# Predictive analysis for SCF: what is possible and what is not

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## Can you imagine the ideal SCF world? There are stable material flows across all channels and borders.

We have a fully digitalised workflow at the financing level, without any loss of time or efficiency. Decisive criteria with regard to ESG issues are fully taken into account. Last but not least, SCF players have optimum planning security, thanks to the use of AI-based predictive analysis tools, ensuring maximum resilience even during major upheavals in the global markets.

Back to reality. Global material flows are unstable and will remain so in the future. We are (unfortunately) still relatively far from comprehensive digitalisation of the entire SCF and consideration of all ESG factors. What is available today, however, are technologies that help us analyse existing data streams and use them to make predictions about potential financing risks and disruptions, as well as possible opportunities. We are talking here about machine learning (ML).

### The basis: data, data, data

Supply chain relationships can be highly complex as they involve many different players on the supplier and customer side. According to an estimate by the Boston Consulting Group, more than 20 parties are usually involved in a typical trade finance transaction*. Therefore, there is no shortage of data from all the related (sub-)networks: whether payment behaviour, demand trends, defaults, limit utilisation, etc., the historical information is sometimes already available to SCF providers when it comes to long-term customer relationships. However, the availability of data does not automatically make it usable.

**Excursus: of supercomputers and exaflops**

Enormous computing power is required to process huge amounts of data - especially for training within AI models. It is therefore not surprising that the global demand for powerful computing machines has increased exponentially since the start of the AI boom. Countries around the world are currently investing huge sums of money in the expansion of supercomputers - knowing that access to enormous computing power will be one of the strategic advantages in the future**. To give just one example, China is planning to increase its computing power to a total of 300 exaflops by 2025, with one exaflop comprising the power of two million laptops working in parallel. However, cloud computing and collaborations also enable smaller companies to train and utilise AI models with the necessary computing power (see also "Critical factors" detailed on page 7).

## Agile systems for dynamic markets

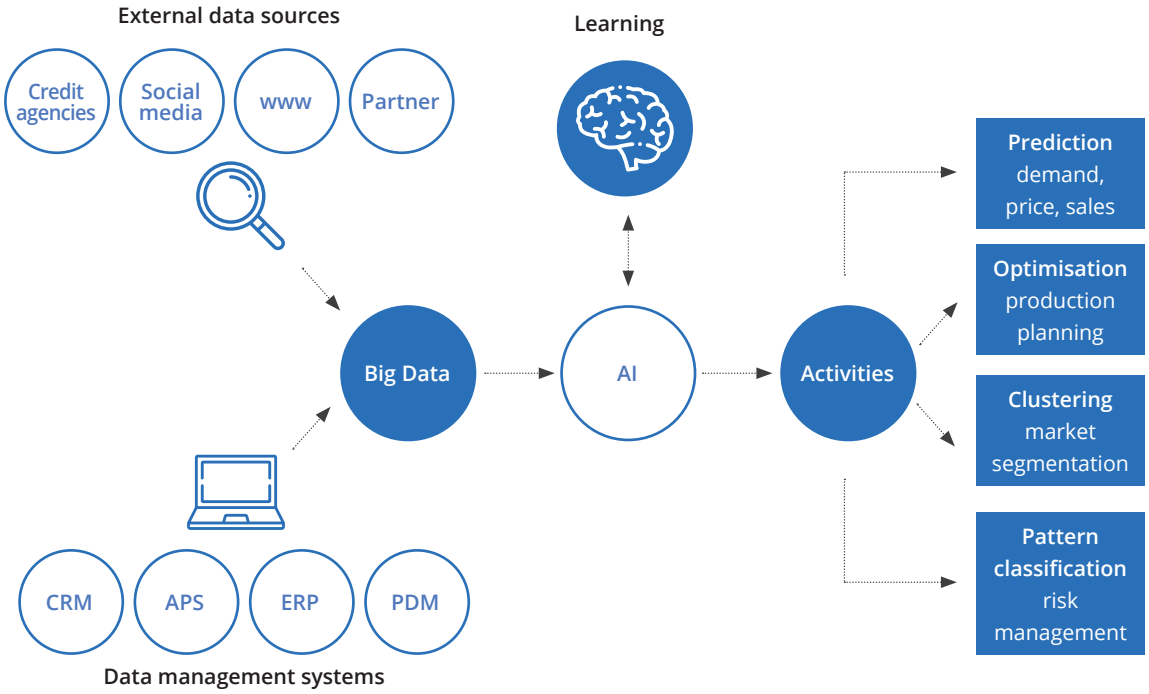
The next logical step is to generate knowledge from the existing databases that can help us make decisions. The aim here is to train a data model in such a way that it is able to output relevant labels such as low risk, medium risk or high risk (supervised learning), with the help of certain parameters (analogous to the evaluation of a customer by an employee). In a further development stage, the system continues to learn independently and attempts to find and categorise relationships between the data (reinforcement learning). It can access not only "internal" available data from the individual management systems (such as payment behaviour and financial reports, etc), but also "external" data such as general market trends, data from partners and information sources, as well as information from the web (articles, social media). The ultimate aim is to map the dynamics of the markets in an agile, self-learning system.

