

A Review of AI-Driven Business Intelligence in Consumer Finance Risk Control

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Abstract

As artificial intelligence (AI) and business intelligence (BI) become more common in consumer finance, the limits of traditional credit-risk systems are becoming easier to see. Conventional models still depend heavily on credit-bureau records, so customers with little or no formal credit history can be difficult to assess. This paper uses a systematic literature review to examine how AI and BI are being used in credit-risk assessment, with particular attention to alternative data, credit-invisible customers, model explainability, and regulatory compliance. The literature indicates that combining AI with BI can improve risk identification for long-tail customer groups by using a broader range of behavioural and transaction information. However, complex models also increase the difficulty of transparency management and regulatory compliance. Based on these findings, this paper proposes an analytical framework from three dimensions: algorithm, system, and compliance. It aims to provide a reference for financial institutions seeking to optimize intelligent risk control modeling.

Keywords

Artificial Intelligence; Business Intelligence; Consumer Finance Risk Control; Credit Invisible Customers; Alternative Data.

1. Introduction

In recent years, as the financial industry has become increasingly digitalized, business intelligence and artificial intelligence have been increasingly applied to credit scoring and risk assessment. According to the World Bank, 79% of adults globally now have an account, showing the expansion of formal financial services. However, traditional credit scoring models still rely heavily on structured data, such as credit records, financial information, and repayment history. This creates difficulties for customers with limited or no credit history. For example, the Consumer Financial Protection Bureau reported that 26 million adults in the United States were “credit invisible”. These credit-invisible customers may be difficult to evaluate through traditional models and are therefore more likely to be excluded from formal financial services. Financial institutions have therefore started to look beyond credit-bureau records, using machine learning and deep learning to examine sources such as online purchasing records, mobile-payment data, and patterns of consumer behaviour when estimating default risk.

AI-based models have an advantage over traditional linear approaches because they can capture more complicated relationships among variables. This is particularly useful when lenders are trying to assess long-tail or credit-invisible customers, whose risk profiles may not be well represented in conventional datasets. The gain in predictive power, however, comes with a trade-off. Many advanced models are difficult to interpret, and staff or customers may not be able to see clearly why a particular risk judgement has been made. This black-box problem can conceal bias and create additional compliance risks. As financial regulation

becomes more demanding, institutions are expected to show not only that a model performs well, but also that its decisions can be explained and justified.

Much of the research on explainability in credit-risk assessment has concentrated on technical tools such as SHAP and LIME. These methods have made progress in improving model transparency. However, existing studies still pay limited attention to how explainable models can be embedded into real financial business processes, organizational management, and regulatory frameworks. Meanwhile, different studies define and evaluate “explainability” in different ways, leading to a fragmented body of research. Therefore, this paper reviews the literature on credit risk assessment in the context of the integration of business intelligence and artificial intelligence, with a central focus on the identification and governance of credit-invisible customers. The application of alternative data, model explainability, and regulatory compliance are discussed as supporting dimensions rather than separate research directions. On this basis, this paper proposes a three-dimensional analytical framework of “algorithm–system–compliance” to examine how AI-driven BI can improve risk identification while maintaining transparency and regulatory accountability. This framework aims to provide a reference for financial institutions in intelligent risk control modeling and model management.

2. Literature Search Strategy and Research Method

2.1. Research Method and Data Sources

This study adopts a systematic literature review approach to collect and synthesize existing research on the application of AI-driven business intelligence in consumer finance risk control. The subject brings together several closely related areas, including artificial intelligence, business intelligence, credit-risk assessment, credit-invisible customers, alternative data, and model explainability. Looking at these themes together is useful because the issue cannot be understood from a single technical or financial perspective. A systematic review makes it possible to compare findings across these different strands of research in a structured way.

The literature was collected mainly from China National Knowledge Infrastructure (CNKI) and Web of Science. CNKI was used to identify Chinese-language studies on consumer finance, fintech risk management, credit reporting, and credit-invisible customers, while Web of Science provided international research on AI, BI, credit-risk assessment, and explainable AI. The review was limited to work published between 2015 and 2025. This period was chosen because research on AI applications in financial risk control expanded rapidly during the past decade and became much more concentrated in recent years.

