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Review Article

Business Intelligence and Analytics in U.S. Financial Services: Evidence on Lending Decisions, Risk, and Governance

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Abstract

Banks, FinTech lenders, and other U.S. financial-service firms increasingly use analytics to screen borrowers, verify information, price risk, allocate credit, monitor conduct, and support operational decisions. This structured narrative review synthesizes 47 U.S. empirical studies published between 2010 and August 2026. The evidence is concentrated in mortgage, consumer, small-business, marketplace, and related lending, with additional studies of bank information technology, information-sharing systems, automated underwriting, application programming interfaces, regulatory technology, robo-advice, and artificial intelligence-related operational risk. Several studies associated digital verification, alternative data, and stronger information-processing capability with faster processing, wider credit access, better screening, or improved loan performance. Others reported higher default, mispriced risk, suspicious lending patterns, persistent pricing disparities, and operational losses. Findings varied by setting and research design. Across the settings represented in the evidence base, analytics contributed most to decision quality when information was credible and decision-relevant, useful complementary information was retained, analytical signals influenced institutional action, and incentives, governance, risk controls, and monitoring supported appropriate use.

Categories: Banking and financial services, Decision Support, Computational Intelligence and Information Management

Keywords: business intelligence and analytics, financial services, decision-making effectiveness, information quality, fintech, analytical capability

Introduction And Background

Financial-service organizations depend on information that can be assembled, checked, interpreted, and acted on under time pressure. That dependence has deepened as lending, pricing, fraud control, customer assessment, and risk management have become more data-intensive. Recent Federal Reserve evidence gives some sense of the scale: about 30% of U.S. firms in finance and insurance reported using artificial intelligence (AI) in 2025, while 63% of workers in the sector reported using generative AI for work. Firm-level AI adoption in finance had increased 127% over the year ending September 2025 (Allen, 2026). AI captures only one part of the analytical infrastructure now used across financial services, but the figures show how rapidly computational tools are entering routine financial work.

Business intelligence and analytics (BI&A) provides a broader framework for understanding that capacity. Chen et al. described BI&A as the technologies and analytical practices used to work with increasingly large and diverse data resources (Chen et al., 2012). Later work shifted attention toward organizational capability. Gupta and George treated analytics capability as a combination of data, technological resources, technical and managerial skills, and other

organizational resources that enable firms to extract value from analytics (Gupta and George, 2016). In finance, that distinction matters because access to more data or more sophisticated models does not by itself establish that a better decision has been made.

Financial research does not always use the BI&A label for these capabilities. Studies instead examine bank information technology, alternative data, machine learning, digital verification, application programming interfaces (APIs), information-sharing systems, and RegTech. Their decision functions nevertheless overlap. Some technologies enlarge the information available to an organization; others verify information already available, improve its movement across organizational boundaries, or automate parts of classification and screening. Reported outcomes are mixed, ranging from faster processing and stronger screening to higher subsequent default, missed risk signals, pricing disparities, and operational losses.

Decision quality is treated here as more than processing speed or predictive accuracy. It is examined through several dimensions: screening and risk discrimination, the appropriateness of pricing and credit allocation, subsequent performance, conduct and compliance outcomes, and operational consequences. Faster processing or broader access may therefore represent an efficiency gain without necessarily indicating a better underlying decision.

This study uses a structured narrative review design. The included studies vary substantially in financial-service setting, analytical capability, research design, and outcome measurement. Findings are synthesized thematically rather than combined into a single effect estimate, with attention to recurring patterns, conflicting results, and the conditions under which similar analytical capabilities produce different outcomes.

Although the review addresses financial services broadly, the available empirical literature is concentrated in lending and credit-related decisions. Evidence from other activities, including investment advice, broker-dealer compliance, information infrastructure, and operational risk, is comparatively limited. Because most of the evidence comes from lending, the conclusions are most secure for credit-related decisions. Other financial-service functions remain too thinly studied to support the same level of confidence.

The review examines what BI&A has actually changed in financial decision-making and why similar analytical capabilities have produced different outcomes across settings. Figure *1* summarizes the pathway used to organize the synthesis.

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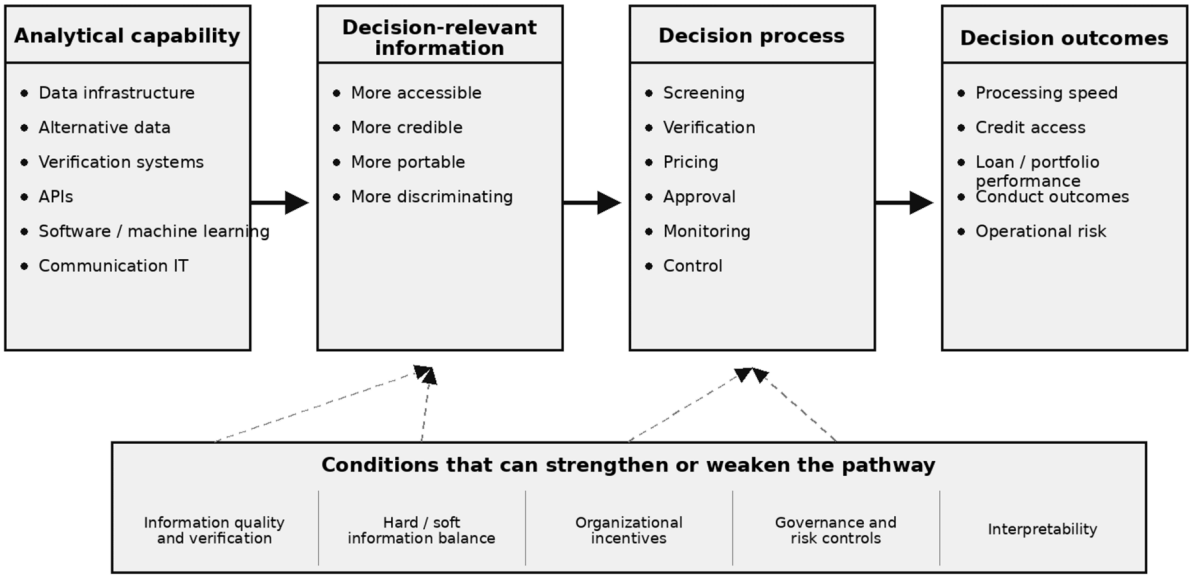


