

# Comparative Study of Application Areas, their Economic Impact of Machine Learning & Blockchain Technologies in Cloud Environment

Sunil Pandey

Research Scholar (Engineering)  
Madhav University, Rajasthan

Dr. Mohammad Akram Khan

University Guide,  
Madhav University, Rajasthan

**ABSTRACT**-This study has provided invaluable insights into the multifaceted applications and significant economic implications of state-of-the-art technologies. A thorough analysis of various application domains has clearly established the substantial potential of machine learning and blockchain technologies in boosting operational efficiency, strengthening security measures, and encouraging innovation within cloud-based environments. The concrete economic impact, seen through cost reductions, revenue growth, and resource optimization, highlights their capacity to bring about transformative changes across a wide range of industries, particularly in the financial and healthcare sectors. This investigation emphasizes the crucial role of technology adoption in shaping the direction of cloud computing and the broader economic landscape. It facilitates well-informed decision-making and strategic planning in the digital era. During the pivotal year of 2022, characterized by remarkable innovation and substantial investments in Applied AI and Cloud Computing, there was a proliferation of cloud services catering to both individual users and businesses. This expansion unlocked immense potential and fostered competition based on expertise rather than mere scale. The emergence of Machine Learning Engineers, working alongside Research Scientists and Data Scientists, expedited the translation of AI research from theory to practical applications. However, Data Scientists continue to wield significant influence, particularly in the Medical/Pharmaceutical and Government/Public Services sectors. From a technical performance perspective, the rise of Vision Transformers has opened new horizons in Computer Vision, promising exciting technological advancements in the near future. Nonetheless, a comprehensive analysis reveals that the narrative of AI adoption in India is still in its early stages. While a few urban centers are making strides in crafting AI strategies, much of the country remains relatively inactive. Similarly, cloud computing, a cornerstone of the Fourth Industrial Revolution, is still in its initial phases of adoption across the continent. Despite the potential for AI to revolutionize numerous enterprises and industries, its progress in India is hindered by a pervasive lack of trust. The absence of a mature risk awareness framework and essential controls has impeded the practical application of AI. As

a result, advancements in AI have barely moved beyond proof-of-concept and isolated solutions.

**Keywords** - Comparative Study, Application Areas, Economic Impact, Machine Learning, Blockchain Technologies, Cloud computing

## I. INTRODUCTION:

The introduction of blockchain and machine learning technologies, particularly in the context for cloud computing, has had far-reaching effects on the global economy. In the field of machine learning, companies are making use of the sophisticated algorithms and computing resources made available by cloud platforms in order to mine massive and intricate datasets for actionable insights. This allows for more informed choices, superior product development, and streamlined operations. The ability to easily scale the machine learning models in the cloud ensures that they are affordable and accessible to businesses of all sizes[1]. However, blockchain technology is undergoing a cloud-based revolution due to its inherent characteristics for decentralisation, transparency, and security. Smart contracts, supply chain tracking, & other forms of safe and effective transaction facilitation have helped to cut down on waste and fraud. Distributed ledgers can be deployed and managed by businesses with no costly hardware or software upgrades thanks to cloud-based blockchain solutions. Additionally, the cloud-based convergence for machine learning & blockchain technologies is encouraging creative approaches. In order to improve security and anticipate trends, blockchain data is being analysed with machine learning algorithms. For better automation and choice-making, smart contracts and blockchain-powered dApps are incorporating deep learning capabilities. A new wave for efficiency, security, & innovation across industries is being ushered in by the combination for

blockchain and machine learning technologies in the cloud, which is reshaping company models, optimising processes, lowering costs, and boosting economic growth. No single machine or organisation can exert total control over a blockchain network because of this technology's emphasis on decentralization [2]. Instead, it's dispersed among all of the connected nodes in the chain. A nodes is any machine that contributes to the optimal operation of a blockchain. Each node stores an identical copy of the blockchain, except for the minimal amount of data that must be updated, stored, or verified in response to each new mined block added to the chain. Due to the immutability of a blockchain, every transaction can be easily checked and audited. To ensure honest dealings, a special alphanumeric identifier is assigned to each user. Data that is publicly available and scheduled around legal requirements helps maintain network integrity or inspires trust among network users. As a result, blockchains are generally regarded as a technology that improves confidence in the system[3].

There is a lot of unrealized potential in using machine learning in economics, but there are also a lot of roadblocks. The difficulty of understanding and making sense of the various machine learning models is a major problem. Estimates from machine learning algorithms may be harder to interpret than those from more traditional econometric models. There's also the risk of the garment being too big. When a machine learning model is overly complex and fits its training data too closely, a problem known as overfitting occurs. When the model "overfits" the data, this issue arises[4]. This can cause problems with the generalisation performance and the accuracy of the forecasts when applied to newly collected data. When applied to the study and forecasting of economic phenomena, machine learning (ML) shows great promise.

trends and making prudent choices. Financial, consumer spending, and market-related data sets are just some of the many that can be analysed with the help of machine learning algorithms. It would be challenging to recognise patterns and trends using conventional methods of statistics, but with the help of such algorithms, it will be possible to do so. Previously impossible to predict economic trends like inflation, GDP growth, & unemployment rates are now within reach, thanks to the advent for machine learning and the subsequent development of predictive models. The field of risk management is just one area of economics that is being profoundly affected by machine learning[6]. Machine learning algorithms can be applied to the analysis of large datasets in order to spot risks and develop countermeasures. Economists can benefit from this technology because it can help them anticipate economic downturns and plan for their mitigation. One other technique that could be used to examine financial data for signs of fraud or error is machine learning. By doing so, financial crises can be avoided and financial stability can be increased. The economy will strengthen and stabilise as a result of economists' ability to devise measures to reduce danger. Machine learning is simplifying the process of making prudent financial decisions. Machine learning algorithms are increasingly being used to analyse financial data, as they can spot trends and provide insights to aid economists in their deliberations[7]. Machine learning has many uses, some of which include tracking stock prices, finding promising investment opportunities, and developing risk-minimization plans. Machine learning can also be used to analyse customer data and track trends. Economists can use this data to increase sales by catering to specific populations with tailored marketing campaigns. Machine learning has the potential to help businesses and governments make better financial decisions, which would be good for the economy as a whole. The field of economics is one of many that has seen significant success with the application of machine learning (ML)[8]. It provides cutting-edge methods for examining voluminous economic data, forecasting future outcomes, maximising present choices, and bettering future policymaking. The advent of blockchain and machine learning (ML) has had far-reaching effects on the global economy, especially in the field of cloud computing. Both innovations hold great promise for fostering widespread economic development and reshaping numerous sectors[9].

