Available online www.jsaer.com

***Journal of Scientific and Engineering Research*, 2024, 11(9):1-11**

Research Article

ISSN: 2394-2630
CODEN(USA): JSERBR

A Study of the Effects of Artificial Intelligence-Driven Automation on Jobs in the Banking Sector

Kartheek Pamarthi

Masters in Computer Science
Email: kartheek.pamarthi@gmail.com

Abstract Technology adoption is important to assess the usage of technology and includes parameters other than automation potential. India is seen to be a country at high-risk of bearing the brunt of AI-led automation. It will impact its large workforce which is low-skilled and having low level of education. Decoupling of India's GDP growth with employment growth has already been seen with an employment elasticity of 0.2 in the period from 2019-2024. This is a worrying trend for a country such as India and its demographic dividend. A study of the future of jobs in the Indian market forecasts that by 2022, 9% of India's workforce will be employed in jobs which do not exist today and 37% in jobs with a substantial change in the skill set requirements. 43% of India's current workforce is at risk of potential displacement due to adoption of intelligent technologies. AI also creates an uncertainty in the minds of the existing workforce rife with fear that their jobs will be taken over by machines. Some of the current slowdown in fresh hiring and retrenchments in companies is being attributed to the adoption of automation and AI technologies in tasks and jobs. The ongoing pandemic has further accelerated the adoption of automating technologies in business Research studies to understand the implications of the forthcoming change are needed by multiple stakeholders like policy makers, business leaders, workers and students to proactively address the potential displacement of workforce. Given India's unique position in the current technology landscape, there is also a potential to turn risk into opportunity and gain competitive advantage by providing a future-ready workforce to the world. This research is a focussed study on the potential impact of AI-led automation on jobs in banking sector in India. It is focussed in geographical, sectoral, functional and technological scope. The study objective is to produce sharp insights for the stakeholders in the banking industry in India and for providing a blueprint for similar research in other industries in future.

Keywords banking industry, Artificial Intelligence, Future of Jobs

1. Introduction

Artificial Intelligence (AI) is empowering businesses with a range of new capabilities to create autonomous systems that essentially deal directly with end users and make independent decisions without human intervention. In doing so, AI and autonomous systems aim to simulate human intelligence, and incorporate human-like traits such as reasoning, perception, problem solving and planning into machines [1]. Artificial intelligence technologies have been around for more than three decades, but their true potential is being seen only now due to the availability of other ecosystem parameters like high-speed telecommunication, enhanced computing power and availability of a large amount of data. World Economic Forum in their report on 'Future of Jobs' identify the key technologies listed in Table 1.1 as drivers of change for the future of jobs.

Table 1: Technology Drivers of Change for Future of Jobs

Driver of change	Applications
Mobile Internet and Cloud Technology	Enabling improved service delivery and employee productivity. Cloud technologies enable access to processing power with no local requirements thus boosting spread of service delivery models on internet.
Advances in Computing Power and Big Data	Enabling utilization of advanced intelligent technologies which generate and consume huge tranches of data.
New Energy Supplies and Technologies	Discovery of new technologies to unleash traditional energy supplies like shale oil thus impacting the geopolitical equilibrium at the global level.
The Internet of Things	Sensors and devices in day-to-day living leveraging advanced communication highways and processing power to provide enormous data for AI technologies to consume and interpret.
Advanced Robotics and Autonomous Transport	Advanced robots with improved dexterity, intelligence and senses which are useful in manufacturing jobs and in service jobs as a replacement of human labour. Partly or completely autonomous vehicles can be deployed as soon as 2020 if suitable regulations are in place.
Artificial Intelligence and Machine Learning	Knowledge tasks which have been considered as human only bastion are now being automated with intelligent technologies like machine learning, voice recognition and natural language interfaces

The current study is focussed on artificial intelligence and machine learning as the key technology drivers which are enabling the automation of knowledge tasks with focus on the Indian banking sector.

Automation comes into play when a machine does the work that was earlier done by a human being or could never have been done by a human being [2].

