Artificial Intelligence in FP&A:

The Future is Here

FP&A Trends
Research Paper 2020

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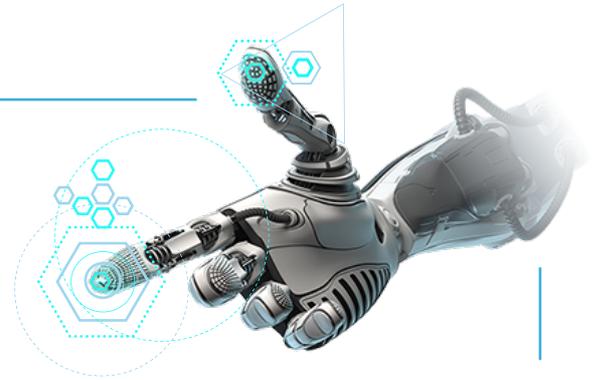
1. Introduction

Identifying the challenges and success factors of AI/ML

Each year we conduct a survey on the trends within financial planning and analysis (FP&A) and the value it brings to the organization. Some of the key findings include:

- Too much time (42%) spent on low-value activities, such as data collection and validation, prevents most FP&A departments from working on high-value activities, such as insight identification, that can better allow FP&A to provide strategic advice.

- On average, only 26% of FP&A's time is spent on driving actions and insight generation.

Unfortunately, these factors have not changed much since the survey began in 2017, except in a group of organizations that we call **best in class**.
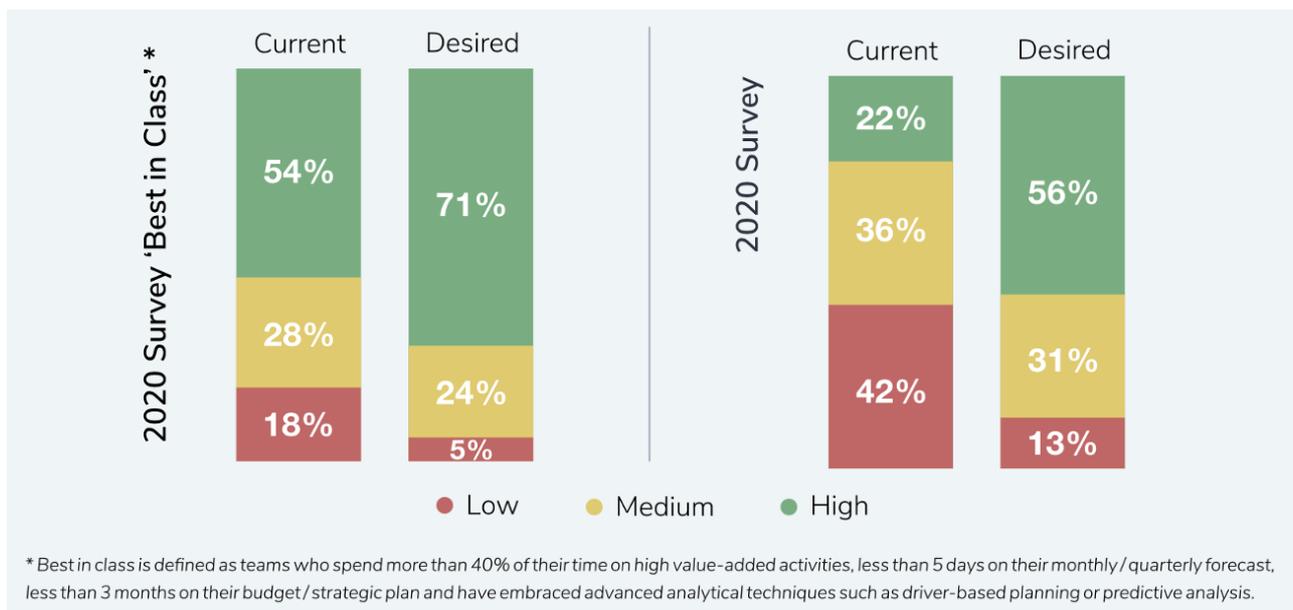

*Best in class is defined as teams who spend more than 40% of their time on high value-added activities, less than 5 days on their monthly/quarterly forecast, less than 3 months on their budget/strategic plan and have embraced advanced analytical techniques such as driver-based planning or predictive analysis.

Fig 1: Comparison of best in class organizations vs the average when looking at the value of activities where FP&A spends its time (current vs desired state)

A major reason why **best in class** organizations spend more time on high value-add activities is found in their use of technology within FP&A. The **best in class** group invested more in systems than the average company. These systems for planning and analysis had better integration with transactional systems, and as a consequence could produce forecasts faster and with more accuracy. The last survey also showed that 30% of **best in class** organizations were leveraging artificial intelligence (AI) or machine learning (ML) systems and another 50% of organizations were planning to invest in these systems over the next 1 or 2 years.