## I see what you don't see!

In this case mapping means, in particular, being able to recognise patterns that would not be visible to humans and/or previous methods. These patterns can then be interpreted and serve as the basis for further recommendations, warnings or decisions, for example, indications of possible risks from fraud. As already mentioned, the system's ability to learn improves over time, leading to increasingly accurate results.

## Example scenario

Let's go through an example of how ML can be used to generate usable results in the area of SCF. Let's assume that the user of such a tool is a medium-sized international financing bank. Ideally, the bank already has a historical database with information on payment behaviour, other key financial figures (balance sheets, annual reports, KPIs, etc), and external information (ratings, credit insurance, etc) on its existing customers. The latter are part of a supply chain, either as a supplier/seller or as a buyer/customer.




*Source: Relevant advanced technologies for trade and supply chain finance, Whitepaper by Commerzbank and Fraunhofer IML, 2022*

Initial analyses are then carried out on the basis of the collected historical data to help us understand what the data is saying. Specifically, the aim is to identify decisive factors that could have an influence on the subsequent output. For example, were there unusual events such as COVID that should be eliminated as a factor? What are the reasons behind certain patterns and behaviours? Once we understand these factors, the actual learning process begins in which we teach the ML system to predict what might happen in the future. In this so-called training database, external data from the WWW is incorporated, in addition to the determined parameters (as mentioned, based on specialist expertise, among other things) in order to map current developments and trends.

Our trained ML system now establishes properties and (new) connections, which in turn lead to specific activities. These are, for example, predictions about the probability of customer failure within the supply chain due to regional or industry-specific disruptions, or due to fraud. This means that you are not just content with a purely descriptive analysis based on historical data, but also receive (ever-improving) predictions about likely scenarios in the future. However, as soon as external changes occur that are categorised as systemically relevant, the ML model must be adapted accordingly. In this case, it must be retrained. Such changes could, for example, be far-reaching regulatory adjustments on the markets.

The real highlight is that such ML-based predictive analysis tools can be used for the entire customer ecosystem. In other words, if a customer is categorised as probably risky, all the players in the system who have a relationship with them are also analysed and assessed accordingly. The result is an intelligent SCF cockpit that generates indications of potential risks in real time - not just selective y, but in the form of a "big picture". Of course, the whole thing also works in the direction of potential opportunities: the bank receives information on which sectors, regions, etc. harbour particular potential that can be exploited accordingly.

## Critical factors

What about computing power and the associated costs? As already mentioned, there are very large amounts of data to be processed. This requires correspondingly large capacities of computing power. With on-premise solutions, this would involve relatively high investment in software and hardware. Cloud computing opens up new possibilities here without having to pay horrendous sums for storing and processing the data. Nevertheless, there may be an objection that the use of AI/ML is only reserved for players that are large and financially strong enough. One solution here would be to form partnerships to create synergies - between banks and fintechs, for example.

Other concerns would be an over-reliance on AI-based systems, which can lead to considerable losses if misinterpreted. At this point, it should be expressly mentioned that results based on AI should not be used completely without reflection. After all, AI is not a 100% replacement for humans, but rather serves as a support to achieve more accurate or new results more quickly. Finally, the handling of sensitive data (GDPR) is also viewed critically. In any case, appropriate security standards must be observed and continuously monitored.

## Summary

Supply chain finance can utilise AI and ML to exploit enormous potential that has so far remained untapped. By training existing customer data in ML models, recommendations, hints and warnings can be generated for possible events in the future. Such a predictive analysis approach must also be critically scrutinised - for example, in terms of the cost-benefit ratio, data security and reliability. However, such risks can be minimised with the help of cloud computing and efficient cyber security concepts.

**Notes:**

**Boston Consulting Group 2017*

***Guido Appenzeller, Matt Bornstein, and Martin Casado, Navigating the High Cost of AI Compute, Andreessen Horowitz, April 27, 2023, https://a16z.com/navigating-the-high-cost-of-ai-compute.*