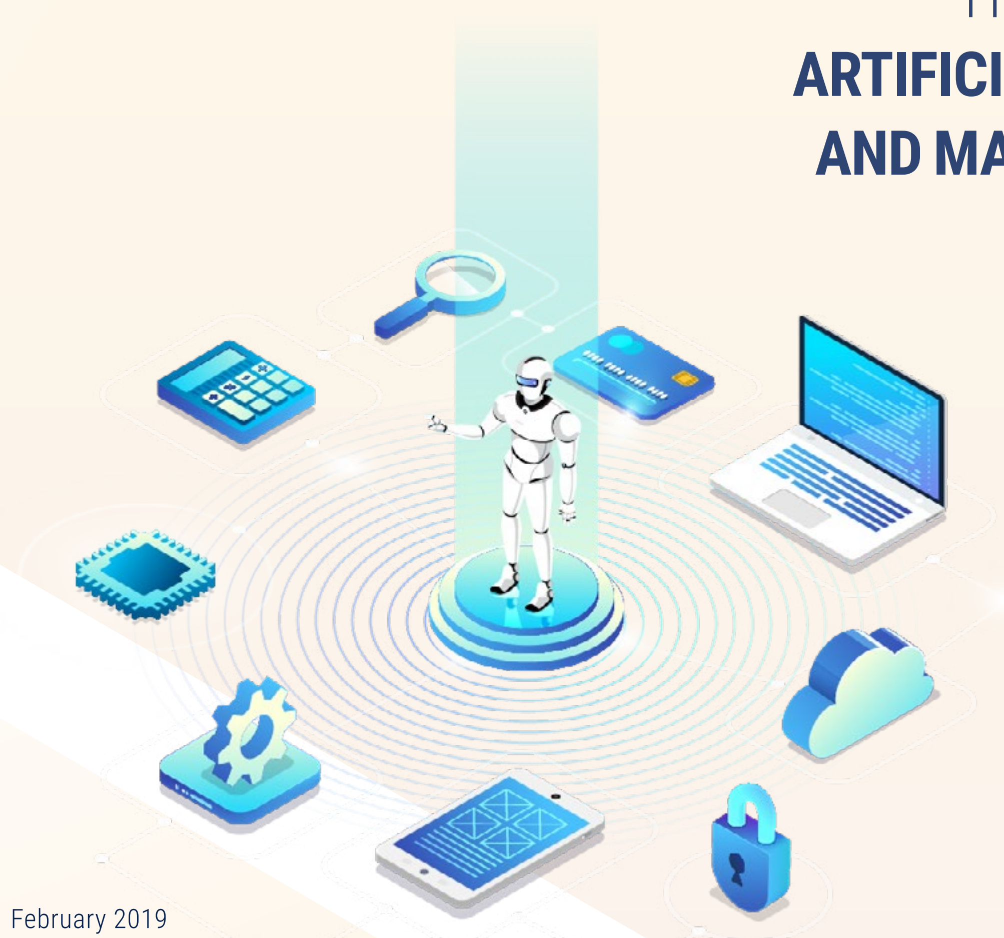
AI INNOVATION PLAYBOOK

PERCEPTION VERSUS REALITY IN PAYMENTS AND BANKING SERVICES

HOW FIs ARE USING **ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING**



The AI Innovation Playbook, a PYMNTS and Brighterion collaboration, analyzes the survey response data of more than 200 financial executives from commercial banks, community banks and credit unions across the United States. We gathered more than 12,000 data points on financial institutions with assets ranging from $1 billion to more than $100 billion, then generated a comprehensive overview of how they leverage AI and ML technology to optimize their businesses. This study details the results of our extensive research.

February 2019

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The AI Innovation Playbook was done in collaboration with Brighterion, and PYMNTS is grateful for the company's support and insight. PYMNTS.com retains full editorial control over the findings presented, as well as the methodology and data analysis.

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INTRODUCTION

Modern financial professionals share their offices with more than just human coworkers: They also work alongside algorithms.

Technological innovation has produced a whole new type of financial institution (FI) — one staffed both by humans and algorithmic tools, and driven by what most think of as artificial intelligence (AI). As technologies like these grow more ubiquitous, FIs are continuously redefining how they can be best utilized to help human professionals perform their jobs more effectively.

In this environment, it is more crucial than ever for FIs to understand the intricacies of what makes their automated "staff" so unique, and how to successfully integrate that personnel into their wide workforces.

The term "AI" has caused quite a bit of confusion, however. In truth, only a small share of FIs uses what can be called true AI.

The average bank uses 2.7 supervised or unsupervised learning systems — including data mining, neural networks and business rules management systems (BRMS) — but these are not true AI, which is used by just 5.5 percent of FIs. Despite not technically being AI, supervised and unsupervised learning systems are nothing to sneeze at. They are versatile tools that do everything from streamlining credit underwriting to fighting internal fraud, with 58 percent of FIs using data mining for the former and 59.5 percent using BRMS for the latter.

Modern FIs need to automate to remain competitive, which presents a question: Do they and their human employees know how to use these algorithmic tools?

The AI Innovation Playbook, a PYMNTS and Brighterion collaboration, explores how modern FIs are leveraging the most advanced supervised and unsupervised learning systems to optimize their businesses. To learn how algorithmic tools like deep learning, data mining and AI systems are being applied, and whether they are applied effectively, PYMNTS surveyed approximately 200 bank managers from FIs ranging in size from $1 billion in assets to more than $100 billion.

Several factors were taken into consideration when determining different learning systems' effectiveness when performing a selection of operations including credit underwriting, fraud prevention and payment and banking services. The speed, accuracy, operating cost and scalability at which these systems functioned determined their effectiveness within the FI.

The results were surprising and, in some cases, alarming. Most banks use the technologies they have available, which are not necessarily the technologies that are most effective. Data mining, which has a 70.5 percent adoption rate among FIs, may be the most popular, but that doesn't make it the best tool for the job.

Instead of tapping into data mining as a one-size-fits-all solution to enhance their operations, banks should focus on using it where it stands to make the most impact. This could mean implementing it to support payments services, for example. Just 45.0 percent of banks employ data mining in this area, despite the technology being uniquely suited to support these services.

FIs are making similar mistakes with their implementation of other learning systems, like BRMS, fuzzy logic and neural networks. With an adoption rate of 59.5 percent, BRMS is the most common system banks use to enhance their fraud protections operations — but it is also one of the least effective for the job.

These numbers demonstrate that it is not enough for a bank to use learning systems; they also need to understand that just as two human employees with different jobs often cannot perform each others' work, different learning systems often cannot be used interchangeably to perform any given task.

That so many FIs do not seem to grasp this fact signals a deep need for education among their decision makers. They do not currently seem to understand that they're missing the best bang for their buck when it comes to their AI and machine learning (ML) investments.

Here is what FIs need to know to ensure they don't make the same mistake.

WHICH FIs USE WHICH LEARNING SYSTEMS: **A RECAP**

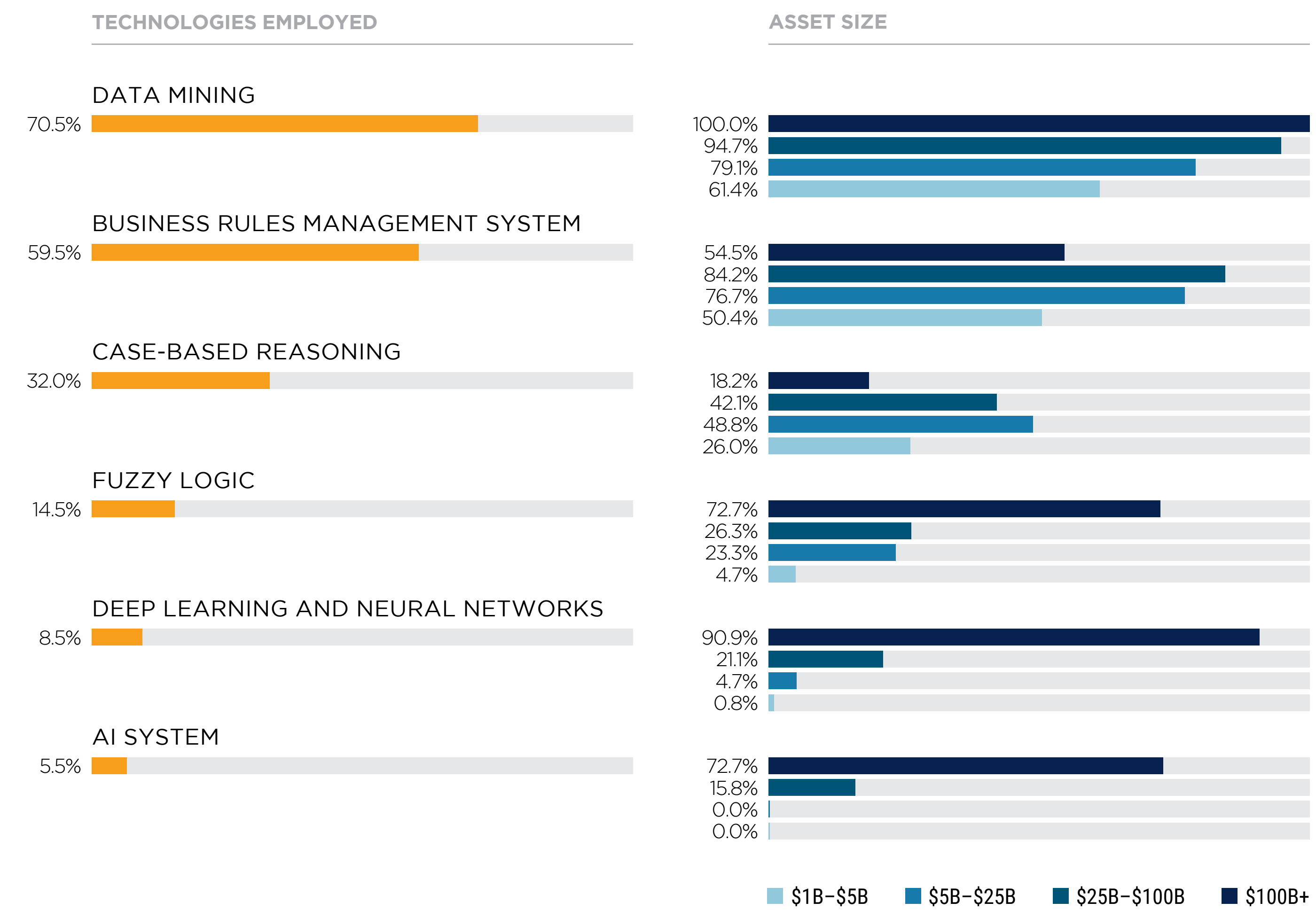
AI is one of the biggest buzzwords in banking, though only 5.5 percent of FIs are equipped with true AI systems. Moreover, those that have these systems are among the largest banks. As much as 72.7 percent of the FIs with more than $100 billion in assets use AI systems. That number drops to 15.8 percent for those with between $25 billion and $100 billion, and no banks of any other size have employed AI systems.