The level of interest was so notable that in 2018 FP&A Trends set up a **AI/ML FP&A Committee**, primarily to investigate how these technologies were being applied to FP&A. Members of this committee included organizations who were users and practitioners and thought leaders who had

experience in implementing AI or ML solutions. At committee meetings, members discussed the issues they had faced, what they had achieved, and the lessons they had learned.

Today, the topic of AI and ML is becoming more mainstream, but there is still confusion about what exactly AI and ML represent, and whether or not these systems have the ability to transform organizations. With this in mind, we commissioned a more in-depth research project to delve deeper into its current usage, the value generated and its potential for a future role within FP&A. The research involves representatives from organizations using or implementing AI and ML solutions, recognized thought leaders, and business professors within academia.

The result is this paper that covers the elements crucial for any organization approaching AI or ML for the first time including challenges, methods and key success factors. We also looked at two potentially contentious issues. One, whether AI and ML will replace FP&A staff, and two whether AI and ML is useful during times of unprecedented uncertainty.

The authors would like to thank the members of the committee and other respondents who gave up their time in helping with the content. These include contributions from:

Antoine Chabert, Product Manager of AI and ML for FP&A Audience and Predictive Planning at SAP

Flavio Caruso, CFO Cluster Europe at Sandoz

David Farnell, Regional Analytics Engagement Manager at Janssen

Tanbir Jasimuddin, Director of Finance at Vardags

Patrick Jung, Senior Manager at Horváth & Partners Management Consultants

Lawrence Maisel, President at DecisionVu Group, a thought leader in predictive business analytics

Takeshi Murakami, Group Finance Manager at Microsoft Japan

Frederick Peeters, VP Finance and Strategy, Steel Wire Solution at Bekaert

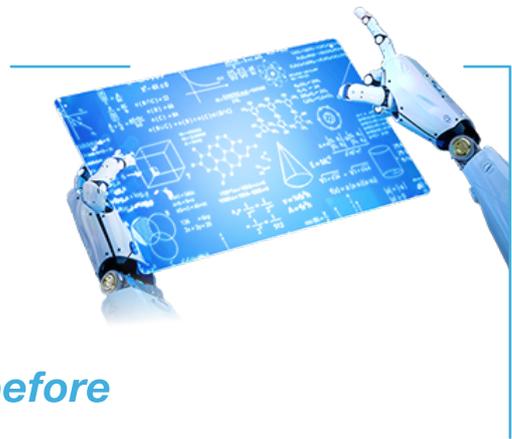Tanja Schlesinger, Vice President of Business Intelligence OneSource Germany at Deutsche Bahn

Paulo de Souza, Head of School of Information and Communication Technology at Griffith University

Stefan Spiegel, CFO, Switzerland, at SBB Cargo AG

Larysa Melnychuk

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2. The case for Artificial Intelligence and Machine Learning

Doing things that were not possible before

Today's business world is more fast-moving, unpredictable, and complex than at any other time in history. A key role of FP&A is understanding the past in order to predict the future, so it can support organizational decision-making and the development of plans and forecasts. Today, this is not a once-a-year process, but a continuous activity driven from data that is both internal and external to the organization.

Data is key. Paulo de Souza of Griffith University explains that if organizations want to forecast behavior based on patterns, those patterns can be revealed through large amounts of data. However, data that is unstructured makes drawing insights really difficult. This is a task that is practically impossible for humans to do.

To build models it is essential that organizations understand the data of the factors that affect their performance, in order to generate a reliable outlook of the future. This requires an evaluation of the causal relationships that exist within the data to then build, test and verify planning models that are going to be informative. This is where AI and ML comes in.

David Farnell of pharmaceutical company Janssen, believes that AI and ML provide FP&A with "a lot more tools than in the past". He explains that with only a spreadsheet, they were previously stuck with just one way of constructing a forecast, deducing a simple trend based on aggregated data. With AI and ML they are now able to generate forecasts at a detailed level using the most appropriate technique for each product and location. At an aggregated level, they have found these predictions to be far more reliable than traditional forecasts.

Paulo observes that with AI and ML, "You can do things that you were not able to do before. You can look at huge amounts of data, something that would have been impossible in the past, and you find those elusive patterns fast." He also goes on to say that it is the combination of human intelligence and AI that makes the difference, "Together they make the whole world possible."

However, Paulo stresses the real intelligence is not simply with AI but lies in the human interpretation. He clarifies that "patterns should come to you as an input for you to make a final decision." Paulo uses the term **enhanced intelligence** which signifies the combination of a human and AI. He believes this will play as an important advantage to keep organizations afloat in times of big events, such as the pandemic, and ultimately help contribute to their overall success.

3. What is AI and ML?

AI and ML, like many other technical terms, are often deemed vague and can be subject to abuse, which can result in confusion. However, what is clear from our research is that active users of AI and ML have a much clearer understanding of their meanings and the distinction between each of them. These are the definitions that the majority of our interviewees agreed upon:

- **Artificial intelligence (AI)** is an umbrella term for a technology range that can mimic the cognitive functions of the human mind. AI enables machines to make assumptions, test rationale, and learn autonomously.