2.2. Search Keywords and Screening Criteria

The search used both Chinese and English terms, although the keywords are presented here in English for consistency. The CNKI search covered terms such as 'artificial intelligence', 'business intelligence', 'consumer finance risk control', 'credit risk assessment', 'non-credit-bureau data', 'alternative data', 'credit invisible customers', 'long-tail customers', 'explainability', and 'fintech risk control'. Similar terms were used in Web of Science, including 'Artificial Intelligence', 'Business Intelligence', 'Consumer Finance', 'Credit Risk Assessment', 'Alternative Data', 'Thin-file Customers', 'Credit Invisible Customers', 'Explainable AI', and 'FinTech Risk Management'.

Rather than relying on single keywords, the search combined related terms so that the results would be more closely aligned with the research question. Typical combinations included 'Artificial Intelligence AND Credit Risk Assessment', 'Alternative Data AND Credit Invisible Customers', 'Non-Credit-Bureau Data AND Consumer Finance Risk Control', and 'Explainable AI AND Credit Risk Assessment'. Using these combinations helped narrow a broad fintech literature to studies directly concerned with consumer credit and risk assessment.

Studies were included when they addressed AI, BI, machine learning, credit scoring, consumer-finance risk control, alternative data, credit-invisible customers, or model explainability. To qualify, an article had to be published between 2015 and 2025, be available in full text, and provide theoretical discussion, empirical evidence, model comparison, or a systematic review relevant to credit-risk assessment. General fintech discussions, work centred on non-credit areas such as investment, insurance, or payment systems, duplicate or substantially overlapping studies, inaccessible full texts, news reports, commentaries, and promotional material were excluded.

2.3. Literature Screening Process and Analytical Approach

The screening process followed the main stages of PRISMA: identification, screening, eligibility assessment, and final inclusion. Searches were first carried out in CNKI and Web of Science, after which duplicate records were removed. Titles, abstracts, and keywords were then checked to remove studies with only a weak connection to the topic. The remaining full texts were reviewed in more detail to determine whether they dealt directly with AI or BI in consumer-finance risk control, the identification of credit-invisible customers, the use of non-credit-bureau data, or model explainability.

The initial search produced 128 studies: 63 from CNKI and 65 from Web of Science. After duplicates and clearly irrelevant records were removed, 74 studies remained for title and abstract screening. A full-text review reduced this number to 22 core studies. The relatively high exclusion rate reflects the breadth of the original search. Many papers discussed fintech or artificial intelligence at a general level but did not examine the specific issues at the centre of this review, namely consumer-finance risk control, credit-risk assessment, credit-invisible customers, alternative data, or explainability.

3. Thematic Classification Framework

The selected literature shows that AI-driven BI in consumer-finance risk control is not simply an algorithmic issue. The effectiveness of a model also depends on how it is used inside a business process and how the resulting decisions are governed. For that reason, the literature is organised thematically rather than chronologically. Three closely connected dimensions are used: algorithm, system, and compliance.

The algorithm dimension concerns the models and data used to assess credit risk. Research in this area asks whether machine learning and deep learning can predict default more accurately and whether alternative information can improve the assessment of credit-invisible and long-tail customers. Transaction records, consumption patterns, and mobile-payment histories can add useful variables when formal credit-bureau data are sparse. Their value, however, depends on data quality, and they may introduce instability or bias if the underlying information is incomplete or poorly governed.

The system dimension focuses on the role of BI in turning analytical results into operational decisions. BI has traditionally been associated with data integration, reporting, and visualisation, but in consumer finance it can also connect AI outputs to pre-loan approval, in-loan monitoring, and post-loan management. Put simply, AI produces predictions, while BI helps place those predictions within the workflow in which lending decisions are actually made. The compliance dimension addresses the risks created by more complex and data-intensive models. Better prediction does not remove concerns about opacity, privacy, bias, or regulatory responsibility. Financial institutions must be able to explain how a decision was reached, show that the data were used lawfully, and demonstrate that model outcomes are fair and defensible. These three dimensions provide the structure for the literature review that follows.