In fact, larger FIs were more likely than smaller ones to be using four of the six learning systems in our study, including AI, data mining, fuzzy logic and neural networks. All banks with more than $100 billion in assets used some form of data mining, 90.9 percent had adopted neural networks and 72.7 percent used fuzzy logic.

FIGURE 1:

Implementation of learning systems

Percentage of FIs that adopted certain learning systems, by size



Rather than use more advanced tools, smaller FIs were more apt to tap into rules-based learning systems like data mining and BRMS. Larger banks were still more prone to adopting these types of tools, though. Data mining was the most popular learning system for banks holding below $5 billion in assets at 61.4 percent — a number that's considerably less than the 100 percent adoption rate among banks with more than $100 billion.

Larger FIs also used more learning systems than smaller ones. Banks with more than $100 billion in assets used an average of 4.1 systems, with 81.8 percent employing four or more algorithmic tools. At the other end of the spectrum, the banks with the lowest value in the study — those holding $1 billion to $5 billion in assets — employed an average of just 1.4 learning systems, with 59.1 percent having implemented just one.

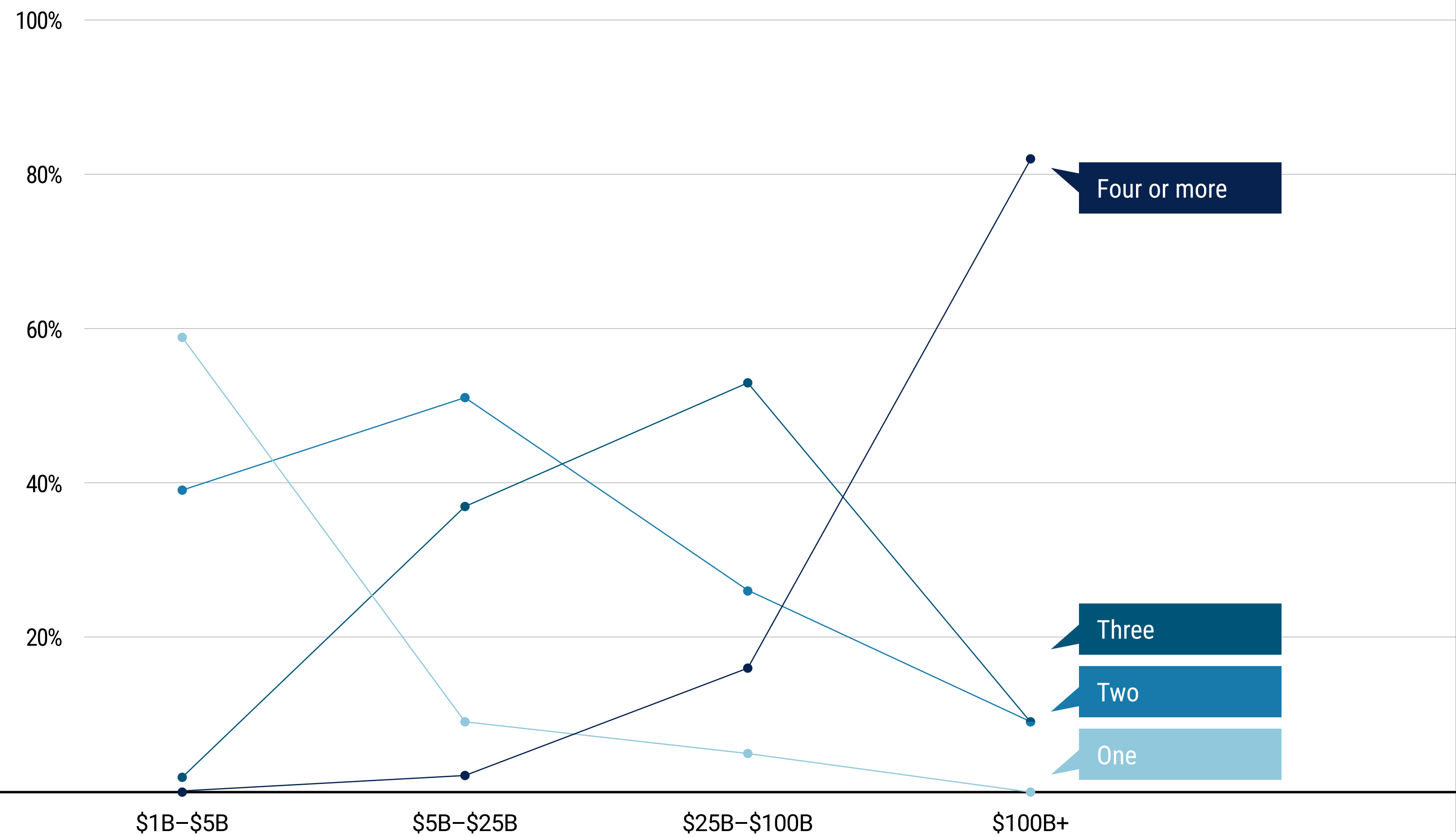
Learning technologies have obviously taken hold in the financial industry, but the issue of whether banks are using these systems correctly remains.

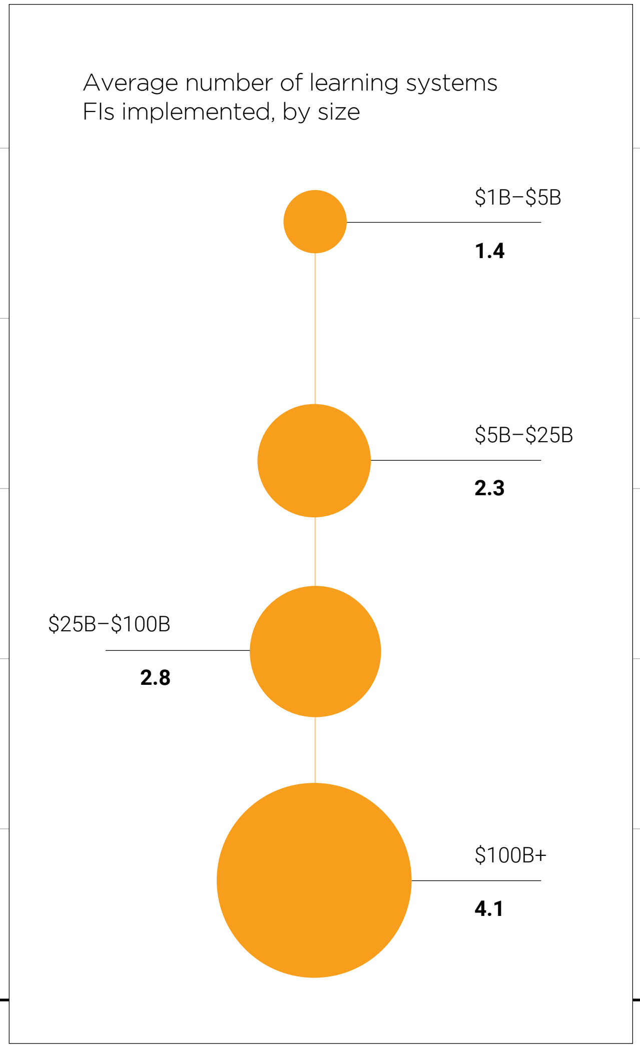
4.1

Average number of **algorithmic tools** used by banks with more than $100 billion in assets

FIGURE 2:

Number of learning systems used by banks of different sizes
Number of learning systems FIs implemented, by size





HOW FIs CAN LEVERAGE **SMART AGENTS** FOR SMARTER SERVICE

Though ML tools have become commonplace in recent years, AI systems are still quite rare. Rarer still is the use of a smart agent, one of the most advanced AI systems on the market.

Smart agents learn and make real-time observations from interactions with human users. They use this knowledge to create virtual representations of every entity with which they interact, building a digital profile that optimizes customer-facing payments and banking services. The difference between smart agents and other ML systems is that the former focus on individual subjects as opposed to applying a standard calculation to a large group. This allows FIs to offer hyper-personalized financial and payments services.

If there are 200 million cards in an ecosystem, there will be 200 million smart agents analyzing and personalizing their services to a degree that other ML systems cannot accomplish. ML systems do not account for individual members' unique attributes in their calculations, instead treating groups of consumers as just that: groups.

Moreover, smart agents can gather information on any number of actors in an ecosystem, from consumers to point-of-sale (POS) terminals to merchants and so on. The information they gather is then used to teach these agents how best to manage different operations. This ability to personalize on a large scale sets true AI systems apart from the rest — and is a task at which smart agents excel.

As useful as smart agents are, very few FIs actually utilize them. Rather, they often substitute a combination of sophisticated ML tools for true AI systems, but decision makers need to understand and accept that ML offerings are not viable substitutes for true AI. ML simply cannot carry out certain functions without considerable human intervention, and using it in these areas produces little benefit compared to what can be achieved with smart agents.

Low usage does not mean FIs — especially larger ones — are not interested in smart agents. Approximately 64 percent of those holding more than $100 billion in assets reported being "very" interested, and an additional 9 percent were "extremely" so. Interest levels were somewhat lower among smaller FIs, but were still quite high. Forty-two percent of those holding between $25 billion and $100 billion were "very" interested, and that number was 47 percent for those with between $5 billion and $25 billion. Some smaller banks also expressed interest in smart agents, with 13 percent of FIs holding between $1 billion and $5 billion saying they would consider adopting the technology.

Evidence suggests that smart agents will become more and more common in the financial sector as time goes on. For now, though, they continue to remain among high-earning FIs.

