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ARTIFICIAL INTELLIGENCE-DRIVEN PROCESS AUTOMATION – IS IT REAL THIS TIME

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Abstract: *The disruptive potential of AI is being compared with that of electricity or steam engine. While automation of tasks and processes in banking is not a new concept, the pervasive nature of automation using intelligent technologies is on a different scale. This paper is based on extensive literature review and qualitative data gathered by the researcher from experts and practitioners in the fields of automation and banking. The article begins with building a logical yet easy to comprehend technology framework for process automation in banking. It further demonstrates the convergence effect of the framework using a sample business process in the retail lending space. The article concludes with establishing the real-nature of the technological impact on banking automation and hopes to assist the bankers in understanding this complex technological space.*

Keywords: *Intelligent automation, Convergence, Process, Banking*

Introduction

"ARTIFICIAL INTELLIGENCE [Al] and other developments in computer science are giving birth to a dramatically different class of machines that can perform tasks requiring reasoning, judgment, and perception that previously could be done only by humans. Will these machines reduce the need for human toil and thus cause unemployment?" (Nilsson, 1984)

In their 2004 book titled 'The New Division of Labor: How Computers Are Creating the Next Job Market,' noted MIT and Harvard professors Frank Levy and Richard J Murane had pointed out the near impossibility of replicating human cognitive processes such as driving in traffic (Brynjolfsson & McAfee, 2011). And yet in February 2018, the state of California, USA, has passed a law where for the first time, companies will be able to operate autonomous vehicles in public places without a safety driver behind the wheel (Hafner, 20). In 2011, the author had presented a paper recommending the of futuristic technologies such as AI and robotics for low-end routine tasks as well as supervisory work (Jayanthi & Pooja, 2011).

Evidence suggests that artificial intelligence technologies are coming out of hype mode of more than three decades due to other enabling ecosystem developments. It is also suffering from overuse and misplaced use in many cases due to its highly complex nature. This article seeks to deconstruct the technical mystery surrounding AI. It also seeks to evaluate the relative maturity levels of the basket of AI-related technologies, which are contributing to a technologically conducive ecosystem. AI is

termed as a general-purpose technology; however, we limit our discussion here to only to process automation in banking. In the process, the authors create a unique conceptual framework focussed on intelligent process automation in banking as a use case. The authors provide evidence of the usage of the framework with one common use-case from banking, which is unfolding in the current times. The objective is to spawn more detailed process reviews and discussions in the banking community to proactively address these impending changes.

DECONSTRUCTING ARTIFICIAL INTELLIGENCE

AI, digital, automation though different terms, are often used interchangeably and represent numerous technologies demonstrating certain key characteristics. Generally, AI comprises technologies such as deep learning, neural networks, natural language processing (NLP), machine learning, robotics & cognitive computing. Many times, AI is treated synonymous with cognitive systems or autonomous systems as well since they imbibe human-like traits of reasoning, problem-solving, learning, judgment, and decision-making. Many other studies have also defined AI in a similar manner comprising technologies like - speech recognition, NLP, semantic technology, biometrics, machine & deep learning, swarm intelligence and chatbot/voice bots (Stancombe et al., 2017), (Dawar & Lacy, 2017), (McKinsey, 2017).

An illustrative list of some of the popular technologies comprising or leading up to AI and relevant in the context of process automation is presented in Table 1.

Technology	Example
Artificial Intelligence	Machine Learning, Supervised Learning, Transfer Learning, Cognitive Computing, etc.
Neural Networks	Artificial Neural Network, Deep Learning, etc.
Robotics	Soft Robotics, Humanoid robotics, etc.
Automation Product Categories	Unmanned aerial vehicles, Chatbots, Robotic Process Automation, etc.

Table 1: AI Technologies

Source: (McKinsey, 2017)

Another useful way of defining Artificial intelligence in the context of automation can be derived based on task characteristics such as one taken from a recent TCS report. The report defines AI as those set of technologies that can perform the following four tasks:

> ***"Sense*** *– Being able to recognize images, sound, voice, video, and other 'unstructured' data (as well as structured data that has appeared in computer databases for years)*
> ***Think*** *– Deciding what such digital data means, and doing so at lightning speed based on algorithms*
> ***Act*** *– Determining what to do about insights after arriving at them*
> ***Learn*** *– Being able to continuously and automatically refine the knowledge and algorithmic models of an AI system based on its interactions with digital data; increasingly, such learning is referred to as 'machine learning.* "" (TCS, 2017)

The discussions and arguments in this article leverage these concepts and definitions to build the progress, placement, and contribution of the various components of an AI-driven process automation framework -**''The Great Convergence Framework (GC Framework".** While it is too early to see any mass-scale implementations of the framework and/or its variants, the authors take reference of one use-case from banking to demonstrate the deployment of the framework in real-life situations as a precursor to the future state of process automation in banks.

METHODOLOGY

Due to the forward-looking nature of the topic, and the lack of specific empirical studies in this context, we follow a rather non-traditional approach in this article. We do not report new data, demonstrate the existence of a new variable, or test hypotheses. Instead, the principal contribution of this article is to bring out linkages among seemingly disparate technological developments to create a cohesive, logical framework – GC Framework.

