.

¹⁸ Hauptert, p. 339.

¹⁹ Ali et al., p. 1.

²⁰ Evans and Miller

²¹ Evans and Miller

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

Recent cases against Facebook for Fair Housing Act (FHA) violations²³ focused on ads for housing, but also apply to ads for mortgages. 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 Act²⁷ raise important questions about fair access to information about mortgage loans. 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 further 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

²² Ibid.

²³ National Fair Housing Alliance.

²⁴ Jan and Dwoskin.

²⁵ Brown, Austin.

²⁶ Ballard Spahr.

²⁷ Humber and Matthews, p.

²⁸ Aronowitz, Golding, and Choi, p. 2.

who 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 unscorable.³⁰ Such factors can only be considered 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 rent and utility payments had a positive impact on consumers’ access to credit, although the opposite was true for remittance payments.³⁴

A recent study conducted by FinRegLab 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 residences³⁶, 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 tradelines.³⁹ Thus, adding these

²⁹ Ramirez et al., p.5.

³⁰ Kreiswirth, Schoenrock, and Singh.

³¹ Perry and Schnare.

³² Cochran, Stegman, and Foos, p. 10.

³³ Turner et al., p. 32.

³⁴ CFPB, “Report on the Use of Remittance Histories,” p. 24.

. Cochran, Stegman, and Foos.

³⁶ Drehobl and Ross, p. 4.

³⁷ Byrne and Portanger, p. 331; Carley and Konisky, p. 571.

³⁸ National Consumer Law Center

³⁹ Cochran, Stegman, and Foos, p. 20.

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 likely to exacerbate the effects of past marketplace discrimination.⁴⁴ Moreover, research suggests that

⁴⁰ Choi and Young

⁴¹ FinRegLab, "The Use of Cash-Flow Data," p. 27.

⁴² Friedman and Nissenbaum, p. 330; Martin and Nissenbaum, p. 251.

⁴³ Blattner and Nelson, p.29.

⁴⁴ Hauptert, p. 340; Odinet, p.1757.

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 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

⁴⁵ Perry and Schnare.

⁴⁶ FHA, p. 137.

⁴⁷ Schnare, “Alternative Credit Scores,” p. 24.

⁴⁸ IBM Cloud Education.

⁴⁹ Brown, Sara.

⁵⁰ Akinwumi et al., “An AI Fair Lending Policy Agenda,” p. 4.

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; as such, they are viewed as possibly producing more accurate, consistent, and efficient decisions. Depending 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 the extent to which they would 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 socio-political 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 Brookings paper, 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 bias in 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

⁵¹ Ibid.

⁵² FinRegLab, "The Use of Machine Learning," p. 9.

⁵³ Arnold, Dobbie, and Hull, p; Martin, p. 129

⁵⁴ Schwartz.

⁵⁵ Collier.

⁵⁶ Guynn; Rosen, Garboden, and Cossyleon

⁵⁷ Ibid.

⁵⁸ Kroll, p. 8.

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

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.

⁵⁹ Johnson, Pasquale, and Chapman, p. 500.

⁶⁰ Rothwell and Perry.

⁶¹ Folk and Chen.

⁶² Williamson and Palim, p. 8.

⁶³ House Canary, p. 4.

⁶⁴ Perry et al.

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. The authors suggested that existing legal, policy and regulatory frameworks lag woefully behind in understanding these technologies or how best to oversee their application.⁶⁵ 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.⁶⁶ 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.⁶⁷ Davis et al. 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.⁶⁸

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, adopting, evaluating, and monitoring digitalized tools. These perspectives could help inform recently proposed legislation (e.g., the H.R.6580 Algorithmic Accountability Bill proposed by Senators Wyden and Booker, and Representative Yvette Clarke) intended to expand FTC enforcement of AI in housing, financial services, and other industries.⁶⁹ 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

⁶⁵ FinRegLab, “The Use of Machine Learning,” p.119.

⁶⁶ Kluttz, Kohli, and Mulligan, p. 137.

⁶⁷ Akinwumi et al., p. 12.

⁶⁸ Davis et al.

⁶⁹ Kaye; <https://www.wyden.senate.gov/news/press-releases/wyden-booker-and-clarke-introduce-algorithmic-accountability-act-of-2022-to-require-new-transparency-and-accountability-for-automated-decision-systems>

fewer frameworks for proactive responsible digital transformation that could provide solutions to systemic barriers to mortgage credit in current market structures.

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.

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 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.⁷⁰ 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, suggest 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 adopted 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

⁷⁰ Davis et al.

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 with regard to the “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.⁷¹ 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.”⁷² 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 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.⁷³ 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.

⁷¹ Myers.

⁷² Ajunwa, p.1671.

⁷³ Thomas and Uminsky, p. 1.

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 et al.'s notion of algorithmic reparation.⁷⁴ 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.

⁷⁴ Davis et al.

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