



AIism™ Insights

Succinct highlights of AI strategy & transformation trends and topical themes

Volume 1, Issue 10, October 2020

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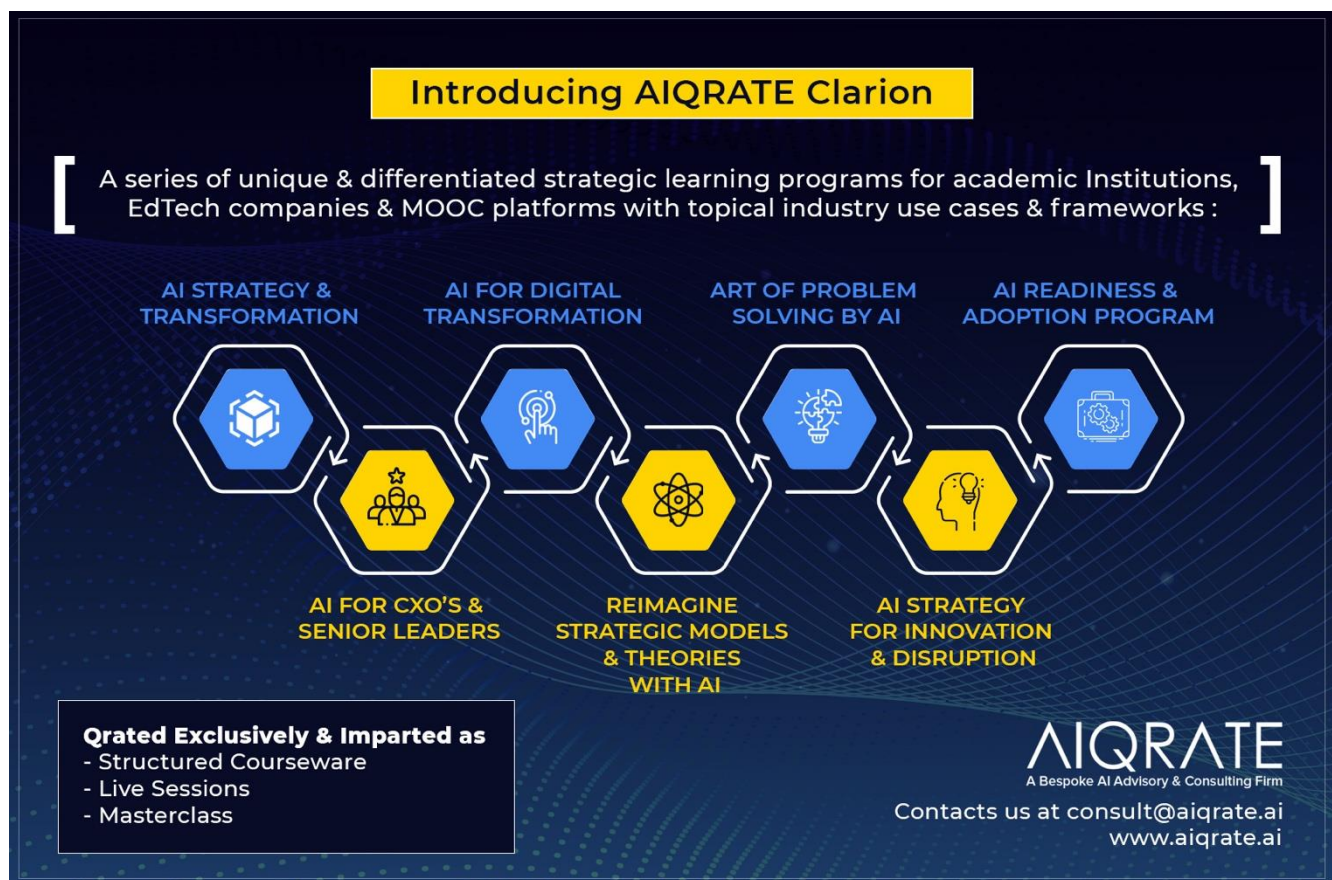
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AIQRATE
A Bespoke AI Advisory & Consulting Firm

Introducing AIQRATE Clarion

A series of unique & differentiated learning programs exclusively curated for Academic Institutions, EdTech Firms and MOOC Platforms

Artificial Intelligence (AI) has swiftly become the most aspirational learning opportunity for students & professionals; as the demand for learning programs in AI grows rapidly, the quality and relevance of AI specific programs has remained sub optimal. How do Academic Institutions, EdTech companies & MOOC platforms cope with the need to provide best learning & skill building to the future & existing workforce in this transformational area?