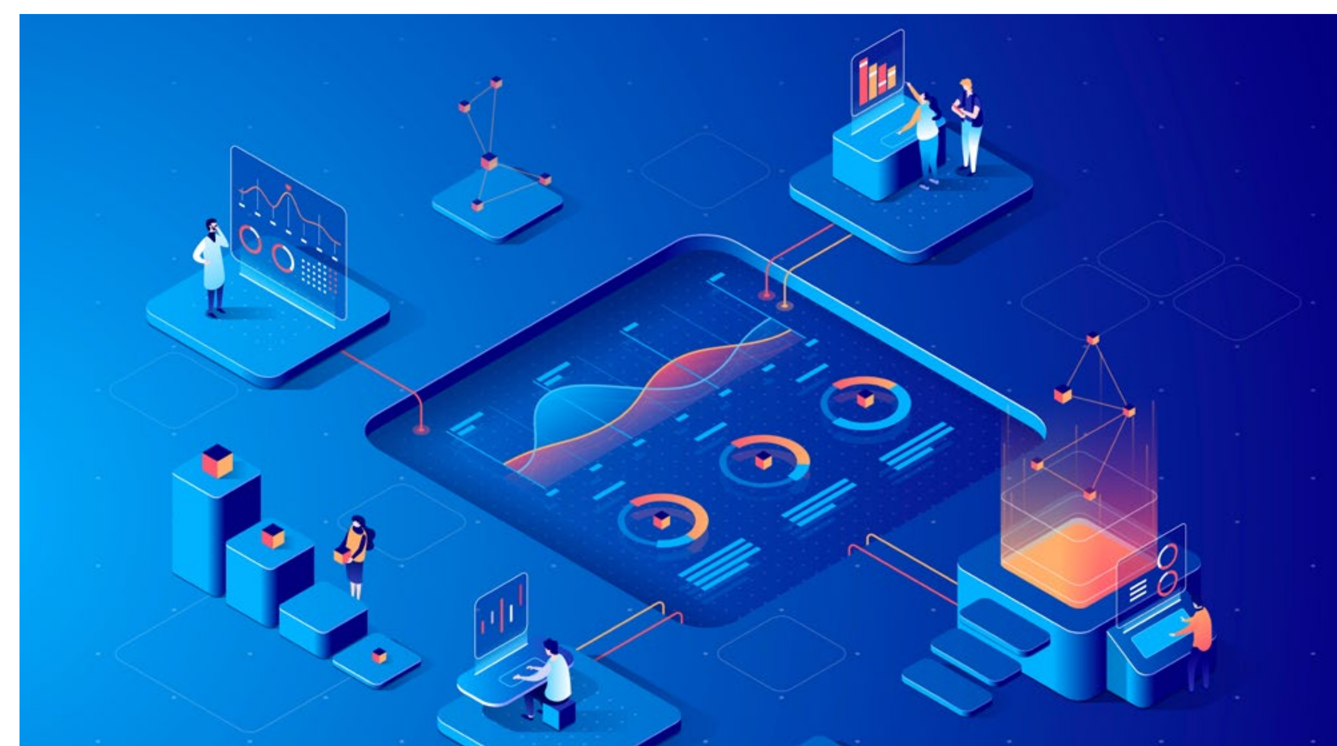
DATA MINING: MAKING THE MOST OF THE MOST COMMON LEARNING SYSTEM IN FINANCE

While most FIs have implemented some sort of supervised or unsupervised learning system, our survey results suggest that many didn't know how to effectively employ these technologies. This was particularly evident in their use of data mining.

Most FIs use some form of data mining technology for almost everything, and with an implementation rate of 70.5 percent, it was by far the most popular learning system among those in our sample. Banks used it in far more areas than were appropriate, however, including those in which it is highly inefficient. This means they weren't capitalizing on what the technology had to offer.

Data mining is a highly versatile tool that can add value in a variety of areas, and there are certain operations for which the technology is simply better suited than others. Unfortunately, only a minority of FIs were using it in this way. Among the 70.5 percent that had it in their arsenal, a surprisingly large portion failed to introduce data mining into the areas in which it could make the most impact: payments services, merchant services and collections.

Data mining is most effective in payments services, yet only 45.0 percent of FIs



leveraged the technology for this purpose. In other words, just 63.8 percent of those that used data mining technology were doing so for one of the tasks for which it is best suited.

Data mining is not the only instrument that can improve payment service operations, though. AI systems and BRMS can help FIs navigate and make use of expansive collections of data, making them effective tools as well. BRMS, used by 26 percent of FIs, is the second-most common learning system used for this purpose. AI systems, despite their effectiveness, were only implemented by 2.5 percent of FIs, making their presence quite rare in this scenario.

AI and BRMS are typically used to perform functions that would otherwise be carried out by data scientists. Though supervised and unsupervised learning systems have become more advanced, they are still no match for human professionals. To get the most out of the huge volumes of data that FIs collect, then, FIs still need to employ well-trained human workers.

Moreover, these workers are best at performing payments services not only for individual consumers, but also for businesses. This is another reason data mining is the best learning system to enhance FIs' merchant service operations: It allows data scientists to perform their jobs more effectively. As such, it made sense that data mining was the most popular learning system our sample

2.5%

Share of FIs that used **AI systems** to enhance **payments services**

FIGURE 3:

How FIs use learning systems to enhance their payment services

Learning systems' usage versus effectiveness for payments services

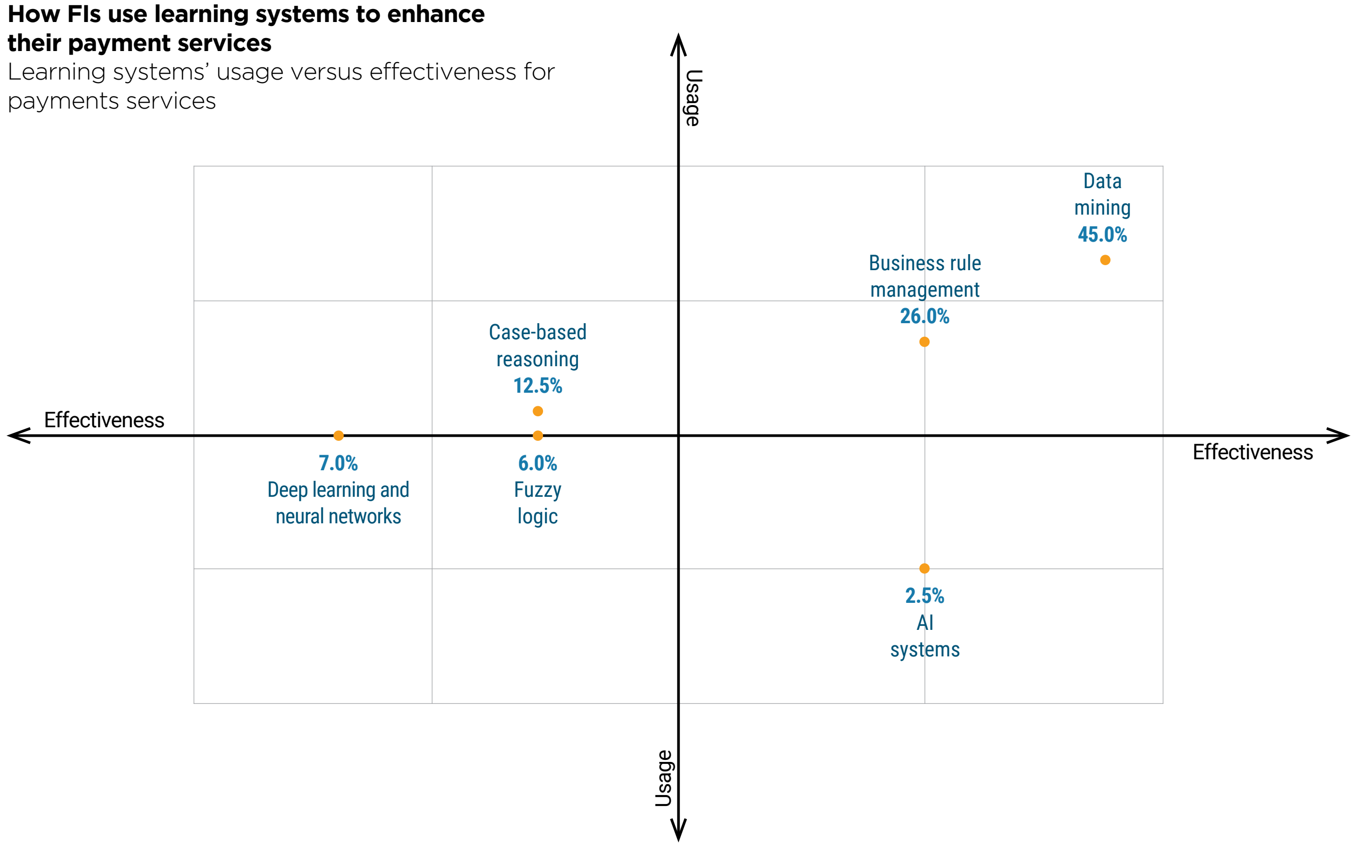
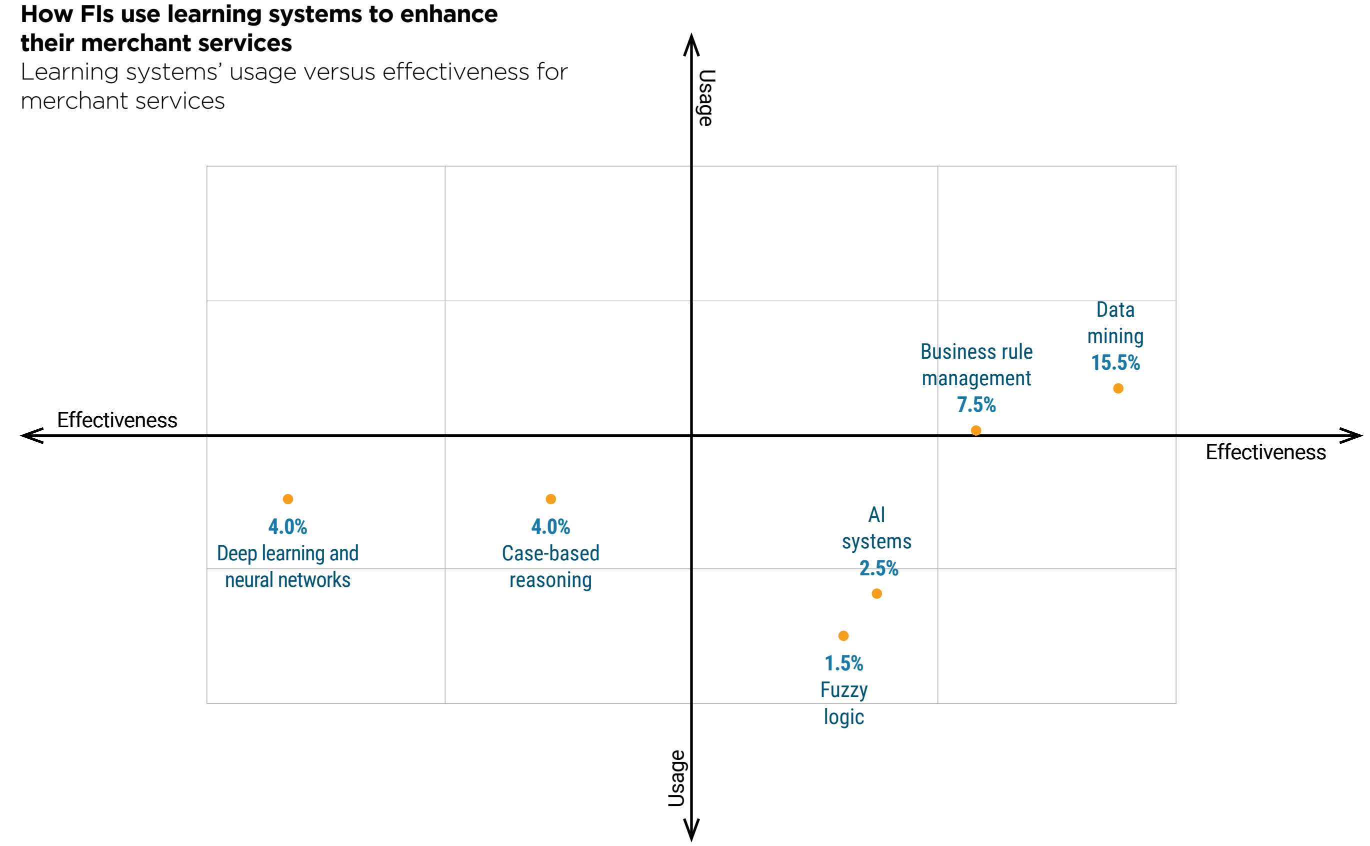


FIGURE 4:

How FIs use learning systems to enhance their merchant services

Learning systems' usage versus effectiveness for merchant services



banks used to enhance merchant service operations.