#### ➤ Cost Efficiency and Scalability

✓ **Cloud Computing:** The cost-effective solutions offered by machine learning or blockchain technologies are made possible by their use of cloud computing. Businesses can reduce their initial investment in infrastructure and maximise their use of available resources by taking advantage of cloud computing's scalability.

#### ➤ Improved Decision-Making and Productivity:

✓ **Machine Learning:** Algorithms that use machine learning (ML) can sift through mountains of data to find patterns and trends that can help businesses make better decisions. This optimises processes &

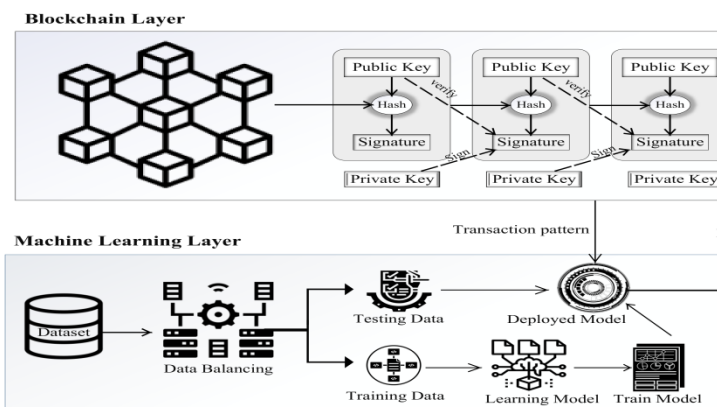


Figure 1 Impact of Machine Learning & Blockchain Technologies in

The ability to quickly and accurately analyse massive amounts of data is one of machine learning's greatest contributions to economics. Machine learning algorithms can quickly and accurately sift through massive amounts of data, both new and old, to find patterns and make predictions[5]. As a direct result, economists have a simpler time foreseeing economic

resource allocation across industries, increasing productivity and efficiency[10].

- **Enhanced Security and Trust:**
  - ✓ **Blockchain:** Blockchain uses cryptography and distributed ledgers to ensure that all transactions are safe and transparent. Because of this, industries like finance and healthcare, where data security is of paramount importance, can feel more comfortable storing data in the cloud.
- **Supply Chain and Logistics Optimization:**
  - ✓ **Blockchain:** Organisations can improve supply chain and logistics transparency and traceability by adopting blockchain technology. Because of this, less money will be lost to fraud, and less time will be wasted due to mistakes or delays[11]–[14].
- **Smart Contracts and Automation:**
  - ✓ **Blockchain:** With the help of blockchain technology, "smart contracts" can be created and executed with ease. This expedites procedures, increases reliability, and guarantees precise financial dealings at lower cost[15].
- **Tokenization and Crowdfunding:**
  - ✓ **Blockchain:** By tokenizing assets, a wider variety of investors will have access to investment opportunities. This can help the economy grow by opening the door to new types of funding and giving a boost to fledgling businesses and ambitious projects that would otherwise have trouble getting off the ground.

## II. LITERATURE REVIEW:

Farhani 2023 et. al As the capabilities of machine learning & deep learning have grown, numerous effective intrusion detection systems have been created. This sort of study is included. These two layers of protection are compared and contrasted in this research. The current machine-based system for intrusion detection can be further subdivided into subcategories according to the detecting method, data source, design, or operation style that it employs. Some of these communities include: Future directions for IoT security and understanding its detection of intrusion mechanism are discussed. This paper details a blockchain-based security model for protecting the transmission of data in the Internet of Things (IoT)[16].

Hu 2022 et. al Traditional methods of estimating tourism demand rely heavily on multivariate regression techniques or single-variable time series. These function-based prediction models have shown some promise in tourism projection, but they cannot match the precision with which a feed-forward neural network (FFNN) captures the relationship among tourist supply and demand. An FFNN has been shown to outperform regression and time-series forecasting algorithms when applied to tourism data. This study contributes to the first-ever use for deep neural networks to the growth of tourist demand by combining a hybrid FFNN or chimp optimisation algorithm for learning (i.e., FFNN-ChOA) in a nonlinear demand for tourism dataset. There is no way that regression

models, time-series models, or traditional backpropagation networks of neurons can compete via FFNN-ChOA in terms for prediction accuracy [17].

Garg 2022 et. al The proposed model optimises resource allocation to the execution of programmes in the cloud computing setting with the goals of reducing power consumption and increasing efficiency. The model achieves this goal by placing premium on punctual output in cloud-based applications through careful management of interdependencies and strict adherence to deadline constraints. The goal of this algorithm is to dynamically deploy or undeploy VM instances in the underlying physical machines to meet the shifting demands of individual jobs, as well as to select the optimal VM for each computing task. Virtual machine (VM) power consumption trends and host resource limitations. In order to reduce energy costs, the model prioritises swiftly powering down unused VMs and making on-the-fly decisions about VM placement & allocation.

Technology proves that the proposed method works. The study demonstrates that the EVMP algorithm is superior to PESVMC in terms of energy efficiency, execution speed, or meeting dependencies and deadlines. Since the EVMP algorithms is better able to make informed decisions for VM placement, it uses fewer resources and produces fewer emissions. Simultaneously, the model's flexible approach to placing virtual machines (VMs) ensures that all work will be completed efficiently and on time. The EVMP algorithm effectively overcomes the shortcomings for static VM allocation & consolidation, which often cannot adapt to the permanently changing needs of workloads [18].