Introducing AIQRATE Clarion, a series of unique & differentiated strategic learning programs exclusively curated for Academic Institutions, EdTech companies & MOOC platforms with topical industry use cases & frameworks covering critical facets of AI led learning interventions for mainstream and executive education programs. AIQRATE works closely with academic institutions, EdTech players as a strategic learning partner

in building discerning AI programs and also works with them in building an ecosystem with bespoke AI awareness sessions & masterclasses, augmenting industry connect, re-skilling academia, infusing industry use cases and job ready learning frameworks.

Reach out to us at consult@aiqrate.ai for additional details or to schedule an exploratory meeting

AIQRATE Webinar Specials: CXO Series this month

AIQRATE WEBINAR SPECIALS: CXO SERIES

India's Fintech Revolution:
Strategic Perspectives for Growth & Scale

Speaker
VINAY BAGRI
CEO & Co-founder
NIYO Solutions

Moderator
SAMEER DHANRAJANI
CEO & Co-founder
AIQRATE Advisory & Consulting

Friday, September 4th 2020
6:30 – 7:30 p.m. IST
9:00 – 10:00 a.m. ET

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**AIQRATE WEBINAR SPECIALS:
CXO SERIES with**

Vinay Bagri
CEO & Co-founder
NIYO Solutions Inc.

Vinay Bagri is a business strategist turned entrepreneur with more than 18 years of experience and domain expertise in the corporate world working with diverse organizations like Parle, 3M, ICICI Bank, Standard Chartered, ING, and Kotak Mahindra Bank. Having spent over a decade in leadership roles across unsecured lending, retail liabilities, corporate salary, and retail banking strategy, Vinay brings a deep understanding of distribution and retail banking to the table.

AIQRATE WEBINAR SPECIALS: CXO SERIES

AI and Design:
Human centric Approach & Perspective

Speaker
GEETIKA KAMBLI
Managing Partner
Future Factory

Moderator
SAMEER DHANRAJANI
CEO & Co-founder
AIQRATE Advisory & Consulting

Thursday, September 3rd 2020
6:30 – 7:30 p.m. IST
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**AIQRATE WEBINAR SPECIALS:
CXO SERIES with**

Geetika Kampli
Managing Partner
Future Factory

With an MBA in marketing, an engineering degree, and a strong design practice, Geetika brings an unusual confluence of business, technology and design to her work at the 'Centre For Behavioural Research', at Asia's leading innovation and design firm, Future Factory. Her work at the Centre, is focused on designing technology through a user centered design approach. Over the past 15 years at the Centre, she has helped consumer and technology companies, as well as government/industry bodies across Asia, launch successful products by leveraging consumer behaviour.

AIQRATE Global AI Adoption Report 2020

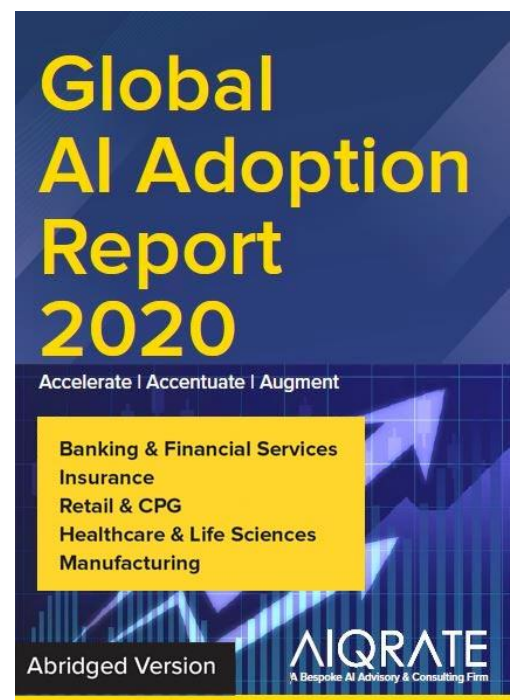
AI has become the most talked about business lexicon in boardrooms amongst the CXOs across industries. The strategic aspects of problem solving at scale, upping the ante on innovation & transformation and amplified decision making through AI are the three radical game changing levers for the enterprises, GCCs and startups. Enterprises have started realizing the efficiencies and growth opportunities that come with the adoption of AI.