The GC framework is embedded in an extensive literature review. Over 50 articles, research studies, journal papers from traditional and non-traditional sources were scoured to provide the technology base for the framework. The findings were adapted to process automation in banking and validated for the Indian banking context via qualitative content analysis of face-to-face in-depth interviews from 28 experts both from the supply-side and demand side of the automation equation. The supply-side respondents comprise implementers, consultants, system integrators in the area of process automation, and the demand side respondents comprise senior bankers involved in either implementing the technology or using the same in business processes. A detailed profile of the participants in the study (n=28) are provided below:

S.No.	Code	Primary Category	Role	Organisation Profile
1	IN01	Bank	Banking Consultant	Large public sector bank
2	IN02	Bank	Ex-Generall Manager IT	Large public sector bank
3	IN03	Bank	Deputy General Manager	Large public sector bank
4	IN04	Bank	Deputy General Manager	Large public sector bank
5	IN05	Bank	Deputy General Manager	Large public sector bank
6	IN06	Bank	Vice President	New private sector bank
7	IN07	Bank	Vice President	New private sector bank
8	IN08	Bank	General manager	Reserve Bank of India
9	IN09	Bank	Zonal Head	New private sector bank
10	IN10	Bank	CEO	Business Correspondent
11	IN11	Bank	Deputy General Manager	New private sector bank
12	IN12	Bank	Chief Operating Officer	New private sector bank
13	IN13	Bank	Assistant General Manager	Large public sector bank
14	IN14	Bank	Assistant General Manager	Large public sector bank
15	IN15	Bank	Assistant General Manager	Large public sector bank
16	IN16	Technology	Chief Technology Officer, Banking & Financial	Large IT/ITES company

			Services	
17	IN17	Technology	Global Head - Digital Transformation	Large IT/ITES company
18	IN18	Technology	Assistant Vice President	Large IT/ITES company
19	IN19	Technology	Founder & CEO	Fintech
20	IN20	Technology	Ex-Head BPO	Large IT/ITES company
21	IN21	Technology	IT Consultant & Member	Task Force on Artificial Intelligence for India's Economic Transformation, Ministry of Commerce & Industry
22	IN22	Technology	CEO	Fintech
23	IN23	Technology	Head Corporate Strategy	Large IT/ITES company
24	IN24	Technology	IT Consultant	Large IT/ITES company
25	IN25	Technology	Chief Technology Officer, Banking & Financial Services	Large IT/ITES company
26	IN26	Technology	Assistant Vice President	Large IT/ITES company
27	IN27	Technology	Vice President	Large IT/ITES company
28	IN28	Technology	CEO	Fintech

The outcome is an internally consistent analysis that, while firmly grounded in published work, creates a new business-friendlyly intelligent process automation framework.

CONCEPTUAL MODEL – TECHNOLOGY SELECTION, GROUPING, AND PLACEMENT

The critical input to various technologies in the ecosystem comes from the literature review. The development of individual technologies is well established in the literature. The proposed framework, though embedded in technology elements, needs to bring out the business impact of one or more of these technology elements working together. For this purpose, we also need to assess the selection of technologies comprising the framework. The following six specific frameworks were studied and compared for relevance.

1. TOE Framework – Technology – Organisation – Environment
2. Diffusion of Innovations
3. Technology Readiness Level (TRLs) originally conceptualised by NASA
4. Gartner Hype Cycle and technology maturity levels
5. Reinforcement Loops
6. Motivation Theory

(Gartner Inc, 2018), (Gartner Inc., 2017), (Gartner Inc., 2017), (Gangwar & Date, 2015), (HOTI, 2015), (Botha & Atkins, 2005), (Olechowski, Eppinger, & Joglekar, 2015)

Each of these frameworks is industry standard used in varying scenarios, whether it be technology adoption in enterprises (covered by TOE and Diffusion of Innovations), or assessment of maturity level of specific technologies (TRLs and Gartner hype cycles), etc. It has to be noted here that no one theoretical framework for innovation implementation or technology assessment covers complex technologies and systems such as the ones selected for our GC Framework. However, we do take inspiration from the Gartner Hype Cycle and technology maturity levels to validate the selection of the technologies included in the GC framework.

We studied the Gartner Hype Cycles for some of the technologies selected for the GC framework (Gartner Inc., 2017), (Gartner Inc, 2018), (Gartner Inc., 2017). To our satisfaction, we found almost all the technologies placed in the enablement layer are out of the 'embryonic' phase and either in the 'emerging,' 'adolescent' or 'early mainstreaming' phase according to Gartner (detailed explanation of the maturity levels is given in the Annexure1). This means that the technologies selected for the framework have entered industries and businesses as technology solutions. This creates a sound foundation for the proposed framework.

The placement and grouping of technologies for bank process automation was done using the primary data collected from the interviews in response to the following questions:

Question (1): "We have seen in the past automation in banking services have either pushed tasks towards a self-service model, e.g., delivery channels or has codified some parts of rule-driven processes, e.g., credit scoring. In your view, what is different this time around with industry talking about 'intelligent automation' from a task and process perspective in banking?"

Question (2): "I will list some categories of popular automation technologies. Please rate their importance in its potential impact on Indian banking in the next ten years?"

Question (3): "Please provide any other technology which is not stated above but is very important in banking automation?"

The findings and results have been discussed below.