- **Machine learning (ML**) is a subset of AI that uses different methods (or algorithms) to continuously learn from the data, identify relationships and record trends.

- **Predictive analytics** is the analysis of historical data, together with external data points, to identify patterns and behaviors. It uses statistical models, such as time-series, regression or correlation analysis, as well as ML algorithms to answer specific questions on what will happen next.

- **Prescriptive analytics** builds on the capabilities of predictive analytics, providing a course of action that could be taken based on the program's predictions.

We have a companion paper entitled **Digital FP&A: The Power of AI and Human Intelligence** that looks at AI and ML in more detail. It explains how AI works and how it augments human intelligence to transform the role of FP&A.

4. User case studies

AI and ML are together having a big impact within FP&A. Here are a few case study examples from organizations that we interviewed during the research.

4.1 Improving forecast confidence

Moving to AI and ML in 3 months

One fast-growing company we interviewed, operates within the FinTech industry.

The problem

Forecasting was performed from a bottom-up perspective, with each unit submitting their view based on their own pipeline analysis and discussions with local business managers. This process gave a low level of accuracy due to several pain points.

- The company's fast growth, combined with a fast growing industry (40-50%), made forecasting more difficult.

- Growth in a new industry meant a limited understanding of the real business drivers.

- The production of a forecast often took over a week and many FP&A hours spent on non-value-add activities.

- There was a clear existence of conscious and unconscious bias across teams. Some sales teams were very aggressive in their forecasts where others were too prudent.

The overall result was a lack of confidence in the forecasts since they were often more than 5% out from actuals each period. This made it hard to make the right decisions. Therefore, managers within FP&A started to look at other tools, and that is how the AI and ML project came about.

The solution

The company started with a prototype. The success criteria was very simple: Can the ML project generate forecasts that are more accurate than the current bottom-up method?

A small team within FP&A was assembled to answer this question, and they sought help as required from people with a technical background. The next step was to assemble the transactional data sitting in different silos into a single repository and clean it. Once this was done, the team divided the data into two segments, namely training and testing. The idea was to use the training data to train the ML model and the remaining data to be used for testing the predictions made by the model. As an experiment, this transactional data was also combined with a range of external economic drivers to see which combinations had the most impact on predicting results. Overall, the process to produce a working prototype took around 3 months.

The impact

The prototype was a great success. The FP&A ML team were able to produce forecasts within a day, with a variance of less than 2%. This was considered to be a great improvement on their old process. Confidence levels in the model's ability to predict the future are now high. Yet, while the models offer results that are reliable, the company continues to develop and test them to ensure their integrity and uncover all business drivers.

4.2 Budgetary control

Reducing the variance between budget and actual results

Another organization we interviewed is responsible for a government's education portfolio. This involves a large amount of funding distributed across 72 organizations who are in charge of delivering educational services in their area.

The problem

Over the years discrepancies between budget estimates and money actually spent, increased. For example, at the start of the year, the budget projected a considerable shortfall in funding. Revised forecasts submitted during the year would indicate an even bigger funding gap. Yet, at year end, the actual results showed an underspend vs funding received. According to manager of the FP&A group, this caused a major problem as they had to raise money at a very real cost when they saw the deficit forecast, only to find it wasn't required after all. This was money that could have been put to better use elsewhere.

The solution

The company embarked on a number of actions, including forecast scrutiny and enforced monthly reporting but they did not work. COVID-19 only made this worse as money needed to be invested into Personnel Protective Equipment (PPE) and other related requirements, but all estimates provided were inaccurate. The company therefore turned to AI and ML to see if these systems could assess the numbers in a way that would allow the teams to better plan expenditure and deploy funding as required.

The first step was to perform a **proof of concept**. The FP&A team used a simple linear regression model as a base line and compared it with each individual budget line. As expected, there was a high correlation with things like the number of children being served, where they lived and the number of staff employed. After further analysis the FP&A team had a good result where they could predict, with 99% confidence, the budget requirements for 44 out of their 72 organizations. However, that left 28 still somewhat unexplained.

For these FP&A turned to ML where they experimented with a number of specialized algorithms until they found one that worked. In doing this FP&A had to use their business knowledge as they found that blind, unsupervised learning did not give good accurate results. They also found that trying to forecast total aggregated numbers did not work as there were too many variations between the individual organizations.

The impact

The best results came when the FP&A team used their knowledge to direct AI and ML towards the items that should be correlated. This required the setting up of separate models for each organization and budget line, such as staffing and transport, before aggregating the results. In doing this the variance between budget and actual fluctuated between 1.6% to 7.7%, which was still better than the manual process. The company's next step is to go back further than the 5 years they are currently using. They believe that by incorporating more data, the models will progress further.

4.3 Real-time business simulation

Enabling the organization to work together

We interviewed a multinational company that manufactures a wide range of business and industrial imaging products and optical devices. This includes products from copiers and laser printers to medical and graphic imaging products.