Though it was the most popular learning system overall, only 15.5 percent of our FIs used data mining to enhance such offerings. That number was slightly higher among those that used data mining in general, but was still just 22.0 percent.

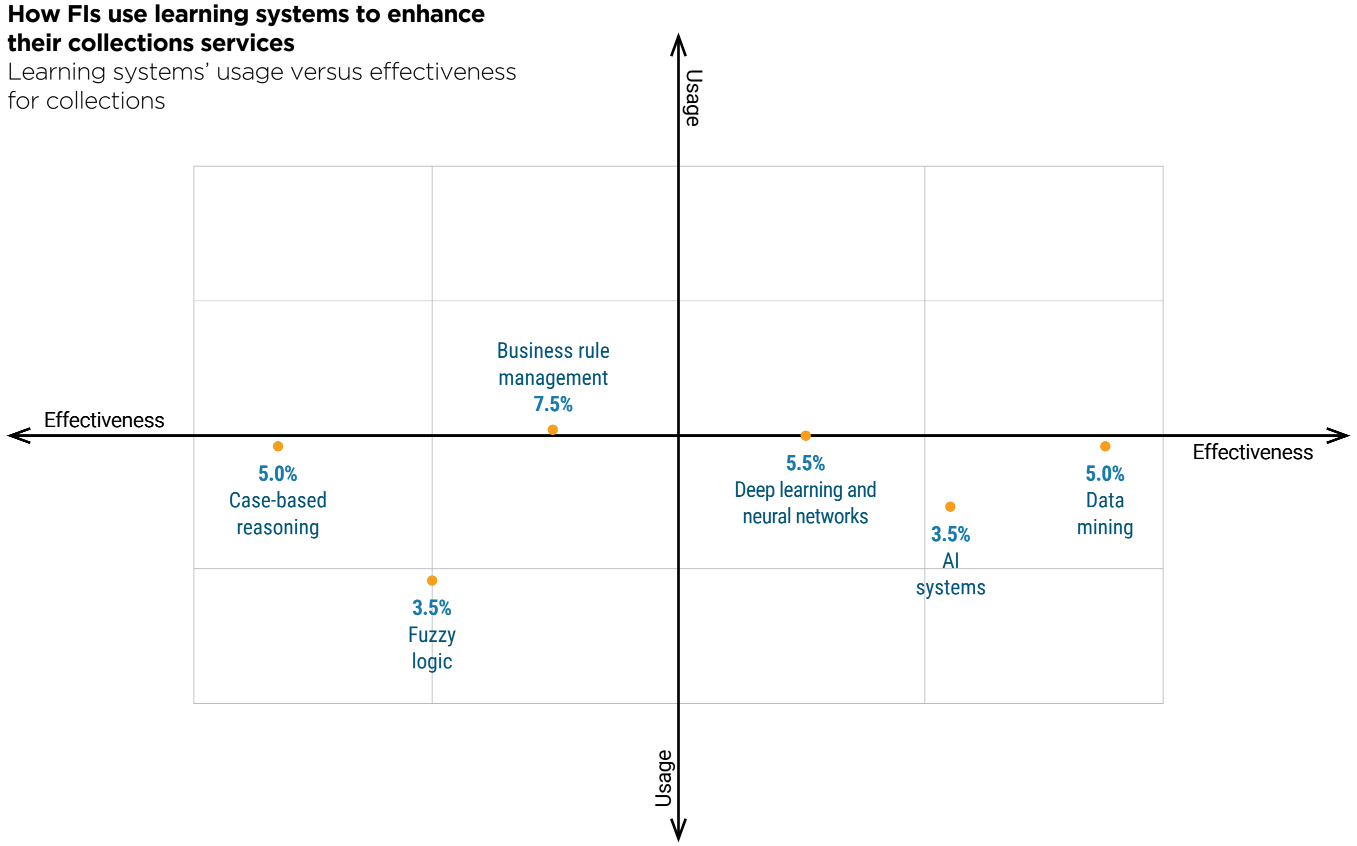
An even smaller portion leveraged data mining to enhance their collections services. As few as 5.0 percent of all FIs did so for this purpose, meaning that of the 70.5 percent of banks that were already using data mining technology, just 7.1 percent implemented it to make their collections services easier and more efficient.

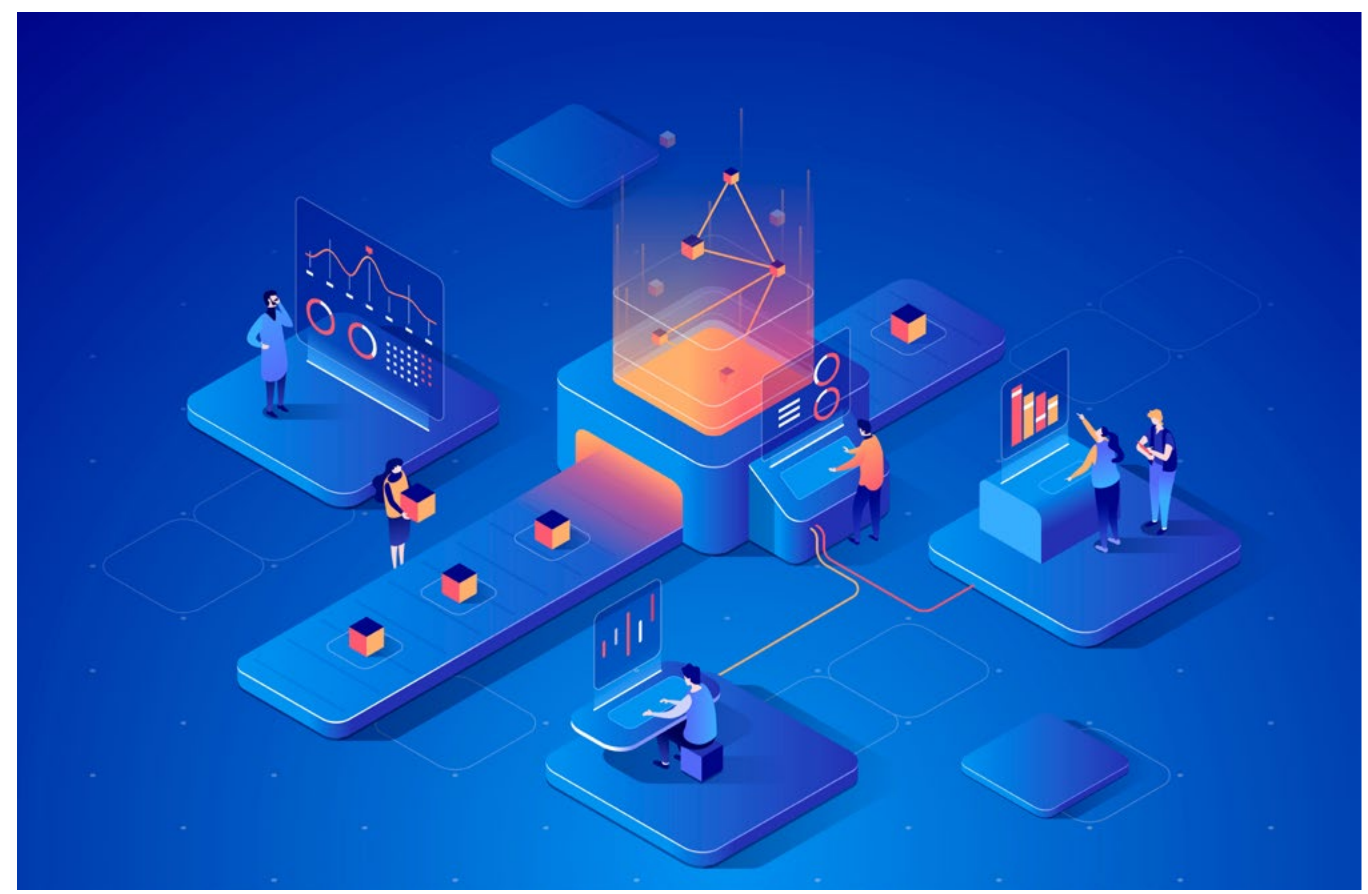
It was obvious that most banks were not using data mining to its full potential, but there are two ways to contextualize this fact. On one hand, most decision makers do not appear to understand the technology's potential and, therefore, are not getting their largest return on investment (ROI). On the other hand, these FIs have tremendous opportunity for growth and development.

15.5%
Portion of FIs that used **data mining** to enhance **merchant services**

FIGURE 5:

How FIs use learning systems to enhance their collections services
Learning systems' usage versus effectiveness for collections





BEYOND DATA MINING: WHEN RULE-BASED SYSTEMS JUST DON'T CUT IT

Most FIs were in the weeds when employing supervised and unsupervised learning systems. They were underutilizing data mining, and doing so in all the wrong ways when they *were* using it — usually as an ineffective substitute for more advanced technologies, like neural networks and AI systems like smart agents.

