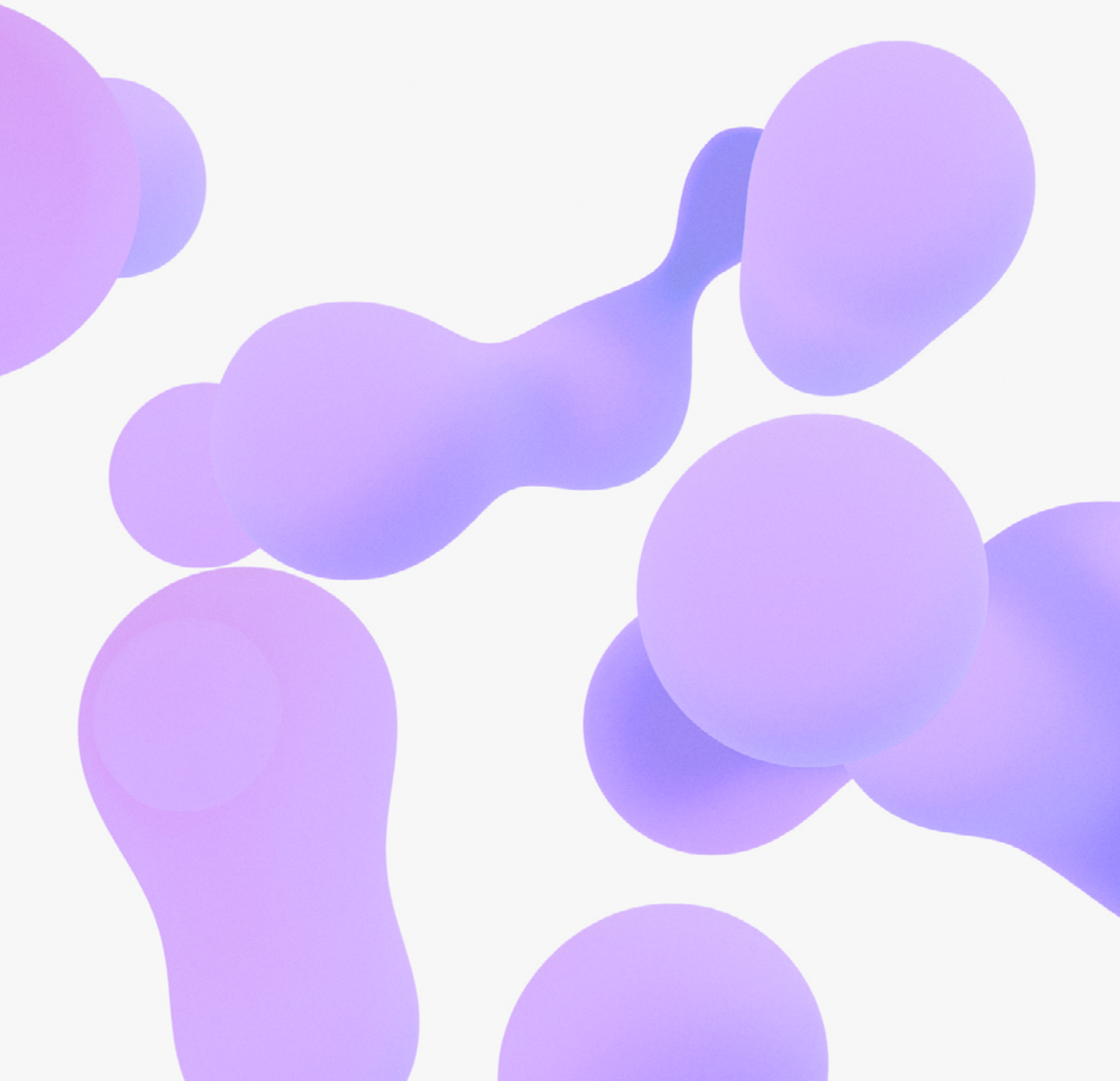
The Promise of AI in Banking

Redesigning Financial Services



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Editorial

Artificial intelligence (AI) represents a strategic opportunity for banks. The potential benefits extend well beyond mere efficiency improvements to step up the customized value proposition banks deliver to their clients. For the last five years, AI-driven solutions have focused mainly on buzzword applications like chatbots and robo-advisors. However, in the latest evolution of AI applications, many banks are realizing the strategic relevance of embedding AI technologies into various units of their business systems. The benefits range from building efficiencies and saving costs in areas like fraud detection, improved risk management and optimized anti-money laundering to enhancing the client investment experience (and financial health) through the deployment of personal finance management (PFM) solutions that help clients better manage budgets and wealth.

