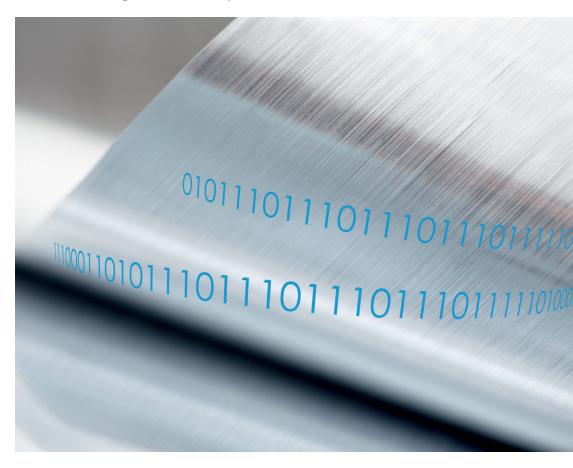
Unlocking the digital opportunity in metals

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Authored by:

Lapo Mori Tamim Saleh Richard Sellschop Michel Van Hoey

Unlocking the digital opportunity in metals

When it comes to the adoption of new technologies, the metals industry has a history of long lead times. While the industry has made continued investments in process control and optimization, it has been slow in implementing new digital technologies – especially when compared with industries like banking or media. However, over the last few years, the pace has picked up for metal companies, too. Innovations in analytics, mobile solutions, and automation have found their way into the industry, and are propelling significant efficiency gains. This acceleration is driven by 4 key shifts:

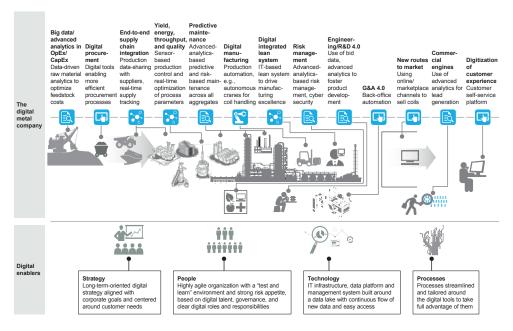
- First, the amount of data available has increased exponentially over the last few years. The metals industry is deploying more and a wider range of sensors including vibration, optical, and sound sensors and data storage has become far less expensive. As an illustration, we estimate that today's cost of data storage represents only 2 percent of the storage cost 5 years ago.
- Second, increases in computational power and the development of new analytic methodologies enable metal production companies today to conduct highly sophisticated analysis of this data. Traditional statistical methods that could process no more than a handful of production parameters are giving way to machine-learning algorithms capable of crunching through numerous factors concurrently, even when those factors lack linear relationships.
- Third, mobile technology is now also available to the shop floor, and is contributing
 to significant productivity gains through more effective field-force management and
 streamlining of processes (e.g., in maintenance).
- Finally, automation is finding more widespread applications in both production and support functions. The spread of automation is driven by the quest for efficiency: labor costs are ever increasing (e.g., 80 percent increase in US labor costs since the 1990s), whereas the costs of robots and automation are steadily declining, and systems are becoming ever more reliable.

In the past, the most important driver of the competitiveness and value creation for a metal production company was its structural position on the cost curve. Going forward, data will gain more and more value compared to the physical product itself, and the top value creators will stand out from the rest by how effectively they capture and leverage data. The stakes are high: our research suggests metal producers that harness the full potential of a digital transformation can increase their EBITDA margins by up to 6 to 8 percentage points.

Significant impact from digital reinvention

Today, most metal producers are experimenting with digital use cases along the entire value chain (Exhibit 1).

EXHIBIT 1 Digital will change metal players' full value chain



SOURCE: McKinsey

We define "digital" to encompass three categories of opportunities, which are unlocked by a set of enabling technologies and approaches:

- Advanced analytics and artificial intelligence applied to a broad range of data that plants generate from production and maintenance processes is the most important digital lever. This category typically accounts for more than 50 percent of the total gains from digital adoption.
- **Robotics and automation** contribute another 20 to 30 percent of the total improvement opportunity by eliminating the need for human intervention in non-decision-making functions and by further improving process control and stability.
- Process digitization and software automation that streamline manufacturing, maintenance, and back-office processes, and connects workers equipped with mobile devices to instructions and data at all times, can add another 20 to 30 percent to EBITDA gains.
- Unlocking potential through enabling technology and processes, including Internet of Things (IoT), sensors, cloud, mobile, agile development, and design thinking.

