



DECISION
MANAGEMENT
SOLUTIONS

Operationalizing AI

Beyond AI Pilots With Digital Decisioning

Dedicated to DecisionsFirst™

 www.decisionmanagementsolutions.com

 info@decisionmanagementsolutions.com

 1+650-400-3029

Sponsored by



Version 1 June 19, 2020

By James Taylor

CONTENTS

Applying Machine Learning to Make Better Decisions in Insurance

Three Major Hurdles to Successful ML/AI Adoption

Digital Decisioning Puts AI to Work

Infusing Machine Learning Into Operations With Digital Decisioning

Six Steps to Moving Beyond an AI Pilot Project

Beyond Pilots With Digital Decisioning

Businesses are made or broken by the quality of the decisions they make. How well does this offer target this customer? Does this machine need to be serviced now or can it wait? Is this transaction legitimate or suspicious? Will this customer make the payment they have just promised? The quality of these and many other decisions can be improved with technology.

Artificial intelligence (AI) and machine learning (ML) offer tremendous potential for improving these decisions. ML algorithms can identify at-risk customers, fraudulent claims, failing machines, competitive orders, and cost-effective suppliers. These insights can help organizations be more productive and effective, not just more efficient. When infused into customer touch points, ML can drive a better, more personalized and differentiated customer experience. Line-of-business leaders can focus on managing the business, not handling individual transactions.

Applying Machine Learning to Make Better Decisions in Insurance

When a leading insurance provider needed to increase sales through its agency channel, they took a cross-sell and upsell approach using ML. By applying ML to their data, it became clear that different combinations and product sequences were more effective with different customer segments, but it wasn't clear how to use this insight to reach their goal.

The team determined the decision could be automated to answer this question: "What additional product or extension should be offered to this customer?" Automating this decision meant understanding policy and regulatory restrictions on which products could be sold to which customers. It meant checking the products the customer already had in their basket to prevent overlaps or contradictions in the products to be offered. And, after eliminating those products, it meant applying insights from ML to choose the best among the remaining products.

Sales agents were already using a mobile app to gather data in their process. With the decision automated in a decision service, the app could use targeted data insights and simply recommend the next best offer for the customer. Customers were offered compelling, relevant offers in real time and nearly one fourth accepted.

Millions of dollars in new premiums were sold, resulting in increased commissions for agents. The company experienced an almost 100% uptake across the agency force, along with offer acceptance rates that range as high as one in four and growing.

Three Major Hurdles to Successful ML/AI Adoption

Like our insurance provider, every line of business in every industry is under pressure to deliver revenue growth, while maximizing productivity. AI and ML can help achieve those objectives. But most projects fail to proactively address certain challenges and remain perpetual pilots or experiments. They can't make it into production, and they can't be truly operationalized unless these challenges are addressed. To operationalize ML, a broader view of AI is required.

1. Innovation and Disruption

Startups and "born digital" companies are taking full advantage of new data sources and ML. They have the freedom to completely change the way they do business and reinvent themselves, putting ML and AI at the center.

While it's easy for startups to innovate and take an ML-first approach, established companies can't change everything because an algorithm tells them to. Being established and reliable is a key part of their value proposition. Therefore, they need ways to innovate that are not disruptive to operations or customers. They need AI and ML to be additive, without throwing out what they already know. There is a real opportunity for established companies to apply AI centers around small operational improvements, such as improving retention or offer acceptance by a few percentage points or slightly reducing maintenance costs.

2. Humans and Machines

Established companies have invested in their people, which involves bringing on new talent and ensuring they keep the talent they have already developed. They know who makes good decisions and each person's strengths. They are looking for ways to scale the expertise of their people and help them use data and insights to improve decision-making.

Leading companies recognize that ML trained on historical data is a powerful way to predict the future. But they also recognize that it will tend to replicate decisions as they were made in the past. New strategies, updated regulations, and changed policies require a forward-thinking business expert to be part of the solution. Their staff—their expert human decision-makers—plays an important role.

Some view ML as a way to replace people, but this dismisses the knowledge and expertise of human decision makers. In reality, AI and ML augment the work of human decision makers and change their current decision making for the better.

3. Regulation, Control, and Trust

Many businesses are highly regulated. Therefore, building trust with regulators and auditors to make sure the business operates legally and appropriately is an important and major responsibility.

