Future of B2B Credit Management: AI, Automation, and Real-Time Data Integration

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Abstract: ***As IT and Finance undergo digital transformation, there is a crucial opportunity to reevaluate and optimize credit management processes. Many credit management teams across industries face challenges in accurately assessing credit risk of B2B (Business-to-Business) customers due to evolving factors, including compliance complexities (e.g., GDPR), bulk sales orders, customer data quality from external sources, new customers lacking credit information, one-time customers, and customers with different names or subsidiaries. Additionally, organizations often grapple with internal sales backlog issues, such as unfulfilled orders that are not linked to accounts receivable sub-ledger entries. Many of these processes rely on manual judgment and interventions from credit management teams, leading to delays in decision-making, potential credit risks, and increased workloads. Inaccurate credit exposure can significantly impact an organization's financial performance. This paper aims to assist credit management teams and enterprises in fine-tuning their credit risk management processes for B2B customers. It emphasizes real-time integration solutions, including AI-driven approaches, to automate the integration of customer sales data from inquiry to financial transactions as well as payment history and credit information from external sources. The proposed system employs advanced machine learning models to dynamically predict customer credit risk and provide real-time insights to credit management teams. Additionally, the paper advocates for creating a real-time feedback loop based on credit decisions and shifting the traditional credit check process to incorporate risk assessments during the inquiry and quotation phases, thereby enhancing customer service and improving sales cycle efficiency.***

Keywords: B2B customers, Risk Assessment, real-time System integration, Credit risk management, data quality, Artificial Intelligence, Machine Learning.

1. Introduction

The credit management and collection processes play a pivotal role in maintaining an organization's cash flow and managing credit risk. Effective credit management ensures that businesses can assess the creditworthiness of customers, minimize bad debt, and optimize working capital. However, many organizations face significant challenges in integrating comprehensive insights from sales and financial data, which hampers their ability to make informed credit decisions.

To better understand the complexities involved, it is essential to define B2B customers. B2B customers, or Business-to-Business customers, are organizations rather than individual consumers. They are also referred to as commercial customers, enterprise customers, or channel partners.

It is crucial to examine the sales and finance processes for a B2B customer from inquiry to invoice. In a typical sales and distribution process flow, a customer inquiry generally starts with a quotation, moves to a sales order once accepted, and then progresses to the delivery of goods or services. After delivery, the sales and distribution process conclude with the generation of customer invoices, followed by a finance process that involves accounting and payment collection.

At the heart of both processes is the credit check, which evaluates the customer's credit limit and exposure using both internal sources (such as customer master data and payment history) and external sources (such as third-party credit scores). If the customer passes the credit check, the sales order proceeds; otherwise, it is halted.

Each of these stages presents unique challenges for credit management teams, particularly as organizations adapt to an increasingly digital landscape.

Credit managers encounter several critical issues that hinder effective risk assessment:

- Compliance Complexity: Regulatory frameworks, such as the General Data Protection Regulation (GDPR), impose strict limitations on the access and sharing of customer data. This compliance complexity restricts credit managers from obtaining a complete view of a customer's creditworthiness, especially when external data sources are involved.
- Inconsistent Data: A common problem is the reconciliation of sales data with accounts receivable systems. For example, unfulfilled orders that remain uninvoiced can create gaps in risk assessments, making it difficult to gauge the true financial exposure associated with a customer.
- Delayed Decisions: The reliance on manual reviews of customer creditworthiness often results in slow decision-making processes. This not only elongates credit approval times but also leads to delays in order fulfillment, negatively impacting customer satisfaction and cash flow.
- New Customer Risk: Evaluating the credit risk of new customers presents a unique challenge, particularly when there is a lack of historical financial data or established credit profiles. Traditional assessment methods may struggle to accurately gauge the risk associated with these customers.
- Manual Judgment: Credit managers frequently rely on personal judgment when reviewing customer credit histories. This reliance can lead to inconsistencies in risk assessment and decision-making, exposing the organization to potential credit risks.
- Customer ID Discrepancies: Organizations often deal with the same customers operating under different names across

various geographic locations. This situation complicates the aggregation of customer data and hinders the evaluation of overall credit risk.