At metal companies, we see digital use cases deliver the largest impact in following areas (Exhibit 2):

Yield, energy, and throughput (advanced analytics). Analytics techniques applied to big data and the use of new sensors can strengthen process control and boost plants' hourly profit by optimizing process parameters used to balance yield, throughput, recovery, and material costs. For example, yield, energy, and throughput (YET) analytics alone can improve EBITDA by 2 to 3 percentage points (reducing manufacturing costs by 3 to 5 percent, and leading to significant debottlenecking opportunities).

EXHIBIT 2 Digital opportunity map for a metal player

QUANTIFIED OPPORTUNITY HEATMAN AFTER WALKTHROUGH DIAGNOSTI

		Mining and beneficiation	Iron making	Rolling and coating	High ■ Medium ■ Lo
Manufacturing	Yield				
	Energy				
	Throughput				
	Value-in-use				
	Quality	000144			
	Maintenance				
	Labor prod.	000111			
Commercial	Sales		-		
	Supply chain	MANANA			
Procurement	Procurement				
G&A	G&A				
	Total				

SOURCE: McKinsey

YIELD CASE STUDY

Using advanced analytics to optimize recipe specifications

A global steelmaker was scrapping or downgrading converter heats based on deviations of individual chemical elements outside its defined operating window. It noticed, however, that in spite of these deviations, overall mechanical properties were still in line with customer specifications. In an effort to reduce both yield losses and alloying costs, the company developed a "Yield Strength Index," a predictive model of mechanical properties based on multiple linear regressions of the full basket of chemical elements. The model was calibrated with the help of multiple linear regression analyses of comparable steel grades, covering 85 percent of the total product portfolio. This reduced downgrading, improved hot charging, reduced ferroalloy consumption by 0.6 EUR/ton, and allowed for higher P targets at the convertor.

YIELD CASE STUDY

Using self-learning advanced analytics to boost yield

A European steelmaker wanted to reduce the 18 percent share of slabs exceeding its width tolerance of ±20 mm. An advanced process model was developed using historical data to predict slab widening as a function of steel and process parameters, incorporating self-learning capabilities (it automatically adapts prediction coefficients based on the actual widening data from the past 5 days). Using this model to control the mold width settings dynamically, the company was able to reduce under-width from 3 percent to 1 percent and over-width from 15 percent to 4 percent, leading to very significant downstream yield gains.

THROUGHPUT CASE STUDY

New sensors to boost throughput

An international steel group was facing a bottleneck on some of its pickling lines. Analysis showed that line operators were limiting strip speed in the bath to ensure complete pickling and avoid quality defects. The root cause: the lack of an objective measurement of pickling quality; standard inspection was done visually and depended heavily on the operator and the prevailing situation. The company developed and implemented an in-line pickling quality sensor, using dark field LED spectroscopy. After 3 years of industrial use, the sensor allowed the group to reduce quality-related costs by 40 percent and to increase throughput by 3 percent.

THROUGHPUT CASE STUDY

Using advanced analytics to improve process control

An Asian integrated steelmaker was reaching a temperature hit rate of only 55 percent at the CAS-OB in its steel shop, causing speed reductions at the caster (when the temperature was too high) and steel ladle returns (when the temperature was too low). A through-chain database was built by linking historical data for steel ladle parameters and CAS-OB equipment state and process parameters. The process control model based on neural networks immediately improved temperature hit rates to 70 percent (a USD 1.2 million opportunity in caster throughput). Over time, the self-learning model reached a temperature hit rate of >90 percent, both by improving the CAS-OB process understanding and by setting clear constraints for upstream processes.

 Quality (advanced analytics). Applying advanced analytics techniques on a throughchain data set can quickly identify the root causes of quality issues, and machine learning can automatically define optimal recipes for new products/grades.

QUALITY CASE STUDY

Using advanced analytics to resolve quality problems

A European steelmaker was facing a high (above 20 percent) and variable (0-40 percent) rejection rate on the mechanical properties of a major new product family, leading to extensive value leakage in direct and indirect costs. A year of traditional hypothesis-driven analysis failed to identify the root cause of the problem. However, by using classification advanced analytics techniques on more than 300 variables of through-chain data – covering chemical composition, shift and maintenance logs, and process parameters – the company quickly succeeded in identifying the process parameters responsible for the rejections. A neural-network model allowed it to optimize the production formula, bringing the rejection rate to less than 1 percent in just 10 weeks.