Tiwari 2022 et. al Traditional image filtering techniques are inadequate for denoising images. Many different algorithms for machine learning suffer from information loss not only at the filtering stage but also at other points in the process. When using a network of convolutional neural networks (CNN), the pooling process can cause internal data representation to become mismatched or disappear altogether. Low-intensity digital photos can benefit from the use of repetitive filtering because it gets rid of the artefacts left over of every filtering function. The multilayer wavelets transform (MLWT) is used in securely protected cloud computing authorisation as a method to process characteristics made from a number of filter bands. There is significant information loss in digital photographs as a result of the feature extraction & processing steps in this scenario. Innovative windowing blocks are being added to the layer architecture, and autoencoder-based deep neural network techniques are tackling these issues. Here, we take into account magnitude and phase information to construct a deep learning system that can efficiently denoise digital photographs. We compared our proposed method to others already available, including the peak signal-to-noise ratio (PSNR), the structural similarity index (SSIM), and others, to show that it was superior for low-density digital images [19].

Chen 2022 et. al The results show that daily planning is the key to efficiently managing the current state of distributed

generation, energy storage systems, and public connection. Economically, running a microgrid over time yields results that are consistent with what was seen the day before. Total daily operating costs for the microgrid come to 4668 yuan, and by keeping the surplus power at 500 to 600 kW, we can keep the microgrid from draining its batteries too quickly, increase their lifespan, and reduce our costs. The simulation findings indicate that the overall power imbalance in the microgrid can mitigate the volatile output of distributed generation through regulated load shedding. Whenever the load characteristics are irrelevant, controllable distributed generation can reduce output volatility. The proposed economic dispatch model has the potential to boost the microgrid's data security, information storage, and information release, and it can also serve as a general roadmap for the expansion of the national power grid and the power sector [20].

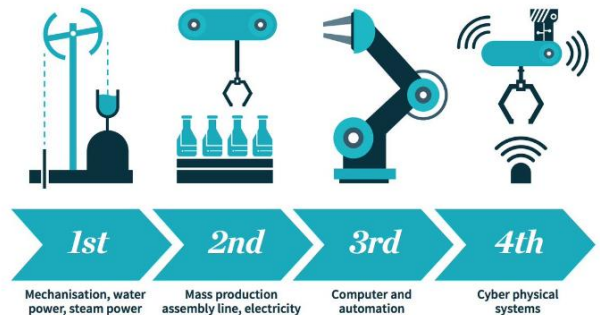


Figure 2 The Industrial Revolution

Table no. 1 literature summary

Authour/Year	Algorithm	Perameter	Reference
Lei/2022	Machine Learning	95%	[21]
Jiang/2022	deep reinforcement learning	99%	[22]
Li/2022	virtual machine (VM) packing	95%	[23]
Chen/2022	CRNNH (Convolutional Recurrent Neural Network Hashing)	92.8%	[24]
Sajid/2022	Support Vector Machine (GA-SVM)	98%	[25]

### III. PROPOSED METHODOLOGY

#### • Proposed Methodology of Industrial Revolution

The proposed methodology involves conducting an extensive literature review to understand the current landscape, followed by data collection and EDA. The study will focus on the selection of diverse application areas where both machine learning and blockchain are deployed in cloud environments. A comparative analysis will be carried out, evaluating their strengths, weaknesses, and integration methods, while also considering performance metrics and real-world case studies. Challenges and limitations will be addressed, leading to future trend assessments and recommendations for organizations. Ethical considerations and appropriate research methodologies will be emphasized throughout the study.

#### A. Data Information

In parallel with our previous annual surveys conducted in India 2017, 2018, 2019, 2020, and 2021, our undertaking for this year encompassed the execution of an all-encompassing industry-wide survey aimed at offering an exhaustive insight into the prevailing landscape of data science and machine learning. The survey was made accessible to respondents from September 16, 2022, through October 16, 2022, ultimately garnering a substantial dataset comprising 23,997 responses. Post the data purification process, the dataset emerged as a comprehensive repository for exploration. This dataset comprises a wealth of information, encompassing both quantitative metrics regarding the demographics of individuals engaged in data-related roles, the status of machine learning implementations across diverse sectors, and invaluable insights for prospective data scientists seeking to enter this burgeoning field. Notably, the dataset is unique in that it provides access to the entirety of raw data, in contrast to offering solely the consolidated survey findings. This distinctive characteristic facilitates an in-depth analysis of the dataset by analysts, affording them the autonomy to uncover insights and patterns according to their specific research interests.

#### B. Perform EDA (Exploratory Data Analysis)

Exploratory Data Analysis (EDA), sometimes referred to as EDA, is an essential preliminary stage in the field of data analysis. During this phase, the fundamental characteristics and attributes of a dataset are thoroughly examined and summarised with the main goals of improving comprehension of the dataset's inherent structure, identifying inherent patterns within the data, and uncovering new insights that may be hidden within the dataset. Exploratory Data Analysis (EDA) comprises a wide range of approaches and methodologies that involve the construction of graphical representations of statistical information, the generation of statistical summaries, and the utilisation of data visualisation tools to help the exploration and comprehension of data. Essentially, exploratory data analysis (EDA) plays a pivotal role in the data analysis procedure, facilitating well-informed decision-making, hypothesis formation, and the development of future analytical approaches.