FIGURE 1: Conceptual pathway linking business intelligence and analytics capability to decision quality in U.S. financial services.

Source: Authors. API, Application Programming Interface; IT, Information Technology

Review

Methods

This study used a structured narrative review design. The search was conducted in August 2026 and covered ScienceDirect, Oxford Academic, Wiley Online Library, INFORMS PubsOnline, Emerald Insight, and SAGE Journals. Retrieval was supplemented by backward and forward citation tracing and publisher-level verification of potentially eligible studies. The search record was reconstructed and updated on August 25, 2026, because the original search did not preserve reliable platform-level retrieval and duplicate counts.

The initial search combined the concepts of business intelligence and analytics, financial institutions, and the United States: ("business intelligence" OR "business analytics") AND (bank* OR lender* OR "financial institution*") AND ("United States" OR U.S.). Because much of the relevant financial literature does not use the BI&A label, subsequent searches expanded the capability terms to include information technology, digital lending and origination, alternative data, machine learning, algorithms, automated underwriting, credit scoring, risk-based pricing, digital verification, APIs and open-data infrastructure, information sharing, RegTech, FinTech, mortgage information infrastructure, and robo-advisory systems. These were combined, as appropriate, with decision-related outcomes including screening, underwriting, approval, pricing, processing time, credit access, credit limits, default and delinquency, fraud or misconduct, portfolio allocation, collateral valuation, and operational risk. Search syntax was adapted to the functionality of each platform.

Studies were eligible for the core synthesis when they were peer-reviewed, English-language original empirical studies published between January 2010 and August 2026; examined a U.S. financial-service setting; evaluated BI&A or a functionally equivalent data, information-processing, or analytical capability; and linked that capability to an observable institutional decision or downstream decision-related outcome. Conceptual papers, commentaries, vendor materials, preprints, studies without a U.S. empirical setting, and studies in which technology adoption could not be connected to a financial decision or consequence were not included in the core evidence base.

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Figure *2* presents the reconstructed study-selection process, showing the 69 unique candidate studies and the 47 included in the core synthesis. Original platform-level retrieval totals, duplicate-removal counts, and reason-specific exclusion counts were not preserved. Each study was reassessed against the eligibility criteria. Forty-seven met the criteria for inclusion in the core empirical synthesis. The remaining records were not included in the core evidence base; where relevant, selected studies were cited only to clarify mechanisms or boundary conditions. Because the original search did not prospectively retain study-level disposition counts, a numerical breakdown of excluded and supporting records is not reported.

Most core studies concerned mortgage, consumer, small-business, marketplace, or Paycheck Protection Program (PPP) lending, with a smaller group examining bank operations, credit unions, broker-dealers, information infrastructure, credit-limit management, and automated investment advice. For each core study, the review recorded the financial-service setting, analytical capability examined, decision or outcome studied, research design, principal empirical finding, and limitations relevant to interpretation. Studies were then compared thematically across four recurring domains: scale, access, and processing capacity; screening, pricing, and automated allocation; information architecture and intermediation; and governance, fairness, and downstream risk. Heterogeneity in technologies, units of analysis, research designs, and outcomes precluded meaningful statistical pooling. No Preferred Reporting Items for Systematic Reviews and Meta-Analyses procedure or meta-analysis was applied.

To distinguish evidentiary strength, each core study was classified according to its principal empirical design. Categories included randomized experimental evidence; quasi-experimental designs using natural experiments, difference-in-differences, instrumental variables, regression discontinuity, or other plausibly exogenous variation; longitudinal or panel observational studies; comparative or cross-sectional observational studies; and descriptive, audit, or model-based analyses. These classifications describe the principal evidentiary basis of each study rather than constituting a formal risk-of-bias score. Causal interpretations were given greater weight where the study design supported them, while findings from observational studies were interpreted as associations unless stronger identification was demonstrated (Table *1*).

Study	Setting	Capability examined	Study design/evidentiary basis	Principal decision-related finding
(Doblas-Madrid and Minetti, 2013)	U.S. commercial credit	Credit-bureau information sharing	Quasi-experimental; staggered credit-bureau entry/natural experiment	Credit-information sharing changed contract outcomes and reduced repayment problems.
(Einav et al., 2013)	U.S. subprime auto finance	Automated credit scoring	Longitudinal observational; before-and-after credit-scoring adoption	Automated scoring increased profit by roughly $1,000 per loan and improved risk-based screening and targeting.
(Sedunov, 2017)	U.S. small-business lending	Back-office and web-based bank technology	Bank-level panel observational analysis with endogeneity robustness tests	Bank technology was associated with how banks made small-business lending decisions.