The finance director is an unusual individual since he has qualifications in both finance and data science. His interest in data science started when he was trying to solve some challenges the company experienced in the finance function. The main area was sales forecasting, a process that took a lot of time, was inflexible and inaccurate. Finance was also looking for a way in which the organization could work together and where time was spent on business opportunities rather than on data processing tasks."

The problem

The company's sales process is top-down where general growth targets are given to business units that are then connected to the business drivers and operational key performance indicators. To accommodate this process, the finance team were using hundreds of Excel files to prepare individual models which were then consolidated into one financial company plan. However, finance often received data that was not validated, was removed from reality, and where participants could not see the business logic of what the company's senior management were proposing".

The solution

To overcome these challenges, FP&A developed a sales model of the business which described the logic of the business within ML algorithms. Algorithms were chosen as a best fit for individual business lines. The developed sales model was then used to predict sales results. These results were fed into a single multidimensional model which acted as a central place where both individual business units and senior management could view forecasts, at an individual or consolidated level.

Deciding on which algorithms to select were not obvious to begin with. FP&A started out with the product lines that had the most impact and tried different models for them. The team used linear regression on various combinations of key products with the best linear models selected where the model's strength (technically known as the coefficient of determination) exceeded 0.5. Past experience had shown that these models were very robust against volatility, changes, or unpredictable behaviors.

Where the linear models showed poor performance time-series methods such as Holt-Winters, were used. This resulted in better predictions of trends and seasonality, with a minimum prediction error (MSE).

The impact

The models are stored on a central server with connection to the various underlying systems. This has enabled FP&A to build an interactive, real-time, planning solution.

The way it works is that sales managers input some basic assumptions for various scenarios they would like to generate. As soon as they enter a number the model starts its calculations. Around 40 seconds later the results are returned as a multidimensional model that can be viewed through BI tools or Excel Pivot tables. At this point, the sales manager can change assumptions and produce a revised set of results.

With this approach the managers within the organization are able to analyze many different approaches to the business, with finance acting as advisers and making changes to the models in the background in consultation with the managers. The final targets are stored and used for evaluating performance of the business units throughout the year.

4.4 Business process optimization

Evaluating the impact of change on the business

SBB Cargo is a subsidiary of Swiss Federal Railways (SBB) specializing in rail freight.

The problem

For years, finance at SBB had relied on their traditional accounting system for planning. Although this provided details of cost allocation and margin contribution, it did not offer a clear insight into methods to improve efficiency or performance. Stefan Spiegel, CFO, commented "We had accurate cost allocations, but we didn't know how financial performance would be affected if we lost or acquired a new customer. We couldn't say directly what was happening in the business."

They decided to leverage AI and ML to build multiple models, for the different business areas, that were customer-centric. The objective was to simulate operational activity behavior and understand its impact on financial performance. Stefan explained, "We wanted to know what would happen if we made a business shift. For example, how new customers impact all aspects of the business. The models we developed allow business and finance leaders to dynamically see what's happening to margins and cost."

The development

Initially, SBB had been using a driver-based model for planning. However, this was not detailed enough to optimize resource planning. There was typically a mismatch of around 5% between forecast and actuals, which meant there was a lot of waste in the process.

The company sought to overcome this difference by using AI and ML models at a detailed level for their forecasting process. This meant creating forecasts for each customer, location, day and time, something that was simply not possible with traditional planning tools.

SBB then spent time understanding the business rules surrounding their operational processes. For example, what employees and customers were really doing. The team also documented the decision options managers actually have. With this information the team were able to build a model that would use the AI and ML predictions to simulate the impact of individual decisions. For example, when and where cargo could be picked up, and the choice of train connection. The final goal of SBB is to develop a digital twin of the logistics network, so that the effects of management decisions can be exactly simulated and changes in gains and losses easily predicted.

The impact

The resulting model links their accounting and Enterprise Resource Planning (ERP) system to the operations' planning and scheduling applications. This allows them to see the impact of business choices on other activities. The model then produces direct business recommendations. Stefan said, "We found that if we place the shipments in an intelligent way into our logistics network, we can improve asset utilization by more than 20%... Of course, the hardest part is to unlock this potential as all business processes need to be changed and customers have to accept and adopt the new pick-up and delivery modes. But the way to do it is shown very clearly."

4.5 Real-time forecasting

Automating the forecast and reporting process

Another company interviewed operates one of the world's largest diversified travel platform. They have access to hundreds of thousands of properties and receive more than 750 million website visits a month, across 200 travel booking sites, in more than 70 countries. That is a lot of data on which to make decisions!

The problem

Forecasting is a major activity within their finance department, which took a lot of effort and many hours to produce. The results were not very good and did not clearly indicate future necessary action. In order to use AI and ML to automate their P&L forecasting, they recognized that they did not have the expertise or the tools to achieve it. To overcome this drawback, they engaged a specialist firm to help them understand how to use the appropriate algorithms.

