

# Summary



## INSIGHT SESSIONS: HOW TO BECOME DATA-DRIVEN

On 5 Virtual Fridays in May and June, experts discuss with real life examples how big and mid-sized companies can start or develop their data-driven initiatives.

### KEY TAKEAWAYS 'Scaling digital transformation in the chemical & process industry'

Effectively scaling analytics is more important than ever, and a challenge for many organizations. Jose Manuel De La Hoz (Solvay) and Adriaan Van Horenbeek (SAS) explain how machine learning and mathematical optimization are helping to digitally transform Solvay.

Solvay considers digital transformation as an opportunity to *reinvent the company*, and to *rethink the way they work, interact and address customer needs now and in the future*.

Priorities are to optimize costs, increase profitability, streamline key processes, enhance process performance, and optimize maintenance. The key is to start small and move forward by testing and learning: *fail fast and adapt whenever needed*.

- \* *Variability* in the process and a wide combination of process parameters observed in the past, are key to fully leverage advanced analytics.
- \* The journey of advanced analytics at Solvay: (1) Make sure you have the right data & data architecture; (2) exploration and analysis of the data, find cases to further investigate; (3) detect, optimize and implement the best analytical models; (4) embed analytical models to optimize the process; (5) monitor the accuracy of the models and continuously improve.
- \* Lessons learned for future projects:
  - A good team and governance are key
    - *Communicate in all directions*: bottom/up and up/bottom. Drive communication to connect with people and explain how you want to apply digitization.
    - Select a digital person on each site to collect doubts and fears. This person should be well-organized, a good communicator and a good listener.
    - *Integrate data scientists and IT support* from the beginning.
    - Define a person to *ensure the traceability* of the whole process, from model creation, modification to implementation.
  - Replication: consider every project as a "grass root project", even if you had previous successful experiences, although you can leverage learnings and assets to scale and repeat fast.
  - Always check *variability* in the parameters that are important from the process point of view, not only from a statistics point of view.

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## KEY QUESTIONS

**We were overwhelmed by your questions during the live Q&A. Since it was impossible to respond to all of them individually, our speaker selected some very interesting ones.**

### **How were these new working methods perceived by the people of the factory?**

In the beginning, it was a challenge and people didn't understand the value of advanced analytics. They were skeptical at first. Communication is crucial and you have to make it clear that implementing advanced analytics is to make the life of the people in the plant better, and of course, also to improve the business. In the end, they were convinced about the new way of working and the business benefits it brings.

### **How to find real added value and encourage decision makers to invest in analytics and machine learning?**

First, it's crucial to identify the right plant to start with, and to draw a clear business case on how advanced analytics can improve the business. Then, we performed a diagnostic and looked at explained variability and at the gap to optimal performance. We ran a "what-if" scenario on historical data to see what the result would have been of using this model and optimization. Then you have an idea of the potential, decide on the design, and implement. If you don't have value at the end of the diagnostic, don't invest your time and money. The diagnostic is there to find fast or fail fast in order to keep the focus on the projects that are really returning the appropriate value.

### **How much time was needed from idea to POC running on the first real model?**

There is a big difference between the first plant implementation and the ones that followed afterwards. Running just the diagnostic at the first plant took around 3 months. However, this was still without a dedicated team, and it was the first time. So, there was still a lot of learning and change management involved. Full implementation at the second plant took 3 months; we put the people together from the beginning and translated our experience from previous projects into repeatable assets and methodology. If you think it's important, you need to allocate the resources.

### **We have some experience with "language barriers" between chemists/process engineers and data scientists. How did you manage to make them understand each other?**

To have a multi-disciplinary team work well, you need to put them together and after a while they start speaking the same language. Spend time together to understand the process and analytics. Make loops to improve communication. Moreover, the role of a business translator is crucial in here. Someone who understands the chemical process and also has knowledge about advanced analytics and how it can be applied. Another important thing is to start the modeling exercise with simple white box models first and only later progress into the very advanced machine learning models. By doing so, the engineers build confidence in the models that are being built as they can interpret them. And on the other side the data scientists get insights in how the chemical process works by discussing the relations between input and output with the engineers. Later on, shift focus to model performance by building more advanced models, but by that time everybody is already on the same page.