4. Literature Review

4.1. Traditional Consumer Finance Risk Control and the Identification Challenge of Credit-Invisible Customers

A central task in consumer-finance risk control is to estimate the likelihood that a borrower will default before credit is granted. Traditional systems generally rely on structured variables such as credit records, income, outstanding debt, and past repayment performance. These data are standardised, relatively stable, and straightforward to quantify, which explains why banks and consumer-finance companies have used them for many years. Credit-scoring models also help lenders apply a more consistent approach to borrower assessment and can make credit approval more efficient [1]. More broadly, conventional financial risk management has been built around existing financial records and credit histories, making it most effective for customers who already have a track record within the formal system [2].

The weakness of this approach becomes more obvious as consumer finance reaches a wider range of borrowers. Credit-invisible customers are a particularly important example. In this paper, the term refers to people with no formal credit record, only limited information on a credit report, or no previous borrowing history. A thin credit file does not necessarily mean that a person is a poor borrower, but traditional models have little evidence on which to judge that person's creditworthiness. Young people entering employment, freelancers, small-business owners, occasional users of financial services, and first-time loan applicants can all fall into this category. When information is scarce, lenders may treat these applicants as uncertain risks and reject them even when they may have the capacity to repay.

Traditional credit scoring commonly relies on scorecards and logistic regression. These methods remain attractive because their structures are relatively transparent and their results are easier for financial institutions and regulators to interpret. A lender can, for instance, explain how income, debt ratios, or previous overdue payments influence a credit score. The same simplicity can become a limitation when the available data are sparse or when behaviour is represented by many fragmented and interacting variables. Conventional models therefore tend to work better for established borrowers than for customers who lack formal credit records but may still have stable repayment capacity.

Credit invisibility is therefore more than a missing-data problem. It also exposes the limits of existing data sources, model design, and service coverage. Heavy reliance on credit-bureau information makes risk assessment easier for lenders, but it may also exclude people who are financially capable yet have not built a conventional credit history. This gap explains why recent research has turned to AI models, non-credit-bureau information, and BI systems as possible ways to broaden risk assessment without abandoning risk discipline.

4.2. Application of AI and Non-Credit-Bureau Data in Credit Risk Assessment

As consumer finance has shifted online, lenders have gained access to information that was rarely available in traditional credit assessment. FinTech platforms have changed the structure of financial intermediation, and digital platform data have become increasingly important to credit decisions [3]. Alongside credit-bureau records, institutions can now consider data such as online transaction flows, mobile-payment frequency, account activity, device information, and patterns of user behaviour.

AI models are well suited to this broader data environment because machine learning and deep learning can identify nonlinear relationships and interactions across large numbers of variables. Different techniques, however, serve different purposes. Scorecards and logistic regression remain useful where interpretability and regulatory acceptance are priorities. Random forests and gradient-boosting models are better able to capture complex relationships in transaction and behavioural data. Deep-learning models may be valuable for very large and complex

datasets, although their lower transparency creates stronger governance requirements. Model choice should therefore reflect more than prediction accuracy; data quality, sample size, interpretability, and business use also matter. Whatever method is selected, performance needs to be tested through procedures such as cross-validation, hold-out testing, and out-of-sample testing so that apparent gains are not simply the result of overfitting.

Research has been applying machine-learning techniques to consumer credit risk for more than a decade [4]. Benchmark studies indicate that ensemble methods, including random forests and gradient-boosting trees, often outperform logistic regression in default prediction [5]. At the same time, the wider literature on machine-learning credit scoring makes clear that stronger performance is not automatic: results depend heavily on the quality of the data, the choice of features, and the particular lending context [6].

Alternative data are especially relevant when formal credit information is limited. Digital footprints, for example, can provide useful signals for credit assessment [7]. Evidence from FinTech lending platforms also suggests that alternative data combined with machine learning can influence both approval decisions and risk pricing [8]. Research on a Chinese FinTech firm reaches a similar conclusion, showing that non-traditional information can supplement credit-bureau data and improve credit scoring when used with machine-learning methods [9].

For credit-invisible customers, the practical attraction of alternative data is that it can help build a fuller picture of financial behaviour. Transaction habits, consumption frequency, account activity, income flows, and indicators of repayment capacity may offer information that is absent from a formal credit report. These variables cannot replace a credit history completely, but they can reduce the information gap that makes credit-invisible customers difficult to assess.