The solution

They developed two systems to support the forecasting process:

- The first was a driver-based, bottom-up model that operates in the cloud to provide, what finance calls, their momentum view. It comprises of a set of AI and ML driven modules that have their own definitions, logic and drivers. They are very detailed. Forecasts are produced from a bottom-up perspective for over 10,000 combinations, representing each line of business, each point of sale, and each client. In the past this would have involved over 100 people, it is now done automatically.

- The second is a room pricing model that forecasts prices at each location and line of business while estimating the length of stay. It is used to detect patterns in transactions within

the above momentum model, which is then used to forecast the length of stay. Interestingly, a range of AI and ML, along with statistical algorithms, are applied within the system. The best one is automatically selected for each product and location.

One of the main design criteria was to fully automate the whole process. Finance wanted to avoid any manual processes that would slow things down. This required all data, used by the models, to be combined into a single database, which the models could then access.

Results from the models are automatically returned to users who can then make overrides. An override is where a party, either the FP&A team or the businesses, have an opportunity to include initiatives that will be in addition to the forecast. This provides them with two forecasts, the momentum and the initiatives. To support this setup, the FP&A team have a few analysts who check that the logic is working and who also work with the business on any overrides.

The impact

The project has been a huge success and has been well received by the business. Rather than just receiving a forecast, FP&A are now able to understand them and discuss with the business about what is driving the business. Tangible benefits include:

- Reducing the forecast process by around 30,000 FTE hours each year.

- Data driven momentum is automatically generated from existing trends so senior managers can see what is going on in each individual market.

- Ability to see in real-time what is driving the business in certain markets so management can make faster decisions, something that would have taken two months previously.

5. Challenges of using AI and ML
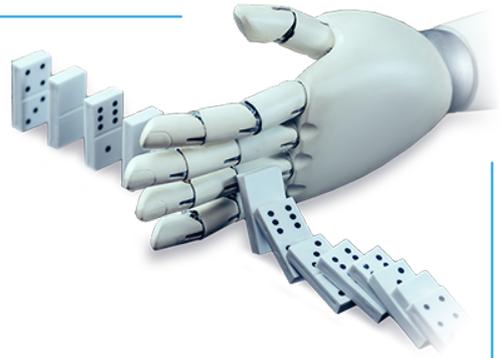
Things that can prevent the success of AI and ML

As you would expect of any new technology, there are many challenges to overcome, particularly one surrounded by significant hype. The following are the most common challenges.

Culture

Adopting AI or ML means a change in the way things are done. One of our respondents found that his FP&A department "didn't want to let go" of their spreadsheets and their way of doing things. He recalls "They have a lot of tribal knowledge in terms of what they do" so for them this was a big limiting factor. Using AI and ML required them "to be more open, be more engaged, and allow others to come into the fold and let them help."

Trust

This is similar to the previous point in that people see AI and ML as a black box that they do not understand. David Farnell, Regional Analytics Engagement Manager at Janssen, commented "It's a big learning curve. For people to be able to take the output of a predictive model and trust it enough to use it for some fairly major decisions that can have a big impact on resources and teams." Paulo de Souza, Head of School of Information and Communication Technology at Griffith University, likens the black box train of thought to the reasons for not believing in climate change, "despite all the evidence, everything is based on an uncalibrated (i.e. you can't prove it to be right) model and sentiment."

Data quality

All interviewees stressed data quality as a major issue. Some found that data from the past was often missing or had changed in its definition over time. There may also be errors within the data that may not be seen. To close these gaps, FP&A need to really understand the data being used and have an in-depth knowledge of the particular business area that it relates to. Data verification is no easy task and can be time consuming.

Other interviewees noted "data has to be clean, structured and well organized… we really worked hard to make sure that data from our ERP system was good quality." "If the data is bad, it will deliver the wrong results."

Related to this is the issue of siloed data. Patrick Jung, Senior Manager at Horváth & Partners Management Consultants claims "Many organizations still have lots of data that is not connected – it's siloed somewhere in a database. Most of these organizations don't even know that the data exist." This then leads to the perennial topic of a single source of truth.

Other issues cited were not having enough data for ML to learn from, and that data needed to be correctly labelled for the algorithms to work properly.

Knowledge gap

Nearly all interviewees had no knowledge or experience of AI or ML when they started their AI project. This is further complicated by the fact that a Data Scientist is often required to choose the ML algorithms necessary and be able to interpret the results. However, Data Scientists rarely have a detailed knowledge of the business or an understanding of what the data represents. This leads to a big knowledge gap that can only be overcome through careful collaboration.

Not understanding how ML works and why certain algorithms work better than others can impact the ability of FP&A to explain the results. Patrick Jung: "In FP&A, you want to give context to your data, you want to tell a story but the [lack of knowledge] makes it rather difficult."

Fear

There is a known fear within finance that AI is going to replace their job. This is one risk that has some merit as the aim of AI and ML is to replace manual tasks and improve process efficiency. This is nothing new in that all industrial evolutions of the past have eradicated jobs. However, AI and ML will generally require human involvement, it is simply that it will look different. This will be covered later in section 9 of this paper.

Other challenges

The above challenges were cited by most interviewees. However, there were another couple of issues raised by individuals.