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(Buchak et al., 2018)	U.S. mortgage lending	Online origination technology/FinTech production process	Quasi-experimental; difference-in-differences using regulatory shocks	Technology explained a material share of FinTech/shadow-bank mortgage expansion and affected pricing/supply.
(Jagtiani and Lemieux, 2018)	U.S. consumer lending	FinTech online lending platform	Comparative loan- and market-level observational regression	FinTech lending penetrated areas less served by traditional bank branches.
(Sutherland, 2018)	U.S. commercial lending	Credit-reporting/information-sharing technology	Quasi-experimental; staggered credit-bureau participation	Credit reporting altered lenders' reliance on relationship information.
(Walke et al., 2018)	U.S. credit unions	Risk-based pricing enabled by automated credit scoring	Quasi-experimental observational design using propensity-score matching	Adopters expanded loan availability; delinquency was lower for some adoption cohorts.
(Fuster et al., 2019)	U.S. mortgages	Digital mortgage origination/technology-based lending	Quasi-experimental loan-level analysis using exogenous mortgage-demand variation	~20% faster processing without higher subsequent default.
(Jagtiani and Lemieux, 2019)	U.S. consumer lending/LendingClub	Alternative data + machine-learning-based credit grading	Comparative and predictive loan-level observational analysis	Internal grades diverged from FICO while retaining predictive value.
(Agarwal and Hauswald, 2021)	U.S. bank lending	Online versus in-person information-production channel	Comparative observational analysis of online and in-person lending channels	Disclosure and lending channel changed the information used in credit availability and pricing.
(Di Maggio and Yao, 2021)	U.S. personal credit	FinTech hard-information underwriting	Matched individual-level longitudinal observational analysis	FinTech borrowers showed higher subsequent default than comparable traditional borrowers.
(Jagtiani et al., 2021)	U.S. mortgage lending	FinTech marketing/application and digital origination	Mortgage-level and geographic comparative observational analysis	FinTech mortgage channels were associated with different patterns of credit access.

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(Lewellen and Williams, 2021)	U.S. mortgage market/Massachusetts	Mortgage Electronic Registration System (MERS)	Quasi-experimental panel design exploiting MERS-partner adoption	MERS reduced transaction frictions, expanded mortgage credit supply, and was associated with higher foreclosure rates.
(Bartlett et al., 2022)	U.S. mortgage lending	FinTech origination / algorithmic lending channel	Observational loan-level analysis with risk-equivalent pricing identification	Risk-equivalent racial pricing disparities persisted in FinTech and traditional channels.
(Chan et al., 2022)	U.S. auto lending	Electronic employment verification	Quasi-experimental; difference-in-differences around digital employment verification	Origination rose after employment became digitally verifiable, especially for weak-score borrowers.
(Erel and Liebersohn, 2022)	U.S. PPP lending	FinTech digital distribution	Quasi-experimental analysis exploiting PPP introduction and pandemic demand shocks	FinTech lending reached areas with weaker pre-existing banking relationships.
(Liberti et al., 2022)	U.S. equipment finance	Reciprocal commercial credit-information sharing	Quasi-experimental; staggered information-sharing adoption	Information-sharing adoption expanded access for higher-quality borrowers and altered lender participation.
(Pierri and Timmer, 2022)	U.S. commercial banks/mortgages	Bank information-technology adoption	Quasi-experimental bank and loan-level analysis including instrumental-variable estimates	Higher pre-crisis IT was associated with fewer non-performing loans; evidence favored screening.
(Allen et al., 2023)	U.S. mortgage lending after natural disasters	FinTech automated mortgage-lending capability	Quasi-experimental; exogenous natural-disaster demand shocks	FinTech lenders supplied credit more elastically after disasters without worse risk-adjusted outcomes.
(Balyuk, 2023)	U.S. consumer credit	Online peer-to-peer/FinTech lending information spillovers	Quasi-experimental; regression-discontinuity design	FinTech borrowing generated information spillovers that affected subsequent access to bank credit.

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(Griffin et al., 2023)	U.S. Paycheck Protection Program	Rapid FinTech origination/automated processing	Large-sample observational fraud-indicator analysis with external validation	FinTech-originated PPP loans were more likely to trigger potential misreporting indicators.
(McCanless, 2023)	U.S. consumer lending/Upstart partnerships	Alternative-data machine-learning credit scoring	Algorithmic audit/observational model analysis	Alternative inputs materially affected loan outcomes; partner banks increased balance-sheet allocation to platform loans.
(Balyuk and Davydenko, 2024)	U.S. online lending	Platform software/automated credit evaluation	Descriptive and observational platform-level market-structure analysis	Platform software performed central loan-evaluation functions and shaped automated funding allocation.
(Charoenwong et al., 2024)	U.S. broker-dealers	RegTech/internal-control technology systems	Quasi-experimental analysis of regulation-driven technology investment	Technology investment was followed by fewer complaints and misconduct, but higher costs.
(Cornelli et al., 2024)	U.S. small-business lending	Proprietary FinTech scoring	Comparative and predictive loan-level observational analysis	Proprietary FinTech scores better predicted subsequent loan performance than traditional scores.
(Howell et al., 2024)	U.S. Paycheck Protection Program	Automated lender processing	Quasi-experimental analysis of lender automation during the PPP	Automation changed credit access and the size of racial disparities in PPP lending.
(Janbek and Bancel, 2024)	U.S. conforming mortgages	FinTech borrower screening	Comparative loan-level observational analysis	FinTech lenders served lower-score borrowers while showing better subsequent mortgage performance.
(Kang, 2024)	U.S. syndicated lending	Commercial satellite data	Quasi-experimental; difference-in-differences using satellite-data availability	Satellite data reduced institutional-lender participation and was followed by worse loan terms in covered settings.

