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USING ARTIFICIAL INTELLIGENCE FOR SCORING AND CREDITWORTHINESS EVALUATION OF CLIENTS IN DIGITAL BANKING

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Summary. *Credit scoring is the process by which banks and lenders evaluate a borrower's creditworthiness – essentially predicting the risk that a customer will default on a loan obligation. Traditionally, credit scoring has relied on statistical models and expert-designed scorecards using a limited set of financial variables (such as income, outstanding debts, and past repayment history). These traditional models, most commonly logistic regression-based scorecards, became industry-standard because of their interpretability and regulatory acceptance. In essence, a simple weighted sum of factors (e.g. debt-to-income ratio, credit history length, etc.) produces a score, and the simplicity of such models makes it easy for risk managers and regulators to understand how each factor influences the decision. Over decades, methods like linear discriminant analysis and logistic regression proved effective and were relatively easy to implement and explain. However, these conventional approaches have limitations in predictive power because they assume a linear or simple relationship between inputs and credit risk. This has opened the door for more complex approaches.*

In recent years, artificial intelligence (AI) and machine learning (ML) techniques have begun to reshape credit scoring practices in the banking industry. The rise of big data, increased computational power, and the fintech revolution have enabled the use of advanced algorithms to improve risk assessment. AI-driven credit scoring refers to using complex ML models – from tree ensembles to neural networks – to predict default risk. These models can automatically detect nonlinear

patterns and interactions in vast datasets, potentially improving predictive accuracy beyond what traditional scorecards achieve. Particularly in the context of digital banking, where services are delivered primarily online and decisions often need to be made in seconds, AI methods offer the speed and scalability that legacy scoring systems struggle to match. Digital banks (sometimes called neobanks) often have no physical branches, so they rely on online data (such as real-time transaction records, device information, or even social media data) and automated models to make lending decisions instantly. AI techniques are well-suited to harness these rich data sources and to update credit decisions rapidly as new data arrives. For example, online lenders can analyze thousands of data points per customer – far beyond the handful of variables in a typical traditional credit report – to refine credit risk estimates. As a result, AI-based scoring models in digital banking promise more inclusive lending (bringing in customers who might have been rejected by rigid traditional criteria) and more dynamic risk management that adapts to new information.

Theoretical Foundations: From Traditional Models to AI. The evolution from traditional credit scoring models to AI-driven approaches can be understood as a shift from human-crafted rules and simple statistical classifiers toward data-driven, self-learning algorithms. Traditional credit scoring typically uses scorecards, which are tabulations of points for different attributes of a borrower. For instance, a borrower's age, income level, and repayment history might each contribute a certain number of points; the sum yields a credit score. These scorecards are often based on logistic regression – a statistical method that predicts the probability of default (a binary outcome) from predictor variables. Logistic regression has been the backbone of credit scoring for decades. It remains popular because it produces coefficients for each factor that can be easily interpreted: one can clearly see how, say, an increase in income or a certain level of existing debt affects the default probability. Banks and regulators value this transparency. In fact, simplicity and transparency were not just conveniences but necessities – under financial regulations and consumer protection laws (in the US and Europe, for example), lenders often must explain adverse decisions to applicants. A straightforward linear model makes it easier to provide reasons (e.g. "loan declined due to high debt-to-income ratio").

Despite their clarity, traditional models are limited in capturing complex, nonlinear relationships in data. Borrowers are heterogeneous, and risk factors might interact (for example, a modest level of debt might be harmless for a high-income borrower but risky for a low-income borrower; such interaction is not straightforward to capture in a purely linear model). Machine learning methods provide a way to automatically discover these interactions and nonlinear patterns