- **Differentiating between a problem and a symptom.** One person made the point that quite often what we perceive as a problem might actually be a symptom. Solving or modelling the symptom does not help get to where the real problem or real driver exists.

- **Problems that are too complex.** Patrick Jung found that when the problem was too complex because of too many influences, such as weather prediction, the process is almost doomed to fail. That is because "big problems… take forever to deliver". He mentioned "I also see people try to solve a simple problem with AI and ML that they could have solved with pen and paper." In these cases, the results will take longer and call into question the value of AI/ML.

- **Believing that AI alone will produce correct answers.** This is almost the opposite of the trust issue mentioned earlier. Larry Maisel, an experienced practitioner in the use of AI, believes that the number one pitfall in using AI is not recognising the need for human intelligence. To look at an AI generated outcome and to think that it will happen is a mistake, regardless of the degree of mathematical certainty it holds. He emphasises that information generated by AI is best when it is balanced with human insight and judgement.

6. Success factors for new users approaching AI or ML

What every new user needs to do

Based on the above challenges, interviewees recommend the following actions for new users.

Have a clear idea of the problem you want to solve

Organizations should not use AI or ML for technology's sake. This will prove nothing and will be just a distraction. David Farnell also makes the comment that it is very easy to create AI and ML models that generate complexity. To avoid this, new users should first have a good understanding of the problem to be solved, the results that they want to achieve and know where they can get hold of good quality data. They should then ask the question: Will AI or ML make this better, faster or cheaper? Once the answer has been established as yes, they can then seek support to make it happen.

Attain C-level support

Much like with any other project that has the potential to change the organization, funding and support from the C-level is vital for AI or ML. Senior executives need to appreciate how the systems will add value to the business and how they will impact the different aspects of the organization's value chain. To be successful, AI and ML will eventually need to be a part of the organization's culture, education and embedded within its business processes.

Prepare the whole organization for AI

Once there is C-level support, it is time to educate the rest of the organization. Several of our interviewees did this as part of a general education program on what AI and ML is, the improvements to company performance they may bring and case study examples. Other organizations involved academics from universities to present how AI/ML technology will change the world. The aim of all this was to help deal with the issue that AI is seen as a black box that no one knows understands, and to pave the way for a pilot study. Companies also used this education to clarity that the aim of the new AI and ML systems was not to replace people but to enhance individual skills so they could add more value.

Start with a pilot study run by a small team of experts

The point of the pilot study is to experiment, learn, and prove the worth of AI and ML to the broader organization in a short period of time. For most interviewees this involved using historic data from the last several years to forecast the most recent historical months. This gives an indication of how reliable AI predicted results could be.

By experts, we mean people that really understand the problem and can translate it into an action plan to deliver a proof of concept. With a small pilot team, organizations can focus and remain agile but the team needs the right skills. Typical teams are cross-functional consisting of one FP&A member, one business manager from the selected pilot area, one IT person to manage the data, and one data scientist to choose and code the algorithms. This team should be dedicated to the pilot without any other responsibilities. If the organization does not have experience in AI or ML they should seek to recruit an external specialist. Success will then help get the support of the broader organization.

Focus on data availability and quality

Obviously, data is necessary to answer specific questions, so it is important to ensure that sufficient historic data is available. Where data does exist, the master data must be clean. The clean-up process can be a lot of work but it is key for success. Ensuring sufficient data, for AI and ML to learn, may mean looking back five to ten years depending on the business area. The data also needs to be a single source of truth, so that algorithms are using the same data to answer specific questions.

Experiment

Organizations need to experiment and try things out because AI and ML are still relatively new within the context of FP&A. This will allow companies to find patterns in the data that could not be found otherwise. However, results that do not make any sense should be treated with caution.

Perform a slow roll-out

Most interviewees are taking a cautious approach to rolling out their AI and ML solutions. This helps stave off any fears within the organization about the technology and gives the business time to resolve any issues with the models during the roll-out without too much impact. Frederic Peeters, VP Finance and Strategy, Steel Wire Solutions at Bekaert, has championed a pilot AI model for demand planning. This pilot used an agile approach, with a small team, of cross-functional experts to first experiment with different techniques (e.g. Prophet, Lasso, neural networks) before rolling out a framework to the wider organization. The first objective was to gain sufficient accuracy during different sprints, starting at around 50 percent accuracy and reaching more than 95 percent accuracy on 90 percent of the volumes. Only after the desired accuracy level was attained, was the green light provided to embed AI demand planning as a baseline for a broader Sales & Operational Plan pilot as well as longer term planning purposes. The new process will still provide global input owners the opportunity to override the proposed data where required. Both steps in this gradual implementation process are meant to support managers with their understanding of the value that AI and ML can bring.

Communicate results

It is important to be honest about what AI and ML can achieve. Inform people about the success of the achievements and any issues that need to be overcome. It is still everyone's responsibility to ensure the models are supplied with good data and that the results make sense. AI and ML systems are not magic, but are valuable tools that managers can use to make informed, unbiased decisions.