- Limited Visibility: Without real-time integration of sales and financial data, credit management teams lack visibility into total credit exposure. This is particularly problematic for unfulfilled or non-invoiced sales orders, which may significantly impact cash flow.
- Fragmented Data: Data is frequently scattered across disparate systems such as Enterprise Resource Planning (ERP), Customer Relationship Management (CRM), and financial ledgers. This fragmentation makes it challenging to form a cohesive and comprehensive view of a customer's credit risk profile.
- Late-Stage Credit Checks: Often, credit checks are performed too late in the process, typically at the sales order stage. This timing can lead to rejected orders or significant delays in fulfillment, adversely affecting customer relationships and revenue streams.

Given these challenges, this paper aims to assist Credit management team and enterprise application processes in fine-tuning their credit risk management processes. The objectives of this paper are to:

- Develop an AI-driven system that leverages internal and external data to automate the credit risk assessment process.
- Improve the accuracy and timeliness of credit risk assessments by incorporating real-time data from multiple sources.
- Shift the point of credit risk assessment to the inquiry and quotation stages, reducing risk earlier in the sales cycle.
- Create a feedback loop for credit decisions to facilitate predictive analysis.

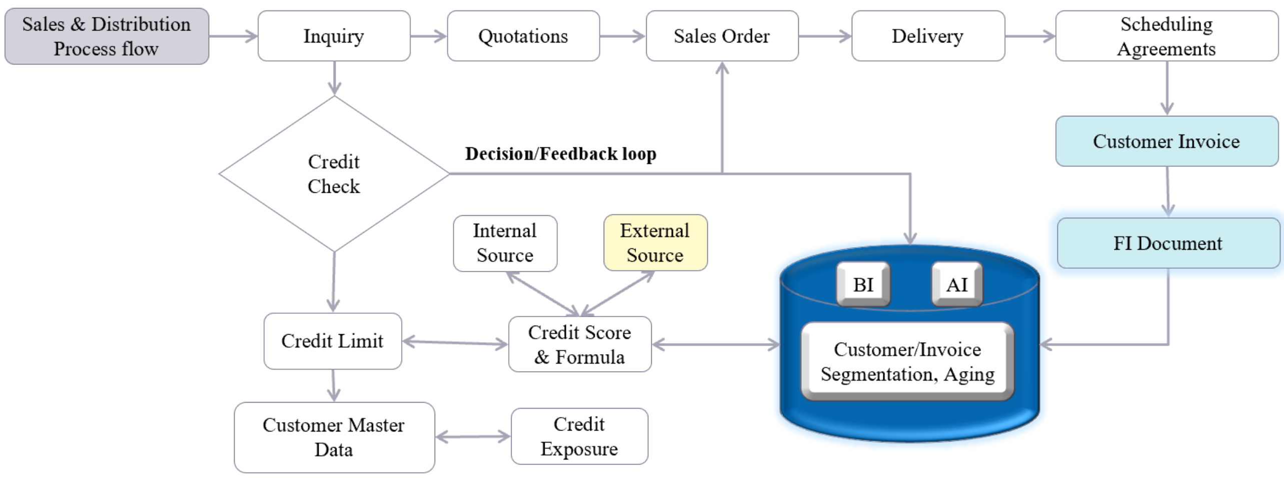


Figure 1: Credit Management system and real time process integration into BI and AI

2. Components of a Credit Risk Formula

Before the data analysis is done, its important to understand components of Credit risk management. In credit management process, a credit risk score typically draws from a combination of financial and operational data, which are weighted according to their impact on credit risk. Below are key components used to formulate a credit risk score:

2.1 Sales and Payment History (from Sales and Finance process)

Historical payment performance, including the timeliness of payments, overdue invoices, and the frequency of payment delays.

Metric: Ratio of paid invoices to total invoices, or average days late on payments (Days Sales Outstanding, DSO).

$$Payment\ History\ Ratio = \frac{Paid\ Invoices}{Total\ Invoices}$$

2.2 Sales Orders and Unfulfilled Orders (from Sales process)

Sales orders that have been placed but not yet fulfilled or invoiced. These unfulfilled orders represent a potential risk as they may inflate the customer's credit limit.