Looking ahead, to capture the opportunity around the integration of AI technologies, banks are well-advised to first determine the use cases best suited to their respective needs. This report attempts to provide a useful overview of such use cases in a way that will hopefully both drive a discussion and help some institutions develop a clear, holistic strategy around the integration of new technologies.

We hope you enjoy reading the report.

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Introduction

Artificial intelligence (AI) technologies are increasingly pervasive, but in the banking industry, the implementation of AI applications is still in its infancy. As these technologies continue to mature, banking offers the ideal application area for such intelligent applications. Facilitated by decreasing costs of data storage and processing, as well as rapid advances in AI technologies, banks today have a major opportunity to formulate an AI strategy and deploy AI applications.

Such new technologies can help automate crucial processes, improve human decision-making in terms of speed and accuracy, and even help offer more tailored advice to clients. The demand for such capabilities is also rising from the client side. Indeed, the use of online and mobile banking applications among customers has increased by an estimated 20%–50% [1]. These changes will likely remain intact in a post-COVID world. In fact, over three-quarters of surveyed bankers believe that artificial intelligence will make the difference between the leading and lagging banks of the future [2].

However, in practice, a clear action gap is discernible, and there are a couple of reasons for this. For example, in many institutions there exists an outdated technology core with legacy systems and widely distributed datasets that complicate collaboration between business and technology teams. Moreover, many banks suggest that a key reason for inactivity in this space is the difficulty in identifying key use cases. This report attempts to offer just that: use cases that are transforming the way banks operate, using language that clearly describes the underlying technology in a simple way.

[1] https://www.mckinsey.com/industries/financial-services/our-insights/ai-bank-of--the-future-can-banks-meet-the-ai-challenge
[2] https://www.temenos.com/insights/white-papers-reports/eiu-2020/

Defining artificial intelligence

Automation is not new. The rise of computers and the ensuing wave of automating many traditional production lines have increased productivity in the manufacturing industries. However, in the past, automation was largely limited to narrow environments such as production lines and repetitive administrative tasks that are easy to translate to an algorithm. What makes the current wave of AI different is its increasing ability to detect patterns from unstructured data and recognize far more nuanced patterns, allowing it to automate more complex processes and tasks. More specifically, AI enables computers to perceive, learn, reason, and assist in decision-making to solve problems in ways that mimic human thinking.

AI systems are already being used in our daily lives to answer questions, translate languages, optimize power consumption, operate factories, write news stories, drive vehicles, and diagnose medical issues. Barriers to adoption have lowered, driven by greater access to computing power, greater datasets, and cloud computing.

One of the most important types of AI is machine learning (ML), an algorithmic system that can recognize patterns and learn. ML is a subset of AI, imitating the learning process of humans, and has become one of the key AI technologies used by the financial services industry.

Use cases

The following pages discuss the current challenges faced by banks and financial companies, and demonstrate how AI applications can help to solve those challenges. This report also offers key recommendations for executives.

1

Data quality management in practice

2

How machine learning can be applied to process mining to improve efficiency

3

Data mining can help banks generate insights from data

4

Anti-money laundering procedures & AI: the perfect match

5

Risk management

Data quality management in practice

The availability of sufficient, good-quality data is often a prerequisite for the deployment of AI methods. However, data quality issues can be solved with ML-driven data remediation.