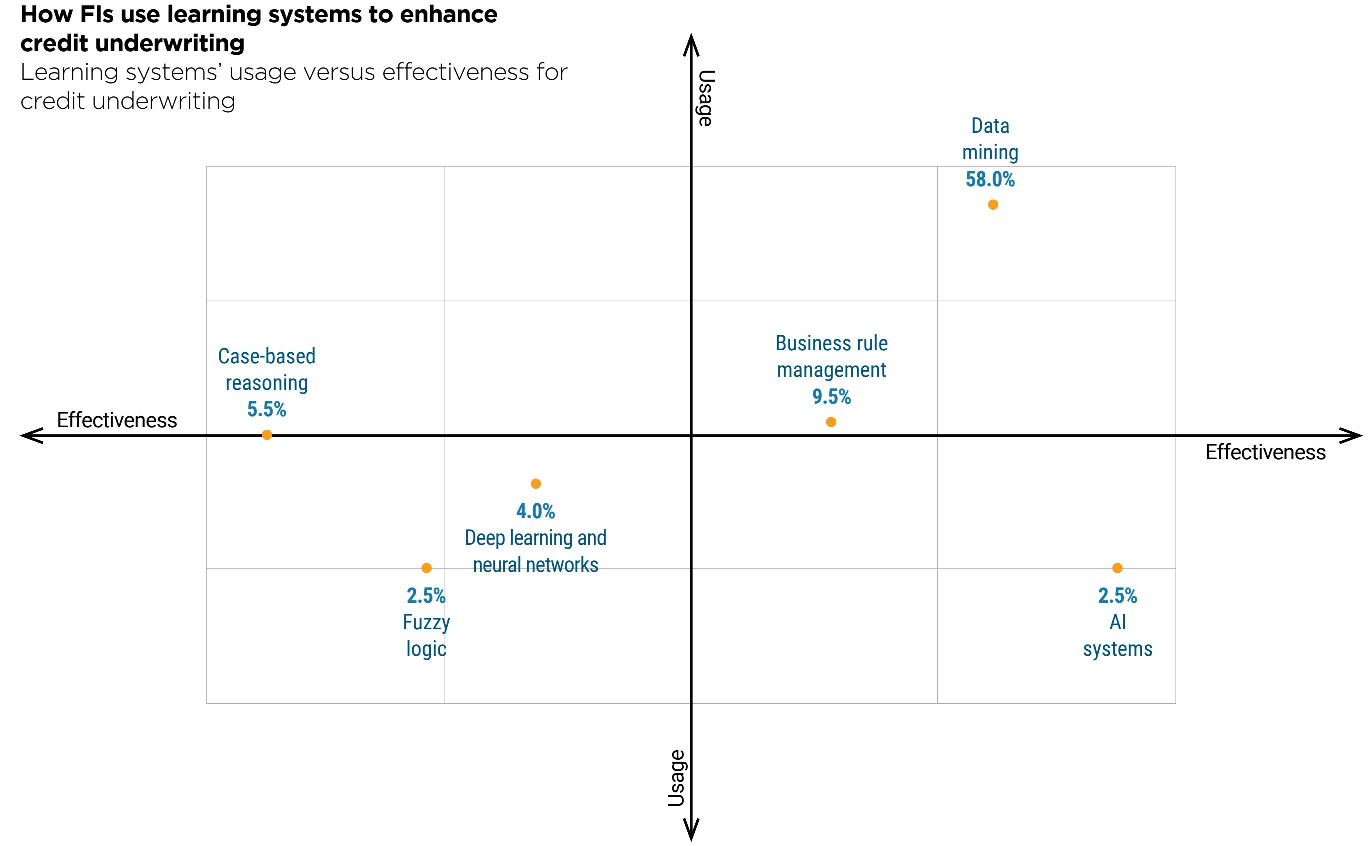
This may be because most people have a very limited understanding of what data mining actually is. Banks' decision makers seemed to think of it as a form of AI, or a comparable substitute. This was evident in the way they used data mining to perform highly complex operations, many of which it could not perform as efficiently as a more sophisticated system.

In every single area best-suited for AI — including customer lifecycle management, internal and external fraud protection, credit underwriting and credit and financial risk protection — most banks were using data

FIGURE 6:

How FIs use learning systems to enhance credit underwriting

Learning systems' usage versus effectiveness for credit underwriting



mining instead. These tools are excellent at collecting data, but they cannot synthesize original ideas or apply it for a practical purpose. These are tasks only AI systems can carry out without human assistance, making them a far more effective tool for such operations.

Consider the case of credit underwriting: Data mining was the most common learning system employed at 58.0 percent, but the second-most effective. AI systems were ranked best for credit underwriting, yet only 2.5 percent of all FIs used them in the process.

In other words, just 45.5 percent of FIs with AI systems were using them to optimize credit underwriting operations, leaving an astonishing 54.5 percent not utilizing it in one of the potentially most impactful areas. Instead, they were using other, less effective systems.

At 54.5 percent, data mining was also the most common learning system banks used to optimize customer lifecycle management — a task that would be more effectively managed by deep learning technologies and AI. Despite this, just 2.5 percent of all FIs use AI for this purpose.

Of the 5.5 percent that used AI systems, 54.5 percent were not getting the most value out of their investments. Once again, they were using data mining in this area instead.

If FIs want data mining to enhance customer lifecycle management, they need to employ specialists who can interpret the collected data. Only then can this data be applied to a practical use. Thus, FIs must not only pay for the data mining software, but also for the employees who are necessary to make use of the collected information.

It was even more egregious that just 1.5 percent of FIs were using neural networks to enhance customer lifecycle management. This tool was also more effective at this task than data mining, but just 17.6 percent of those that had neural networks were using them in this way. This bolstered our conclusion that many decision makers have no idea what these learning systems are capable of accomplishing.

The most peculiar way that sample FIs used data mining, though, was for fighting credit risk, financial fraud and internal fraud. There was once a time when data mining was an effective way to fight fraud, but those days are long gone. The tools used by hackers and fraudsters are more advanced than ever and increasingly automated. Most are more than capable of bypassing rules-based security systems, however, and once they crack the code, they're in. This means that rules-based learning systems such as data mining are not sophisticated enough to fight fraudsters.

Both deep learning and AI systems are better options because they are not based solely on "and/or" rules. They can go beyond basic programming and formulate original concepts and solutions to unique problems.

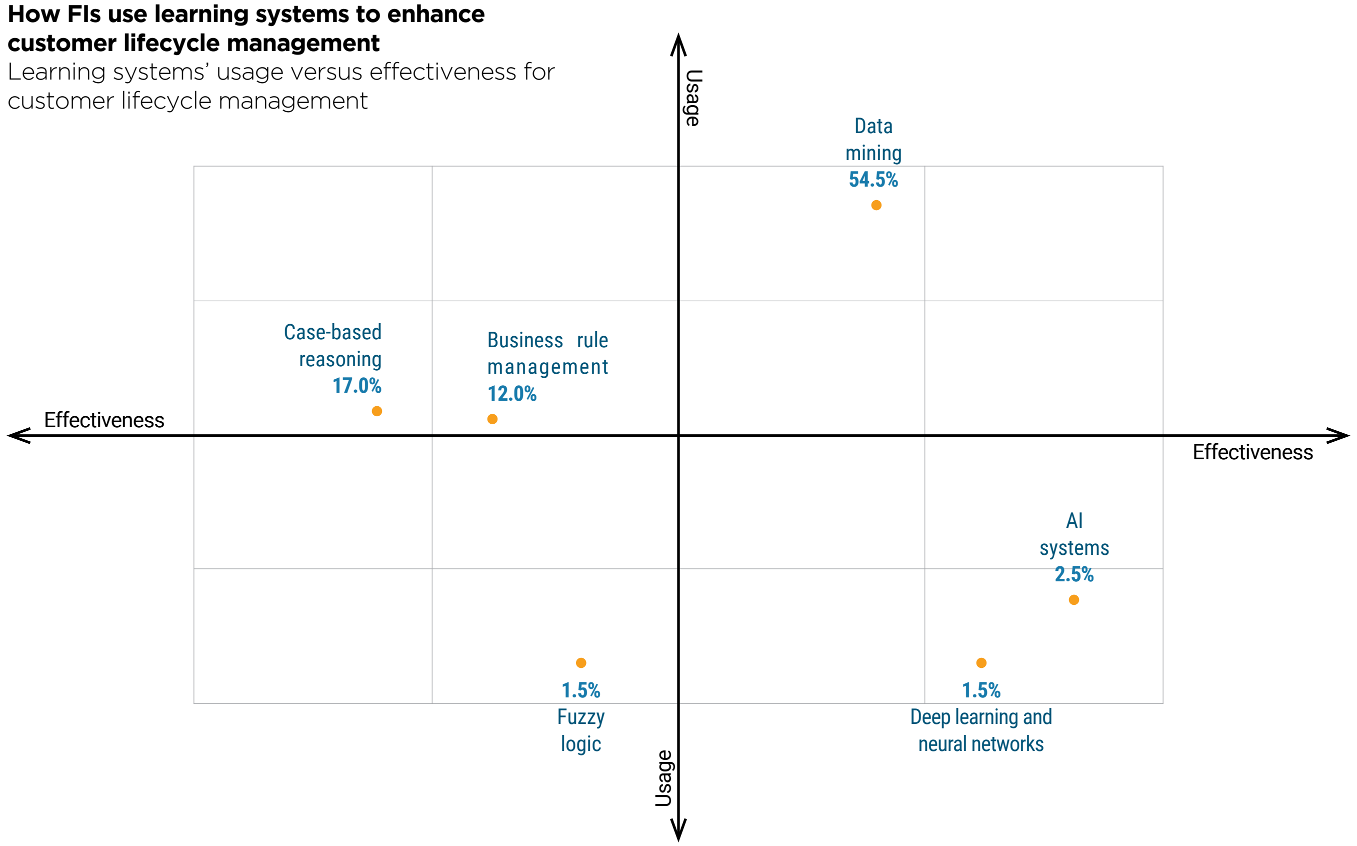
Nevertheless, BRMS and case-based reasoning were the two learning systems most commonly used to fight internal fraud. Case-based reasoning is the least effective algorithmic tool to do so, but is still used by 12.5 percent of sample FIs.

This could result from one of two things: Either banks did not understand what these technologies could do, or they had not upgraded their systems since the time when case-based reasoning was considered a

FIGURE 7:

How FIs use learning systems to enhance customer lifecycle management

Learning systems' usage versus effectiveness for customer lifecycle management



viable security solution. In either case, their internal fraud systems were seriously lacking.

Even when using learning systems to combat credit risk and financial fraud, though, many FIs were in the dark. The three most effective tools to combat fraud and credit risk are AI systems, fuzzy logic and neural networks, in that order, but none of these was the most common tool used by banks to do so. Instead, 70.5 percent used data mining to fight fraud — every single sample bank that reported using data mining technology.

To be fair, every FI in the sample that had implemented AI systems also used them for this purpose. This would normally be considered a good sign in a market full of uninformed decision makers, except it seems that every sample FI used every type of learning system they had to do the same.

The FIs in our sample were not kidding around when it came to protecting against financial fraud and credit risk, however. It appears their strategy was to come out swinging and throw everything they had into it.