Automation of human toil has been happening since the invention of tools. Industrial revolutions (IR) have defined significant periods of automation in human history, each driven by a unique set of technologies of those times. From a technology perspective the 1st Industrial Revolution was characterised by the invention of steam as a source of power and the 2nd Industrial Revolution was driven by electricity and the invention of the internal combustion engine [3]. The 3rd Industrial Revolution was a digital revolution driven by the internet and mobile technology communications. We are currently in the 4 th Industrial Revolution in which intelligent technologies or AI-led automation technologies as listed in Table 1.1 above, are expected to drive the changes in industry, business and society. From an impact point of view, the impact of 1 st and 2nd IRs was primarily felt in manufacturing sector leading to replacement of low-skilled workers with machine-skilled workforce and white-collared workers. In the 3rd IR, the service sector started getting impacted leading to the hollowing out of the middle-skill jobs by automating routine service tasks. Hence, each IR can be defined in terms of the technologies driving the IR and the impact of IR on work [4].

In the 4th IR, AI-driven automation is spreading further deep in the service sector and those tasks commonly defined as non-routine and difficult to automate are at risk of getting automated using intelligent technologies [5]. For example, non-routine tasks such as navigating a car through city traffic or deciphering the scrawled handwriting on a personal cheque, were beyond the ambit of automation till a decade ago. Today, the problems of navigating a car and deciphering handwriting are sufficiently well understood and many related tasks can thus be specified in computer code and automated.

2. Literature Review

Jobs will move from low-skill, rule-based tasks to high-skill complex roles. As with the past industrial revolutions and introduction of new technologies, while there will be disappearance of jobs in certain sectors, there will be a creation of new jobs and sectors all together. In this context this chapter provides a comprehensive review of the current literature relevant to the aspects of automation in services industry with special relevance to India. The main objectives of the literature review were to set the context and scope for

automation and identify research gaps leading to the research objectives. Finally, the literature reviewed also explains the research design and methods adopted in this study [6].

in [7], "Race against the machine: How the digital revolution is accelerating innovation, driving productivity, and irreversibly transforming employment and the economy", have called digitalisation enabled technological progress as 'Creative Destruction'. They have argued that technological progress does not benefit everyone equally in the society. It creates unfair advantage to certain section of skill groups (called 'Superstars' in the book!) while laying to waste certain others. They contend that the main reason for this uneven distribution of benefits is the inability of institutions and skill providers to adapt to the speed of changes brought about by technology.

Automation helps humans in achieving outcomes primarily by fully or partially carrying out tasks which were earlier undertaken manually. It has been seen that rarely has automation fully substituted humans by performing all the tasks performed by the person in completing a function. Rather automation has introduced structural changes to tasks or has introduced new tasks and activities that did not exist previously [8].

Advances in data storage and analysis techniques led to the enhancement of basic process automation to areas which augmented human labour in undertaking complex tasks such as exception management and customer service [9]. The research study goes on to say that the latest threat to human activity is in the form of cognitive automation or intelligent automation. This comprises multiple areas such as machine learning, computer vision, natural language understanding and generation used in combination to automate cognitive tasks.

Historically, humans have been automating work even before the invention of machines and sources of power such as steam and coal. Automation in its simplest form has been an integral part of human development. For example, invention of tools, domestication of animals and the invention of wheel, augmented human effort with alternate methods of doing work. However, in a formal sense, the journey of automation is typically discussed in the context of the Industrial Revolutions. Each Industrial Revolution has been driven by an underlying general-purpose technology1 which is the key driver in its power to transform work and society [10].

The introduction of the electrified mechanised assembly lines further automated numerous manual, repetitive jobs and replaced them with tasks requiring operations and maintenance of machines, a largely blue-collared skilled job. It was also observed that along with the bluecollared workers, there was an increase in the share of non-production white-collared workers required to manage the entire setup of the factory. Improved transport infrastructure (though not an automating technology in itself) had led to an expansion in markets from local areas to far flung markets. This increased the complexity of factory operations leading to an increase in the number of managerial and clerical employees employed by industrial units [11].

The 3rd Industrial Revolution or the digital revolution was characterised by the transformation of all things analog and mechanical to digital. Officially started in the 1980s the digital technologies were complemented by developments in other technologies like sensors, mobile devices and hardware. The 3 rd Industrial Revolution brought services into the ambit of automation. In manufacturing, General Motors had already started automation in the 1960s with the introduction of its first industrial robot. In the 3rd industrial revolution due to digital technologies, service industry like airlines became automation pioneers with the introduction self-service processes backed by the computer-based automation technology [12].