The foundation of any AI application is the data upon which it is based. Thus, data quality (DQ) management is critical to the success of an AI strategy. But data quality issues can be observed in many datasets across banks' front- and back-office value chains. In fact, in a recent international study, 87% of employees named DQ issues as the main reason why their organizations failed to successfully implement AI [1]. This section addresses data quality and potential solutions to some of the most common challenges to get the foundation right.

The challenge

Data quality is generally defined as "data that are fit for use." Appropriate data quality management should detect and, if possible, remediate any data quality issues. A data quality issue is not always easy to differentiate from an outlier or a specific value relying on business reasons. This is why understanding the business context is key. ML-driven analytics can help better organize datasets.

Good data is ARCA

Accurate	Relevant	Consistent	Accessible
The data is correct and complete	The existing data is useful	The existing data is standarized and easy to understand	The required data is available for the right users

Source: Insider Intelligence, RFS.

[1] https://www.businesswire.com/news/home/20210324005134/en/Alation-State-of-Data-Culture-Report-Reveals--Barriers-in-Adopting-Artificial-Intelligence

There are a number of different DQ issues that can occur during the data life cycle. This report defines four distinct phases or activities within the data life cycle:

Four phases in the data lifecycle

1. Data creation	2. Data maintenance	3. Data protection	4. Data usage
Data are acquired and created. This happens, for example, when new customers are onboarded. Common problems here are incorrect and missing data.	Data are unified and maintained. This includes updating customer data or correcting data recorded in phase 1.	Data are protected. They are stored securely but are available if an employee has to identify a customer or when client information needs to be retrieved. It is essential here that identity fraud is prevented.	The last category of activities involves finding and using data. This step is important, for example, when recommendations are made to a customer based on their data.

The solution

ML-based data remediation can help companies solve DQ problems and support DQ management activities. The techniques can be used in all four data life cycle phases.

In the first phase, ML can help with the creation of new data and ensure that instances with missing data are minimized, for example, by automatically filling in certain data. To achieve this, a predictive model can be created that uses existing data from the customer, compares it to complete data from other customers, and makes an assumption for the missing data based on this information. When the model reaches a high accuracy, missing data can be updated automatically.

In the second phase, machine learning can be used to automatically detect duplicates or to automatically correct incorrect data. Duplicates occur frequently; the problem is that they are often not identical duplicates. For example, a customer is entered twice in the system because there are two ways of writing the name. To identify such duplicates, the cosine similarity of text pairs can be computed. The closer the value is to 1, the more likely it is to be a duplicate.

Applications in finance industry

One example of a real-life application of machine learning in the area of DQ management for financial services occurs in the front office:

ML methods may be applied to the onboarding process of new clients, where the associated data (i.e., client name, client type, client gender, address, country, client-specific features, etc.) are collected and entered into the IT system of the financial institution. If the missing values are required information, normally they should not be allowed by the process. ML methods can be applied to detect inconsistencies in the client profile (e.g., between the provided addresses and countries), therefore improving the DQ for any subsequent customer relationship management or flagging any suspicious/erroneous client data.

Conclusion

Data is an important resource. To tap this potential, the quality of the data is key. To this end, ML can help institutions use more of their datasets by improving its quality in a systematic way.

How machine learning can be applied to process mining to improve efficiency

Many processes in banks have grown organically over time to an elevated level of complexity. Process mining can help better understand the processes, reduce the complexity, and improve efficiency.

The challenge

As organizations embrace digitalization and build vast IT landscapes, it is challenging for business leaders to have a transparent overview of all business processes. Traditionally, a company's business processes are analyzed and modeled based on interviews and workshops with both customers and employees. While these methods may provide interesting insights, they take a long time, cost a lot of money, and rarely provide the full picture of what is happening right now. Most banks hardly use the data that are available to them and that would show them how efficiently their processes are running. Gaining an overview of the numerous processes is the first step to increasing efficiency.

The solution

Process mining analyzes the data behind its operations. This starts with analyzing operational data that originates from event log files. An event log is similar to a black box of an airplane and notes all processes and actions of a computer, usually located in an enterprise resource planning system.