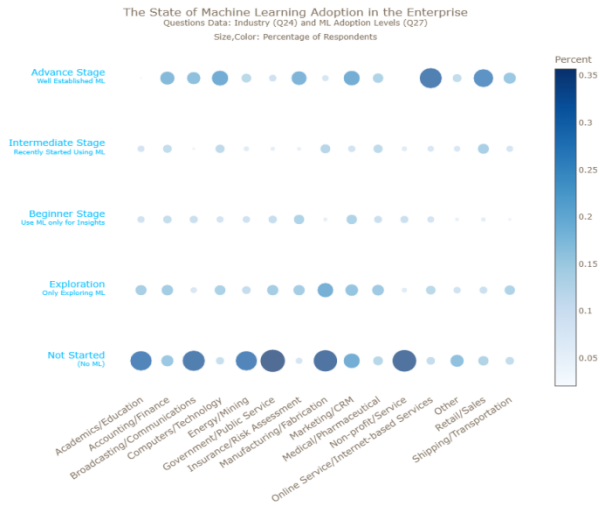


Figure 3 The State of Machine Learning Adoption in the Enterprise

Figure 3 depicts the prevailing state of machine learning implementation in the corporate domain, specifically focusing on the industrial sector in India. This graphic depiction offers valuable insights regarding the level of adoption and integration of machine learning technology across different industries in the Indian environment. This study provides a complete analysis of adoption trends, patterns, and disparities within several industrial sectors, with a particular focus on the influence of machine learning in determining the future of Indian firms

Retail/Sales Sector

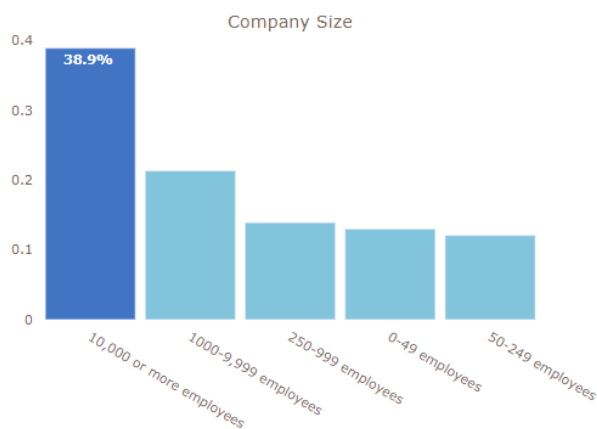


Figure 4 Company Size

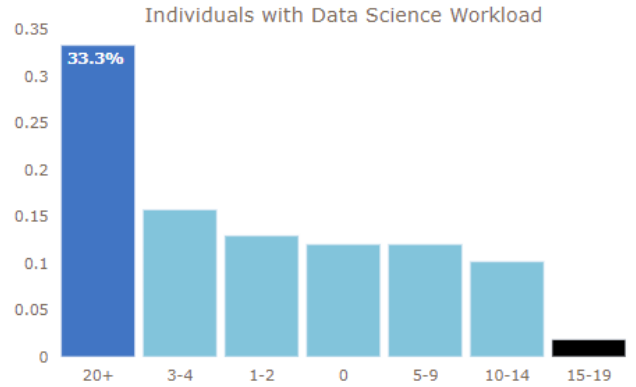


Figure 5 Individuals with data science workload

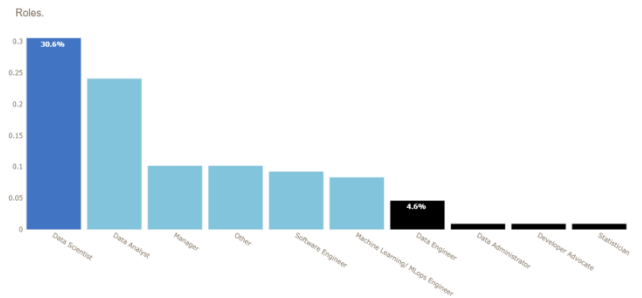


Figure 6 Sales sector roles

Figures 5 to 7 provide an elucidation of the underlying reasons for the comparatively lower rates of adoption found within the retail and sales industry. The incorporation of technology poses distinctive issues within the retail industry. Distributed retail enterprises, which possess multiple physical locations, heavily depend on technology to enable crucial back-office operations, including supply chain and warehouse management. Simultaneously, they strive to provide a consistent and improved customer experience, often employing in-store Wi-Fi, throughout their diverse establishments.