70.5%
Share of FIs that used **data mining** to **fight fraud**

FIGURE 8:

How FIs use learning systems to enhance internal fraud protection
Learning systems' usage versus effectiveness for internal fraud protection

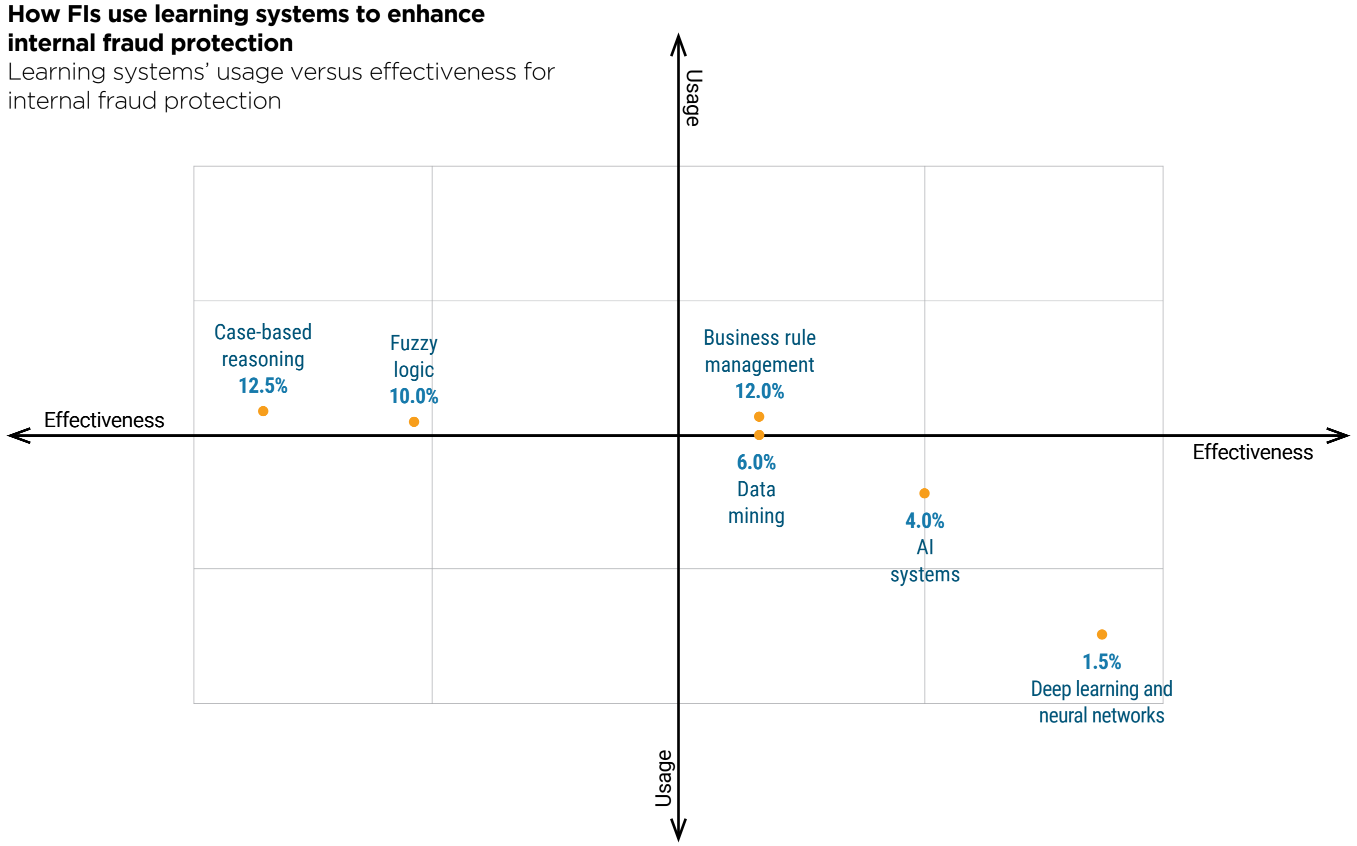
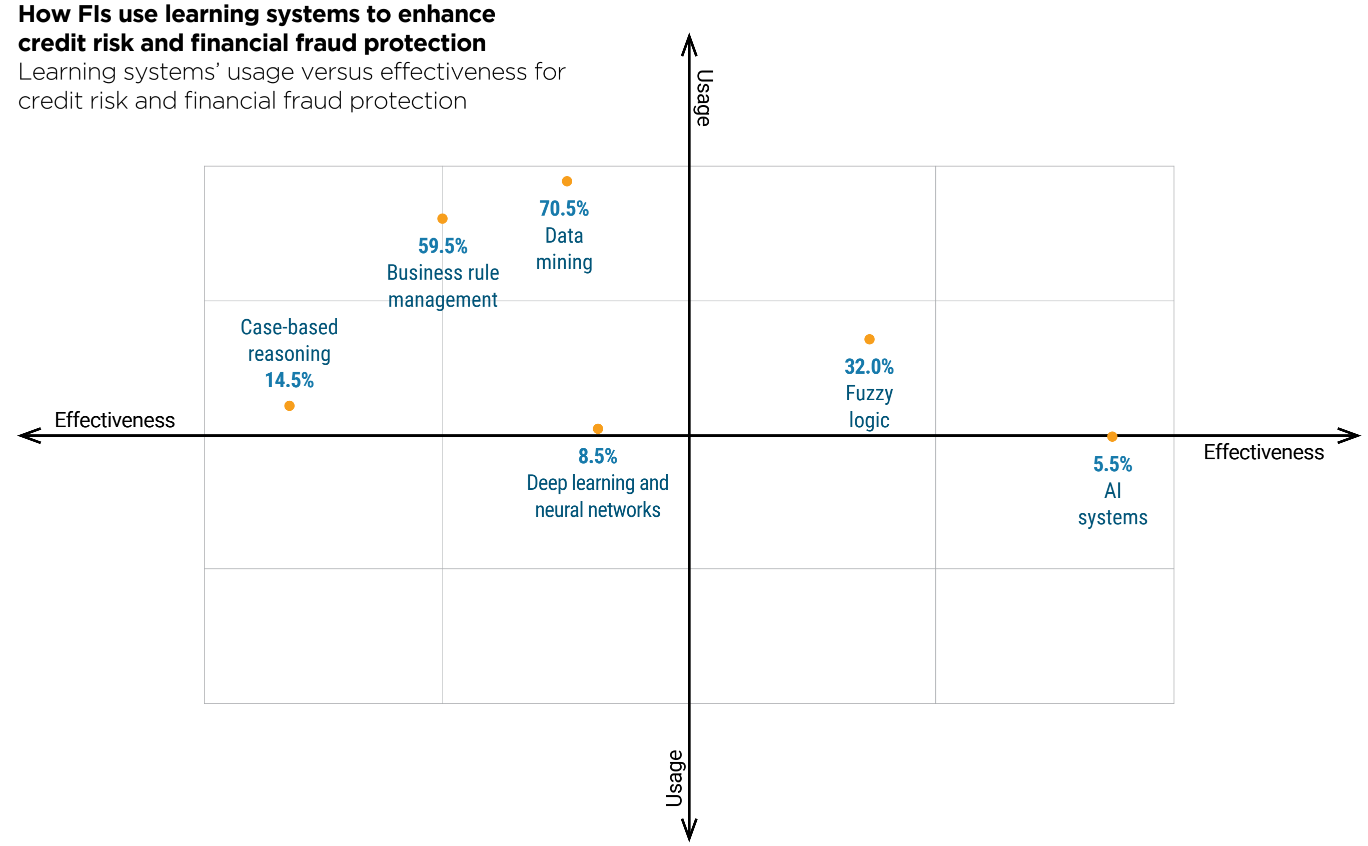


FIGURE 9:

How FIs use learning systems to enhance credit risk and financial fraud protection
Learning systems' usage versus effectiveness for credit risk and financial fraud protection



WHY BANKS SAY THEY USE **LEARNING SYSTEMS**

Judging by how they were using the learning systems in their arsenals, FIs seemed to consider fighting internal fraud to be their first and foremost priority. They leveraged every available algorithmic tool to ensure they were rooting out fraud and avoiding credit risk. While this is important, FIs were using considerably less technology to optimize customer-focused operations like payments and merchant services.

It appears that most FIs valued learning systems like BRMS and neural networks less for their ability to provide customers with the latest, greatest banking services and more for their ability to reduce costs.

TABLE 1:

Benefits of select learning technologies
Portion of respondents who cited select features as supervised and unsupervised learning system benefits

	MEDIAN	Business rule management	Data mining	Case-based reasoning	Fuzzy logic	Deep learning and neural networks	AI systems
Reduced manual review	55.4%	49.6%	**71.6%**	57.8%	**44.8%**	52.9%	63.6%
Reduced manual exception management	51.5%	47.1%	54.6%	50.0%	**41.4%**	52.9%	**63.6%**
Reduced payments fraud	43.1%	**17.6%**	28.4%	39.1%	**65.5%**	47.1%	63.6%
Improved customer satisfaction	43.0%	44.5%	39.0%	**32.8%**	41.4%	58.8%	**63.6%**
Reduced false positives	37.9%	42.0%	**27.7%**	34.4%	41.4%	29.4%	**54.5%**
Reduced managing fraud personnel	36.8%	21.0%	**15.6%**	21.9%	51.7%	58.8%	**63.6%**
Improved money laundering identification	31.3%	**16.8%**	18.4%	28.1%	34.5%	**52.9%**	36.4%
Improved fraud prevention	30.5%	**16.8%**	22.0%	39.1%	58.6%	17.6%	**63.6%**
Decreased credit and portfolio risk	25.0%	20.2%	**58.2%**	26.6%	**17.2%**	23.5%	27.3%
Reduced charge offs	24.3%	31.1%	**9.2%**	25.0%	17.2%	23.5%	**63.6%**
Improved delinquent debt collection	19.2%	17.6%	10.6%	**25.0%**	20.7%	23.5%	**9.1%**
Improved borrower identification	18.5%	19.3%	**70.9%**	7.8%	**3.4%**	17.6%	27.3%
Improved targeted banking services	17.4%	14.3%	**63.8%**	20.3%	17.2%	17.6%	**9.1%**

Respondents expressed greater concern about enhancing their companies' internal efficiencies compared to providing better customer service.

When asked to cite the biggest reasons learning systems were valuable to their organizations, respondents' most common response was that automating operations reduced dependence on human review.

Approximately 55 percent of the FIs that used learning systems said their key benefit was that they required less manual intervention. Other common reasons included reduced need for manual exception management (51.5 percent), reduced chance for payment fraud (43.1 percent) and, finally, improved customer satisfaction (43.0 percent).

In simple terms, banks wanted to automate their operations so they could be less reliant on human intervention, which can be costly in terms of both money and time. This goal is understandable, but it raised a question: If banks are so eager to automate their internal operations, why aren't they utilizing the technologies available to them?

Decision makers' ignorance has been made apparent, but it's possible that they had other, more tangible concerns. Learning systems can reduce costs and streamline operations, but they also have their limitations.

In some cases, those limitations were simply that decision makers were unsure how to quantify the tools' ROI. This was the second-most commonly cited limitation for learning systems as a whole, but fuzzy logic boasted the most difficult ROI calculation. Of the FIs that used it, 48.3 percent said they have not been able to quantify this metric.