During the 3rd industrial revolution automation of the office-based services can be said to start with the advent of the typewriters, dictaphones and calculators [13]. While these office machines reduced the cost of doing the task and improved speed and accuracy, it also gave rise to an educated class of office workers who were also skilled in operating machines – a combination of education and skill [14]. Bar-code scanners and cash machines at retail shops transformed the work and skill requirement of check-out cashiers from making and totalling bills to scanning and packaging products [15]. Studies on the impact of computers-led automation indicate a change in the occupational structure particularly of middleskilled workers such as office staff. Routine tasks were getting automated and work was moving to lower-skill services occupations [16]. A study done by [17] on the US labour data between 1980 and 2005, showed a growth in the share of services occupations in 1990s after a decline in the earlier years, and a hollowing out of the middle-skilled workers.

3. Methodology

Research Process Based on the concepts outlined the researcher has compiled the research process as a series of steps as depicted in Figure 2:

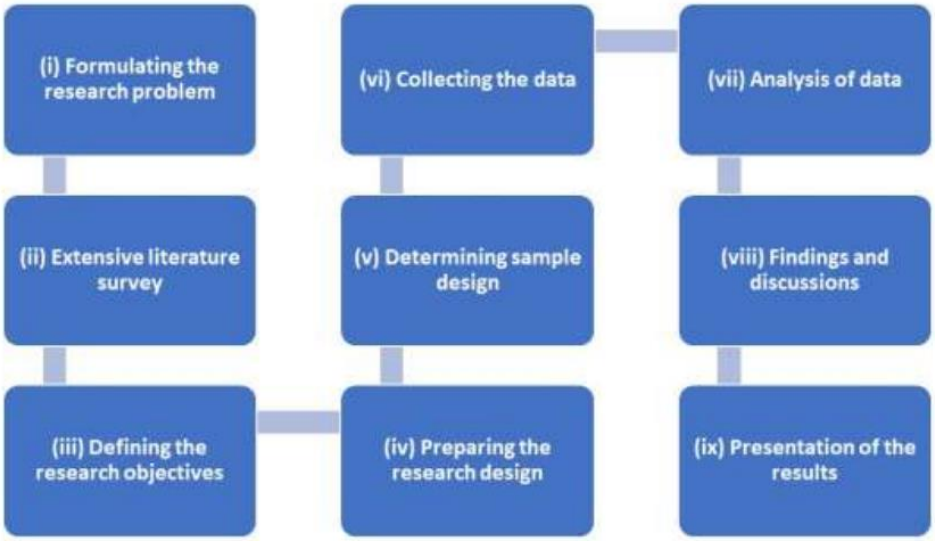

Figure 1: Steps in a Typical Research Process

Every research aims to solve a research problem. Articulation of the research problem is an important step in the research process as it provides the direction and context of the study being conducted. Literature review on the past work conducted by other researchers is the next step in the research process. Literature review reveals important aspects of the research gap, possible research designs, variables and scales which have been used in previous research and other information relevant to the current study. This information is useful in the entire duration of the study, hence needs to be conducted thoroughly and extensively. Based on the research gap identified during literature review, research objectives are outlined, the research design and sampling design determined. The actual study comprises the activities of data collection and analysis. The results are discussed in the context of the research objectives as well as any relevant results of past research. Finally, the summary and conclusion of the study is presented to the consumers of the research.

Preparing the Research Design

Research design is essentially a blueprint or a plan for conducting the research. While its contents vary with the context and type of research, research design as outlined in Kothari (2004) and Marczyk, DeMatteo, and Festinger (2005) typically contains the following:

a) A research approach and the detailed method to be used for studying the research problem.

b) Techniques and tools proposed to be used, tests and test conditions if any along with the type of instruments to be used in the study. In case secondary data is being used for the study, the research design also contains sources of data and the process of accessing and recording data.

c) For primary data a clear mention of the target population, sampling plan and method of identifying the correct sample is required. This is very critical as the sample needs to be representative of the population and determines the quality and integrity of data collected.

d) The methods used for processing and analysing quantitative and qualitative data as the case maybe. Upfront identification of these methods so that the tools and techniques of data collection can be chosen and designed accordingly.

The design forms the theoretical structure within which the research is conducted and facilitates the collection of relevant information in the most efficient manner and aligned to the research problem.