Importantly, process mining can generate useful insights for an organization. This step, called "process discovery," helps companies better understand their actual processes. A seamless view of a process from beginning to end can be generated, allowing banks to monitor the process as it operates. This way, bottlenecks, inefficiencies, incorrect steps, and even compliance issues can be identified. By quickly extracting and reading these event logs, process mining software builds an instant visual model of a given flow: a process graph. In a next step, process discovery can be further enhanced by including rules-based analytics, which help identify patterns related to potential inefficiencies in speed and workload, errors, compliance issues, and risks.

Applications in finance industry

Loans processing

The loan application process of many banks is known to be onerous and time-consuming. Indeed, the loan application steps usually take several days, and one reason for this lengthy process is its complexity. Process mining is an excellent way to take some of the complexity out of the process by creating a detailed model of the loan process, identify bottlenecks and other inefficiencies, find non-compliant activities and, of course, increase speed as the overall goal. In one example, the process helped a bank identify that queries significantly increase process times, and preemptively solve the queries. Moreover, process mining tools monitor process performance and costs, making it easier to intervene quickly when delays are imminent.

Invoicing process

A Swiss bank was interested in holistically understanding their invoicing process globally. This was based on leveraging the process mining analysis on the purchase-to-pay process rolled out across multiple sectors. The challenges encountered in this analysis were the heterogeneity of IT systems across countries to capture the invoicing process. System logs collected across countries were harmonized, allowing the organization to achieve a better understanding of the efficiency of resource allocation, identify bottlenecks or performance issues, and detect deviations from defined de facto process flows.

Conclusion

Combining process mining and AI offers a strong potential for a data-driven understanding and management of processes. This can help banks save costs and improve efficiency, and help management make better, data-driven decisions.

Data mining can help banks generate insights from data

Banks own a fortune in data. Often, only a fraction of this data is used to sharpen the bank's value proposition. However, the available data can be used to automatically generate insights and recommendations, especially in the area of market research. This way, tailored research reports can be generated in real time.

The challenge

Bank customers generate large amounts of data through the numerous transactions they perform. These data offer untapped potential for banks to better understand their customers or to better address market trends. Analyzing these large amounts of data manually is time-consuming and costly. Moreover, to turn the data into valuable and actionable information, advanced processing techniques are required.

The solution

Data mining describes a process of analyzing large datasets to automatically identify hidden or previously unknown but relevant insights about patterns, connections, and changes in the data. Data mining is not new to banking. In the past, data-mining techniques were used, for example, to predict expected default rates for credit applicants.

Below is a brief description of different data-mining techniques:

- The most used data-mining techniques are **classification algorithms**. Classification methods use pre-classified data examples to create a model that can automatically classify new data into appropriate groups. The goal is to derive a general rule from past experiences.

  Credit risk applications are a good example of classification methods. This approach uses algorithms that automatically classify new credit applicants as good or bad applicants based on past credit applications and the outcome of these approved credits.

- Another category of data-mining techniques is **clustering**, which can be used to divide objects with similar characteristics into specific clusters. The difference between classification and clustering is that with the latter, there are no predefined classes into which the groups are divided. New classes with similar characteristics are formed without making a judgment.

- In **association**, a pattern is detected based on the relationship of one data point with another. Association techniques can be used, for example, to detect whether two particular products are often purchased together. Accordingly, association techniques can be used to generate customer behavior insights.

- The last category of data-mining techniques are **regressions**. Regressions can be used to build forecasts. In regression, the goal is to predict continuous values, i.e., the output of a regression is a number, not a category. Again, the goal is to find relationships among different variables.

Applications in finance industry

The presented data-mining techniques are applied in many different areas, including customer segmentation and to analyze the profitability of specific customer groups, credit scoring and prediction of risky cases, and also in the field of investments.

Customer segmentation and tailored advice

Customer segmentation has historically been done based on a client's age and assets. However, this classification does not provide the necessary granularity to understand a client's needs and offer tailored advice. Other data points could include psychographic data, life events, relationships with other customers, behavioral patterns, and service preferences. Transaction data is valuable as it enables banks to identify payment and other behavioral patterns. These holistic profiles can then be used to offer the customer tailored products and services on preferred channels. This data can also be used for cross-selling and upselling, since businesses are typically more likely to sell products to existing customers than to acquire new customers.