This changes the basis of consumer-finance risk control. Instead of judging a borrower only by previous loans and repayments, an institution can also consider how that person behaves across digital financial settings. The approach may be particularly useful for applicants who have little formal borrowing history but leave consistent behavioural or transaction signals elsewhere.

There are, however, important limits to this approach. Non-credit-bureau data are collected from many sources and are not always consistent in quality or format. Missing values, noise, and rapidly changing behavioural patterns can weaken model stability. Some variables may also correlate with default without having a clear causal relationship to it, which raises the risk of misleading predictions. Privacy is another concern. Behavioural and device data can be sensitive, and unclear consent or opaque collection practices may expose institutions to serious compliance problems.

AI and alternative data can therefore widen the range of customers who can be assessed, but the technology is only useful when the supporting data and governance are credible. Reliable inputs, meaningful features, proper user authorisation, and strong oversight are necessary if better prediction is to translate into better risk control. Without these safeguards, the same tools that reduce information gaps can create new forms of operational, legal, or reputational risk.

4.3. The Role of BI Systems in Consumer Finance Risk Control Decisions

BI in consumer-finance risk management has developed beyond the production of routine statistical reports. Earlier BI systems were mainly used to summarise business performance and visualise what had already happened. With the growth of big data and AI, the focus has shifted towards predictive analytics and decision support. The BI&A 3.0 framework describes this broader development, in which BI incorporates big data, artificial intelligence, and real-time analytics [10]. This provides a useful basis for understanding the idea of AI-driven BI used in this paper.

In a traditional setting, BI brings data together and presents indicators such as loan volume, delinquency rates, customer profiles, and business growth. Once AI is added, the system can do more than display historical information. It can combine data from multiple sources, run predictive models, and feed model results into risk-control decisions. The distinction is important: the value lies not only in the model itself, but also in the system that makes its output usable by the business.

Across the credit lifecycle, BI can support decisions before, during, and after a loan is issued. Before approval, it can combine credit-bureau and alternative data to support scoring. During the loan period, it can monitor changes in customer behaviour and flag emerging risks. After lending, it can contribute to customer profiling and collection management. In this arrangement, AI is mainly responsible for prediction, whereas BI connects data, models, and operational decisions.

Bringing AI into a financial workflow also requires more than technical integration. Research on credit-scoring feature selection suggests that machine-learning models are more useful in practice when expert judgement and business knowledge are incorporated into the modelling process [11]. The growth of digital finance has also increased the need for stronger institutional data governance and risk-control capabilities [12]. AI-driven BI therefore includes data interfaces, business rules, manual review, organisational responsibilities, and compliance checks in addition to the algorithm itself.

This broader view is particularly important when dealing with credit-invisible customers. A single model score may not provide enough evidence for a final decision. Consider an applicant with no formal credit record but stable income inflows, regular spending patterns, and consistent account activity. Rather than rejecting the person automatically, a BI system could combine these signals and direct the application for further review. Its value lies in bringing scattered information together so that the lender can form a more continuous and balanced judgement of risk.

One limitation of the current literature is that many studies concentrate on model performance in test datasets but say less about what happens after a model is deployed in a real financial organisation. A model that works well in an experiment may behave differently when it is exposed to live data, changing customer behaviour, operational delays, or manual intervention. System reliability, the speed of data updates, human review, and compliance procedures can all influence the results in practice. Therefore, research on AI-driven BI should not remain only at the level of algorithm optimization. More attention should also be given to system deployment and coordination with actual business processes.

4.4. Model Explainability and Regulatory Compliance Challenges

While AI models improve the ability to identify credit risk, they also create problems related to opaque decision-making. Many complex models, especially ensemble learning and deep learning models, may achieve strong predictive performance, but their internal decision-making mechanisms are often difficult to understand. This issue is particularly sensitive in consumer finance, because the output of a risk control model can directly affect whether a customer is able to obtain a loan.