FINDINGS & RESULTS - 'THE GREAT CONVERGENCE' FRAMEWORK

In 2017, Accenture and Digital Transformation Initiative (DTI) of the World Economic Forum (WEF) published a report evaluating the impact of technology-based innovation on jobs across ten industries. The report charts out the 'cumulative technological capability' available today due to the simultaneous peaking of various technologies. The time graph plot in the report clearly shows the demise of older technologies like mainframes & client-server, and a convergence high towards 2020, for digital technologies including AI, IoT, smart machines, big data, etc. (Dawar &

Lacy, 2017). A similar sentiment is echoed in a paper by the IBA Global Employment Institute,

> *"the term Industry 4.0 comprises the technical integration of cyber-physical systems (CPS) into production and logistics and the use of the 'internet of things' (connection between everyday objects) and services in (industrial) processes – including the consequences for a new creation of value, business models as well as downstream services and work organisation. CPS refers to the network connections between humans, machines, products, objects, and ICT (information and communication technology) systems*." (Wisskirchen, et al., 2017: 12)

Overall, the collective power of select technologies to transform the automation landscape amplifies multi-fold as compared to their power if taken individually. This amplified effect that we will call 'The Great Convergence' (GC) is depicted in figure 1. The detailed building and placement of each component of the framework, as well as individual evidence substantiating the maturity level of the component, has been detailed in the next section.

The GC framework has been conceptualised as a building known as 'Intelligent Process Automation.' It has got two layers viz. Foundation layer and the building or the Enablement layer. The Foundation layer forms a conductive base for leveraging the technologies of the Enablement layer. The Enablement layer, in turn, has been modeled around the key characteristics of AI technologies viz. learn, think, interact, and decide (TCS, 2017). Even though some of the earlier technologies included in the framework may not strictly conform to these characteristics, they do lead up to newer technologies that imbibe these characteristics, thus providing a time-continuity in the framework.

The framework illustrates the continuum and convergence of technological progress individually and collectively. It is important for us to understand that technological disruption and changes happen incrementally on a continuous basis all around us.

The Foundation Layer

GC starts with the foundation layer comprising of:

1. Data Management
2. Hardware Infrastructure
3. Communication Highway

Data management - According to a 2016 IBM estimate, around 90% of data in the world today has been created in the last two years. A mind-boggling 2.5 quintillion (a quintillion in the US is a billion, i.e., 10^{18}) bytes of data gets generated every day (Seagroatt, 2017). Data forms the input for any machine-led automation. Traditionally, routine manual tasks are automated by breaking them down into well-defined flow charts and incorporating the same in software programs and scripts (Acemoglu & Autor, 2011). Input triggers a pre-programmed action or a set of actions resulting in the desired outcome.

Data management technology covering data storage, retrieval, and analysis uses systems with machine learning algorithms that can discover patterns in large heterogeneous data sets, commonly called big data. Machine learning algorithms use this big data as trainer data to mimic human understanding of context and experience (Frey & Osborne, 2013).