Operationalize the results

Be careful that AI and ML do not end up in the cemetery of proof of concepts. Often people have good ideas and great aspirations of what technology can do, but if it cannot be operationalized and used in their day-to-day jobs, then becomes a waste of time. Right from the beginning it is important to know how any solution is going to be rolled out and how it will fit within the overall planning and reporting process.

7. Benefits of using AI and ML
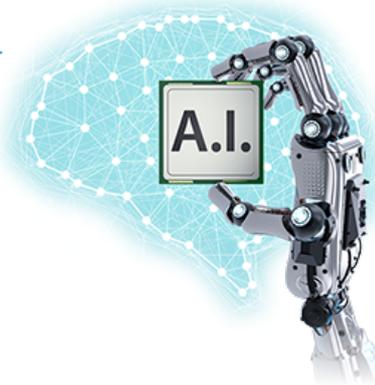
How AI and ML add value to an organization

Our interviewees are passionate about the value contributed by AI and ML. The main benefits that are realized are as follows.

Speeding up processes

Everyone reported that AI and ML helped speed up their forecasting and planning processes. One company reported that their previous forecasting process took almost a week, which they can now do in a day.

Most companies also found that they were able to answer questions quicker. This was, for example, because they were able to make changes to the model which then generated a fast answer. The models are also able to spot changes in business drivers without human intervention. FP&A can use this to run a variety of scenarios and provide management with the information they need to make faster, more informed decisions.

Better use of resources

As a consequence of speeding up processes, all interviewees similarly reported resource savings. Previously these resources were spent on low-value activities such as collecting and organizing data. When these low-value activities are automated as part of an AI and ML project, FP&A are free to spend their time on improving performance. There are also resource savings outside of FP&A. One interviewee said that, in relation to forecasting and budgeting, "the workload of not only finance but also for the rest of the business decreased quite a lot, so the reaction has been positive … something that they very much appreciate."

One organization reported that AI and ML forecasting has shown them the potential to reduce reliance on bottom-up forecasts. They said, "We are working towards shifting to a more centralized approach, where forecasts come from models, while regions and countries only input the expected one-offs, not captured by models."

Forecast accuracy

This is often one of the driving forces for introducing AI and ML. Again, all interviewees reported an ability to produce more accurate forecasts, but this was pre-COVID19. The main reason for this accuracy is that AI and ML are able to detect trends and patterns at a detailed level using algorithms best suited for their purpose. These are then aggregated to produce a high-level forecast. In the past this was not possible due to the volume of data involved and the availability of suitable systems.

Improving accuracy has a big knock-on effect. For some, this has meant a reduced level of stock outs, a reduced number of write-offs, and optimized stock and inventory management. All of these improve profitability and cash.

Better insights

AI and ML are able to detect patterns and correlations, between both internal and external data, that are not always obvious. This improves understanding of the business and can sometimes give early warning signs that drivers are changing.

Eliminating bias

Tanja Schlesinger, Vice President of Business Intelligence OneSource Germany at Deutsche Bahn, makes the point that humans make decisions based on data. This data can be heavily influenced by experience, gut feel and biased view, none of which can be codified for a machine to analyze. AI and ML, on the other hand, is only influenced by data, which the human mind cannot examine in as much detail as AI. Knowing this can help managers recognize bias and think more deeply on why the machine may be right.

8. How AI helps with unforeseen events

The value of AI and ML when historic data does not indicate the future

Unexpected events, such as COVID-19, have the power to totally disrupt a business and cannot be forecast through the simple analysis of historic data. AI and ML depend on historic data to make predictions about the future. Therefore it is quite natural to ask whether AI and ML can help in unprecedented situations. After all AI and ML cannot even be used to look for black swans, they are located through human screening.

Based on our interviews, there are two ways in which AI and ML help organizations in times of great uncertainty.

> **Establishing the next new normal.** Larry Maisel, an experienced practitioner in the use of AI, makes a good point when he says that the future will always be different from the past. Following a **black swan** event, Larry suggests there are two things organizations can do. First, they can adjust the data for past anomalies. Second, they can chart the rates of recovery to see if the forecast trajectory may return to a predictable level of business performance. This insight can then be used to make appropriate business decisions concerning the next normal.

> The key here is that AI and ML systems constantly review the data and update their own models of future event possibilities. For a human to detect any new, reliable pattern takes a long time. Our interviewees thought it would take around two or three years to spot a trend using traditional methods. However, many believe that AI will accelerate the time it takes to once again produce reliable predictions, far faster than any human could.

> **Generating scenarios:** Organizations are using AI and ML to see how drivers have changed and how those drivers have affected performance. AI and ML also help companies look out for new and hidden drivers. With this information they are able to evaluate a range of scenarios and support a faster decision-making process.