■ Value-in-use (advanced analytics). One of the main value levers for metals players is a rigorous and data-driven selection and optimization of the raw material mix, which can – depending on the starting situation – lead to a potential uplift of 1 to 2 percentage points in the EBITDA margin.

VALUE-IN-USE CASE STUDY

Using advanced analytics to optimize scrap mix

A European steelmaker introduced a value-in-use model to optimize the scrap mix in the converter. Taking into account the scrap price, availability and characteristics (chemical and physical), the plant constraints (e.g., Zn content of dust, size of scrap loaders, logistics constraints in the scrap hall), the specific factor costs (e.g., refractories, lime), and finished product constraints, the company dynamically optimized its scrap menu and was able to reduce scrap cost by 10 percent.

■ Maintenance (advanced analytics). Predictive maintenance that assesses machine usage and failure patterns can help reduce expensive downtime. When applied to critical equipment such compressors, pumps, and motors, such maintenance can cut downtime by as much as 40 percent, major revisions by 5 to 10 percent, and operational costs by 2 to 10 percent. In addition, digital workforce management can increase the efficiency of maintenance teams and create workload transparency for better and faster prioritization.

PREDICTIVE MAINTENANCE CASE STUDY

Using advanced analytics to predict equipment failure

A global base metals smelting group was grappling with downtime and associated production losses due to unexpected failure of a blower occurring on average more than once a month. It also frequently had to divert maintenance resources from planned maintenance tasks to breakdown repair activities, reducing the efficiency of the maintenance team. A predictive model, leveraging existing sensors to collate operating and equipment data, was able to predict imminent failure on average 7 days in advance with an accuracy of 81 percent. This allowed the group to plan and synchronize maintenance interventions and prevent additional time lost due to re-planning, expediting, and procuring parts and avoiding failure and damage cascading across assets.

- Direct labor productivity (robotics and automation). The automation or robotization of production steps (e.g., crane operations, sampling activities, maintenance automation) can lead to a reduction of direct labor. Even in the developed world, however, the business case for automation will require additional throughput, or better process control to deliver attractive paybacks.
- Sales (advanced analytics, end-to-end process digitization). Introducing digital tools in sales can automate tracking and management tasks, while online channels can replace traditional direct sales and better demand forecast analytics can extend the order books to small customers. Advanced analytics, meanwhile, will improve lead conversion rates and enable dynamic pricing based on competitor and market factors, delivering a projected margin improvement of 2 to 4 percentage points. At the same time, given that the end-user industries of metals (e.g., automotive, energy) are discovering the power of big data and advanced analytics, more and more customers are requesting that the products delivered are accompanied by a set of critical process parameters linked to that product.

- Supply chain (advanced analytics, end-to-end process digitization). Analysis of trade-offs between order quantities, inventory, and transportation costs can improve both long-term planning and real-time scheduling. For example, modeling complex manufacturing systems and supply chains to dynamically optimize their financial performance typically improves EBITDA margins by 2 to 3 percentage points (1 to 2 points from direct savings, plus a significant uplift of throughput).
- Purchasing and supply management (advanced analytics, end-to-end process digitization). Faster, deeper, and automated analysis of spend data and price variances can lead to price opportunities in the form of automated adjustments of supplier bills, as well as improved compliance and fraud identification. Leading suppliers are now also automatically triggering quarterly e-auctions, with automated evaluation and contracting. The most sophisticated metal players have started to apply digital tools (e.g., satellite imaging to monitor stocks and vessel waiting queues) to make raw material price forecasts. Such tools can improve the EBITDA margin by 1 to 2 percentage points (cost savings of 2 to 3 percent).
- G&A (end-to-end process digitization). In support functions, the main drivers of improved efficiency and effectiveness are automation, analytics-based decision making, and digitizing and using platform business models for the provision of standardized processes.
- Business model innovation (end-to-end process digitization). A number of metal companies are leveraging digitization to completely re-invent their business models. This ranges from creating digital sales and supply chain platforms to sharing (and valorizing) data at coil level with customers.

Holistic approach to scale the digital transformation

While most metal players are successfully experimenting with the development of individual digital use cases, few are successful at scaling the breadth of implementation needed and realizing its positive impact.