Retail/Sales Sector Skills

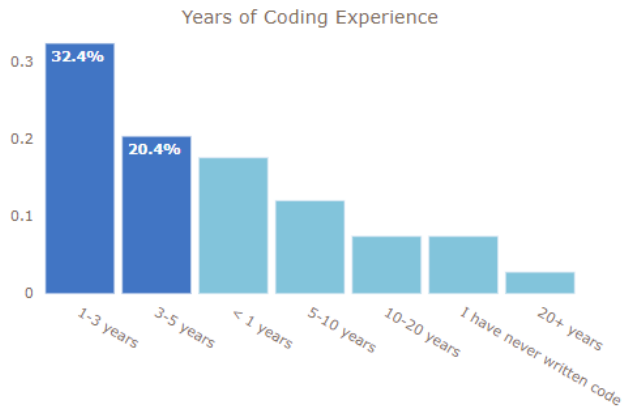


Figure 7 Years of coding Experience

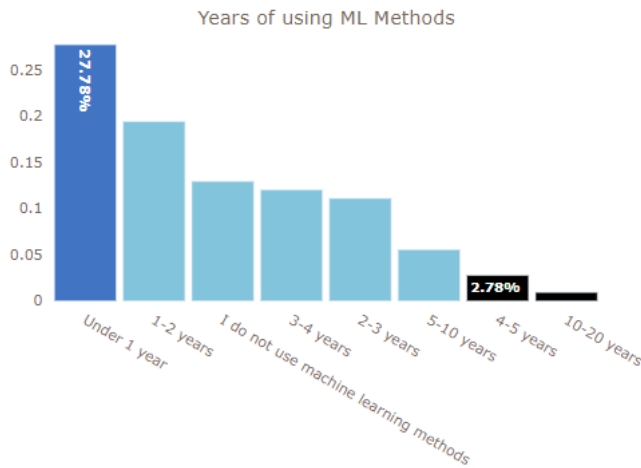


Figure 8 Years of using ML method

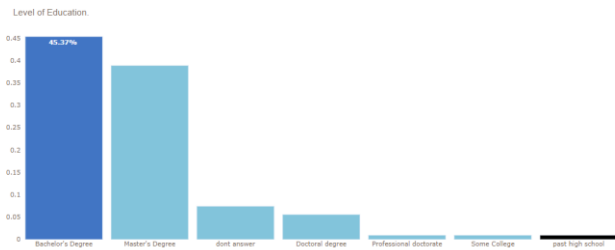


Figure 9 Level of education

30% of the participants indicate possessing less than one year of experience in machine learning, indicating an increasing inclination towards machine learning technology. The data also demonstrates that the predominant educational attainment in the Retail/Sales industry is at the Bachelor's degree level, indicating the educational profiles of professionals in this field. Significantly, a considerable proportion of companies operating in the Retail/Sales sector can be categorised as having 0-49 employees, which indicates the predominance of small and medium-sized organisations within this industry. Furthermore, a considerable number of participants reported that their organisations have no employees involved in data science tasks, indicating a restricted implementation of data science operations. The data presented indicates that the role of a Data Analyst is the most common occupation within Retail/Sales organisations, highlighting the importance of data analysis in the workforce makeup of this industry. The aforementioned insights combined provide a comprehensive comprehension of the workforce mix, educational backgrounds, and trends in technology usage within the Retail/Sales sector.

Online Services/Internet-Based Service Sector

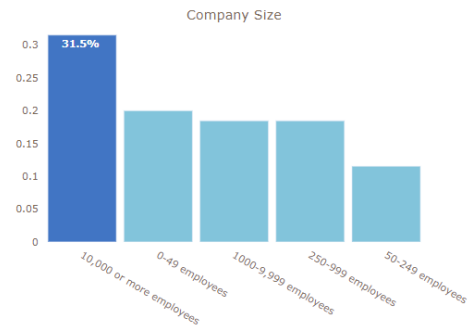


Figure 10 Company Size

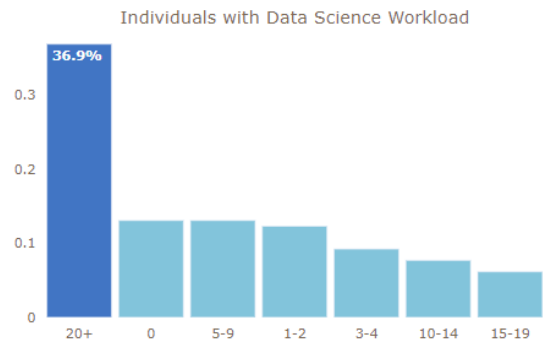


Figure 11 Individuals with data science workload

Figures 7 to 9 provide a complete overview of the demographic and distinctive aspects of the Retail/Sales industry. The data presented indicates that a considerable majority of participants in this industry have coding experience of less than one year, highlighting the presence of a relatively inexperienced coding workforce. Moreover, over

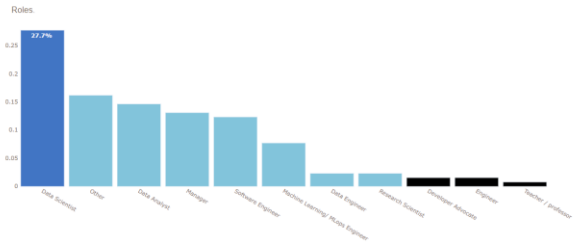


Figure 12 Online services role

Online Service/Internet-Based Service Sector Skills

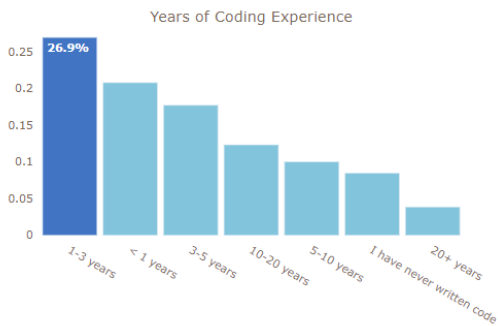


Figure 13 Years of coding experience

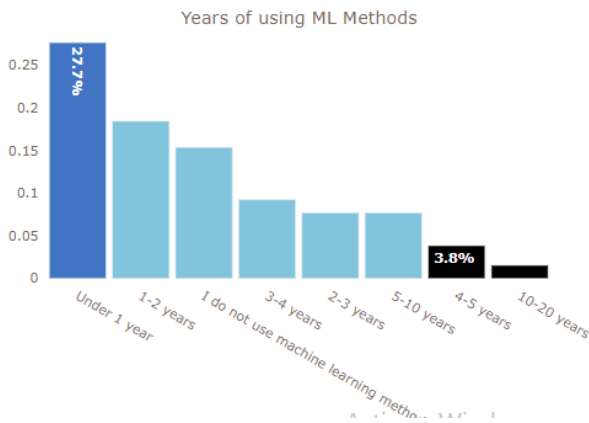


Figure 14 Years of using ML methods

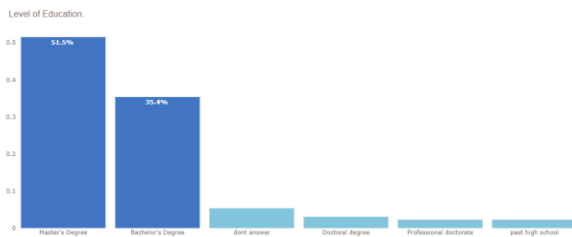


Figure 15 Level of education

Figures 10 to 15 jointly illustrate the notable levels of adoption of artificial intelligence and machine learning (AI/ML) within the Online Services/Internet-Based Services sector. This occurrence may be primarily attributed to the rapid development of internet usage and services in India. These numbers reveal some significant industry-specific insights. Initially, it is worth noting that around 36% of individuals surveyed in this particular industry possess coding experience ranging from 1 to 3 years. This finding suggests that the workforce in this sector possesses a moderate level of skill in coding. Regarding the domain of machine learning (ML) expertise, a significant proportion of participants exhibit a duration of 1-2 years, which signifies the considerable attention and financial commitment dedicated to ML technologies within the industry. Moreover, an analysis of the educational landscape within the industry reveals a nearly equal distribution between those holding Bachelor's and Master's degrees. This observation highlights the different educational backgrounds of professionals engaged in this particular subject. The majority of companies in the Online Services/Internet-Based Services sector have a workforce size ranging from 0 to 49 employees, indicating the significant presence of small and medium-sized organisations. Finally, a significant proportion of participants indicate that their respective organisations have a workforce consisting of 1-2 individuals that are actively involved in tasks linked to data science. This highlights the organization's proactive stance towards deriving insights from data. The amalgamation of these statistics provides a comprehensive perspective on the integration of AI/ML technologies into the Online Services/Internet-Based Services sector, situated within the dynamic framework of India's swiftly developing internet environment. The aforementioned data offers significant contributions in terms of understanding the workforce composition, educational backgrounds, firm scales, and level of engagement with data science within the sector. These findings collectively demonstrate the industry's forward-thinking approach in adopting advancements in artificial intelligence and machine learning.