Metric: Ratio of unfulfilled orders to total sales volume.

$$Unfulfulled\ Order\ ratio = \frac{Unfulfilled\ Orders}{Total\ Sales\ Order}$$

2.3 External Credit Score (from third-party sources, stored in FI or customer/vendor master data)

External credit scores from agencies such as Dun & Bradstreet or Experian, which provide insights into the customer's overall creditworthiness based on their public financial information.

Metric: Credit score provided by external sources, normalized against industry benchmarks.

$$Normalized\ External\ Credit\ Score = \frac{External\ Credit\ Score}{Industry\ Avg\ Credit\ Score}$$

2.4 Credit Exposure (from Finance process)

Current credit exposure based on the customer's existing credit limit, outstanding AR, and new sales orders.
Metric: Ratio of current exposure (outstanding AR + sales orders) to the credit limit.

$$Credit\ Exposure\ Ratio = \frac{Outstanding\ AR + Open\ Orders}{Credit\ Limit}$$

2.5 **Internal Risk Factors** (specific to the organization's policies)

This could include custom risk flags such as the industry sector the customer operates in, geopolitical factors, or the size of the organization. In ERP, these custom fields can be added to the customer master data.

Metric: Risk factor weighting based on internal policies (e.g., an industry-specific risk multiplier).

3. Credit Risk Score Formula

The credit risk score in an ERP system could be formulated as a weighted average of these factors. The weights (α,β,γ,δ,€) are determined based on historical analysis of how each factor correlates with credit risk in the specific business context.

$$CR\ Ratio = \alpha \frac{Payment\ Histoy}{Total\ Sales} + \beta \frac{Unfulfilled\ Orders}{Total\ Orders} + \gamma \frac{Credit\ Exposure}{Credit\ Limit} + \delta \frac{External\ Credit\ Score}{Industry\ Benchmark} + \text{€ x}\ Internal\ Risk\ Factors$$

Where:
- α,β,γ,δ,€ are the relative weights assigned to each metric, based on the company's risk tolerance and historical data.
- Payment History measures how reliable the customer is in paying invoices on time.
- Unfulfilled Orders captures the risk of sales orders inflating the customer's credit limit.
- Credit Exposure Ratio ensures that a customer doesn't exceed their allocated credit limit.
- External Credit Score gives insight into the customer's broader financial health.
- Internal Risk Factors consider organization-specific risks (e.g., industry or geopolitical factors).

4. Data Insights

A six-month sample of historical sales and financial transaction data was utilized to calculate credit scores through traditional semi-automated process with manual judgement and intervention. This same dataset will be used further then fed into the AI model for training purposes. The data included key financial indicators such as Sales history, payment history, unfulfilled orders, accounts receivable, Internal credit formula and external credit ratings. Below is the calculation applying a credit risk score formula to the sales and finance data for a sample customer.
- Payment History: 85% of invoices are paid on time.
- Unfulfilled Orders Ratio: 10% of sales orders remain unfulfilled.
- Credit Exposure: Current exposure (AR + open orders) is 80% of the credit limit.
- External Credit Score: 700, with an industry average of 750.
- Internal Risk Factor: 1.2 (due to the customer being in a high-risk industry).

Using weights of α=0.3, β=0.2, γ=0.25, δ=0.15 and ϵ=0.1, the credit risk score is calculated as:

Credit Risk Score= (0.3×0.85)+(0.2×0.10)+(0.25×0.80)+(0.15×700/750)+(0.1×1.2)

Credit Risk Score=0.255+0.02+0.20+0.14+0.12=0.735

Thus, the customer would receive a credit risk score of 0.735 on a scale of 0 to 1, with 1 being the highest possible risk. Based on this score, the organization may decide to adjust the customer's credit limit, request additional payment guarantees, or impose stricter payment terms.

5. AI Methodology

The AI based solution is developed using machine learning techniques to create a customer-matching algorithm, predictive models for credit risk assessment, and data visualization tools to display the integrated reports. The methodology includes:
- Data Collection and Preprocessing: Sales order data, Account receivable entries, and customer metadata from the company's ERP systems.
- Customer Matching Algorithm: Machine learning model was trained to match customer records across different datasets, including handling discrepancies like multiple customer IDs or name variations.
- Predictive Modeling: Models were developed that predicts credit risk based on both historical AR data and sales backlog information.
- Reporting Integration: Reporting interface was built that allows users to move between AR and backlog reports seamlessly, displaying integrated KPIs.