9. The role of the FP&A professional in using AI and ML
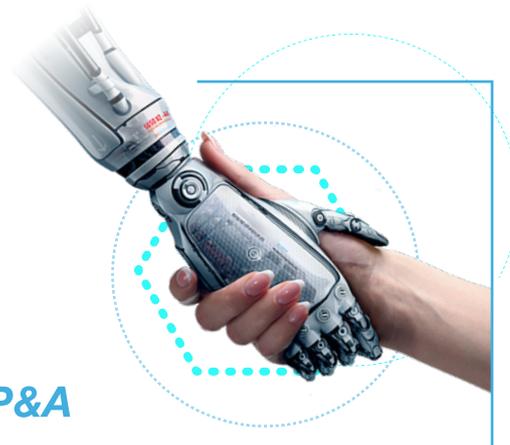
Reasons why AI/ML will not replace FP&A

Will AI or ML replace the humans that make up FP&A? Although many believe that a number of manual tasks will either be eradicated or substantially reduced, other finance roles will expand, and new ones will be created.

Thought leader, Larry Maisel, believes that the number one pitfall when using AI is not recognising or using human intelligence. He claims that, "Looking at an AI generated outcome that has a certain nuance of mathematical certainty, and thinking that it will happen is a mistake."

To begin with, AI and ML models do not have the ability to assess context. They cannot take into account human conversations between customers and staff or understand what competitors are doing. They cannot spot **black swans** and its potential consequences until after the event, nor can they judge the mood of an industry. These are all areas where humans excel.

Next, AI and ML algorithms, at present need to be chosen carefully or they will produce inaccurate results. Data scientists tend to be great at using different algorithms, but they typically do not understand the intricacies of the data or the challenges faced by ground staff. This is where FP&A plays a significant role to connect the science with the different stakeholders to make sure all different market aspects have been considered.

When it comes to predictions, it is important to remember that AI and ML models are not perfect. Organizations should never just go with the predictions produced. The results need to be checked to ensure that they make sense and tweaks can be made, to the predictions, in order to account for actions not considered by the models. Larry Maisel notes that information generated by AI is typically best when it is balanced with human insight and judgement.

AI and ML models are not able to produce a full profit and loss (P&L), balance sheet or cash flow statement. Although they can produce parts of these documents, the different elements still need to be brought together by FP&A into one consistent story that can drive appropriate actions.

Finally, the different processes, planning, budgeting and forecasting, need to be considered when evaluating where AI or ML may play a role. Each of these processes sit firmly within the FP&A team's remit.

With the above in mind, some jobs that existed 20 years ago will be gone, but new roles will be created that never existed in the past. FP&A staff will continue to play a key role in ensuring the organization stays afloat.

10. Conclusions

AI and ML will be a game changer

FP&A teams moving towards digital systems will transform the value it delivers. All processes are fully integrated, automation provides real-time monitoring and forecasting, and insights allow management to focus on the options available to the organization.

All of our interviewees believe that AI and ML will be game changers. They feel that the companies who will succeed in tomorrow's world are those that have more advanced models and a more advanced understanding of underlying business dynamics. This is where AI, together with ML, plays a big role in analyzing large amounts of structured and unstructured data, revealing key trends and relationships that can support the decision-making process. This is something that humans cannot do with traditional tools, but AI and ML systems allow insights to be drawn quickly from many sources of information.

The world of finance is changing. Today there is a new generation of senior finance professionals that can bridge the gap between finance and data science. A number of our interviewees were finance people who have also studied AI and ML academically. As a result, they are able to do things that FP&A could never do before and therefore lead FP&A through a transition from low-value traditional accounting practices to a high-value digital future. In doing so they increase their effectiveness as a strategic business partner and improve their ability to guide the organization through times of considerable uncertainty.

Larysa Melnychuk

Larysa is a passionate Financial Planning & Analysis (FP&A) professional and influencer who has held senior FP&A roles at leading organizations before setting up the International FP&A Board in 2013. In the last three years, she successfully expanded the Board into 27 chapters in 16 countries across 4 continents.

Larysa is also the founder and CEO at **FP&A Trends Group**, the leading online resource for FP&A professionals. She chairs the **Global AI/ML FP&A Committee** and runs a number of high-profile initiatives in the area of modern financial analytics.

Larysa holds a Master of Science degree in physics of materials and is a qualified chartered management accountant (CIMA), chartered global management accountant (CGMA) and is a holder of an FP&A certification. She is also a member of the exam content writing team for the Association of Finance Professionals (AFP) FP&A certification.

Michael Coveney

Michael Coveney has over 40 years of experience in designing and implementing software solutions that combine 'best management practices' with technology to improve the efficiency and effectiveness of planning, budgeting, forecasting and reporting processes.

He has conducted senior management workshops with leading organizations around the world and led courses for the American Management Association and Antwerp Management School on the topic of Corporate Performance Management.

His energetic style and extensive experience led him to become a regular speaker at many international events and the author of many articles and books. His latest, 'Budgeting, Planning and Forecasting in Uncertain Times' is published by John Wiley & Sons. In recent years he has focused on the role of IT within FP&A departments.

If you have any questions or comments, please feel free to contact us via email **info@fpa-trends.com**.