The biggest reported limitation of supervised and unsupervised learning systems was that they were not transparent enough. Many decision makers could not understand why the tools concluded what they did, particularly for neural networks, fuzzy logic and AI systems. A lack of transparency was cited as a limitation by 45.5 percent of FIs that used AI systems, 52.9 percent of those using neural networks and 55.2 percent tapping into fuzzy logic.

Banks also cited several more tangible learning system limitations, though to a lesser extent. Their fifth-most common qualm was that the technologies required manual intervention, followed by the fact that they did not work in real time. Such factors likely contributed to whether banks invested in learning systems.

TABLE 2:

Limitations of select learning technologies

Portion of respondents who cited select features as supervised and unsupervised learning system limitations

	MEDIAN	Business rule management	Data mining	Case-based reasoning	Fuzzy logic	Deep learning and neural networks	AI systems
Not transparent enough	42.3%	35.3%	37.6%	39.1%	55.2%	52.9%	45.5%
Unable to quantify ROI	35.6%	39.5%	34.8%	34.4%	48.3%	23.5%	36.4%
Limited to the data sets	27.2%	30.3%	40.4%	40.6%	24.1%	5.9%	9.1%
Complicated and time consuming	23.0%	22.7%	23.4%	15.6%	20.7%	35.3%	36.4%
Requires manual intervention	22.6%	37.0%	27.0%	35.9%	17.2%	17.6%	18.2%
Does not work in real time	22.4%	26.1%	34.0%	18.8%	37.9%	17.6%	9.1%
Multiple solution providers	18.9%	20.2%	17.0%	21.9%	13.8%	17.6%	27.3%
Unable to adapt	7.5%	2.5%	5.7%	10.9%	10.3%	5.9%	9.1%
Existing systems work fine	7.4%	4.2%	3.5%	7.8%	6.9%	11.8%	9.1%
Unable to identify behaviors	1.8%	4.2%	3.5%	0.0%	0.0%	11.8%	0.0%

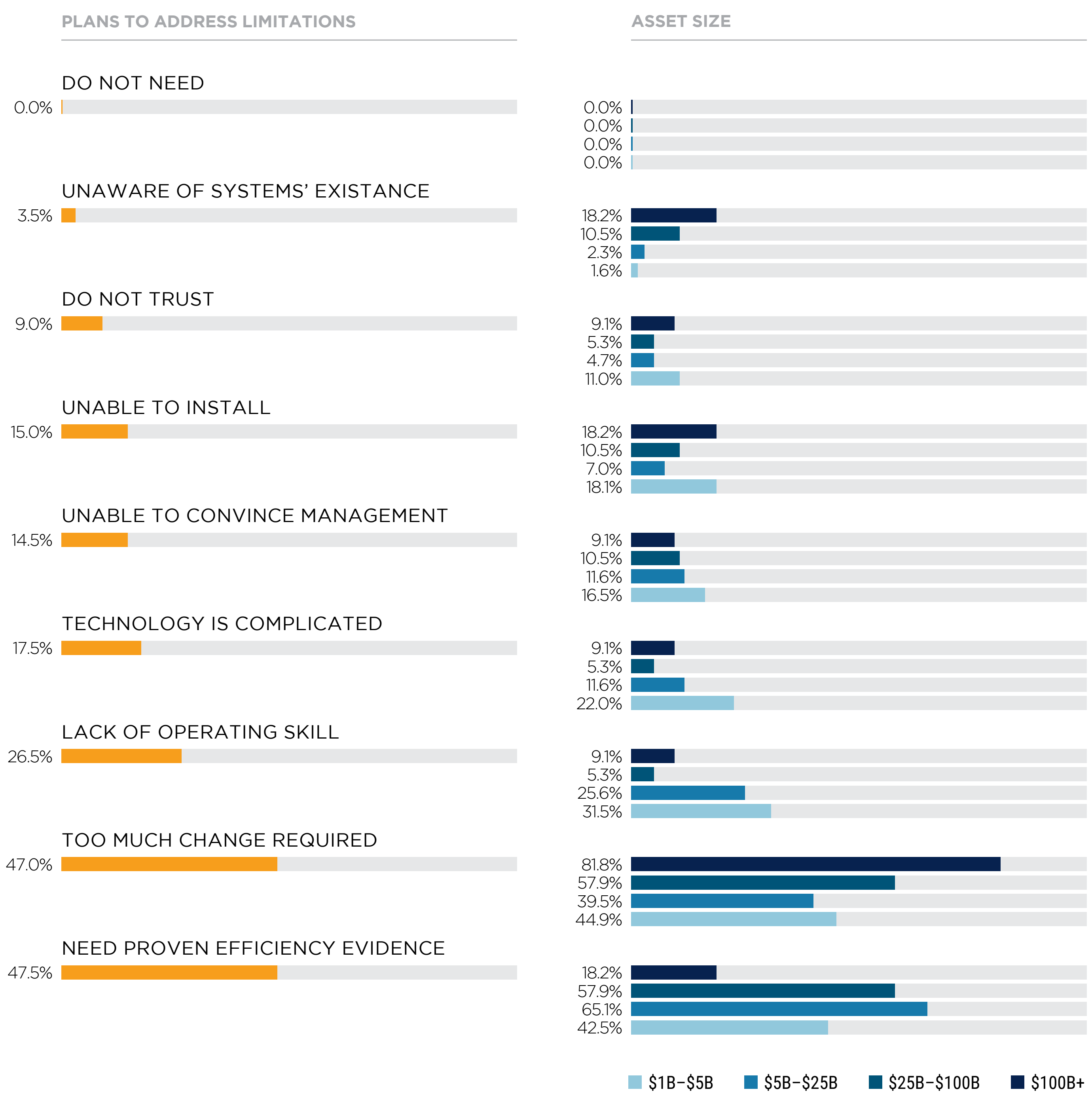
When respondents were asked why they had not yet implemented supervised or unsupervised learning technologies, most cited different motivations. In the end, 47.5 percent did not use these systems because they wanted to wait until there was more business use evidence. Another 47.0 percent simply said that implementing them would be too much of a change from their current systems.

42.3%

Share of FIs that said learning system technologies **were not transparent enough**

FIGURE 10:

How FIs plan to address their current systems' limitations
Share of FIs citing select plans to improve upon their current technological capabilities in the future, by size



Many banks already have their own legacy systems in place, many of which even perform the same operations as learning systems. It's likely that legacy solutions are not as efficient as learning systems, but they are already installed and banks do not have to spend more money to use them. It makes sense that they would wait for confirmation about such technologies' benefits before justifying additional short-term expenditures.

14.5%
Portion of FIs that had not implemented learning systems **because management could not be convinced to do so**

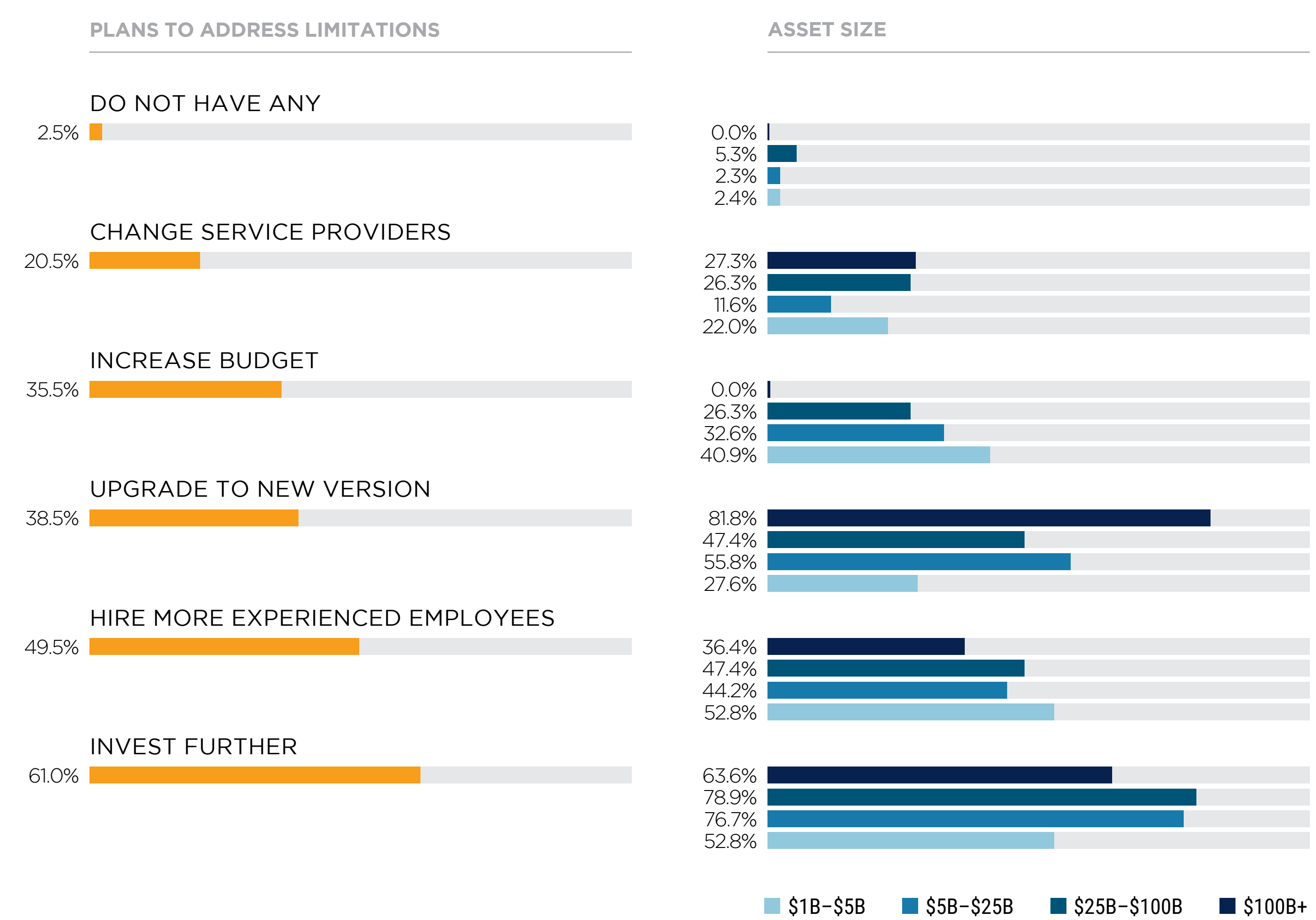
INVESTING
IN THE FINANCIAL FUTURE

Many FIs are hesitant to commit to learning systems without understanding their potential, especially when such a change would require drastic adjustments to the systems they already have in place. For those that already use supervised and unsupervised systems, most would rather address the technologies' limitations by investing more rather than getting rid of them.

Sixty-one percent of all survey respondents said they were planning to invest further in their supervised and unsupervised learning tools. On top of that, 49.5 percent intend to hire more experienced employees and 38.5 percent plan to upgrade their systems.