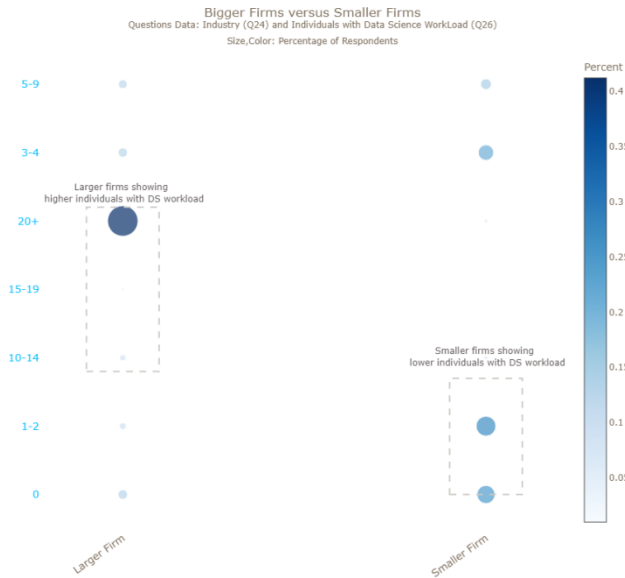


Figure 16 bigger firms vs smaller firms

Figure 16 explores an intellectually stimulating investigation about the disparate rates of artificial intelligence (AI) implementation observed among larger and smaller organisations. In order to examine this inquiry, the data utilised in this study is derived from the responses obtained for question Q25. This particular question classifies firm size into two unique groups.

- Smaller firms are often categorised as establishments with a workforce ranging from 0 to 249 employees.
- Larger firms are typically characterised as organisations that employ a minimum of 250 individuals, with the upper limit extending to companies that have a workforce of 10,000 or more personnel.

The observations derived from this plot are really enlightening. It is apparent that smaller enterprises, which are defined as those employing 0-249 persons, tend to have fewer personnel involved in data science tasks. Furthermore, organisations in question appear to be in the first phases of adopting AI, prioritising a prudent strategy towards the incorporation of artificial intelligence technologies. On the other hand, it is observed that larger organisations, specifically those with 250 or more people, are at the forefront of adopting artificial intelligence (AI) technologies. These organisations demonstrate a significant dedication to data-driven initiatives, as seen by their large numbers of actively engaged workers involved in data science activities. Moreover, it is worth mentioning that larger corporations have achieved a competitive advantage by sustaining the deployment of artificial intelligence models for a period beyond two years. This data-driven analysis effectively addresses the basic inquiry, demonstrating that larger organisations emerge as the

primary adopters of artificial intelligence (AI) technologies. The company's strong dedication to data science tasks and prolonged periods of AI model development places them prominently in the lead of AI implementation, highlighting a clear distinction from smaller companies in the business sphere.

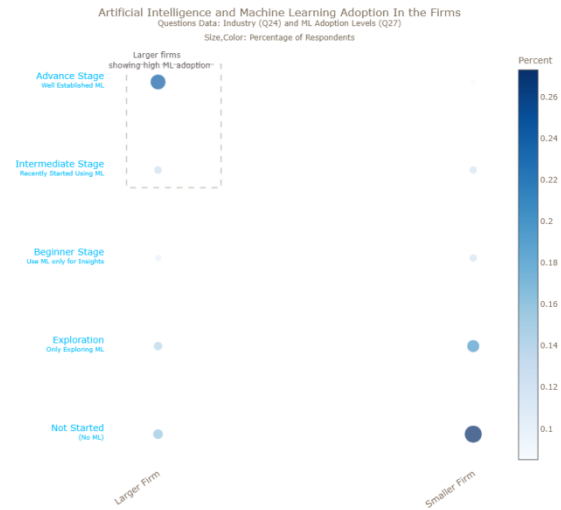


Figure 17 AI and ML adoption in the firms

Figure 17 is a significant visual representation that highlights the crucial importance of Cloud Computing as a fundamental technology that many firms prioritise for implementation prior to engaging with Artificial Intelligence (AI). Cloud computing is a revolutionary platform that significantly enhances the efficiency and cost-effectiveness of integrating artificial intelligence (AI) into enterprises and organisations. The aforementioned objective is accomplished through the supervision of crucial IT infrastructure and services, hence facilitating organisations in fully utilising the capabilities of artificial intelligence. Additionally, this approach mitigates the inherent technical intricacies and financial difficulties typically connected with the introduction of AI. This picture emphasises the inherent synergy between Cloud Computing and AI, illustrating how the former accelerates and enables the integration of the latter, promoting innovation and competitiveness in many areas.



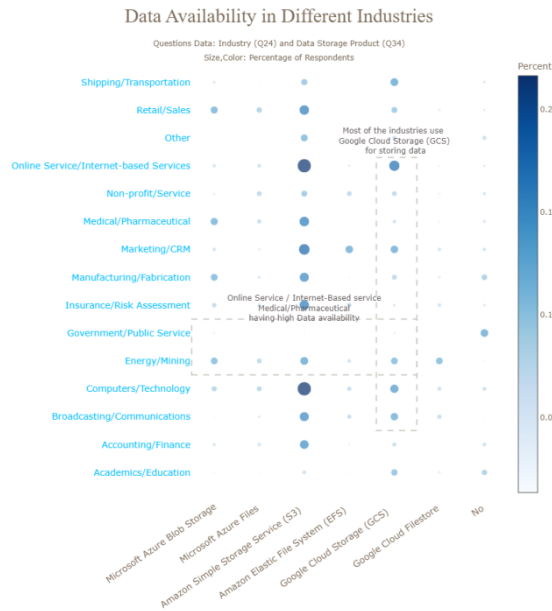


Figure 18 Data availability

Figure 18 is utilized The field of big data and artificial intelligence (AI) exhibits a mutually beneficial and interdependent connection. Artificial intelligence (AI) necessitates a substantial volume of data in order to acquire knowledge and enhance its decision-making capabilities. Furthermore, the field of big data analytics utilises AI techniques to facilitate more effective data analysis. With this convergence, organisations may effectively utilise advanced analytics capabilities such as augmented or predictive analytics, enabling them to rapidly extract actionable insights from their extensive data repositories.