Leaders don't want to adopt ML and AI for fear of running afoul of regulations or risk losing public trust. They don't want to end up in court or in an audit review having to explain that, because of a mistake the algorithm made, they ended up inadvertently breaking the rules. They need to be sure that rules based on regulations and policies are applied every time. But these rules can't readily be captured using ML. Business leaders need to be able to exert control over the decisions being made, conform with regulations, and apply ML and AI.

When they do use ML and AI algorithms, established companies need to understand what those algorithms are suggesting well enough in order to trust them. The algorithms need to be transparent so that regulators, investors, customers, and business partners can trust the results.

Digital Decisioning Puts AI to Work

The most critical lesson learned from successful AI projects is that delivering artificially intelligent operational systems involves more than just the latest ML technologies. One of the most persistently successful technologies for delivering AI is Digital Decisioning with business rules management. Digital Decisioning¹ is a proven approach to success that automates high-volume, transactional, and operational business decisions. This delivers consistent, accurate decisions in real time while providing the business with control and agility.

In the insurance company example we referred to earlier, the COO adopted Digital Decisioning for claims processing. They were able to rapidly improve claims processing for simple claims based on their basic business rules. They added other business rules derived from data analysis to handle waste as well as ML to predict

¹Decision Management, Decision Management Systems, and Digital Automation are all synonyms for Digital Decisioning.

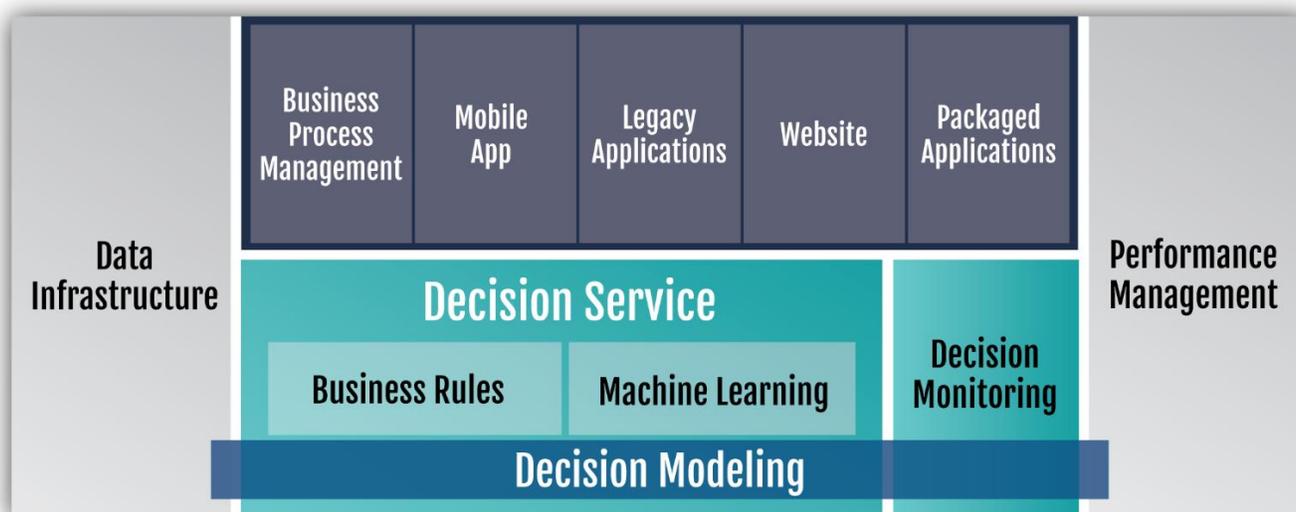
fraud risk. Ten weekly updates were enough to exceed the initial target for straight-through processing—and it exceeded 50% within a few quarters. Costs are down, while accuracy and customer satisfaction are up.

Although Digital Decisioning can deliver business value with just business rules, the most effective Digital Decisioning projects combine explicit business knowledge with the probabilistic analytic insight generated by ML.

For instance, Gartner’s AI techniques framework² identifies that AI requires probabilistic reasoning (delivered by ML or predictive analytic techniques) and optimization techniques (constraint-based reasoning), as well as computational logic (delivered by rules-based systems). Gartner states that “Data and analytics leaders must demystify AI terminology to enable conversations focused on real business problems and use cases rather than on technology jargon.”

A typical architecture for Digital Decisioning is shown below. Digital Decisioning automates each business decision as a decision service. Decision services contain the business rules and ML needed to deliver an intelligent decision to any application context. The business rules and ML algorithms are orchestrated using decision models based on the Decision Model and Notation (DMN) standard. How decisions are made is logged for decision monitoring, so they can be continuously improved, and decisions made can be tied directly to business performance.