At present, SHAP and LIME are two widely used methods for explaining credit risk models. LIME explains a specific prediction by building a simple local model around an individual observation, while SHAP uses feature attribution to show how much each variable contributes to the model's prediction. LIME is useful because it can approximate the prediction process of a black-box model for a specific case with a simple linear model [13]. SHAP, by contrast, explains model results by calculating and assigning contribution scores to individual features [14]. Studies on credit risk have also found that XAI methods can help financial institutions understand model outputs and support financial decision-making [15]. Research on peer-to-

peer lending suggests that clearer explanations can make credit-scoring models easier to accept and use in practice [16]. More recent work has also combined XAI with deep learning in credit-card default prediction, showing that explainability tools are moving beyond theory and into specific risk-control applications [17].

Technical explanations still have limits. Knowing that a feature carries a high SHAP value, for example, does not automatically tell a bank whether that feature makes sense from a business or regulatory perspective. Staff still need to judge whether the relationship is plausible and whether it can be explained clearly to a customer or regulator. Variables such as device type or login time illustrate the problem: a model may find them predictive, but the institution must still justify why they should influence a credit decision. Different explanation methods can also produce different interpretations of the same model, so explanation results need to be tested in the context in which they will actually be used.

Explainable machine learning is therefore useful for more than making a black box appear transparent. In credit-risk management, it can help institutions understand why a prediction was made and decide what action should follow [18]. Research on bank credit assessment similarly argues that XAI should support practical review and decision needs rather than stop at lists of feature importance [19]. The wider finance literature also links explainability to information-system design, organisational trust, and regulatory acceptance [20]. In practice, successful financial XAI depends on the interaction of technical methods, business requirements, regulation, and customer trust [21].

Governance becomes even more important when models use alternative behavioural data. Variables that appear neutral - device type, shopping frequency, geographic location, or software-use patterns - may indirectly reveal information about income, occupation, or where a person lives. A model can therefore reproduce hidden forms of discrimination even when it does not use protected characteristics directly. Credit-invisible customers may be particularly exposed because the lack of conventional credit information gives behavioural data greater weight in the decision. Research on machine learning in credit markets has shown that predictive improvements can be accompanied by unequal effects across groups [22]. Fairness is consequently not only an ethical issue; it is part of financial risk management and model governance.

Taken together, the literature suggests that good consumer-finance risk control cannot be judged by accuracy alone. An effective system needs a model that identifies risk well, a BI environment that embeds the model reliably into business processes, and governance that addresses explainability, fairness, privacy, and regulatory obligations. AI and BI can improve efficiency and help institutions assess customers who are poorly served by conventional credit records, but those benefits depend on how the technology is managed. AI-driven BI should therefore be treated as an organisational and regulatory system as much as a technical one.

5. Conclusion

This review examined how AI-driven BI is being used in consumer-finance risk control, with particular attention to credit-invisible customers. The literature points to four closely connected issues: the limits of traditional credit-reporting systems, the growing use of non-credit-bureau data, the role of BI in turning model outputs into decisions, and the challenge of making increasingly complex models explainable and compliant.

Traditional risk-control models are still useful because they are comparatively stable and easier to explain. However, because they rely heavily on credit records, they still have clear limitations when assessing credit invisible customers and long-tail customers with limited or no credit history.

The combination of artificial intelligence and diverse non-credit-bureau data provides a new path for risk identification in consumer finance. Machine learning and deep learning can process more complex data relationships, while business intelligence can apply model outputs to pre-loan review, in-loan monitoring, and post-loan management. In this way, risk control efficiency and service coverage can be improved. At the same time, complex models also bring challenges such as black-box decision-making, algorithmic bias, data privacy risks, and regulatory compliance pressure. In the assessment of credit invisible customers in particular, models should not only make risk judgments, but also explain the basis of those judgments.

Therefore, this paper argues that intelligent risk control in consumer finance should not focus only on improving model accuracy. Instead, it should be developed within a three-dimensional governance framework of “algorithm–system–compliance”. At the algorithmic level, attention should be paid to risk identification capability. At the system level, model outputs should be effectively embedded into business scenarios. At the compliance level, decision transparency, algorithmic fairness, and the boundaries of data use should be emphasized. Future research may further use real business data to test the practical performance of different models in identifying credit invisible customers, while also examining the regulation of non-credit-bureau data use, the stability of model explanations, and the continuous monitoring and stress testing of intelligent risk control systems.

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