Research Approach

Research design varies with the type of research. Types of research can be determined by factors such as (1) the research purpose or goal, (2) context of research and (3) approach for the research. For the current study the research designs are categorised as follows:

Exploratory research

Research is exploratory when the research problem has not been studied enough in terms of variable definitions and establish the relationship between variables. This kind of research could have an objective to develop hypothesis rather than hypothesis testing. The research design of exploratory research needs to be flexible which encourages discovery of information which facilitates exploration of different dimensions of the problem (Kothari, 2004). According to the following three methods are used in exploratory research designs:

a) Survey of literature – Research builds upon past work to discover new information and problems. Hence, literature review forms the simplest and most effective first step in formulating a hypothesis or a problem. A bibliographic survey of relevant studies and a review of hypothesis used in past research will either lead to a rethink on the past hypothesis or a suggestion of a new hypothesis or discovery of unexplored research areas. The researcher may extend the boundaries of relevant literature to include other research contexts and theoretical constructs which can be applied to the current area of research.

b) Experience survey – In simple terms an experience survey is a survey of people having practical experience in the area of study or with the problem to be studied. Semi-structured and unstructured discussions with such people uncover new variables or provide insight into the possible relationship between the variables or provide a new way of looking at the research problem. This is the most potent exploratory research design used in areas of business and innovation. Here the choice of the respondents and the skill of the investigator both are critical in getting the right results. The discussions can be guided by an interview schedule which ensures systematic questioning and also incorporates sufficient flexibility allowing respondents to bring up new ideas and insights which have not been considered earlier.

c) Analysis of specific examples – Some research problems neither have past research to guide discovery nor sufficient experienced people to survey. In such cases, selected examples, or instances of the phenomenon of interest is chosen for providing relevant insights. In extreme cases even identification of the examples can follow an unstructured path employing multiple approaches. Thus, there is no rule or guideline for this kind of a research design and is dependent solely on the research problem and the context in which the problem is set in.

Research Method

A study could adopt more than one research designs for different parts of the research process. This kind of a method generally called mixed method combines both qualitative and quantitative research, exploratory and descriptive research. Regardless of which research design(s) is(are) adopted it is essential to specify the research methods proposed to be used in the study. Research methods typically operationalise the design in terms of methods for data collection, sampling design, analysis and interpretation based on the scientific method.

Tools and Techniques for Data Collection

For the exploratory and descriptive research designs, there are many techniques of investigation and data collection. Some of the popular ones are:

Case Studies – Case Study is an in-depth examination of one or more entities. These could be people, companies, communities etc. The objective of a case-study is a comprehensive description of the entity or entities under study.

Naturalistic Observation - This technique is used in social and anthropological studies wherein the investigator observes the target population in their natural settings.

Focus Groups - Focus groups are groups of people brought together to discuss the topic at hand for a fixed period. It is an effective technique for market research while launching new products and services to gain insights of people's reactions

Survey Studies - The current study uses this technique as part of the descriptive research or survey design as it is also called. Surveys are done on a large number of people using structured instruments to get the required information. The key steps used in designing the survey are as follows:

1) General objectives - Defining the general purpose and goal of the survey.

2) Specific objectives - Specifying the type of data that will be collected to achieve the specific research objectives.

3) Questionnaire – Incorporating the relevant variables and scales of measurement, types of questions and pretesting the questionnaire are major items in questionnaire development as a tool for enquiry.

Sampling Design

Identifying the target population and the sampling techniques are the basic principles of a sampling design. Most research studies (other than census surveys) are based on selecting a representative sample which mimics the characteristics of the target population and administering the investigation tools to the sample. Thus, a sampling design is constructed before the actual activity of data collection is done. Some of the key sampling designs are given below:

• Deliberate sampling or purposive sampling
• Judgement sampling - Judgement sampling is frequently used in qualitative research where the objective is to get insights and new ideas from specific people or instances.
• Simple random sampling or probability sampling
• Systematic sampling
• Stratified sampling – Used extensively when the population is not homogeneous and can be stratified into sub-populations and sample selected from each stratum.
• Quota sampling – Stratified sampling where the size of the quota for each stratum is proportionate to the size of that strata in the population. Quota sampling is an important form of non-probability sampling.
• Cluster sampling and area sampling
• Multi-stage sampling
• Sequential sampling