We frequently hear questions such as, "Should we take a centralized or decentralized approach?" "What should we make versus buy?" "How is this different to previous technology projects?" and "How do we get after the value rapidly?" There is no standard answer to these questions, and they require careful thought as a digital transformation is designed and executed.

Driving a full digital transformation of a metal company is a complex undertaking: for optimal results, such an initiative must tackle hundreds of use cases, most of which individually produce only modest impact. To succeed, companies need to develop a scalable model, with a set of standards in place covering roles, tools, and working methods.

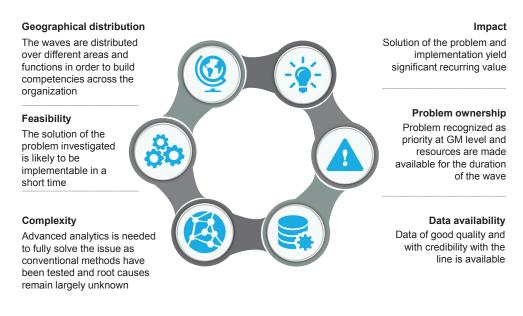
A typical roadmap for scale-up is composed of four building blocks: A. Use case deployment, B. People and capability build-up model, C. Platform, technology, and data strategy, and D. Program and change management.

A. Use case deployment

The challenge in a digital transformation lies in managing hundreds of use cases, some of which have a high impact (multi-million-dollar impact per year), but most of which individually produce only a modest impact (several-hundred-thousand-dollar impact per year).

Typically, metal makers prioritize and deploy the use cases based on a set of criteria such as impact, feasibility, data availability, ownership by the line management, potential capex incurred for implementing the solution, and distribution across the value chain (Exhibit 3).

EXHIBIT 3 Selection and prioritization of use cases need to be evaluated across multiple dimensions



SOURCE: McKinsey

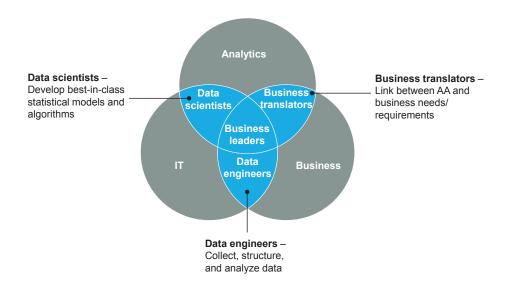
B. People model and analytics academy

While the IT infrastructure, data systems, and technology are important enablers to realize a digital transformation, in most cases the constraining factor in driving the transformation is human capital. Given the long tail of use cases with only moderate to low impact, it is necessary to develop in-house capabilities in advanced analytics, as relying on external service providers is not economic. Companies that are successfully driving digital transformations have made bold investments in the build-up of advanced analytics capabilities, and are often applying an "academy" approach to developing the required capabilities. Certification protocols associated with the training curriculum allow them to build up and track the digital skills of their employees.

A successful advanced analytics program requires a blend of business skills, along with analytics and technology skills (Exhibit 4). All three types of skills are must-haves to generate impact at scale, and to move away from a succession of Proofs of Concept. This range of talent is currently scarce on the labor market, and metals players face significant challenges in attracting it, as they compete with high-tech and financial services companies that are also aggressively recruiting these profiles and typically enjoy higher attractiveness ratings. That said, metal players do, however, tend to have extensive in-house technical and engineering talent well suited to performing data science and translation tasks when supported with proper capability building. Data engineers, on the other hand, typically need to be recruited from outside and often become a bottleneck, as these profiles are not often found in-house, and data management will become more and more a core competency for the business. Given the tight labor market for data engineers, first movers will have an advantage in this race for talent.

These people with their differing profiles need to work together, with the line, and with the IT team in a cross-functional, agile way. Putting the teams into geographic proximity, meanwhile, helps create a collaborative environment where teams share ideas and best practices from different use cases.