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(Kutzbach and Pogach, 2024)	U.S. small-business/PPP lending	Bank technology capability	Mixed observational and difference-in-differences analysis	Higher technology capability was associated with greater lending beyond existing markets and appeared complementary to relationship lending.
(Kwan et al., 2024)	U.S. banks/PPP	Bank IT and digital service capability	Longitudinal shock-based observational analysis using the COVID-19 period	Stronger-IT banks shifted more activity online and originated more PPP loans during the pandemic.
(Liu and Yang, 2024)	U.S. mortgage lending	FinTech mortgage origination	Longitudinal observational analysis with difference-in-differences evidence around corporate relocations; residual endogeneity acknowledged	FinTech lenders expanded mortgage supply around corporate relocations and loosened underwriting relative to peers.
(Rossi and Utkus, 2024)	U.S. wealth management	Hybrid robo-advice / automated portfolio allocation	Longitudinal before-and-after observational analysis of robo-advice adopters	Robo-advice increased indexing, reduced home bias and fees, improved Sharpe ratios, and reduced time spent managing investments.
(Bhutta et al., 2025)	U.S. mortgage lending	Automated underwriting systems versus human decisions	Loan-level observational decomposition using automated-underwriting benchmarks	The study directly compares human and algorithmic mortgage-credit decisions and their contribution to racial disparities.
(Bradley et al., 2025)	U.S. marketplace lending	Digital marketplace lending platform	Quasi-experimental analysis using natural disasters as exogenous shocks	Marketplace-lending decisions and borrower outcomes shifted after disasters, including approval, rates, and delinquency.
(Jansen et al., 2025)	U.S. auto lending/top-10 lender	Automated underwriting algorithm	Randomized experiment	Automated underwriting increased loan profits and reduced default in a large U.S. auto-lending experiment.

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(Lin et al., 2025)	U.S.-listed banks	External APIs/open-data infrastructure	Longitudinal bank-panel and policy-event analysis; API adoption itself observational	API adoption was associated with lower loan-loss provisions and stronger operating outcomes.
(Scherer and Lehner, 2025)	Major U.S. robo-advisor	Automated portfolio recommendation system	Cross-sectional web-scraped recommendation analysis	Across 151,200 investor profiles, goals and horizons shaped allocations while several normative hedging demands were largely ignored.
(Ahnert et al., 2026)	U.S. bank lending	IT-assisted collateral valuation	Quasi-experimental bank/county exposure analysis including instrumental-variable evidence	Stronger bank IT improved complex collateral valuation and reduced time/cost of collateralized lending.
(Balyuk et al., 2026)	U.S. small-business lending	Hard-information processing by FinTech lenders	Quasi-experimental analysis including instrumental-variable identification	FinTech advantage was strongest against hard-information-oriented banks and weaker against local relationship banks.
(Bord et al., 2026)	U.S. credit card market/large issuers	Machine-learning-driven automated credit-limit increases	Regulatory microdata analysis plus structural welfare model	Most limit increases were lender-initiated and automated; borrowing rose after increases, with important welfare implications.
(Di Maggio and Ratnadiwakara, 2026)	U.S. FinTech consumer credit	Alternative borrower data	Quasi-experimental/counterfactual underwriting analysis with exogenous variation for downstream outcomes	Alternative information newly approved a meaningful share of low-score applicants; data content drove much of the gain.
(Doerr et al., 2026)	U.S. FinTech lending/California	Data-environment constraint + nontraditional scoring	Quasi-experimental policy analysis around the California Consumer Privacy Act	After CCPA, FinTech lenders changed screening and showed larger subsequent default declines.

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(Foote et al., 2026)	U.S. mortgage market	Automated underwriting software and data-driven default models	Longitudinal historical observational analysis with economic modeling	The transition from judgment to automated, data-driven underwriting expanded mortgage credit access and changed underwriting standards.
(He et al., 2026)	U.S. commercial banks	Communication IT versus software IT	Bank-panel analysis with policy-induced credit-demand variation	Communication and software investments supported different information functions in lending.
(Jia et al., 2026)	U.S. banks	Bank IT investment/automation	Longitudinal bank-panel observational analysis	Bank IT investment was linked to both screening gains and automation-related lending risks.
(McLemore and Mihov, 2026)	U.S. bank holding companies	Artificial-intelligence capability/investment	Bank-holding-company panel observational analysis	Higher AI investment was associated with larger operational losses, especially under weaker risk management.
(Pursiainen, 2026)	U.S. marketplace loans	Automated underwriting using borrower-supplied information	Loan-level predictive observational analysis	Information inaccuracy predicted unpriced default risk in marketplace loans.

TABLE 1: Core U.S. empirical evidence on analytics capability and decision outcomes (n = 47).

Source: Authors' synthesis of the included empirical studies. APIs, Application Programming Interfaces; IT, Information Technology; FICO, Fair Isaac Corporation.