6. ERP to BI and BI to AI system integration

The traditional credit management tools, software or ERP does not have AI-ML capabilities, so ML models were hosted on Google Cloud Vertex AI and were exposed via APIs. The software can consume these APIs to fetch predictions and integrate them into the reports. BI data models were used to prepare and transform your data as needed for your ML models. Once the data was ready, it was exported to ML environment for training and scoring. The sample dataset included two years of historical data, which was split into training (70%) and testing (30%) sets to evaluate the models.

Data Sources for AI model
1) Internal Data: Sales orders, invoices, unfulfilled orders, AR ledger entries, payment history.
2) External Data: Credit ratings from third-party agencies, public financial records, and social media sentiment analysis.
3) Real-Time Data: Sales inquiries, quotations, and updates from the Credit management software/ERP.

7. AI Modeling Techniques

To illustrate how these AI modeling techniques work in practice, the models were applied to 6 months of dataset of customer sales and finance information. This will demonstrate how the algorithms leverage historical data, external customer data along with real time customer sales data to predict credit risk, classify customers, and segment them into risk categories.

Sample Customers for analysis:

Customer ID	Payment History (% of invoices paid on time)	Unfulfilled Orders (% of total sales orders)	Current Credit Exposure (% of credit limit)	External Credit Score (0-1000)	Industry Avg Credit Score	Internal Risk Factor (e.g., high-risk industry)
C001	90%	5%	60%	720	750	1.13(low-risk industry)
C002	75%	20%	85%	670	750	1.41 (high-risk industry)
C003	50%	30%	95%	620	750	1.64 (very high-risk industry)
C004	85%	10%	70%	780	750	1.0 (low-risk industry)
C005	65%	15%	80%	690	750	1.31 (medium-risk industry)

A broad set of algorithms were selected, and empirical tests were performed using a dataset of historical sales, payment history, and credit exposure. The goal was to evaluate each algorithm's performance on key metrics such as predictive accuracy, classification ability, segmentation effectiveness, and interpretability.

Final three algorithms were chosen.

7.1 Random Forest: Predicting Default Likelihood

Using Random Forest, the model analyzed features such as payment history, credit exposure, and external credit scores to predict the probability that a customer will default on their payments. In this sample:

- Customer C001: With a high payment history (90%) and low unfulfilled orders (5%), the model predicts a low likelihood of default.
- Customer C003: With a poor payment history (50%), high unfulfilled orders (30%), and nearly maxed-out credit exposure (95%), the model predicts a high likelihood of default.

The Random Forest model helped prioritize credit reviews and risk mitigation efforts by identifying customers who are most likely to default.

7.2 Logistic Regression: Classifying Customers as Risky or Non-Risky

Logistic Regression applied a classification model to assign customers into two categories: risky or non-risky. Based on payment history and credit exposure:

- Customer C002: With a relatively low payment history (75%), high unfulfilled orders (20%), and credit exposure nearing the limit (85%), Logistic Regression categorizes this customer as risky.
- Customer C004: With a strong payment history (85%) and moderate credit exposure (70%), this customer is classified as non-risky.

This binary classification helped determine whether stricter credit terms are necessary or if regular terms can be maintained.

7.3 K-Means Clustering: Grouping Customers by Risk Segments

K-Means Clustering divides the customers into distinct risk segments (high-risk, medium-risk, low-risk) based on several factors, including payment delays, external credit score, sales performance, customer businesses, customer sector and type of customer. In this case:

- High-Risk Cluster: Customers C002 and C003 fall into this category due to their poor payment histories and high credit exposures.
- Medium-Risk Cluster: Customer C005 is categorized as medium risk, showing moderate performance across several metrics.
- Low-Risk Cluster: Customer C001 and C004 are considered low-risk based on their strong payment histories and reasonable credit exposure levels.