4. Results and Discussion

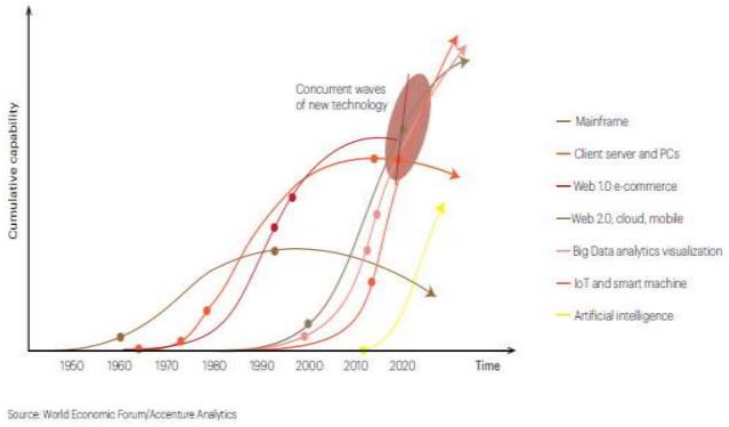

Figure 2: Convergence of AI Technologies and Foundation Components

It has been seen in the literature review that AI is not a new concept and the question posed by Nils J Nielson more than three decades ago (as mentioned in the quotation at the beginning of this section), that same question is being investigated in this study in 2020. The difference between then and now was found in the 4th theme of 'Convergence'. The 'cumulative technological capability' available today due to the simultaneous peaking of various technologies as shown in Figure 3.

Table 2: Cross-tabulation of Indian Banking Occupations

Type of occupation	Management level (Top)	Management level (Middle)	Management level (Junior)	Total
Staff Function	--	4	18	22
Business Function	--	3	21	24
General, Others	3	2	2	7
Total	**3**	**9**	**41**	**53**

The list is given in Annexure1. The banking occupations were further categorized based on management level and type of function. The cross-tabulation of the categorised occupations is given in Table 2.

Table 3: Break-up of Occupations on basis of NIC 2022 Classification

NIC Industry Classification	Number of occupations
Agriculture	1
Automotive	4
BFSI	22
IT-ITeS	14
Legal Activities	1
Media and Entertainment	2
Office Administration and Facility Management	2
Organised Retail	4
Telecom	2
Not Defined	1
Total	**53**

The categorisation of occupations based on National Industrial Classification - NIC 2022 (Source: www.mospi.nic.in) is given in Table 3. Twenty-two banking occupations were found to be mapped to BFSI sector and 31 occupations were mapped to other industries. The second highest mapping of 14 occupations was to the IT-ITES sector and 4 each to retail and automotive sectors. Other occupations were tagged to staff functions like office administration, office support and legal which are common across multiple sectors.

Table 4: Final Sample Composition of the Task Analysis Questionnaire Survey

Respondent Category	Number of completed responses	Number of incomplete /blank responses	Total
Business Correspondents	66	41	107
Retail loan processing executive	59	45	104
Retail operations executive	50	55	105
Teller	47	53	100
Customer Service Executive	51	58	109
Technology consultants	34	21	55
Total	**307**	**273**	**580**

Over 1000 questionnaires were distributed in paper form and as online links to the target sample. A total of 580 responses were received of which 307 responses were complete, while 273 responses were either blank or incomplete. This translates to a response rate of 53% for completion of the questionnaire. The final sample size of respondents which was considered for analysis was 307 of which 273 were bank staff and 34 were technology consultants. The break-up of the sample composition is given in the Table 4.

Table 5: Organisation Mix of Bank Staff

Category of Bank	Completed sample	Percentage
Nationalised	127	47%
Private Sector	74	27%
SBI	72	26%
Total	**273**	**100%**

Technology consultants were from mid-size and large-size technology companies involved in developing and implementing banking technologies. The sampling mix targeted for bank employees was achieved with a deviation of 1%. Respondents from 14 banks provided inputs. The organisation profile of the 273 respondents from banks who completed the survey is given in the Table 5.

Table 6: Respondent Category-Wise Job Experience

Respondent Category	Average Experience of the Respondents who have Completed the Questionnaire
Business Correspondent	4.6 years
Retail loan processing executive	10.9 years
Retail operations executive	12.3 years
Teller	8.2 years
Customer Service Executive	8.4 years
Technology Consultants	7.3 years

Since it was important to establish the credibility of the respondents to provide reliable inputs, data related to their experience profile was also sought in the survey. The average experience of the respondents was 8.6 years, and the job-wise break-up of the experience is given in Table 6.