Scale, access, and processing capacity

Fuster et al. found that FinTech mortgage lenders increased their market share from 2% in 2010 to 8% in 2016 and processed applications about 20% faster than other lenders, without higher subsequent defaults (Fuster et al., 2019). Jagtiani and Lemieux reported that more than 75% of newly originated LendingClub loans in 2014-2015 were made in markets where bank branches had declined; almost 70% were in areas with fewer than 30 branches per 100,000 residents, and roughly 90% were in highly concentrated credit-card markets (Jagtiani and Lemieux, 2018). Buchak et al. documented a wider change in mortgage intermediation: shadow banks' share of originations rose from about 30% in 2007 to 50% in 2015, with FinTech lenders accounting for roughly one-quarter of shadow-bank originations by 2015 (Buchak et al., 2018). Their decomposition attributed about 30% of shadow-bank growth to technological change and 60% to regulatory burden, although FinTech borrowers paid an estimated 14-16 basis-point premium relative to other shadow-bank borrowers.

The capacity advantage became especially visible when credit demand changed abruptly. During the PPP, Erel and Liebersohn found that FinTech lending responded to areas with high COVID-19 case rates and unemployment claims at roughly 10 times the rate of traditional-bank lending, while only about 27% of the associated decline in bank lending could be attributed to substitution toward FinTech. Kutzbach and Pogach reported that a one-standard-deviation increase in bank technology was associated with an 8.3-percentage-point increase in PPP lending (Kutzbach and Pogach, 2024); Kwan et al. found approximately 27% more PPP lending among banks with stronger IT capability and website updates one to two days faster following the emergency declaration (Kwan et al., 2024). Similar responses appeared after natural disasters. Allen et al. found greater mortgage-supply elasticity among FinTech lenders without worse risk-adjusted delinquency outcomes, while Bradley et al. reported 26% higher marketplace-loan demand in low-deposit areas and an approximately 50% reduction in default probability among borrowers receiving hardship payment delays (Bradley et al., 2025).

Not all expansion was accompanied by tighter underwriting. Lewellen and Williams linked Mortgage Electronic Registration System (MERS) adoption to greater mortgage supply but also to higher foreclosure activity (Lewellen and Williams, 2021). Liu and Yang found that FinTech lenders increased mortgage supply following corporate relocations while accepting borrowers with greater default risk (Liu and Yang, 2024). Foote et al., using a longer historical window, associated automated mortgage underwriting with broader access among lower-income households (Foote et al., 2026). Across this literature, technology increased the volume, reach, or speed of lending; downstream credit quality varied.

Screening, pricing, and automated allocation

Automated scoring produced measurable changes in both selection and profitability. Einav et al. estimated an increase of roughly $1,000 in profit per loan at a large U.S. auto-finance company, with about half of the gain coming from improved identification of high-risk applicants and half from larger loans to lower-risk borrowers (Einav et al., 2013). Walke et al. examined risk-based pricing among U.S. credit unions using propensity-score matching. Adopters made more loans per member than comparable non-adopters, while delinquency was lower for some adopter groups (Walke et al., 2018). The pattern suggests that the additional lending went mainly to lower-risk borrowers rather than extending credit primarily to higher-risk members. Jagtiani and Lemieux found that the correlation between LendingClub's internal grades and Fair Isaac Corporation (FICO) scores fell from roughly 80% in 2007 to 35% in 2014-2015, while the internal grades continued to predict default (Jagtiani and Lemieux, 2019). Cornelli et al. found that Funding Circle and LendingClub lent more heavily in areas with higher unemployment and business bankruptcy filings (Cornelli et al., 2024). Their internal credit scores predicted 12-and 24-month delinquencies more accurately than traditional credit scores, with the largest improvement in high-unemployment areas. Comparison with bank lending data also indicated that the platforms reached small businesses less likely to obtain traditional credit and did so at lower cost. Verification could matter as much as model sophistication: Chan et al. found that access to verified employment records increased auto-loan origination by 35.5%, rising to 146% among deep-subprime applicants and 44% among subprime applicants, with estimated lender profit increasing by 19.6% (Chan et al., 2022). At the bank level, Pierri and Timmer associated a one-standard-deviation increase in pre-crisis IT adoption with a 16-basis-point reduction in non-performing loans as a share of assets, with loan-level tests pointing mainly to improved screening.

Randomized evidence reinforces the screening effect. Jansen et al. found that algorithmic underwriting generated 10.2% higher loan profits and 6.8% lower default rates than human underwriting; the difference was small for low-risk loans but widened as borrower risk and decision complexity increased (Jansen et al., 2025). Janbek and Bancel likewise found that FinTech mortgage lenders accepted borrowers with lower credit scores than banks while recording better subsequent performance, particularly in refinancing (Janbek and Bancel, 2024). Di Maggio and Ratnadiwakara found that the FinTech platform approved 15%-30% of low-credit-score applicants who would have been rejected by traditional models, with alternative data accounting for much of the expanded access (Di Maggio and Ratnadiwakara, 2026).

The quality of the underlying information remained consequential. McCanless found that applicants recorded as holding bachelor's degrees received rates approximately 4% lower than otherwise similar applicants with certificate-level qualifications; in one bank-platform partnership, platform-related loans increased from 0.14% to 15.6% of the bank's

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balance sheet within three years (McCanless, 2023). Pursiainen found that inconsistencies and rounding in borrower-reported information predicted later default, yet this additional risk was not reflected in higher interest rates (Pursiainen, 2026). Ahnert et al. found that a one-standard-deviation increase in bank IT reduced the interval between approval and disbursement of small-business loans by 2.7%, or about 2.2 days, but faster processing explained only about 10% of the resulting entrepreneurship effect; improved collateral valuation accounted for more (Ahnert et al., 2026).