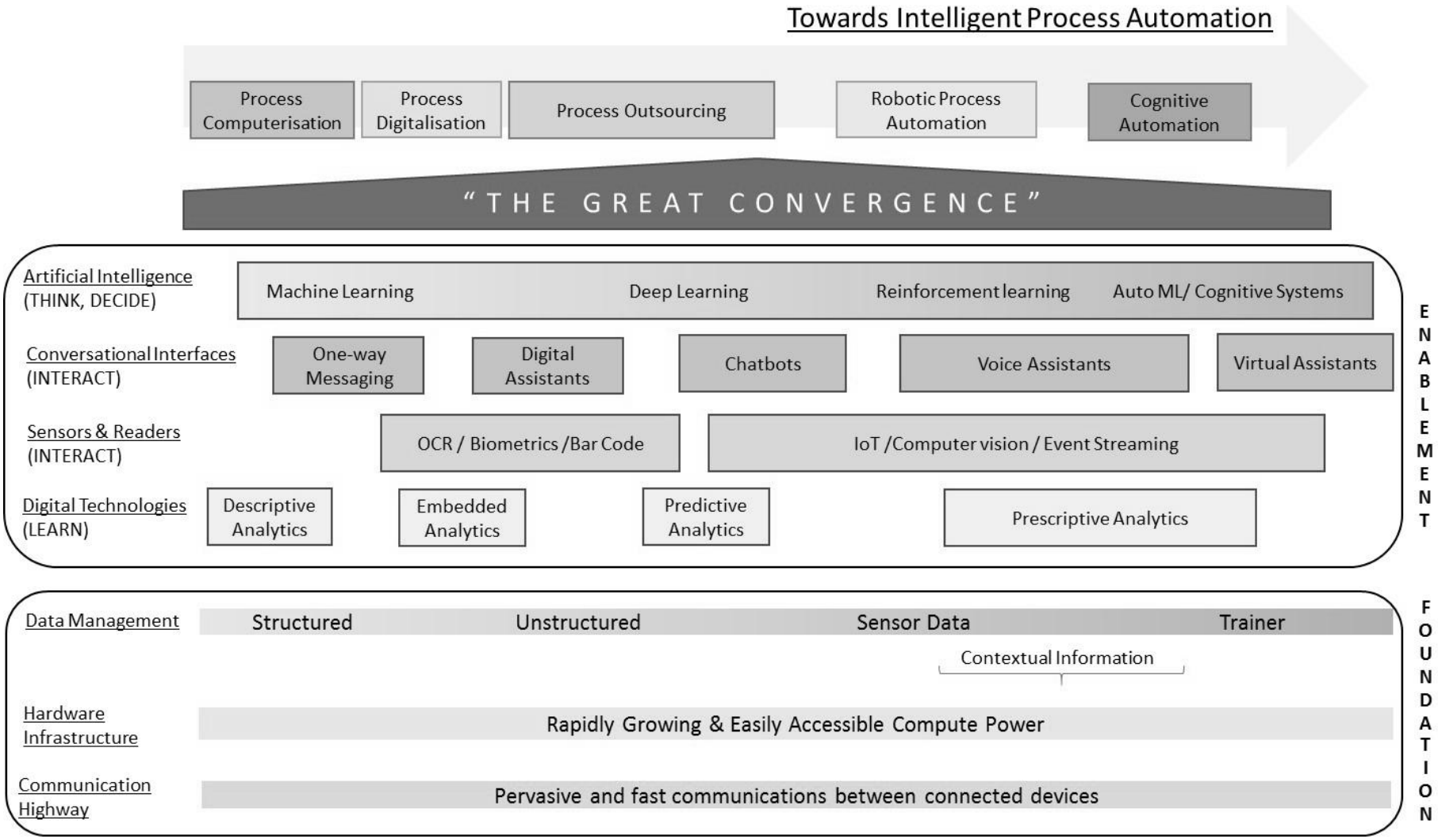

Figure 1 : The Great Convergence - Towards Intelligent Process Automation

For example, taking the case of handwriting recognition, OCR technologies have been around for a long time but with limited practical uses. The true success of an algorithm for handwriting recognition is measured when it can handle data sets containing different styles of writing (Plötz & Fink, 2009). This data, in turn, enriches the algorithm by providing the variety and the contingency elements a technology must manage to form a reliable substitute for human work (Frey & Osborne, 2013), (Plötz & Fink, 2009). Intelligent OCR is now being used in processing service requests and account opening by banks (Manyika, et al., 2013).

Fraud detection is a typical financial services task that benefits from the pattern and trend analysis of huge tranches of data (Chui, Manyika, & Miremadi, 2016). In health care, diagnostics tasks are being automated using trainer data. One recent example is Max Healthcare, which is training an AI tool to generate X-ray diagnostic reports, by feeding it with millions of patient records and the know-how of radiologists as trainer data (Singh, 2018).

Thus, with the progress in data technologies, automation is no longer confined to routine tasks that can be written as rule-based software queries but is extending to non-routine yet predictable tasks which can be translated into well-defined problems using algorithms working on now commonly available big data (Brynjolfsson & McAfee, 2011), (Frey & Osborne, 2013). This finding was also substantiated by our expert respondents.

Hardware infrastructure - The fuel of every technological engine is 'computational power,' and the start of every discussion on computational power is quite obviously Moore's law[1], which has incidentally held ground for decades. A 2011 study in the journal Science showed that in recent times, every new year allowed humans to carry out roughly 60% more computation than possibly could have been executed by all existing general-purpose computers in the year before. (Hilbert & López, 2011)

The exponential increase in computational power has been mirrored by a proportional decline in the unit cost of that power, as has been depicted in figure 2. Cheaper computer power and storage that facilitates faster processing means a system that may have taken a few days to solve complex problems in the 1990s now takes a fraction of that time at a fraction of that cost.

[2] Moore's law, prediction made by American engineer Gordon Moore in 1965 that the number of transistors per silicon chip doubles every year.(Source: https://www.britannica.com/technology/Moores-law accessed on February 12th, 2018)

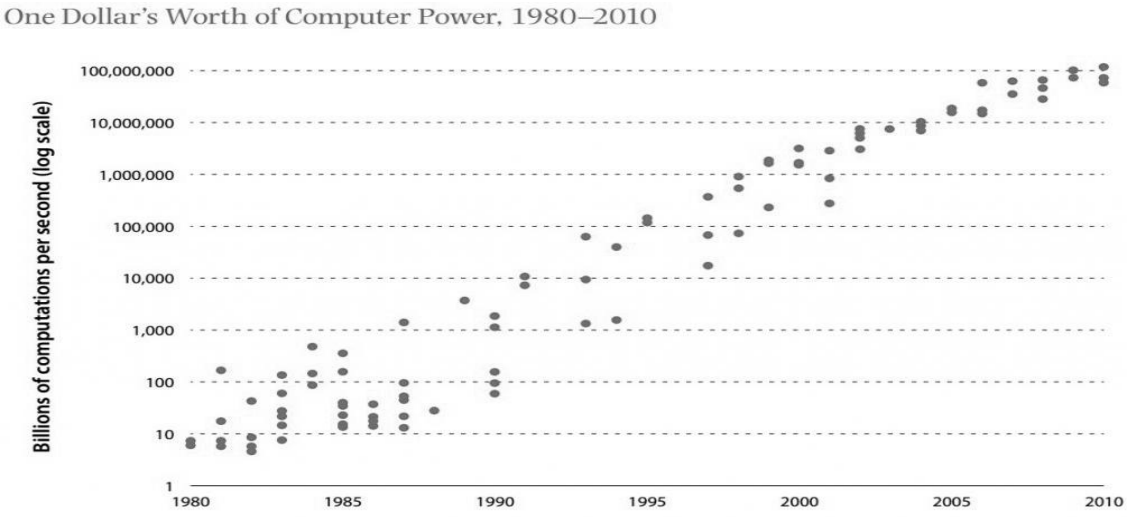

Figure 2: Computer Power

(Source: Nordhaus (2007): updated data through 2010 from Nordhaus, personal website, http://www.econ.yale.edu/-Nordhaus/homepage/, "Two Centuries of Productivity Growth in Computing.")