AIQRATE has undertaken extensive research & analysis with global CXOs/GCC leaders/ Indian business leaders across a spectrum of global knowledge areas and ten parameters to curate first ever report on Global AI Adoption 2020 across five industry segments: BFSI, Retail & CPG, Healthcare, Lifesciences & Manufacturing.

[Global AI Adoption Report 2020 - Abridged Version:](#)

AIQRATE had undertaken extensive research & analysis with global CXOs/GCC leaders/Indian business leaders across a spectrum of global knowledge areas and parameters to curate first ever report on Global #AIAdoption 2020 across five industry segments: #banking & #financialservices, #insurance, #retail & #cpg, #lifesciences & #healthcare and #manufacturing. This abridged version carries salient nuggets from the previously published 6 volumes of the report.

[Read & Download all volumes of Global AI Adoption Reports](#)



AIQRATE In the News

AIQRATE at Leading Institutions

1. **CII:** Session on “Reimagine Industry 4.0 with AI for Scalability & Competitive Advantage” to be held on October 28th, 2020

For Registration please contact 99402 34408 | kazhal.vendhan@cii.in

The manufacturing sector under Industry 4.0 is reshaping itself with AI to achieve new models: additive manufacturing, smart factory, federated production, personalization, connected value networks. This is a critical point for a sector that accounts for 16 percent of Global GDP and 14 percent of employment – where the possibilities for innovation, transformation thru AI comes with new learnings and human capital challenges.

SESSION ON
REIMAGINE INDUSTRY 4.0 WITH AI
FOR SCALABILITY & COMPETITIVE ADVANTAGE

28 October 2020 1500 - 1700 hrs on Cisco WebEx

The Speakers

- Mr. Krishnakumar Natarajan
Chairman - CII BR AI, Digital & Robotics Forum, Co-Founder, Member & Managing Partner, Meta Ventures
- Mr. Sameer Dhanrajani
Chief Executive Officer
AIQRATE
- Mr. Hasit Trivedi
Global AI & Automation Service Delivery Head,
Infosys Limited
- Mr. Manas Agrawal
Co-Founder and CEO
Atria Analytics

DELEGATE FEE *
* GST 18% Extra

CII Member - INR 1000	Non Member - INR 1500
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For Registration, please contact:
+91 99402 34408 | kazhal.vendhan@cii.in | www.cii.in

Confederation of Indian Industry
125 Years - Since 1895

The inexorable shift from simple digitization (third industrial revolution) to innovation based on AI of industry 4.0 has brought about exciting opportunities that policy makers, business leaders and senior executives must pay attention to. Whilst, economic impairment and stunted growth have been deterrents, adoption and adaption of AI is no longer an option.

In order to stay relevant in this highly competitive and fast changing business environment, it is imperative for manufacturers to respond quickly to changing customer demands and maximize new market opportunities. From all indications, we are in an year of significant convergence where AI will propel industry 4.0 revolution and will drive changes in how we do manufacturing, and how we interact with customers, suppliers and wider ecosystem.

Given this background, Confederation of Indian Industry Southern Region is organising a Session "Reimagine Industry 4.0 with AI for Scalability & Competitive

Advantage" scheduled on 28 October 2020. The panel led by seasoned experts will cogitate on the application areas and will provide succinct narrative on leveraging AI to drive growth, scalability and above all, competitive advantage.