Allocation increasingly continued after the initial approval decision. Balyuk and Davydenko documented the transfer of loan evaluation and funding decisions from individual marketplace investors to platform software (Balyuk and Davydenko, 2024). Bord et al. found that lender-initiated automated credit-limit increases supplied nearly half as much additional credit as new credit-card originations and were directed disproportionately toward borrowers already carrying balances (Bord et al., 2026). In wealth management, Rossi and Utkus found that robo-advice reduced average mutual-fund expense ratios from 23 to 10 basis points, increased bond holdings from 25% to 39%, reduced cash holdings from 19% to 2%, lowered portfolio risk by 15.8% and idiosyncratic risk by 27.6%, and increased Sharpe ratios by 16.1% (Rossi and Utkus, 2024). Analytics in these studies affected not only predictions but also the terms, amounts, and composition of financial allocations.

Information architecture and intermediation

Doblas-Madrid and Minetti found that after lenders joined a commercial credit bureau, maximum payment delays fell from 29.65 to 23.31 days, average delays from 6.58 to 5.76 days, and the probability of delinquency lasting at least 90 days from 9.5% to 7.1%, with larger effects among informationally opaque firms (Doblas-Madrid and Minetti, 2013). Information sharing also altered lender-borrower relationships. Sutherland found that relationships whose credit information became shared were 6.9% more likely to end within two years; disclosure of a firm's smaller lending relationship increased exit probability by 6.1%, and renewal following delinquency declined by about one-fifth of its pre-sharing level (Sutherland, 2018). Liberti et al. similarly found that lenders remaining outside an information-sharing bureau lost borrowers to participating lenders, creating pressure for subsequent adoption (Liberti et al., 2022).

Technology changed the mix of information used as well. Agarwal and Hauswald compared online and in-person lending and found that the two channels relied on different information (Agarwal and Hauswald, 2021). In-person lending drew more heavily on confidential borrower information and was associated with greater credit availability but higher interest rates, while online lending relied more on hard information and offered lower rates with less credit availability. Sedunov associated more productive back-office and web technology with less reliance on soft-information lending (Sedunov, 2017). He et al. distinguished communication IT, which was more closely related to production and transmission of soft information, from software investment supporting hard-information processing (He et al., 2026). Small-business credit demand induced more communication spending, whereas refinancing demand induced more software investment. Balyuk et al. found greater FinTech penetration in markets where large and out-of-market banks were more prevalent (Balyuk et al., 2026). Using exposure to Federal Reserve stress tests and Community Reinvestment Act examinations as instruments, they found that FinTech credit substituted more readily for lending by large or out-of-market banks than for lending by small or local banks. The results point to an advantage in processing hard information rather than replacing the soft information produced through local banking relationships. Kang found a related substitution effect after commercial satellite data became available for U.S. retailers: institutional lenders became less likely to participate in syndicated loans, especially for opaque borrowers, and firms losing such participation subsequently received smaller loans, shorter maturities, and higher interest rates (Kang, 2024).

Lin et al. found that API adoption accelerated following the 2021 federal push for data portability and was subsequently associated with higher return on assets and Tobin's Q and lower loan-loss provisions (Lin et al., 2025). Taken with the credit-bureau and alternative-data evidence, these findings show that analytical capability depends partly on the infrastructure through which information is generated, transferred, and retained. Technology can expand available information while also reducing incentives to produce information through existing lending relationships.

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Governance, fairness, and downstream risk

Bartlett et al. estimated that Black and Hispanic mortgage borrowers with comparable credit risk incurred more than $450 million annually in excess interest costs, with similar pricing disparities at FinTech and non-FinTech lenders for government-sponsored enterprise (GSE) mortgages (Bartlett et al., 2022). Howell et al. found a different access effect during the PPP: Black-owned firms were initially 39.7 percentage points more likely to obtain loans from FinTech lenders, and the difference remained 12.1 percentage points after adjustment for firm characteristics (Howell et al., 2024). When smaller banks automated PPP processing, the share of loans going to Black-owned businesses rose by 6 percentage points from a 4.4% baseline; the controlled estimate remained 4.3 percentage points. Bhutta et al., using more detailed mortgage data and race-blind automated-underwriting recommendations, found smaller residual denial gaps of approximately 1-2 percentage points after accounting for borrower risk and information available to underwriting systems (Bhutta et al., 2025).

The PPP also exposed weaknesses in verification. Griffin et al. analyzed 11.5 million loans and found that 23.0% of FinTech-originated loans, compared with 7.1% of traditional-bank loans, triggered at least one primary indicator of possible misreporting (Griffin et al., 2023). FinTech loans were 3.23 times as likely to carry a primary flag and 6.52 times as likely to have it corroborated by another indicator. Across the full sample, approximately 1.41 million of 11.5 million loans, or 12.3%, were flagged by the primary measures. FinTech lenders originated 32.5% of PPP loans but accounted for 60.9% of flagged loans. Charoenwong et al. found that broker-dealer investment in enterprise resource planning (ERP) and related internal-control systems was followed by fewer customer complaints and misconduct events, although technology spending rose and profitability declined, especially among smaller firms (Charoenwong et al., 2024). Following implementation of the California Consumer Privacy Act, Doerr et al. reported lower FinTech loan rates, greater price dispersion, higher denial rates, increased use of nontraditional scoring, and a larger subsequent decline in default than did other lenders (Doerr et al., 2026).