FIGURE 11:

How FIs plan to address their current systems' limitations
Portion of FIs that said they would address limitations in select ways, by size

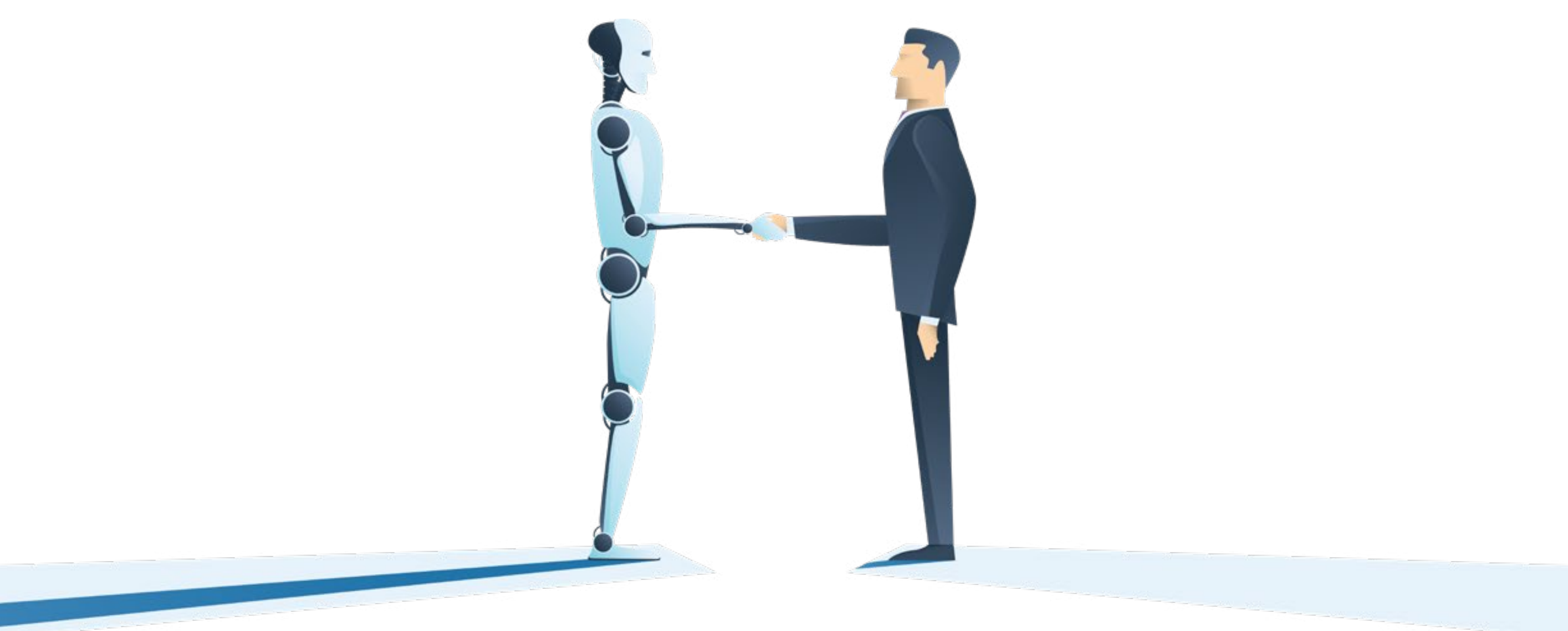


The ways in which FIs would address their systems' limitations changed by asset size. Of those with more than $100 billion, 81.8 percent intended to upgrade their systems. Only 27.6 percent of banks with the lowest holdings would do the same, making them the least likely group to do so. These smaller banks, were the most likely to increase their budgets, however, particularly when compared to those with the largest number of assets. Not one bank with more than $100 billion said this was how it planned to address limitations, but 40.9 percent of those with between $1 billion and $5 billion did.

Larger FIs likely have larger budgets, meaning they would freely be able to upgrade to newer technologies. It would be more difficult for smaller banks with smaller budgets to do the same, as they would first need to address such constraints.

Between these two extremes were banks with between $5 billion and $100 billion, which were most likely to address their systems' limitations by "investing further."

Learning systems are benefiting banks, a fact proven by not only the number that have used them and continue to do so, but because they also intend to continue to invest in them in the future.



CONCLUSION

The verdict is in: Supervised and unsupervised learning systems are here to stay. Banks are using them to enhance nearly all of their operations, from collections to customer lifecycle management to anti-fraud measures and beyond. More importantly, FIs appear to be loving the results. It is no longer a discussion of whether they will or should use learning systems to optimize their businesses, but a matter of realizing how.

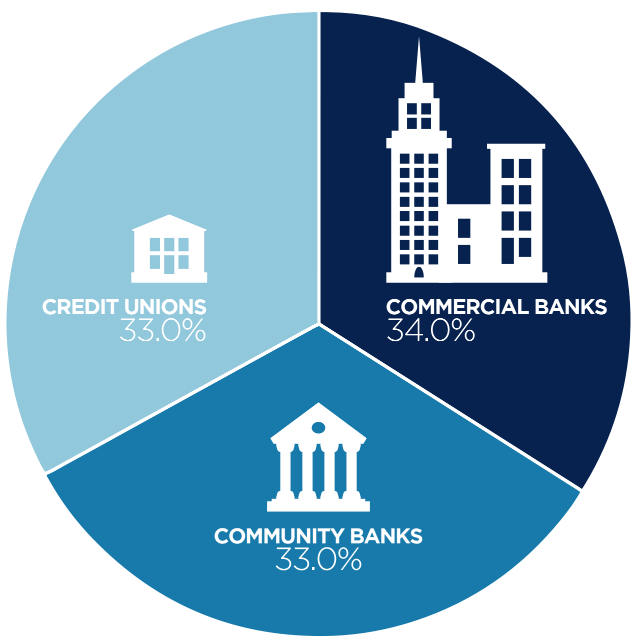
These solutions have quickly taken hold in the financial sector, but they remain largely misunderstood by most of the industry's decision makers. Many do not know the differences between the various supervised and unsupervised technologies, or for which functions they are best suited. As a result, a surprisingly large portion of FIs are using learning systems in ways that do not leverage their full potential.

Banks may not currently be getting their money's worth on these technologies, but the market has tremendous opportunity for growth. FIs must also invest in expanding their knowledge of these versatile and complex tools if they want to make the most of their investments. Having read this playbook is the first step toward more responsible and effective financial decision making.

METHODOLOGY

FIGURE 12:

How banks budget for AI and ML systems
Portion of respondents whose businesses allocate select budgets for AI and ML operations, by size



The AI Gap Study: Perception Versus Reality In Payments And Banking Services, a PYMNTS and Brighterion collaboration, draws its data from an extensive survey that investigated how FIs leverage a wide variety of supervised and unsupervised learning systems to optimize payments, cash flow management, regulatory and credit risk, financial fraud and other business operations. Though most may not qualify as true AI, and despite the fact that both their perceived costs and a lack of understanding hinder their implementation, these learning systems still help businesses alleviate operational pain points.

To learn more about how FIs are leveraging these technologies, we interviewed 200 senior executives at commercial banks, community banks and credit unions with assets between $1 billion and more than $100 billion. The industry distribution of participating firms was almost evenly split, with each representing approximately one-third of the overall sample.

As shown in Figure 12, the vast majority of participating firms held assets between $1 billion and $25 billion, and approximately 15 percent held assets of more than $25 billion.

Participating FIs were also diverse in terms of the number of branches they managed. The sample included banks and credit unions with anywhere from a single branch to more than 5,000 branches across the United States, and half of all the FIs we surveyed managed between one and 25 branches.

FIGURE 13:

Sample distribution, by assets
Portion of respondents categorized by asset value

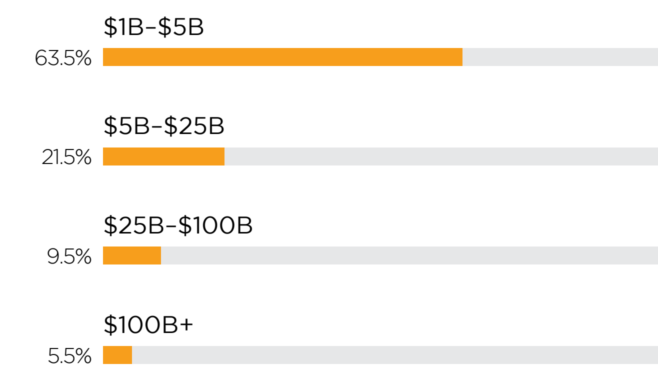
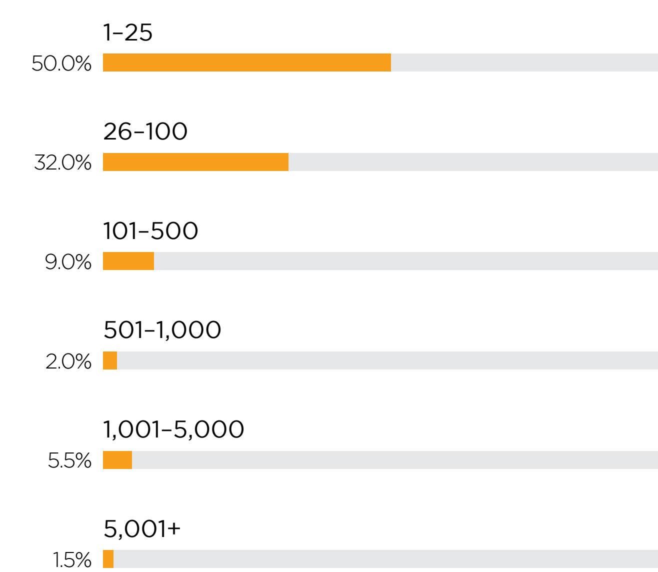


FIGURE 14:

Number of bank and credit union branches
Share of respondents classified by the number of branches they manage



ABOUT

PYMNTS.com

PYMNTS.com is where the best minds and the best content meet on the web to learn about "What's Next" in payments and commerce. Our interactive platform is reinventing the way in which companies in payments share relevant information about the initiatives that shape the future of this dynamic sector and make news. Our data and analytics team includes economists, data scientists and industry analysts who work with companies to measure and quantify the innovation that is at the cutting edge of this new world.

Brighterion mastercard

Brighterion, a Mastercard company, offers a portfolio of artificial intelligence and machine learning technologies, providing real-time intelligence from all data sources regardless of type, complexity and volume. Brighterion's technology is and serves as a general-purpose AI platform across varying industries to manage anti-money laundering, acquiring fraud, omni-channel fraud, early delinquency/collections and credit risk for businesses, governments and healthcare organizations through personalization, adaptability and self-learning that enables discovery, identification and mitigation of anomalous activities.

We are interested in your feedback on this report.
Please send thoughts, comments, suggestions or questions to theaigap@pymnts.com.