2. **ISB:** Live Virtual Programme on Leading with Analytics & Right Data

An intensive live virtual programme on Leading with Analytics & Right Data was delivered for 3 weeks starting 03rd October 2020 by the Centre for Executive Education. Sameer Dhanrajani was part of the faculty of this programme.



The banner features the ISB logo at the top left. The main title is "Leading with Analytics and Right Data" in white text. Below it, the subtitle reads "Power Business Decisions with Precise Insights". Further down, it states "LIVE Virtual Programme | October 03, 2020 | 3 weeks". On the left side, there is a portrait of Sameer Dhanrajani. To the right of the portrait, his name "SAMEER DHANRAJANI" is listed, followed by his titles: "Programme Faculty", "CEO & Co-founder", and "AIQRATE Advisory & Consulting". In the bottom right corner, there is a blue button that says "Apply Now at www.isb.edu" and the AIQRATE logo, which is described as "A Bespoke AI Advisory & Consulting Firm".

This program was attended by CMOs, senior business leaders and division heads from diverse functional backgrounds (Finance, Accounting, Operations and Human Resources) who wanted to hone their skills in data-driven decision making and gain a better understanding of the interface between marketing strategy and business analytics.

CXO Insights:

Managing Bias in AI: Strategic Risk Management Strategy for Banks



AI is set to transform the banking industry, using vast amounts of data to build models that improve decision making, tailor services, and improve risk management. According to the EIU, this could generate value of more than \$250 billion in the banking industry. But there is a downside, since ML models amplify some elements of model risk. And although many banks, particularly those operating in jurisdictions with stringent regulatory requirements, have validation frameworks and practices in place to assess and mitigate the risks associated with traditional models, these are often insufficient to deal with the risks associated with machine-learning models. The added risk brought on by the complexity of algorithmic models can be mitigated by making well-targeted modifications to existing validation frameworks.

Conscious of the problem, many banks are proceeding cautiously, restricting the use of ML models to low-risk applications, such as digital marketing. Their caution is understandable given the potential financial, reputational, and regulatory risks. Banks could, for example, find themselves in violation of anti discrimination laws, and incur significant fines—a concern that pushed one bank to ban its HR department from using a

machine-learning resume screener. A better approach, however, and ultimately the only sustainable one if banks are to reap the full benefits of machine-learning models, is to enhance model-risk management.

Regulators have not issued specific instructions on how to do this. In the United States, they have stipulated that banks are responsible for ensuring that risks associated with machine-learning models are appropriately managed, while stating that existing regulatory guidelines, such as the Federal Reserve's "Guidance on Model Risk Management" (SR11-7), are broad enough to serve as a guide. Enhancing model-risk management to address the risks of machine-learning models will require policy decisions on what to include in a model inventory, as well as determining risk appetite, risk tiering, roles and responsibilities, and model life-cycle controls, not to mention the associated model-validation practices. The good news is that many banks will not need entirely new model-validation frameworks. Existing ones can be fitted for purpose with some well-targeted enhancements.

New Risk mitigation exercises for ML models

There is no shortage of news headlines revealing the unintended consequences of new machine-learning models. Algorithms that created a negative feedback loop were blamed for the "flash crash" of the British pound by 6 percent in 2016, for example, and it was reported that a self-driving car tragically failed to properly identify a pedestrian walking her bicycle across the street. The cause of the risks that materialized in these machine-learning models is the same as the cause of the amplified risks that exist in all machine-learning models, whatever the industry and application: increased model complexity. Machine-learning models typically act on vastly larger data sets, including unstructured data such as natural language, images, and speech. The algorithms are typically far more complex than their statistical counterparts and often require design decisions to be made before the training process begins. And machine-learning models are built using new software packages and computing infrastructure that require more specialized skills. The response to such complexity does not have to be overly complex, however. If properly understood, the risks associated with machine-learning models can be managed within banks' existing model-validation frameworks

Here are the strategic approaches for enterprises to ensure that that the specific risks associated with machine learning are addressed :

Demystification of "Black Boxes" : Machine-learning models have a reputation of being "black boxes." Depending on the model's architecture, the results it generates can be hard

to understand or explain. One bank worked for months on a machine-learning product-recommendation engine designed to help relationship managers cross-sell. But because the managers could not explain the rationale behind the model's recommendations, they disregarded them. They did not trust the model, which in this situation meant wasted effort and perhaps wasted opportunity. In other situations, acting upon (rather than ignoring) a model's less-than-transparent recommendations could have serious adverse consequences.