Later-stage risk remained visible even where technology strengthened initial screening. Jia et al. reported a U-shaped relationship between lending expansion and credit risk: IT investment delayed the point at which credit quality deteriorated, but deterioration accelerated after that threshold (Jia et al., 2026). McLemore and Mihov found that greater AI investment among U.S. bank holding companies was associated with larger operational losses, particularly from external fraud, client-related events, and system failures, and the association was stronger where risk-management practices were weaker (McLemore and Mihov, 2026). Outside lending, Scherer and Lehner examined 151,200 robo-advisor portfolio recommendations and found that investment goals and horizons affected equity allocations, while several hedging considerations predicted by normative portfolio theory were largely absent (Scherer and Lehner, 2025). The governance evidence is mixed: automation improved access and some control functions but did not remove disparities, verification failures, or downstream operational risk.

Discussion

The studies reviewed suggest that the value of BI&A lies less in automation itself than in what the technology changes about the information available for a decision. Automated credit scoring improved lending outcomes where it separated risk more effectively; verified employment data altered approvals because lenders could confirm information that had previously been uncertain; and bank IT improved some lending outcomes by supporting collateral valuation and screening. These are different technologies, but the findings point to a similar mechanism: better analytical capability can reduce an information problem that matters to the decision being made (Chan et al., 2022) (Jansen et al., 2025) (Ahnert et al., 2026).

The strength of inference is not uniform across these findings. Experimental and quasi-experimental studies provide stronger evidence that particular analytical capabilities changed decisions or outcomes, whereas several institution-level and loan-level observational studies identify associations that may also reflect organizational characteristics, borrower selection, market conditions, or other unobserved factors. The synthesis therefore gives greater interpretive weight to findings supported by stronger identification strategies and treats observational associations primarily as evidence of recurring patterns rather than proof of causal effects.

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That relationship becomes less reliable when processing improves faster than verification. FinTech mortgage lenders were able to shorten processing without worsening default in some settings, whereas PPP lending produced a very different result, with substantially more potential misreporting among FinTech-originated loans. Mortgage underwriting operated with established borrower information and repayment histories; PPP lenders were working under exceptional time pressure, government guarantees, and fewer opportunities to verify some applicant information. Technology increased capacity in both settings, but the surrounding decision process differed (Fuster et al., 2019) (Griffin et al., 2023).

Alternative data present another version of the same problem. Some borrowers who appeared risky under conventional scores were reclassified when additional information became available. Other studies identified borrower information that predicted default but was not fully reflected in loan pricing. More variables do not necessarily mean more useful information; the gain depends on whether the data are accurate, relevant to the outcome, and incorporated into the decision in a way that changes action rather than merely adding another signal (Jagtiani and Lemieux, 2019) (Di Maggio and Ratnadiwakara, 2026) (Pursiainen, 2026).

The information-sharing literature pushes the argument beyond predictive models. Credit bureaus, APIs, communication technologies, and external datasets changed the information available to lenders and the way it circulated. The studies linked those changes to differences in screening, pricing, and lender participation. Those changes sometimes improved repayment or widened access, but they could also weaken relationship lending or reduce incentives to produce private information. Hard information is easier to standardize and scale; soft information is often more expensive to obtain and difficult to encode. A financial-service organization can therefore gain data while losing context (Doblas-Madrid and Minetti, 2013) (Sutherland, 2018) (Kang, 2024) (Lin et al., 2025).

Organizational incentives matter because they influence what happens after a signal is produced. Compensation, growth targets, government guarantees, regulatory requirements, and responsibility for model outputs may influence how much verification is considered sufficient and whether an analytical warning affects the action taken. Governance functions address different parts of that problem. Model risk management asks whether a model remains valid and is used within its intended scope; compliance controls address legal and regulatory requirements; auditing provides independent review of process and accountability; monitoring looks for drift, unusual outcomes, fraud signals, complaints, or system failures after deployment. A strong model does not make these functions interchangeable (Charoenwong et al., 2024) (Doerr et al., 2026) (McLemore and Mihov, 2026).

Supporting evidence from Agarwal et al. shows how model-agnostic interpretation methods can be used to examine the variables driving algorithmic lending decisions (Agarwal et al., 2023). The study is retained for its interpretability implications rather than as part of the core empirical evidence base. Figure *2* summarizes the conditions that can strengthen or weaken the pathway from decision-relevant information to downstream outcomes.

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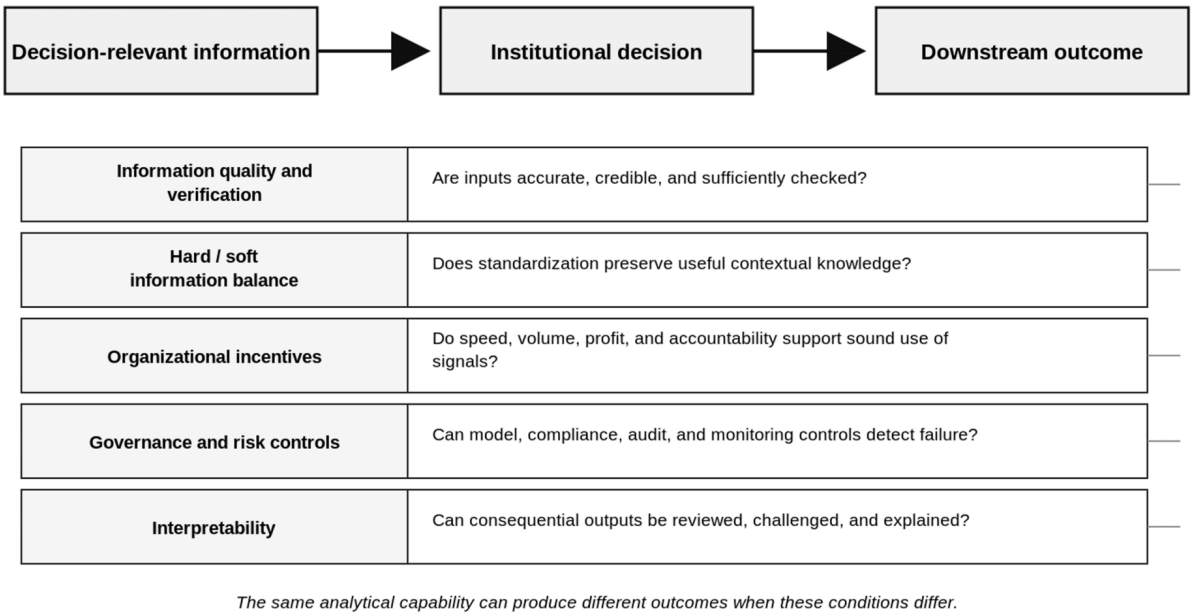