by training on large datasets of past loans. Early applications of ML in credit scoring included decision trees and ensemble models like random forests and gradient boosting machines. These models partition the data based on combinations of attributes, effectively allowing different calculations for different segments of borrowers. They often achieve higher predictive accuracy than logistic regression, at the cost of less interpretability. Over the past decade, studies have shown that tree-based algorithms and other ML techniques can indeed outperform logistic regression in predicting loan defaults, especially as more data (and more complex data) become available. For example, gradient boosting machines or random forest models can automatically handle dozens of input variables – such as detailed transaction histories or behavioral data – and find subtle patterns that a human analyst might not anticipate. An even more powerful class of models, deep learning (neural networks with multiple layers), has also been applied to credit scoring problems. Deep learning can model very complex functions and has the advantage of being able to process unstructured data (like text from loan applications or even images) if needed. Researchers have demonstrated that deep neural networks can improve default prediction accuracy compared to traditional methods, sometimes significantly so. For example, a deep learning model might extract behavioral features from consumers' time-series account balances or payment sequences that would be hard to formulate in a logistic scorecard. However, these gains in accuracy come with reduced transparency, as the internal workings of a neural network are not readily interpretable. This has led to a new focus on "explainable AI" in credit scoring – techniques to interpret complex models (such as SHAP values or LIME for feature importance) so that lenders can still explain decisions to stakeholders.

Importantly, the move toward AI has also expanded the data types used in credit scoring. Traditional credit scores largely rely on credit bureau data (e.g. repayment histories on past loans, number of open accounts, credit inquiries) and basic demographic or financial information provided by the applicant. AI models, by contrast, can incorporate alternative data – for instance, utility bill payment records, e-commerce purchase history, mobile phone usage patterns, social media activity, or even psychometric data from questionnaires. The rationale is that these alternative sources can provide signals of creditworthiness for people with thin or no formal credit files (sometimes called "credit invisibles"). For example, a customer's pattern of paying their cell phone bill on time or the consistency of their monthly expenses might correlate with their likelihood to repay a loan, even if they have never had a bank loan before. Regulatory bodies have noted that using such unconventional data, combined with ML, has the potential to increase credit access for underserved groups. The U.S. Consumer Financial Protection Bureau (CFPB)

observed that alternative data and ML algorithms together can identify creditworthy individuals who would be overlooked by traditional models, thereby expanding access to credit and possibly reducing borrowing costs. At the same time, regulators caution that these innovations must be monitored for risks such as inadvertent discrimination or privacy issues.

Artificial intelligence methods are increasingly embedded in retail credit scoring, complementing and in some cases replacing traditional logistic regression scorecards. Banks now deploy a spectrum of machine learning approaches, including tree based ensembles, neural networks, gradient boosted decision trees, hybrid scorecard architectures and a variety of innovative models. These techniques aim to exploit large structured and unstructured datasets in order to estimate the probability of default more accurately and to support faster and more granular risk based decisions in digital channels.

Decision tree models partition borrowers along successive criteria such as income, indebtedness or repayment history and therefore capture nonlinear relationships between customer attributes and default risk. Ensembles of trees, such as random forests and gradient boosting machines, further enhance predictive performance by aggregating many individual trees that focus on different parts of the feature space. Empirical evidence from both banks and academic studies indicates that such models frequently deliver higher values of Gini coefficient and Kolmogorov Smirnov statistic than benchmark logistic regression models, albeit at the cost of greater structural complexity and reduced transparency for human experts.

Neural networks and deep learning architectures provide an even more flexible class of models for credit risk assessment. By learning multiple layers of representation from the input data, deep networks can model highly complex interactions between variables and are particularly effective with high dimensional or unstructured information such as detailed transaction histories, free text fields in loan applications or audio records from contact centers that may indicate financial distress. A study by Kvamme and coauthors published in two thousand eighteen showed that models trained on customers daily account balance time series can outperform linear benchmarks in predicting default. At the same time, deep learning models are computationally intensive, prone to overfitting when data are limited and often regarded as opaque, which necessitates the use of advanced validation and explainability tools such as methods based on Shapley values.

In practice, gradient boosted decision trees occupy a central role in many contemporary credit scoring implementations, including those of fintech lenders that rely on automated decision engines. These models often achieve state of the

art results in industry competitions and real portfolios and are sometimes combined with classical scorecard techniques in hybrid frameworks that transform complex nonlinear effects into interpretable attributes and partial scores. Alongside these approaches, banks are piloting reinforcement learning for dynamic credit line management, graph based learning that uses networks of relationships between borrowers and counterparties, as well as generative models that analyse borrower communications or construct synthetic credit scenarios. A particularly important stream of innovation is federated learning, in which institutions collaboratively train credit models on distributed data sources while keeping the underlying customer records local. Experience from institutions such as WeBank in China suggests that federated learning can materially improve predictive accuracy by exploiting broader datasets and at the same time comply with stringent privacy requirements.