The degree of demystification required is a policy decision for banks to make based on their risk appetite. They may choose to hold all machine-learning models to the same high standard of interpretability or to differentiate according to the model's risk. In USA, models that determine whether to grant credit to applicants are covered by fair-lending laws. The models therefore must be able to produce clear reason codes for a refusal. On the other hand, banks might well decide that a machine-learning model's recommendations to place a product advertisement on the mobile app of a given customer poses so little risk to the bank that understanding the model's reasons for doing so is not important. Validators need also to ensure that models comply with the chosen policy. Fortunately, despite the black-box reputation of machine-learning models, significant progress has been made in recent years to help ensure their results are interpretable. A range of approaches can be used, based on the model class:

Linear and monotonic models (for example, linear-regression models): linear coefficients help reveal the dependence of a result on the output. Nonlinear and monotonic models, (for example, gradient-boosting models with monotonic constraint): restricting inputs so they have either a rising or falling relationship globally with the dependent variable simplifies the attribution of inputs to a prediction. Nonlinear and nonmonotonic (for example, unconstrained deep-learning models): methodologies such as local interpretable model-agnostic explanations or Shapley values help ensure local interpretability.

Bias : A model can be influenced by four main types of bias: sample, measurement, and algorithm bias, and bias against groups or classes of people. The latter two types, algorithmic bias and bias against people, can be amplified in machine-learning models. For example, the random-forest algorithm tends to favor inputs with more distinct values, a bias that elevates the risk of poor decisions. One bank developed a random-forest model to assess potential money-laundering activity and found that the model favored fields with a large number of categorical values, such as occupation, when fields with fewer categories, such as country, were better able to predict the risk of money laundering.

To address algorithmic bias, model-validation processes should be updated to ensure appropriate algorithms are selected in any given context. In some cases, such as random-forest feature selection, there are technical solutions. Another approach is to develop “challenger” models, using alternative algorithms to benchmark performance. To address bias against groups or classes of people, banks must first decide what constitutes fairness. Four definitions are commonly used, though which to choose may depend on the model’s use: Demographic blindness: decisions are made using a limited set of features that are highly uncorrelated with protected classes, that is, groups of people protected by laws or policies. Demographic parity: outcomes are proportionally equal for all protected classes. Equal opportunity: true-positive rates are equal for each protected class. Equal odds: true-positive and false-positive rates are equal for each protected class. Validators then need to ascertain whether developers have taken the necessary steps to ensure fairness. Models can be tested for fairness and, if necessary, corrected at each stage of the model-development process, from the design phase through to performance monitoring.

Feature engineering : is often much more complex in the development of machine-learning models than in traditional models. There are three reasons why. First, machine-learning models can incorporate a significantly larger number of inputs. Second, unstructured data sources such as natural language require feature engineering as a preprocessing step before the training process can begin. Third, increasing numbers of commercial machine-learning packages now offer so-called AutoML, which generates large numbers of complex features to test many transformations of the data. Models produced using these features run the risk of being unnecessarily complex, contributing to overfitting. For example, one institution built a model using an AutoML platform and found that specific sequences of letters in a product application were predictive of fraud. This was a completely spurious result caused by the algorithm’s maximizing the model’s out-of-sample performance.