EXHIBIT 4 Traditional roles are colliding to form new roles required for an effective advanced analytics organization



SOURCE: McKinsey

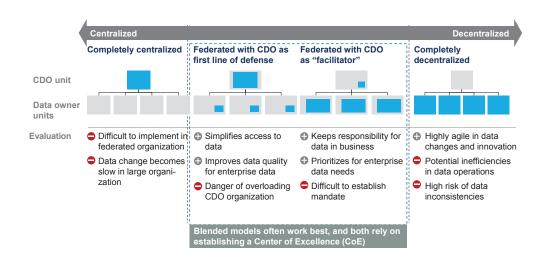
Across the multiple companies we have seen embark on an analytics journey, four organization models stand out, differentiated by the respective level of centralization of the analytics team:

- Centralized model. In this model, all data and analytics resources sit in a central Center of Excellence (CoE), where they handle all types of requests and are officially the owners of the data. This model can help to initially structure a fragmented approach and/or "rescue" very low-quality data. However, it does not prove effective in our view in the midterm to really embed analytics in the line organization, because the interface between the central team and the BUs often proves difficult.
- Federated with CDO (Chief Digital Officer) as a first line of defense. This model also maintains a strong central data team, responsible for data governance, while allowing BUs to manage their own "operational" data with guidance and best-practice sharing from the CoE.
- Federated with CDO as a facilitator. Compared with the previous model, this model entrusts the BUs with a larger role in managing data assets, focusing the CoE on providing guidelines and safeguards, sharing best practices, and hosting resources or assets that can be shared across BUs or that BUs cannot afford individually.
- **Decentralized model.** In this model, BUs are responsible for their own data management, fostering increased agility but hindering the establishment of common standards and the capture of synergies. We also deem this model's impact as limited in the mid-term, as BUs typically continue on a fragmented path and scale-up is very complex.

The illustration below summarizes the different models and their pros and cons (Exhibit 5). As highlighted above, our view is that blended models are the most effective models as they combine BU ownership (and hence ultimately business impact) with central synergies, guidelines, and best-practice sharing. Most companies that are successfully transforming have started with a model with the CDO as first line of defense before transitioning to a model in which the CDO acts as a facilitator.

EXHIBIT 5 Choosing the right organizational archetype is key, along with defining clear roles and responsibilities





SOURCE: McKinsey

C. Platform, technology, and data strategy

The IT infrastructure of many metals producing companies is composed of a set of complex legacy systems, developed over time and integrated during mergers and acquisitions. Currently, most metals companies are measuring and collecting a vast amount of data, yet the accessibility of the collected data is poor. This does not mean, however, that a full IT transformation is required to launch a digital transformation. Most metals players that are embarking on a digital transformation put in place a parallel architecture capable of handling the data and analytics tools. This involves making some choices – for example, around the use of cloud or on-premise tools, the set-up of a data warehouse or a data lake, and what to build versus buy. Data is then gradually uploaded on the platform based on the use cases that are being developed, typically leading to the build-up of a full live-data platform over the course of 12 to 18 months.

The "build" option is new to many companies as it has historically been too expensive and complex to be viable – this has changed with the current generation of digital tools, platforms, and agile development approaches. This opens up a new set of opportunities to create solutions that are specifically suited to a company's needs and take employee input into account, which then helps drive adoption.

Additionally, the organization needs to clarify data ownership and data quality management. In metals companies, data ownership often lies with IT teams rather than with operations and maintenance staff who can benefit most from it, slowing down the potential gains from digital solutions.

D. Program and change management

The introduction of digital requires changing processes to leverage the new tools. For example, implementing a new quality measurement system will require a redesign of the quality process to effectively use this new technology; maintenance will be similarly affected when introducing predictive techniques and digital work management.

Employees tend to embrace digital transformations more enthusiastically than other transformations, making them great vehicles for driving wider change and the adoption of new practices beyond digital. However, the wide scale of a digital transformation requires a company to create a comprehensive change management program, and establish a change management group to oversee the change program, monitor execution and impact through regular reviews and scorecards, ensure training is developed and delivered, and put appropriate communication in place to sustain the momentum.

As in any change program, a digital transformation requires leaders to serve as role models and sponsors who stress the importance of gaining the digital edge. They should emphasize that digital is not about a platform, or an innovation group, or a specific widget; it is about transforming how the organization becomes data-driven, and making the entire organization fast and agile. The results are worth the effort, transforming the culture, improving safety, and delivering significant value to the bottom line.

Authors



Lapo Mori
Partner
Brussels
lapo_mori@mckinsey.com



Tamim Saleh Senior Partner London tamim_saleh@mckinsey.com



Richard Sellschop
Partner
Stamford
richard_sellschop@mckinsey.com



Michel Van Hoey Senior Partner Luxembourg michel_van_hoey@mckinsey.com

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