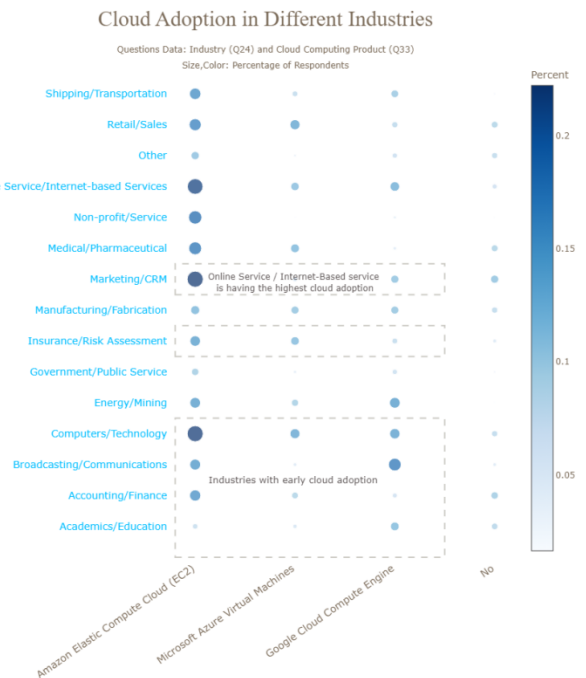


Figure 19 Cloud adoption

Figure 19 serves as a visual representation or illustration that aids in conveying information or concepts in a more accessible and comprehensible manner. Cloud computing is a pivotal technology that numerous firms are expected to embrace prior to the widespread adoption of artificial intelligence (AI). This technology facilitates the cost-effective and streamlined integration of AI into enterprises by assuming responsibility for the operation and maintenance of the necessary IT infrastructure and services. The integration of cloud computing into a company's operations signifies a significant technical transformation. In order to establish dependable procedures for continuous operations, it is imperative for enterprises to acquire the requisite expertise and understanding prior to embracing public cloud solutions.

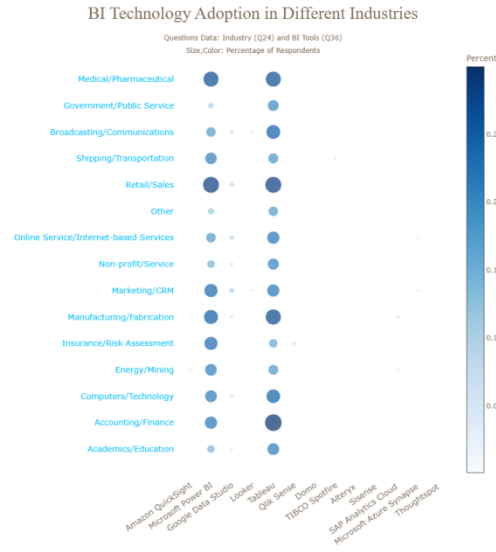


Figure 20 BI technology adoption

Figure 20 illustrates the deployment of Business Intelligence Technology. Business intelligence solutions are highly advantageous for firms as they expedite the process of information analysis and performance evaluation. This enables organisations to effectively mitigate inefficiencies, discover potential issues, explore novel sources of revenue, and pinpoint areas of prospective expansion. There are several distinct advantages that firms can derive from utilising Business Intelligence (BI) solutions, including

- The enhancement of operational processes' efficiency.
- This study aims to provide a comprehensive understanding of client behaviour and shopping habits.
- The precise monitoring of sales, marketing, and financial performance.
- Establishing precise benchmarks using both historical and contemporary data.
- Instant warnings concerning data irregularities and consumer difficulties.
- Real-time sharing of analyses among different departments.

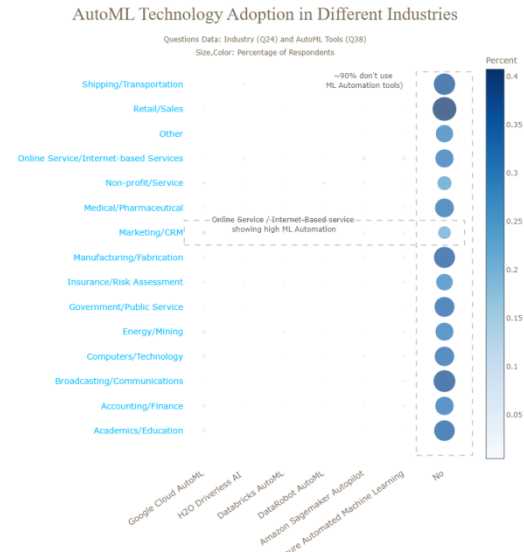


Figure 21 Auto ML technology adoption

Figure 21 illustrates The forthcoming wave of innovation entails democratising access to machine learning capabilities for a wide range of individuals. AutoML tools can be customised to align with the specific requirements of a business, enabling the identification of faults, enhancing accuracy, and expediting the process of developing production-ready models. In the year 2018, Google introduced Google Cloud automated machine learning (AutoML), a service that enables businesses to utilise its machine learning (ML) infrastructure. This infrastructure is constructed using the data supplied by its customers, allowing businesses to train and develop their own artificial intelligence (AI) models. AutoML addresses the practical obstacles associated with traditional machine learning (ML) methods, which are characterised by their labor-intensive nature, reliance on human intervention, and repetitive tasks. By automating the use of AI-driven ML techniques, AutoML effectively resolves these issues in real-world scenarios