The growing reliance on machine learning for credit scoring also amplifies concerns about model risk and ethical outcomes. Data driven systems can inadvertently reproduce historical discrimination embedded in past lending decisions or learn spurious correlations that fail when economic conditions change. Complex models may also exhibit instability when exposed to shocks outside the range of the training sample. For these reasons, banks that adopt artificial intelligence in credit risk management are expected to implement robust model governance frameworks that include rigorous out of sample validation, stress testing under alternative macroeconomic scenarios, continuous performance monitoring and systematic reviews of fairness and explainability. Such practices are essential to ensure that the gains in predictive power offered by artificial intelligence are achieved without undermining regulatory compliance, consumer protection and trust in digital financial services.

Practical Applications in Digital Banking – Global Case Studies. The integration of AI for credit scoring is happening worldwide, with both traditional banks and digital-only “neobanks” leveraging these technologies. The following examples from different countries illustrate the current state of practice and the benefits of AI-driven credit scoring in a retail digital banking context:

In the United States, fintech firms have been early adopters of artificial intelligence in credit underwriting. The platform Upstart illustrates this development, using machine learning models that incorporate a wide range of variables, including education and employment history, to evaluate loan applicants. Under a monitored no action letter, the Consumer Financial Protection Bureau reported that Upstart’s model approved about twenty seven percent more applicants and offered roughly sixteen percent lower average interest rates than a traditional score, without evidence of increased disparate impact across

demographic groups. This case has become an important reference point for the argument that well designed and carefully supervised AI systems can both broaden access to credit and lower borrowing costs while remaining consistent with fair lending requirements. Alongside such fintechs, large banks such as JPMorgan Chase and Bank of America, as well as credit scoring providers like FICO, are also investing in AI based risk models, particularly in online consumer lending, credit cards and auto finance, while operating under strict compliance with regulations such as the Equal Credit Opportunity Act.

China represents a contrasting model in which AI driven credit scoring operates at very large scale within a predominantly digital financial ecosystem. WeBank, founded in two thousand fourteen as the country's first digital only bank, serves hundreds of millions of customers through fully automated mobile lending processes in which credit decisions and limit adjustments are issued within seconds. Its systems combine deep neural networks and ensemble methods trained on extensive data from social media, e commerce and other transactional sources, and are further enhanced through federated learning arrangements that allow collaboration with partner institutions without centralising personal data. Reported outcomes include low non performing loan ratios and extremely low per account operating costs. Ant Group's Sesame Credit, which relies on AI to analyse users' payment behaviour and online activity to generate scores for consumer lending, has similarly expanded access for many young borrowers without traditional credit histories. These developments show how AI and massive data integration can support financial inclusion in China, while also prompting regulators to draft new rules to address risks related to privacy and discrimination.

In Italy, where the banking system is characterised by long established institutions, the diffusion of AI based credit scoring has taken place more gradually and under close regulatory scrutiny. A survey by the Bank of Italy published in two thousand twenty two documented pilot projects in which banks supplement conventional scorecards with machine learning techniques such as decision trees and random forests, particularly in consumer and small and medium sized enterprise lending. These initiatives aim to improve the ranking of applicants along the risk spectrum by exploiting additional data sources beyond credit bureau records. The Bank of Italy emphasised concerns about algorithmic bias and highlighted that, when subject to appropriate governance, AI models are not inherently more discriminatory than traditional logistic regression and may in some cases yield fairer outcomes by reducing spurious correlations. As a result, Italian regulators and industry bodies are developing detailed guidance, including codes of conduct for the processing of data in credit scoring, and many institutions maintain human review or use AI as a challenger model before fully integrating it

into core decision making. This cautious strategy reflects the importance of explainability and accountability within the broader European regulatory framework.

The United Kingdom offers another variant of AI adoption in a context with dynamic fintech activity and proactive regulators. Challenger banks such as Monzo, Starling Bank and Revolut, together with incumbent institutions, are increasingly incorporating machine learning into credit card and personal loan underwriting, fraud detection and credit risk forecasting. A joint survey by the Bank of England and the Financial Conduct Authority in two thousand twenty four found that a large majority of UK financial firms already use AI in some form, with rapid growth over recent years. UK lenders make use of open banking data, with customer consent, to feed transaction level information into models that assess affordability and risk for borrowers with thin credit files. At the same time, supervisory authorities support experimentation through innovation sandboxes while stressing the need for fairness and intelligible explanations of automated decisions, and they have sponsored research on how consumers understand AI based credit denials and approvals. In practice, many UK banks implement constraints on model use, for example by translating complex model outputs into transparent scorecards for communication purposes, which illustrates how AI in the UK is embedded within a broader digital transformation that must remain aligned with consumer protection and regulatory expectations.