Figure 1: Digital Decisioning Architecture



² Artificial Intelligence Hype: Managing Business Leadership Expectations, Published: 5 June 2018 ID: G00343734. Analyst(s): Erick Brethenoux.

This approach allows consistent, accurate decisions to be delivered across all channels. Any channel that needs the decision made invokes the decision service. This executes the business rules and ML models necessary to make the decision and logs how the decision was made. As the business outcomes of decisions are recorded in the channels, this data is combined with the logs (and potentially with external data) to support the continuous improvement of the business rules by experts and ongoing retraining of the ML algorithms.

Infusing Machine Learning Into Operations With Digital Decisioning

To get beyond a pilot, established companies need to approach ML backwards. They need to begin not with ML, but with the decision-making they want to change.

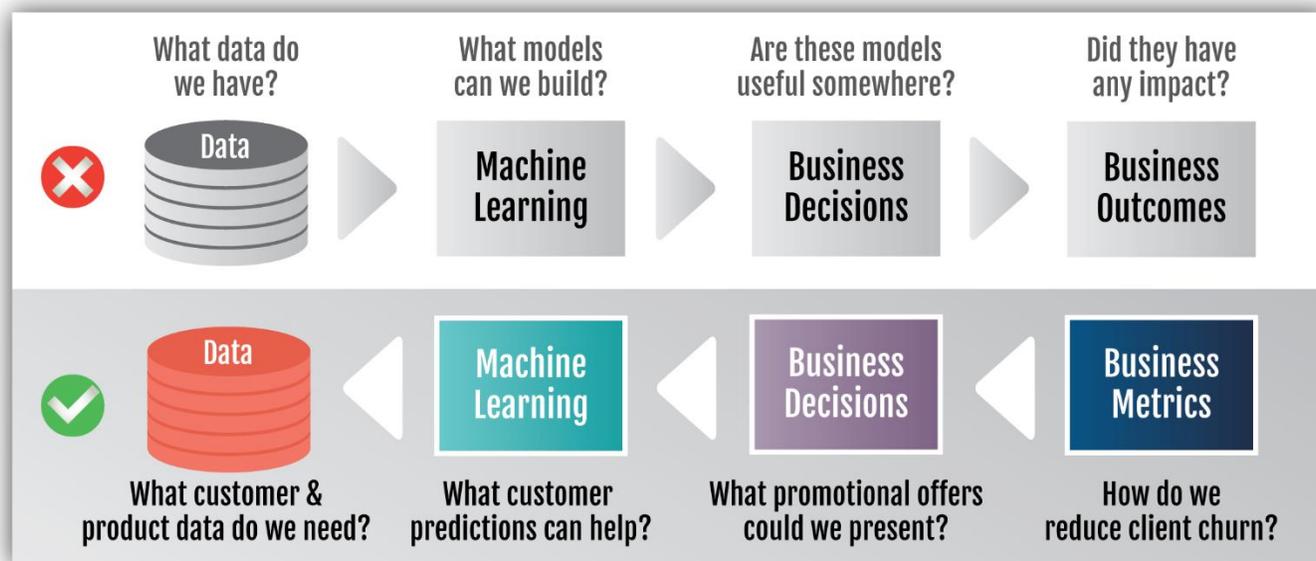
The integration of ML models into decision making is often omitted or neglected by those developing the ML models. For an established company, this is fatal. Established companies have well-defined decision-making approaches and processes. Neglecting to consider how the ML outcome will change established decision making relegates ML to the sidelines. The typical result is a highly predictive, very accurate pilot project.

As shown below, successful projects begin with the business metrics being targeted, identify the business decisions that must change and then identify the machine learning that will be required to make better decisions. Only then is the data analyzed.

“Most companies start their analytics journey with data; they determine what they have and figure out where it can be applied. Almost by definition, that approach will limit analytics’ impact. To achieve analytics at scale, companies should work in the opposite direction. They should start by identifying the decision-making processes they could improve to generate additional value in the context of the company’s business strategy and then work backward to determine what type of data insights are required to influence these decisions and how the company can supply them.”³

³ “Breaking Away: The Secrets to Scaling Analytics,” May 2018 by Peter Bisson, Bryce Hall, Brian McCarthy, and Khaled Rifai, McKinsey.