In feature engineering, banks have to make a policy decision to mitigate risk. They have to determine the level of support required to establish the conceptual soundness of each feature. The policy may vary according to the model’s application. For example, a highly regulated credit-decision model might require that every individual feature in the model be assessed. For lower-risk models, banks might choose to review the feature-engineering process only: for example, the processes for data transformation and feature exclusion. Validators should then ensure that features and/or the feature-engineering process are consistent with the chosen policy. If each feature is to be tested, three considerations are generally needed: the mathematical transformation of model inputs,

the decision criteria for feature selection, and the business rationale. For instance, a bank might decide that there is a good business case for using debt-to-income ratios as a feature in a credit model but not frequency of ATM usage, as this might penalize customers for using an advertised service.

Hyper parameters : Many of the parameters of machine-learning models, such as the depth of trees in a random-forest model or the number of layers in a deep neural network, must be defined before the training process can begin. In other words, their values are not derived from the available data. Rules of thumb, parameters used to solve other problems, or even trial and error are common substitutes. Decisions regarding these kinds of parameters, known as hyper parameters, are often more complex than analogous decisions in statistical modeling. Not surprisingly, a model's performance and its stability can be sensitive to the hyper parameters selected. For example, banks are increasingly using binary classifiers such as support-vector machines in combination with natural-language processing to help identify potential conduct issues in complaints. The performance of these models and the ability to generalize can be very sensitive to the selected kernel function. Validators should ensure that hyper parameters are chosen as soundly as possible. For some quantitative inputs, as opposed to qualitative inputs, a search algorithm can be used to map the parameter space and identify optimal ranges. In other cases, the best approach to selecting hyperparameters is to combine expert judgment and, where possible, the latest industry practices.

Production readiness : Traditional models are often coded as rules in production systems. Machine-learning models, however, are algorithmic, and therefore require more computation. This requirement is commonly overlooked in the model-development process. Developers build complex predictive models only to discover that the bank's production systems cannot support them. One US bank spent considerable resources building a deep learning-based model to predict transaction fraud, only to discover it did not meet required latency standards. Validators already assess a range of model risks associated with implementation. However, for machine learning, they will need to expand the scope of this assessment. They will need to estimate the volume of data that will flow through the model, assessing the production-system architecture (for example, graphics-processing units for deep learning), and the runtime required.

Dynamic model calibration : Some classes of machine-learning models modify their parameters dynamically to reflect emerging patterns in the data. This replaces the traditional approach of periodic manual review and model refresh. Examples include reinforcement-learning algorithms or Bayesian methods. The risk is that without sufficient controls, an overemphasis on short-term patterns in the data could harm the

model's performance over time. Banks therefore need to decide when to allow dynamic recalibration. They might conclude that with the right controls in place, it is suitable for some applications, such as algorithmic trading. For others, such as credit decisions, they might require clear proof that dynamic recalibration outperforms static models. With the policy set, validators can evaluate whether dynamic recalibration is appropriate given the intended use of the model, develop a monitoring plan, and ensure that appropriate controls are in place to identify and mitigate risks that might emerge. These might include thresholds that catch material shifts in a model's health, such as out-of-sample performance measures, and guardrails such as exposure limits or other, predefined values that trigger a manual review.

Banks will need to proceed gradually. The first step is to make sure model inventories include all machine learning-based models in use. One bank's model risk-management function was certain the organization was not yet using machine-learning models, until it discovered that its recently established innovation function had been busy developing machine-learning models for fraud and cyber security.

From here, validation policies and practices can be modified to address machine-learning-model risks, though initially for a restricted number of model classes. This helps build experience while testing and refining the new policies and practices. Considerable time will be needed to monitor a model's performance and finely tune the new practices. But over time banks will be able to apply them to the full range of approved machine-learning models, helping companies mitigate risk and gain the confidence to start harnessing the full power of machine learning.

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AIQRATE works closely with Boards, CXOs and Senior leaders advising them on their Analytics to AI journey construct with the art of possible AI roadmap blended with a jumpstart approach to AI driven transformation with AI@scale centric strategy; AIQRATE also consults on embedding AI as core to business strategy within business processes & functions and augmenting the overall decision-making capabilities. Our bespoke AI advisory services focus on curating & designing building blocks of AI strategy, embed AI@scale interventions and create AI powered organizations.

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