Artificial intelligence in credit scoring provides a set of measurable advantages for retail lenders. Machine learning models can improve predictive accuracy, accelerate decision making to near real time, reduce unit costs for large scale portfolios and support more granular differentiation of risk. By incorporating additional information such as cash flow data from current accounts or records of utility payments, these models can form a more complete view of the creditworthiness of applicants who have limited traditional credit histories, which in turn contributes to wider financial inclusion.

At the same time, the use of artificial intelligence in credit decisions raises significant questions regarding fairness and discrimination. Models estimated on historical data may reproduce patterns of unequal treatment if past lending practices were biased, including through variables that serve as proxies for protected characteristics. Supervisory authorities in the United States, the European Union and other jurisdictions therefore require banks to demonstrate compliance with fair lending rules. Algorithmic audits, tests for disparate impact across groups with similar risk profiles and bias mitigation procedures such as removing or re weighting problematic variables are becoming an integral component of the model development and validation cycle, as illustrated by the monitoring of the Upstart model by the Consumer Financial Protection Bureau.

A further challenge concerns model transparency and explainability. Complex machine learning architectures are difficult for both supervisors and customers to understand, yet many legal frameworks require that individuals receive a meaningful explanation when credit is declined. Banks increasingly rely on post hoc explanation tools that approximate the contribution of each input factor to the model output and translate these into reason codes that resemble those of traditional scorecards, for example by indicating that low reported income or high existing indebtedness played a decisive role. Research in the United Kingdom and other countries examines how to formulate such explanations so that they are both accurate from a technical perspective and comprehensible for consumers with limited financial literacy.

Data protection and cyber security form another critical dimension of artificial intelligence in credit scoring. Advanced models frequently depend on large and sometimes sensitive datasets, including alternative data such as patterns of online behaviour, which raises concerns about consent and acceptable use. Regulations such as the General Data Protection Regulation in the European Union impose strict conditions on data collection, processing and storage, and classify credit scoring systems based on artificial intelligence as high risk applications that require robust governance, documentation and human oversight. Techniques such as federated learning, as in the case of WeBank in China, offer a possible compromise by enabling collaborative modelling without centralising personal data, although the associated regulatory standards are still evolving.

Finally, banks must address a range of operational and strategic issues linked to the deployment of artificial intelligence in credit risk management. Many incumbent institutions rely on legacy information systems, so integrating modern machine learning pipelines may require substantial investment in infrastructure and specialised personnel, including data scientists and model risk experts, which are in short supply in many markets. Guidance from organisations such as the World Bank indicates that these constraints are particularly acute in emerging economies and can widen the gap between technologically advanced institutions and others. At the same time, excessive conservatism carries its own risk, since failure to adopt more accurate models may result in adverse selection, mispriced risk and the continued exclusion of potentially creditworthy customers from formal finance.

Conclusion. The adoption of artificial intelligence for customer credit scoring in digital banking marks a major stage in the development of financial technology, combining advanced data science with practical retail lending practice. Contemporary techniques such as ensemble algorithms and deep learning can materially increase the accuracy and speed of credit risk assessment, which is

essential in digital channels where competition requires rapid and convenient decisions and traditional relationship based lending is increasingly replaced by quantitative models. Evidence from the United States, China, Europe and Ukraine shows that these systems are already delivering higher approval rates, lower borrowing costs and broader access to credit for previously underserved customers. At the same time, the transition toward artificial intelligence in credit scoring must be governed carefully, with particular attention to fairness, transparency and accountability, including systematic testing for bias, the provision of intelligible explanations to customers and robust safeguards for personal data in cooperation with regulators. Looking ahead, further progress is likely to rely on hybrid approaches that combine the predictive strength of artificial intelligence with human oversight and domain expertise, as well as emerging methods such as federated learning and generative models, so that credit scoring systems are not only powerful but also trustworthy and supportive of more efficient and inclusive digital finance under sound theoretical and regulatory frameworks.

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