Market research through algorithms

Artificial intelligence applications can be used in combination with big data to perform market research. Kensho is an AI software company that provides data-driven answers and insights to questions posed in a natural language by performing more than 90,000 actions. The machine learning algorithms analyze large amounts of market data aiming to find correlations between events and asset prices. The data sources include drug approvals, economic reports, monetary policy changes, and political events. The user can further ask the software about the impact of such changes on almost every financial asset. What sets the program apart is the intuitive Google-like search tool and data visualization capabilities that result in a great customer experience. The company's founder claims that a team of analysts would need to spend days to create the kind of answers that Kensho provides in a matter of seconds.

Conclusion

Making better use of existing data is one of the first and most impactful steps for banks to move toward AI. Connections and patterns, which can be identified in customer transactions and market data, can be used to provide more tailored solutions to customers to increase customer satisfaction or to generate automated reports in the research area.

Anti-money laundering procedures & AI: the perfect match

A flood of regulations and rules have driven up banks' administrative costs over the past few years. In this context, AI can be used to ensure compliance with anti-money laundering (AML) regulations. ML models can analyze alternative data sources and, by understanding natural language, flag critical cases automatically.

Artificial intelligence can be used to automate anti-money laundering processes and thus facilitate compliance with regulatory guidelines. Furthermore, operational processes in the area of compliance can be carried out more efficiently and thus productivity can be increased.

The challenge

AML regulations are one of the biggest compliance challenges for banks. Combating money laundering is a highly demanding task and is associated with high costs and risks.

Money laundering refers to the process of taking illegally obtained money and making it appear to have come from a legitimate source. In this process, the origin of the money is “washed clean” through a series of transactions. To prevent money laundering, banks are required under penalty of law to know their customers and the origin of their assets in detail, and to have AML systems in place.

Placement, layering, and integration are the three phases in money laundering schemes:

- Proceeds from criminal activities enter the placement phase, where they are converted into monetary instruments or otherwise deposited in a financial institution (or both).
- Layering refers to the transfer of funds to other financial institutions or individuals.
- In the final phase of integration, funds are used to purchase legitimate assets. Here, illegally obtained money becomes part of the legitimate economy.

To detect money laundering cases, banks have developed AML frameworks. Currently, the typical AML frameworks can be decomposed into four layers:

Anti-money loundering frameworks

1. Data

In the Data Layer, the collection, management, and storage of relevant data occurs. This includes both internal data from the financial institution and external data from sources such as regulatory agencies, authorities, and watch lists.

2. Screening and monitoring

The Screening and Monitoring Layer screens transactions and clients for suspicious activities. This layer has been mostly automated by financial institutions into a multistage procedure often based on rules or risk analysis.

3. Alerts and events

If a suspicious activity is found, it is passed on to the Alert and Event Layer for further inspection.

4. Operations

The decision to block or approve a transaction is made by a human analyst in the Operational Layer.

Existing AML detection systems have a number of problems:

- There are high rates of false-positive alerts that need to be reviewed by the human compliance officer.
- They often miss suspicious activity and emerging risks.
- The scattered data often requires manual and thus inefficient investigations.
- Processes and systems are rigid and not aligned for the ever-changing regulatory requirements.

The solution

Although there are several AI approaches that can be applied in each of the three phases to detect money laundering cases, the hybrid approach is the most efficient one:

Natural language understanding (NLU) and **ontology engineering**—subfields of AI—can help relieve the work burden by providing human experts with an interpretation of language. They can also link relationship visualization based on news data—e.g., the banks' news database and traditional or social media news sources—concerning the potential fraud entity. One approach to identifying money laundering is to define a linked knowledge graph over entities. **Entity recognition** is a set of algorithms capable of recognizing relevant entities (e.g., people, positions, and companies) mentioned in an input text string. **Relation extraction** detects the relationship between two named entity nouns in a given sentence.