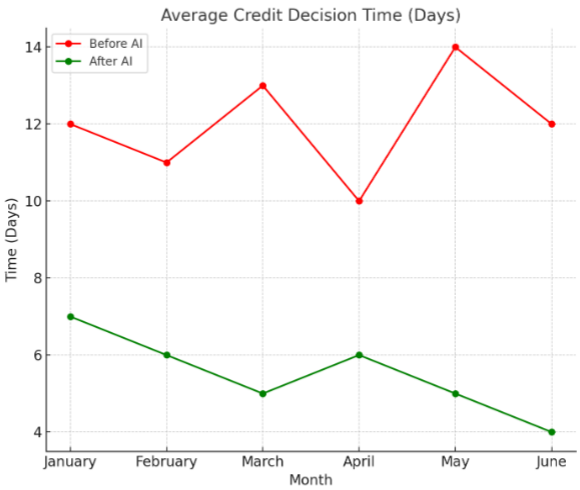
This segmentation will allow credit managers to tailor their strategies for each group, such as providing incentives for low-risk customers or requiring guarantees from high-risk customers.

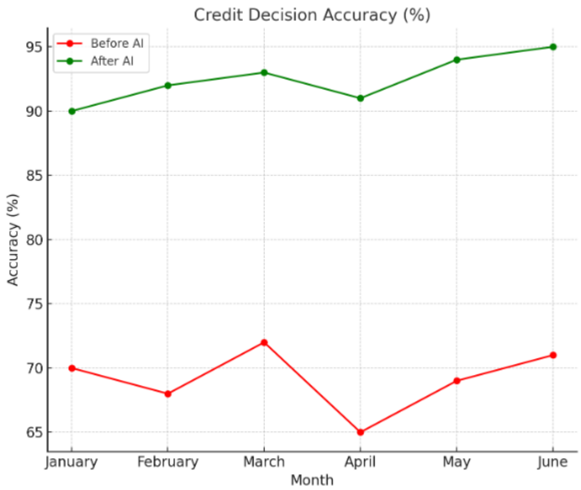
Example of outcomes Based on AI-driven system which would recommend actions based on the credit risk assessments:

- Customer C001: With low risk across the board, the model suggests maintaining the current credit limit and standard payment terms.
- Customer C002: Being flagged as high risk, the system recommends stricter payment terms, such as upfront payments or guarantees, and lowering the credit limit.
- Customer C003: The model advises taking immediate action, such as halting future orders until payments are made and reducing the credit limit significantly.
- Customer C004: Similar to C001, this customer can enjoy standard payment terms due to their low risk.
- Customer C005: As a medium-risk customer, the system may recommend reviewing their credit limit and possibly adjusting payment terms to mitigate potential risk.

After implementation the above recommendations, the model integrated internal sales and AR data with external credit ratings to provide real-time credit risk scores, resulting in:

- Faster Credit Approvals: The real-time AI integrated system reduced credit risk adjustment and credit approval time from an average of 12 days to 5 days, improving order fulfillment speed and customer satisfaction.
- Improved Accuracy: The system's AI model achieved 93% accuracy in predicting defaults, outperforming the previous manual credit check system, which had an accuracy rate of 72%.
- Reduced Bad Debt: Compared to traditional process, the AI driven sample dataset saw a 15% reduction in bad debt after the first quarter of implementation, largely attributed to the earlier identification of risky customers.





8. Continuous Monitoring and Improvement

Once deployed, the model's performance was continuously monitor and updated with new data. A feedback loop was setup where the credit risk prediction can be manually reviewed and used to retrain the model, improving its accuracy over time.

By following this structured approach, an effective AI model was developed to predict credit risk and customer payments.

9. Conclusion

As this paper demonstrates, leveraging AI-driven solutions can address many of the critical challenges faced by credit management teams, such as data fragmentation, manual intervention, and delayed decision-making. By integrating sales, financial, and external datasets, organizations can achieve a more comprehensive and real-time view of credit risk assessment for B2B customers. Furthermore, by fine tuning credit risk process and integrating AI-driven solutions into the credit management process, companies can achieve faster, more accurate credit risk assessments and mitigate risks earlier in the sales cycle. Automating the credit risk assessment process enhances decision-making and helps organizations manage credit more effectively, ultimately improving financial performance and operational efficiency.

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