The third and equally important aspect is the accessibility of high-end servers and hardware infrastructure. Easy access to virtually unlimited storage and processing power is enabled via server farms and cloud technologies abundantly provided by the likes of Amazon, Microsoft, Google, etc. (Gutierrez, Boukrami, & Lumsden, 2015). Cloud models provide the means and availability to deploy power-hungry advanced machine learning algorithms on large amounts of data to get quick outcomes.

Communication highway - The average internet connection speed in the USA has grown from 3.6 Mbps in 2007 to 18.7 Mbps in 2017, a staggering growth rate of over 100% [2]. Closer home, though ranked 89th globally, India was also recording impressive growth in average internet access speed from less than 1 Mbps in 2007 to 6.5 Mbps in 2017 [3]. High-speed communication links and wireless technologies provide the highways for a seamless flow of information and data.

According to the study published in journal Science, the world's capacity for 2-way telecommunication evaluated between 1986 to 2007 grew at 28% per year. It has only risen at a faster pace in the last decade since 2007 (Hilbert & López, 2011). Faster communication enables connected devices to transmit large amounts of information in real-time to back-end systems for processing and for interaction systems to communicate back to front-end systems.

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[3] Source: https://www.statista.com/statistics/616210/average-internet-connection-speed-in-the-us/ accessed on February 17th, 2018

[4] Source: https://dazeinfo.com/2017/06/02/india-internet-speed-growth-q1-2017/ accessed on February 17th, 2018

While this is true in general, our panel of experts interviewed also mentioned communication technology or connectivity as a serious challenge in the Indian Banking context, especially in the non-urban centers where banking services are required to be delivered, and automation could help in doing that in a cost-effective and efficient manner. Connectivity remains a bottleneck for intelligent process automation in banks in India.

1.1. The Enablement Layer

Leveraging the developments in the foundation layer is a set of technologies, which comprise the 'enablement layer.'

Digital technologies (learning) - Earlier we have discussed, machine learning algorithms being able to extract hidden value from millions of heterogeneous data points and sources to apply advanced predictive analytics techniques and unearth useful patterns hereto impossible by humans (Brynjolfsson & McAfee, 2011).

Researchers from MIT Sloan School of Management have hypothesized that every task eventually translates into judgment based on predictions, and hence more accurate predictions make for sound judgments (Agrawal, Gans, & Goldfarb, 2017). If machines can generate reliable predictions and use those predictions to prescribe the next course of action, it will enable automation of tasks with a higher cognitive element. (Agrawal, Gans, & Goldfarb, 2017). Analytics technologies have advanced rapidly from the days of post-facto static reporting to dynamic real-time reporting and now predictive and prescriptive analytics. All this, of course, powered by the great firepower of the foundation layer, as discussed earlier.

In Banking, for example, predictive analytics is extensively used in the areas of risk management and fraud prevention. Mastercard deploys predictive AI to improve the overall accuracy of real-time approvals and false declines of transactions. This reduces operational costs and increases customer shopping satisfaction levels (Stancombe et al., 2017). Probability of loss is another area where, by subjecting loan portfolios to trend and pattern analysis, advanced algorithms predict the probability of default and assist in managing the credit risk of these portfolios (Seagroatt, 2017). The interview responses confirmed the use of AI-powered algorithms in areas like transaction monitoring, AML processing, alternate credit scoring models. This outcome can also be seen abundantly in the use-case detailed in section 6 of this article.

Readers & sensors (interaction) - OCR, bar code readers, and biometric recognition technologies have been around for decades, albeit with limited discrete use in access control, authentication, document management, invoicing, etc. Current sensor technologies falling under the umbrella of connected IoT devices augmented reality, image, speech, and biometric recognition has made sensor data one of the most important sources of big data (Manyika, et al., 2013) . The net effect is a gradual movement from discrete task-based use to integrated end-to-end deployments.

As per the Robotics Federation, the advanced sensors and readers thus form one critical connection between reality (humans, documents, devices) and intelligent algorithms/bots/systems running in the background. (Wisskirchen, et al., 2017). This

combined effect of machine learning with an OCR engine can also be seen in the use-case we detail subsequently.

Natural language processing (interaction) – 19th century heralded the early 'human-computer interaction' technologies like Dictaphones and personal digital assistants (PDAs). The last few years have seen significant developments in the comprehension, processing, and generation of natural languages, the way we commonly see in the likes of Alexa, Siri, Google NOW, and other such virtual assistants. (Chui, Manyika, & Miremadi, 2016) The key difference is the approach where earlier humans were adapting to machine language, and now machines are adapting to human language, the later fostering faster and more user-friendly, 2-way interaction between man & machine. These virtual assistants are powered by technologies that can understand varying accents, interpret conversational contexts, and respond intelligently (Manyika, et al., 2017a).

Such advances in user interfaces enable machines to manage and address a wider range of human requests, thus allowing more non-routine cognitive jobs to become automatable. For example, a company called Smart Action now provides call computerisation solutions that use machine language technology and advanced speech recognition to improve upon conventional interactive voice response systems. (Frey & Osborne, 2013). Many services companies in India are also deploying chatbots and voice assistants for customer services. The use of NLP and NLG is also seen in other forms of communication like email, chats, etc. (FICCI; NASSCOM; Ernst & Young, 2017).

However, there is one India specific challenge brought out by the experts, which is often ignored in global studies. This is the multiplicity of Indian languages, dialects, and accents, which poses a problem in oral communication using NLP/NLG today. Globally, NLP/NLG deployments typically assume single language and a literate language set of users, which is certainly not the case with a service like banking. This is another unique challenge to intelligent process automation in Indian Banking.