Table 7: Codification Scheme

Item	Number of digits	Values
Job	1	1 – Business Correspondent 2 – Retail Operations Executive 3 – Retail Loan Processing Executive 4 - Teller 5 – Customer Service Executive
Task Level	1	1 – Aggregate Task 2 – Task
Variable	2	01 - Expertise 02 - Team management 03 - Finger Dexterity 04 - Customer Interaction 05 - Physical Movement 06 - Task Frequency 07 - Current state of technology adoption 08 - Automation potential
Running number of tasks	2	01-99
Value of the variable	1	1-4

All the respondents are graduate and above. All respondents were found to be experienced and qualified to provide the responses to the surveys. Quantitative data was collected for the tasks falling under the five jobs selected for analysis. For ease of understanding of the respondents, the tasks and variables were in written English. However, for the purpose of statistical analysis it was important to codify the items numerically wherever possible. The codification scheme adopted for data analysis is given in Table 7.

Validating Primary Data

After completing data collection and codifying the data it was important to understand the profile of data collected. This is critical since many tests and statistical analysis tools have assumptions of data types and distributions. The following tools and techniques were adopted to test, validate and understand the profile of final data collected.

Testing Reliability

Research reliability is important in ensuring internal and external consistency of measurement. While external reliability can be measured by repeating the measurement at a later stage and comparing both results, internal

reliability measures that the scale being used for measurement of a construct is reliable. During pilot testing phase, the questionnaires were evaluated qualitatively as well as tested for reliability and validity before proceeding for final data collection using Cornbach Alpha.

Table 8: Reliability Testing for Final Questionnaire

Reliability Statistics	
Cronbach's Alpha	No. of Items
.875	51

The reliability of the final questionnaire was 0.875 which is more than the threshold of 0.7. The individual items were also found to have values above the threshold of 0.7. Thus, the reliability and internal consistency of the scales adopted for final data collected was confirmed and found acceptable.

Table 9: Results of Collinearity Test (VIF)

Coefficients[a]			
Model		Collinearity Statistics	
		Tolerance	VIF
	Team Management	.921	1.086
	Finger Dexterity	.942	1.061
	Customer Interaction	.969	1.032
	Physical Movement	.973	1.028
	Task Frequency	.982	1.018
	Current state of technology adoption	.987	1.013
a. Dependent Variable: Expertise			

Collinearity in the data was tested statistically using Variance Inflation Factor (VIF). VIF is one of the most widely used rules which measures the strength of linear dependencies between independent variables. VIF for independent variables is normally greater than 1 and as such there is no formal rule for an acceptable value. High values of greater than 10 are considered dangerous for use in modelling and low values are generally preferred (Yoo, et al., 2014). The results of the multicollinearity tests are given in Table 8.

Table 10: Test of Normality

Tests of Normality						
	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Expertise	.237	408	.000	.800	408	.000
Team Management	.214	408	.000	.802	408	.000
Finger Dexterity	.240	408	.000	.799	408	.000
Customer Interaction	.336	408	.000	.731	408	.000
Physical Movement	.240	408	.000	.799	408	.000
Task Frequency	.464	408	.000	.520	408	.000
Current state of technology adoption	.277	408	.000	.858	408	.000
a. Lilliefors Significance Correction						

While the K-S test is a popular test for normality, many researchers recommend Shapiro-Wilk's test as it has better power than the K-S test. The results of both the tests are given in Table 9.

5. Conclusion

The classification model for task automation developed earlier is based on technological capability of the AI technologies to automate tasks. Mere presence of automation potential does not signify that the tasks will get automated and hence work will get impacted. For that to happen automation potential must move to automation adoption. However, the distance between technological capability and technology adoption is determined by parameters both technical and non-technical. The purpose of embarking on this study was to evaluate the impact of intelligent automation on jobs in banking industry. Hence the study progressed to the next logical phase of identifying those parameters which are important for technology adoption. This was an exploratory phase in the study which followed a qualitative approach to data collection via interview method. Directed content analysis was adopted for data analysis. Two industry standard technology adoption frameworks TOE and TAM were selected as reference frameworks for analysis. The factors identified using secondary data were mapped to the categories and themes in these frameworks. This created a baseline list of categories, themes and factors impacting implementation of AI using secondary data. Semi-structured interviews were conducted with 28 technology banking experts and data collected was used for primary data analysis. The data when compared with the baseline list of categories, themes and factors created using literature review data resulted in the following key findings.