Figure 2: Deploy Machine Learning Backwards



Six Steps to Moving Beyond an AI Pilot Project

1. Identify operational decisions

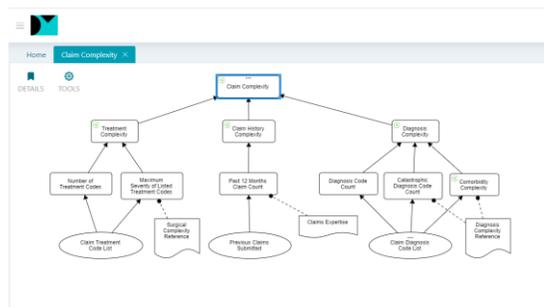
To work backwards, start by identifying the business metrics you want to improve and the decisions that drive these metrics. Find high-volume, operational decisions that need to be made consistently, rapidly, and at scale. These operational decisions are generally part of a single customer interaction or one step in a transactional process. Making each decision better has only a small impact, but the number of times you must make the decision exercises a strong multiplier on the value.

Good candidates are non-trivial decisions where policies, regulations, expertise, and experience all play a role. If it's obvious how to decide, then ML won't have much to offer. But you should also avoid "moon shot" projects to automate decisions that are really complex. Look for practical, technically feasible projects with immediate business impact. For example:

- ▶ Can this claim be paid without further review?
- ▶ At what price can this order be fulfilled in the time requested?
- ▶ What's the next best action to get this account out of collections?

2. Develop business (decision) understanding

Figure 3: A Claims Handling Decision Model



Sources: *DecisionsFirst Modeler*

Now that the decision has been identified, a real business understanding of this decision must be developed. Find out how the decision is made today by working directly with subject-matter experts in business and operations. Use a decision-centric and business-friendly approach like decision modeling to capture the decision-making approach. If the decision is already automated, bring in IT to understand the scope and limitations of existing automation.

You want to establish a logical model of the as-is decision making and understand how the company handles the decision today. It's also vital to know the relevant regulations, policy details, and how exceptions are handled.

3. Frame the machine learning you need

Work through the decision model to find all the places where you can automate decision making. Most likely, it won't be all of it as there are probably some decisions you still want humans to make. After these points have been identified, ML enters the process.

Find the places in the decision that are data driven and identify the ML you need. Can it be used to upgrade that decision, so it's based more firmly on the data? Can additional data be brought in to enhance what you have and develop a more accurate prediction?

Once you've framed the decision, ML can take you even further. What are some unknown factors that may impact your decision?

You don't know which machines are going to break down tomorrow. If you did, you could maintain them today. You don't know who has an undisclosed medical condition. If you did, you could put their claim in the review queue. You don't know who's a money launderer. If you did, you could review their transactions more closely.

You can't know these things for sure, but perhaps you can use ML to predict how likely they are. Think about how you might change the decision-making process if you knew the probabilities.

4. Build machine learning that will make a difference

Now the ML team should be back on familiar ground. They know what the decision needs, what would be useful for the business to know, and how accurate their model will need to be before being adopted. They can find and clean the data they need to develop useful ML models to solve a very specific, well-specified problem.

With Digital Decisioning, the ML team is developing the algorithms to make an established decision more accurate, replacing guesswork and old habits with new and precise data-driven insights.