Artificial intelligence (thinking & decision-making) - The confluence of all layers discussed earlier; artificial intelligence comprises a basket of technologies, models, and algorithms. Four popular terminologies among these are machine learning, deep learning reinforcement learning, and cognitive systems.

Machine learning coined by Arthur Samuel in 1959 is quite simply the field of computer science that gives computer systems the ability to "learn" (i.e., progressively improve performance on a specific task) with data, without being explicitly programmed (Mitchell, 2006) . To be more precise, we say that a machine learns with respect to a task, performance metric, and type of experience and improves its performance at the same task following the same experience (Mitchell, 2006).

This basket of technologies and algorithms, powered by the foundation layer and other enabling technologies, are the brainpower behind AI and are used in varied contexts to simulate human tasks. The technologies on their own are fairly advanced but face some constraints to their ubiquitous use, such as availability of adequately

tagged trainer data, sufficient experience of learning, doing, success & failure, and a narrow range of operation.

DISCUSSION - INTELLIGENT PROCESS AUTOMATION IN BANKING

Service automation has traditionally been an intensive human job requiring typical human cognitive traits of perception, dexterity, reasoning, judgment, empathy, and decision-making. (Agrawal, Gans, & Goldfarb, 2017) . Previous attempts at service automation have essentially been as aids to humans in service delivery. It is typically characterised by input in the form of a data point or information, which is then acted upon by a pre-programmed set of instructions to provide the output (Acemoglu & Autor, 2011).

Hence the traditional approach to task automation using computer-controlled equipment and following certain pre-defined logic and rules gets augmented with the additional steps of learning, thinking, interacting and deciding as depicted in Figure 3.

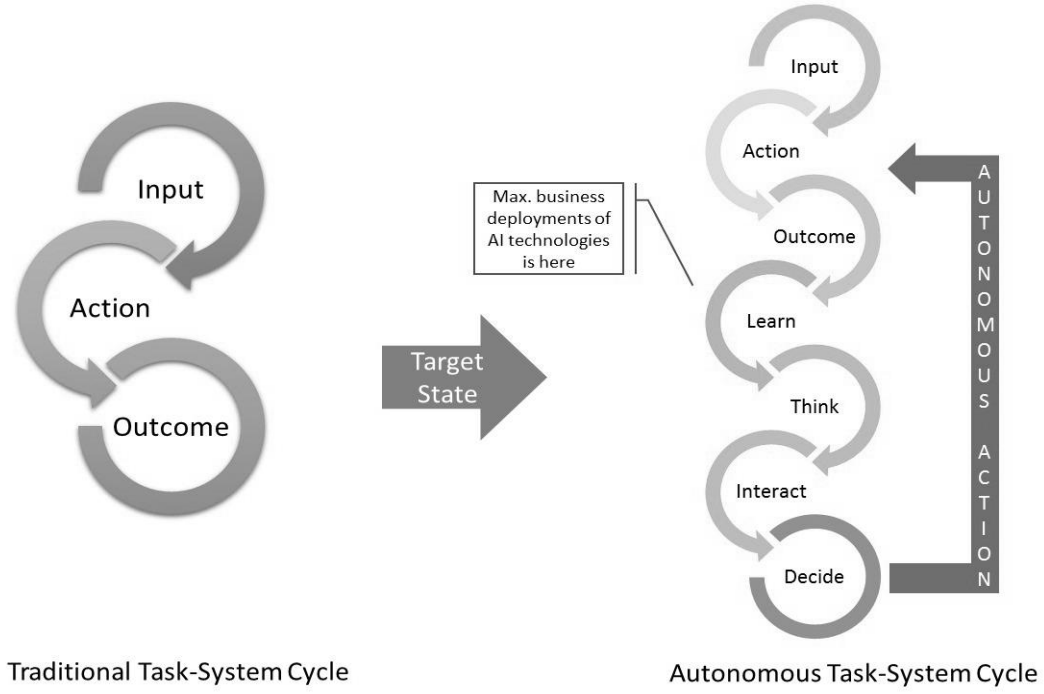

Figure 3 : Process Automation Cycle in an AI-Driven Environment

An AI-driven system not only learns from each process/task iteration, but also from the contextual information of the process itself, much like human learning process. This learning empowers the system to think, decide and initiate at its discretion any interaction between systems and between man-machine for completion of the process.

In order to get an insight into how intelligent automation is unfolding in banking services, we asked our panel of experts the following questions:

Question (1): "how automation in the past differs from intelligent automation now?"

Question (2): "Looking into the future, do you see more automation in the systems the bank uses for delivering its banking services over the next ten years? If yes, which functions? If no, kindly explain in support of your answer".

25 out of 28 experts cited the collective presence of data, computing power, and technology solutions as the fundamental difference in the ability to harness intelligent technologies, especially with reference to banking. The experts were asked to cite examples to support their view. Customer servicing (n=18) and retail loan processing (n=23) were the most frequently cited functions, which, even though they are already automated, are being further automated using intelligent technologies.

We select the 'Processing of a Retail Loan' as a use case to further discuss the GC framework on Intelligent Process Automation. For the sake of simplicity, we take a personal loan application being processed in a fairly automated environment and compare that with the process being executed in the intelligent environment using components of GC. Exception tasks are excluded from the scope of the study as they are handled by the human being in all scenarios. Figure 4 below is a level 0 process chart of a typical retail loan application approval process.