FIGURE 2: Conditions that influence whether decision-relevant information improves downstream outcomes in U.S. financial services.

Source: Authors' creation.

Figure *2* identifies five conditions that can alter the effect of analytical capability on a financial decision. Information quality and verification concern whether the data entering the decision are accurate and sufficiently reliable for the inference being made. Hard and soft information balance reflects the possibility that standardized data improve scale and consistency while displacing contextual information obtained through relationships or direct interaction. Organizational incentives affect how institutions respond to analytical signals, particularly where speed, volume, profitability, or regulatory demands compete with verification and risk control. Governance and risk controls determine how model failures, misconduct, fraud, drift, or operational problems are identified and managed after deployment. Interpretability concerns whether the basis of an analytical output can be examined when a decision requires review or challenge. These conditions influence whether analytical information is translated into a better institutional decision.

Limitations

Most of the studies examined lending, especially mortgages, consumer credit, small-business finance, marketplace lending, and FinTech. Far less empirical work was identified on BI&A in treasury, budgeting, strategic planning, payments, insurance, or internal management decisions. Restricting the review to U.S. financial services improves comparability across regulatory and institutional settings but limits generalization to countries with different credit infrastructures, privacy rules, or banking structures. The mechanisms identified here may be relevant outside lending, but the present evidence does not establish that they operate with the same strength or consequences in sparsely represented financial-service activities.

The review is narrative, and the underlying studies vary considerably in research design, unit of analysis, technological capability, and outcome definition. Formal statistical pooling was therefore not appropriate. Study design, setting, outcome measurement, identification strategy, and the connection between the analytical capability and observed decision were considered during synthesis. However, no validated risk-of-bias instrument was applied across the full evidence base. The design-aware appraisal used here helps distinguish stronger causal or quasi-causal evidence from

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observational associations, but it does not eliminate residual confounding, selection bias, measurement error, or other study-specific limitations. Findings from weaker observational designs should therefore be interpreted as associations rather than estimates of the causal effect of BI&A adoption.

The original search did not retain reliable platform-level retrieval and duplicate counts, requiring reconstruction of the candidate record during revision. Because the original search also did not prospectively retain study-level disposition counts, a numerical breakdown of excluded and supporting records is not reported. This limits the reproducibility of the original identification and screening process even though the revised Methods makes the reconstructed procedure and eligibility criteria explicit.

Publication and availability bias also remain important limitations. The core synthesis was restricted to peer-reviewed empirical studies, which improves source quality but may underrepresent unsuccessful, null, or commercially sensitive BI&A implementations that never enter the published literature. This concern is particularly relevant in financial services, where model failures, internal control weaknesses, operational incidents, and abandoned technology projects may remain proprietary. Because the included studies examine heterogeneous technologies, outcomes, research designs, and effect measures rather than a common effect estimate, formal statistical assessment of publication bias was not appropriate. The synthesis therefore cannot establish whether the published evidence systematically overrepresents favorable or statistically significant results. The evidence is useful for showing where and why BI&A appears to work, but it cannot support a sector-wide estimate of its average effect.

Conclusions

In some lending settings, automated scoring, alternative data, digital verification, and stronger information systems improved screening or sped up decisions. In others, greater automation was linked to weak verification, persistent disparities, pricing errors, or operational losses.

Faster processing or more sophisticated models should not be taken as evidence of better decisions on their own. BI&A appears most useful when it improves the information available to decision-makers without displacing relevant context or weakening verification and oversight. Because most of the evidence comes from lending, these conclusions are strongest for credit-related decisions and should be extended to other financial-service functions with caution.

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

Concept and design: Vera Ogette, Jennifer K. Odumegwu

Acquisition, analysis, or interpretation of data: Vera Ogette, Jennifer K. Odumegwu, Joan E. Obi

Drafting of the manuscript: Vera Ogette, Jennifer K. Odumegwu, Joan E. Obi

Critical review of the manuscript for important intellectual content: Vera Ogette, Jennifer K. Odumegwu

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Conflicts of interest: In compliance with the ICMJE uniform disclosure form, all authors declare the following:

- **Payment/services info:** All authors have declared that no financial support was received from any organization for the submitted work.
- **Financial relationships:** All authors have declared that they have no financial relationships at present or within the previous three years with any organizations that might have an interest in the submitted

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work.

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Data Availability Statements

Data sharing is not applicable to this review. No original datasets were generated or independently analyzed by the authors. The review synthesizes findings from 47 previously published empirical studies, which are identified in the reference list.

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