5. Integrate

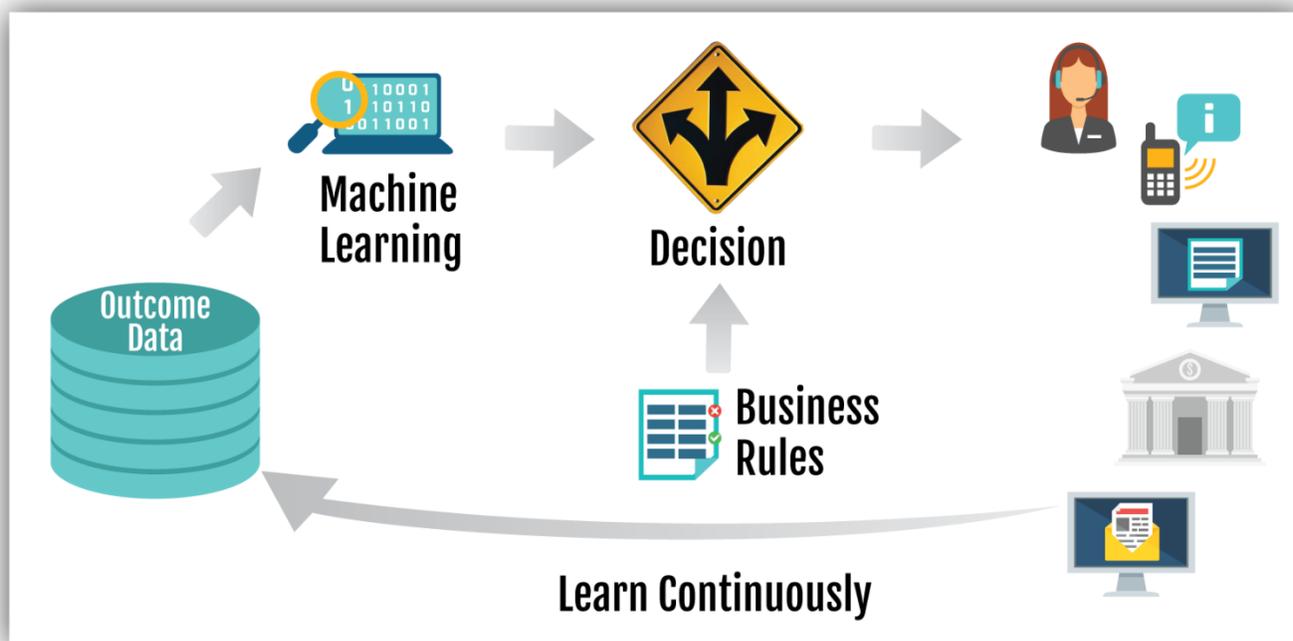
The ML models delivered by the team can be integrated immediately into the decision. The automation is executed and managed using the Digital Decisioning platform. The structure makes it clear exactly where ML plays a role and what that role is. With modern ML deployment and infrastructure, any ML model can be turned into a reliable, managed application programming interface (API) call. With a shared understanding of the decision and a Digital Decisioning platform, these deployed models can be rapidly and effectively operationalized.

6. Iterate

Digital Decisioning lets you close the loop for continuous improvement as shown below. Digital Decisioning platforms generate a lot of data about how decisions are made. With a catalog of decisions linked to business metrics, this data can be used to analyze the effectiveness of the decision-making approach. The structure of the decision shows up in the data captured, making it easy to analyze. Decisions are linked to metrics so business owners can review both how decisions are made and their business outcomes.

When ML gets integrated, the scores and explanations produced by ML algorithms can be incorporated into the process. This data shows opportunities for improvement and allows for old and new approaches to be systematically compared. Based on this analysis, business owners can make changes. New business rules and new ML models can be developed, and the impact of these changes simulated. When the results match business needs, the changes can be immediately deployed to the decision service. Transparency and continuous improvement are the result.

Figure 4: Close the loop for continuous improvement



The next wave of digitization is digital decisioning—the scaling and automating of decision making using a digital platform that combines the insights of AI/ML innovations with the expertise of a human workforce. Whether an established company or in start-up mode, Digital Decisioning with AI helps increase agility to align with ever-changing business objectives, market forces, and customer expectations. The process begins with identifying decisions that could be improved and uses ML to enable data-driven decisions. Iterating along the way, organizations can continually adapt and refine decisions under changing conditions, new regulatory mandates, and many other factors. Rather than disrupting operations, digital decisioning provides additional flexibility and continuous improvements that lead to successful business outcomes over the long term.

Beyond Pilots With Digital Decisioning

Digital Decisioning delivers a model with enhanced speed, consistency, and control. Integrating ML into this process can provide innovative results without disrupting operations. ML, therefore, isn't breaking the decision's connections—it's making the decision better.

But concerns still remain about what this means for the human workforce. ML and human employees each play a key role in Digital Decisioning and must work together to deliver an intelligent Digital Decisioning process. The business and operations teams lead the development of the decision model and "own" the decision. They understand and can control the ML being added and can change the business rules that wrap around ML, determining when and how it gets used. And since most decisions are not 100% automated, the judgement of human employees regarding inputs, handling unusual or difficult cases, or giving final approval are vital to success.

Learn More

To learn more about automating business decisions, visit ibm.com/automation/business-rules



CONTACT US

Decision Management Solutions specializes in helping organizations transform the operational decision-making that impacts businesses every day. We do this through Digital Decisioning, a unique approach that maximizes the value delivered by investments in AI and ML.





DECISION
MANAGEMENT
SOLUTIONS

www.decisionmanagementsolutions.com