References

[1]. Acemoglu, D., & Autor, D. (2011). Skills, tasks and technologies: Implications for employment and earnings. Handbook of Labor Economics, 4(B), 1043-1171. https://doi.org/10.1016/S0169-7218(11)02410-5

[2]. Acemoglu, D., & Robinson, J. A. (2012). The turning point. In Why nations fail: The origins of power, prosperity, and poverty (p. 109). Random House Digital, Inc. Retrieved January 13, 2018, from https://archive.org/stream/WhyNationsFailDaronAcemogluAndJamesA.Robinson1/

[3]. Agrawal, A., Gans, J. S., & Goldfarb, A. (2017). What to expect from artificial intelligence. MIT Sloan Management Review, 58(3), 22-26. Retrieved January 23, 2018, from http://mitsmr.com/

[4]. Akturk, D., Gun, S., & Kumuk, T. (2007). Multiple correspondence analysis technique used in analyzing the categorical data in social sciences. Journal of Applied Sciences, 7, 585-588. https://doi.org/10.3923/jas.2007.585.588

[5]. Alam, M. G., Masum, A. K., Beh, L.-S., & Hong, C. S. (2016). Critical factors influencing decision to adopt human resource information system (HRIS) in hospitals. PLOS ONE, 11(8). https://doi.org/10.1371/journal.pone.0160366

[6]. Al-Hujran, O., Al-Lozi, E. M., Al-Debei, M. M., & Maqableh, M. (2018). Challenges of cloud computing adoption from the TOE framework perspective. International Journal of E-Business Research, 14(3), 77-94. https://doi.org/10.4018/IJEBR.2018070105

[7]. Alshamaila, Y., Papagiannidis, S., & Li, F. (2013). Cloud computing adoption by SMEs in the North East of England: A multi-perspective framework. Journal of Enterprise Information Management, 26(3), 250-275. https://doi.org/10.1108/17410391311325225

[8]. Awa, H. O., Ukoha, O., & Emecheta, B. C. (2015). Integrating TAM, TPB and TOE frameworks and expanding their characteristic constructs for e-commerce adoption by SMEs. Journal of Science and Technology Policy Management, 6(1), 76-94. https://doi.org/10.1108/JSTPM-04-2014-0012

[9]. Berger, T., & Frey, C. B. (2015). Industrial renewal in the 21st century: Evidence from US cities. Regional Studies. https://doi.org/10.1080/00343404.2015.1100288

[10]. Bessen, J. (2015). How computer automation affects occupations: Technology, jobs, and skills. Boston University School of Law. Retrieved July 31, 2018, from http://www.bu.edu/law/faculty/scholarship/workingpapers/2015.html

[11]. Brender, N., & Markov, I. (2013). Risk perception and risk management in cloud computing: Results from a case study of Swiss companies. International Journal of Information Management, 33(5), 726-733. https://doi.org/10.1016/j.ijinfomgt.2013.05.004

[12]. Brynjolfsson, E., & McAfee, A. (2011). Race against the machine: How the digital revolution is accelerating innovation, driving productivity, and irreversibly transforming employment and the economy. Digital Frontier Press. Retrieved December 24, 2017, from http://ebusiness.mit.edu/

[13]. Chang, J.-H., & Huynh, P. (2016). ASEAN in transformation - The future of jobs at risk of automation. International Labour Organization. Retrieved July 31, 2018, from http://www.ilo.org/

[14]. Chui, M., Manyika, J., & Miremadi, M. (2016). Where machines could replace humans—And where they can't (yet). McKinsey Quarterly. Retrieved December 26, 2018, from https://www.mckinsey.com/

[15]. FICCI, NASSCOM & Ernst & Young. (2017). Future of Jobs in India : A 2022 perspective. FICCI. Retrieved December 26, 2017, from http://www.ey.com/

[16]. ETOnline. (2018, March 17). Nobel-winner Paul Krugman warns India story could end with mass unemployment. Retrieved March 18, 2018, from https://economictimes.indiatimes.com/news/economy/indicators/nobelwinner-paul-krugman-warns-india-story-could-end-with-massunemployment/articleshow/63344124.cms

[17]. Gartner Inc. (2017a). Hype Cycle for Cloud Computing. Retrieved May 25, 2018, from https://gartner.com/home