Machine learning helps frame the AI and data-mining tasks of laundering or fraud detection through outlier detection. In this method, one defines what a normal or inlier transaction would appear as for a subject, and then detects any transaction that is sufficiently different to be considered as an outlier.

Ultimately, the meaningful leap forward has led to using, in contrast to conventional machine-learning approaches, **deep-learning** methods to learn feature representations from raw data. In deep-learning techniques, multiple layers of representation are learned from a raw data input layer by using nonlinear manipulations on each representation learning level.

Applications in finance industry

Expert.ai, an artificial intelligence company, has developed a model to increase the accuracy of detecting money laundering cases. AI-based early-detection systems are used to prevent false positives. In this way, Expert.ai could reduce false positives by up to 85%. At the same time, AI-based systems greatly improve the accuracy of suspicious transactions.

Risk management

Volatile markets and uncertain political and economic conditions have given a new importance to risk management. Intelligent algorithms can be used to support and accelerate elaborate risk management processes.

The challenge

A stress test is an analysis that runs hypothetical scenarios to find out whether a bank has enough capital to withstand negative economic shocks. The scenarios include major recessions or financial market crashes. Bank stress tests were introduced in the aftermath of the 2008 financial crisis. At that time, many banks were severely undercapitalized. Consequently, regulators have increased capital and reporting requirements. Banks now have to regularly examine and report their solvency capacity.

These and other risk assessments require a deep understanding of complex and dynamic relationships among many different market and macroeconomic variables. Building rule-based systems requires lots of effort. In fact, banks employ hundreds of compliance experts and take months to successfully conduct such risk assessments.

The solution

However, even ML-based models are inappropriate in many cases because they tend to overfit as they try to create models that can describe the entire underlying data.

Topological data analysis is a method used to visually identify hard-to-detect patterns in high-dimensional datasets. Instead of creating a global model for all the available data, an ensemble of models can then be created. Each model is thus responsible for a different data segment. So instead of building a risk model that covers all subsets of data and allows for a lot of margin of error, models can be built for individual subsets that are more accurate and that reduce systematic errors. From this, statistically significant variables can be automatically identified for each subgroup. This allows previously undetected combinations of variables to be identified, which can then be incorporated into the models. In addition, these models can automatically update themselves when new significant variables are identified from new data.

This way, machine learning algorithms can automatically observe thousands of market and macroeconomic variables. They can then identify which key variables, and in particular which combinations of variables, pose high operational risks.

Applications in finance industry

Citi's AI platform, AyasdiAI Model Accelerator (AMA), can help enterprises in financial services predict and model regulatory risk. Their software helps banks automatically monitor customer transaction data to identify anomalies and ensure that they are compliant with regulatory requirements.

Before working with the AMA to improve their capital planning process, Citi had failed the first two out of three annual Comprehensive Capital Analysis and Review stress tests.

Conclusion

With the help of artificial intelligence algorithms, much more data can be monitored to identify risky market and macroeconomic variables for banks. The use of AI in risk management increases compliance security and reduces the need for human capital and the time required to perform these tests.

Looking ahead

This report has shown that the introduction of AI technologies is no longer a choice but a strategic imperative. The banks that manage change and the introduction of advanced technologies well can expect to operate more efficiently, thus saving costs and offering better customized solutions. The banks that continue to wait will be left behind.

The prerequisite for such applications is of course technological readiness, which is associated with high, long-term investments. But even more important is the human willingness to allow change. Therefore, the biggest obstacle to a successful technological shift is not the technological level but the human level. The topic must be supported and pushed by the executive level. Most CEOs have a long list of priorities, and few are comfortable with the technology to push such projects. Even executives who recognize the danger of digital change and are concerned about how to align their organizations often lack assertiveness. In the top management floor, the knowledge is not available to set a good example for the AI age. The role of the executive has changed dramatically: An effective leader is no longer forced to know all the answers. They must much rather ask the right questions; instead of doing it all alone, they should uphold the role of a future-oriented leader who must orchestrate the right people.

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