The key process steps depicted above highlight the following key features:

1. Automation is discretised using a loan processing system that does standardised standalone functions like calculate a credit score, store and forward loan file, workflow management, structured data uploads, and downloads.
2. The process is mainly orchestrated by a human being, the Loan Processing Executive (LPE). The orchestration is done manually, whether it is logging into multiple systems for credit checks, document verification, or interacting with a relationship manager, etc.
3. While the process is largely rule-driven, any special conditions which could be applicable are manually understood by either the LPE or the approver and manually incorporated in the sanction details.
4. Even though data may be available digitally, there is a large amount of duplicate data entry in various interfacing systems, especially the 3rd party systems. Automation to the extent of manually downloading data from one system and uploading the same in another system may be available in some banks.
5. Documentation remains a paper-based, manual exercise.
6. Credit scoring models rely on traditional parameters manually entered in the system.

The same retail loan process in an intelligently automated environment will look as depicted in figure 5 below:

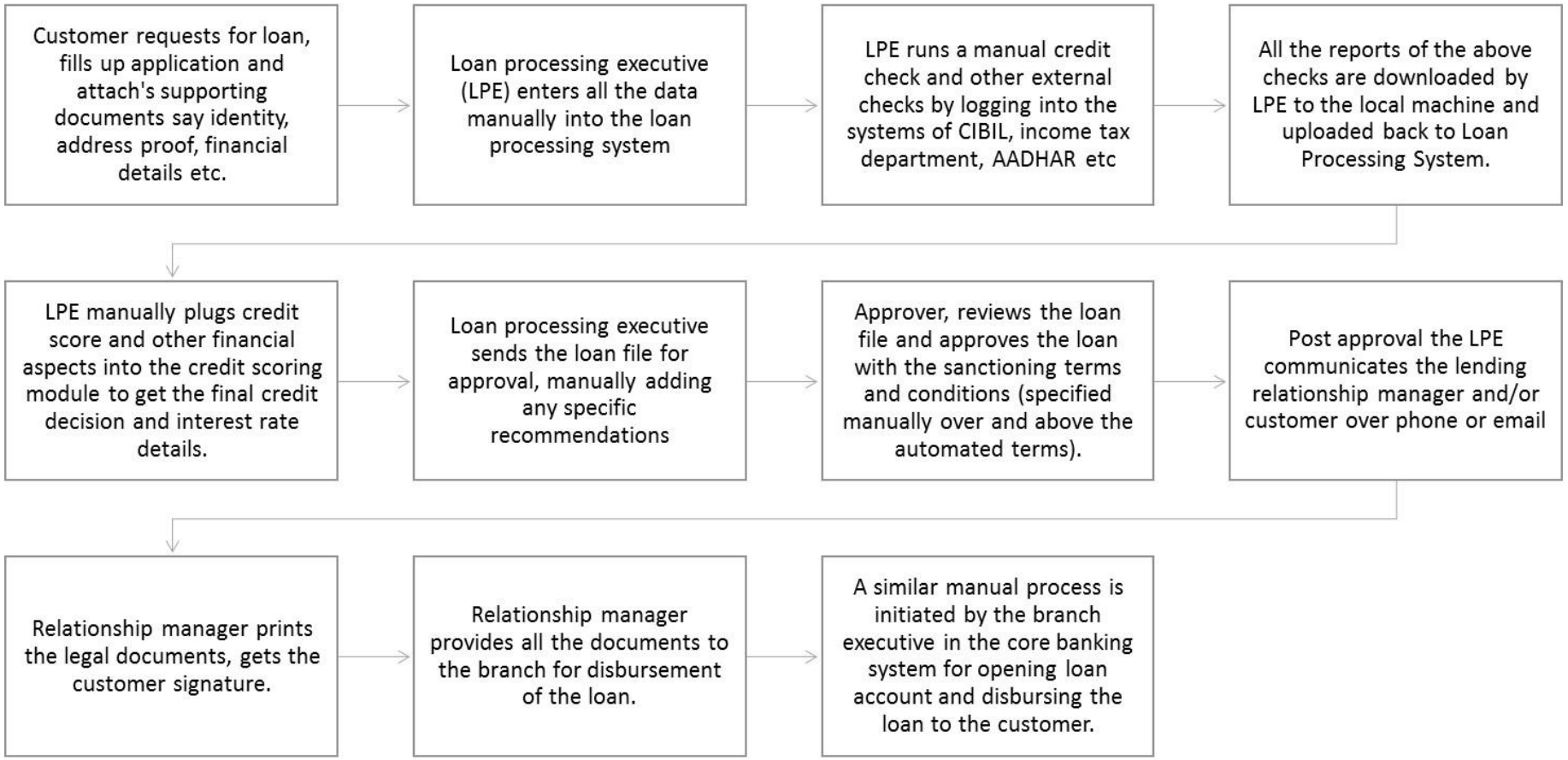

Figure 4 : As-is 'AUTOMATED' process of a Retail Personal Loan Approval

(source: Primary data viz.expert interviews)

Figure 5 : Intelligent Automation process of a Retail Personal Loan Approval

(source: Primary data viz.expert interviews, https://www.unlockinsights.com/blog/use-cases-of-rpa-in-banking-industry/, https://thelabconsulting.com/robotics-in-banking-with-4-rpa-use-case-examples/)

The key process steps in the intelligent automation context have the following characteristics:

1. It is integrated process automation. For example, the handoffs between step 2 to step 3 or from step 10 to 11 are automatically handled by the system, and data flows seamlessly from one system to another in an integrated manner.
2. The process is mainly orchestrated by a BOT (a Conversational Interface, the equivalent of a robot in service setup) managing most part of the process, including interactions with multiple external entities. This reduces turnaround times, improves accuracy, and reduces the manual drudgery of the LPE, who was the orchestrator earlier.
3. BOT itself leverages multiple technologies to execute different tasks. This is where the convergence can be seen. For example, step 4 is executed using OCR with machine learning (Reader plus AI), step 5 is again executed with a base set of rules enriched by machine learning from trainer data (AI plus digital technologies), step number 11 uses natural language processing & generation (Conversational Interface) to 'write' an email to the customer/relationship manager.
4. Even the credit scoring in step 8 moves from traditional scoring models to modern behavioural models (Digital Technologies on Big Data) where data is automatically extracted from various other external databases and social media sites to create a more holistic profile of the borrower.
5. Trust-based digital document exchange is enabled by other intelligent technologies like Blockchain, thus making documentation an automated task.
6. Improved credit scoring and recommendations in step 9 are possible when advanced analytics work on huge volumes of structured and unstructured data of trainer cases. These are fitted by machine learning algorithms to make the recommendations.
7. The BOT exhibits human traits of reading, initiating, writing, sensing, deciding, and recommending; tasks earlier done by the LPE.

Thus, using the convergence of technology components, we can see how the process has evolved from a simple Input-Output-Action to an intelligent process imbibing human-like traits. Our interviews with experts in banking and technology confirm that this scenario is not a futuristic scenario, and many such use-cases are playing out in banks in India and globally even today.

CONCLUSION & WAY FORWARD

Oxford University professors Carl Frey & Michael Osborne, in their seminal paper on job computerisation, have highlighted that one of the key factors driving automation will be the technological advances that allow problems to be adequately specified and these technological advances are also the boundaries for the extent of such automation (Frey & Osborne, 2013). Two significant factors namely 1) movement from technology-literate people to people-literate technology and, 2) convergence of the peaking of multiple technological factors are contributing to expanding technological boundaries (Manyika, et al., 2017b)

At the beginning of this article, we posed the quintessential question plaguing mankind, whether machines will cause mass human unemployment and set out before us the task of confirming that indeed the potential disruption is for real. We have shown with the GC Framework for Intelligent Process Automation that all the ecosystem elements critical to Artificial intelligence and related technologies have emerged from 'hype mode' into 'real business.' Using the GC Framework, we confirm the simultaneous maturity of the technology components, which has been validated using primary qualitative data and demonstrated using a retail loan approval process as a use-case. It further demonstrates that automation is now no longer confined to computerisation of tasks following rule-based procedures but is spreading to any task where data availability becomes a substitute for human knowledge and machine & deep learning algorithms evolve to the ability to simulate human decisions.

Banks across the globe are implementing AI & Machine Learning in banking operations like account opening, loan processing, risk management, customer support, fraud detection, NPA management, etc., and other tasks that are highly process-oriented and data-intensive (Urs, 2017).

One of the surprise findings from discussion with experts was that bankers (both in the public sector and private sector) though having the positional power to make technology decisions do not have enough knowledge and understanding of these technologies. This is a hurdle faced by senior bankers making them averse to making any significant decisions regarding adopting intelligent automation technologies in their core business operations. This article seeks to dispel that confusion among bankers by laying out the various components in a logical, easy to comprehend framework. It is through this article the authors want to initiate discussions in the banking industry with the objective of reviewing processes and proactively addressing the upcoming changes to the benefit of the stakeholders.

LIMITATIONS

Any study in the futuristic area of technology and process automation is a qualified expectation of experts and decision-makers in the field. It is neither a time-series study nor a statistical study of the before/after scenario simply because the events are unfolding as we speak. Thus, it needs to be viewed with pragmatic latitude and skepticism alike.

Also, the GC framework is not strictly a comprehensive time-series graph or a point in time depiction of the maturity of these technologies. There are many more constituent technologies and factors contributing to automation, and there could be overlaps in their development times and maturity levels.

For simplicity, the framework captures only critical milestones in process automation. There are many more emerging and/or adjacent technologies such as Blockchain which have not been captured in this framework. Some of these technologies could have an equally disruptive effect on automation but are currently out of the scope of our discussion here. However, this exclusion does not dilute the main argument favouring the convergence effect.

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Annexure 1

Gartner is a leading research and consulting company specialising in technology related areas. Gartner Hype Cycles provide a graphic representation of the maturity and adoption of technologies and applications, and how they are potentially relevant to solving real business problems and exploiting new opportunities. In these reports Gartner also defines the maturity levels of various business technologies on a 7 stage classification as detailed here:

Maturity Level	Status
Embryonic	• In labs
Emerging	• Commercialization by vendors • Pilots and deployments by industry leaders
Adolescent	• Maturing technology capabilities and process understanding • Uptake beyond early adopters
Early mainstream	• Proven technology • Vendors, technology and adoption rapidly evolving
Mature mainstream	• Robust technology • Not much evolution in vendors or technology
Legacy	• Not appropriate for new developments • Cost of migration constrains replacement
Obsolete	• Rarely used

(source: Hype Cycle for Emerging Technologies, 2017, Gartner id: G00314560, published 21 July 2017)