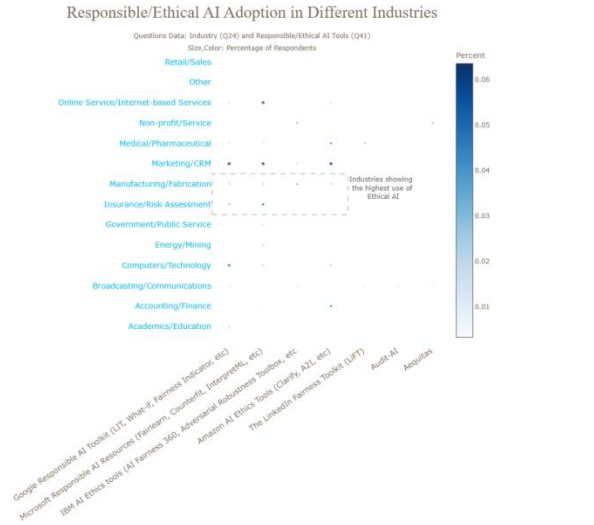


Figure 22 Ethical AI adoption

Figure 22 depicts The concept of Artificial Intelligence often elicits notions of advancement and efficiency. However, the perspective of some is more pessimistic. There are other real concerns that might be raised, including those related to unjust decision-making, workforce displacement, and inadequate privacy and security measures. Furthermore, a significant number of these challenges are exclusive to the field of artificial intelligence. This implies that the current rules and laws are inadequate in addressing these issues. Responsible AI plays a vital role in this context. The primary objective is to effectively tackle these concerns and provide a framework of responsibility for artificial intelligence (AI) systems. The salient feature of this system is the minimal or absence of human involvement in the decision-making process. The utilisation of artificial intelligence (AI) might give rise to numerous prospective challenges, necessitating the establishment of a well-defined strategy by organisations. Responsible artificial intelligence (AI) refers to a governance system that is specifically designed to achieve this objective. The framework encompasses provisions for the collection and utilisation of data, the evaluation of models, and the optimal methods for deploying and monitoring those models.

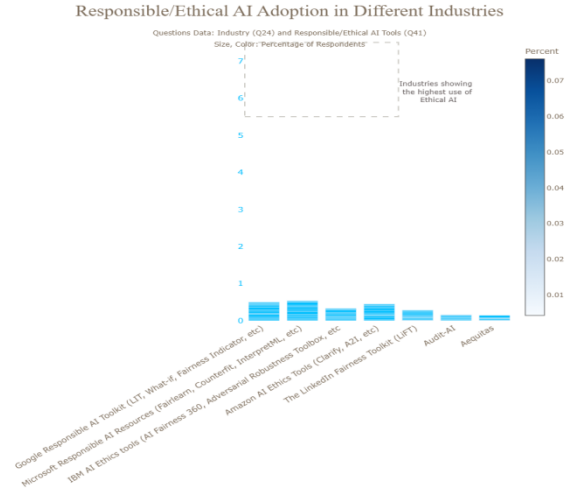


Figure 23 Responsible AI adoption

Figure 23 displays the bar graph. The concept of Artificial Intelligence elicits contemplation on advancements and efficiency. For other individuals, the perspective is comparatively less optimistic.



Figure 24 the state of machine learning adoption in indian countries

Figure 24 depicts the current state of adoption of machine learning in various countries within India.

• Proposed Methodology of Cloud Computing

The suggested process calls for a thorough literature research to comprehend the existing environment, next data gathering and EDA. The study will concentrate on choosing a variety of applications where blockchain and machine learning are used in cloud environments. It will be compared, with their advantages, disadvantages, and integration strategies assessed,

as well as performance indicators and actual case studies taken into account. The resolution of issues and constraints will result in assessments of upcoming trends and suggestions for organisations. The study will place emphasis on ethical considerations and proper research procedures.

A. Exploratory Data Analysis

"EDA" is a term that is frequently used in the industry to refer to exploratory data analysis. The fundamental characteristics of a dataset are reviewed and summarised during exploratory data analysis, which is a crucial first stage in data analysis. The objectives of this phase are to better understand the structure of the dataset, identify patterns within the data, and derive new insights from the data. EDA uses a wide range of techniques and tactics, such as data visualisation and graphical summaries and representations of information.

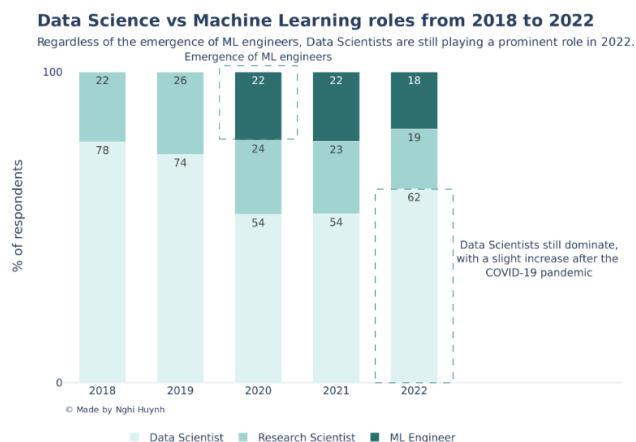


Figure 25 Data Science vs Machine learning roles from 2018 to 2022

In Figure 25, a vertical stacked bar chart with unique sections for each role in the study's results is used to graphically portray the findings. It's vital to remember that although if the sections collectively show how the responsibilities are distributed, the cumulative total may not necessarily equal 100 percent, mostly because of rounding considerations. The use of AI is so widespread that machine learning solutions are increasingly in demand across a range of industries, with an exceptional 4 out of 5 adoption rate score reported in 2021. As a result, the position of ML engineers has become a crucial link between the fields of Data Science, Data Engineering, and DevOps. This trend started in 2020 and has remained popular ever since. On the other hand, data-related positions continue to be dominated by data scientists, with a little increase seen in 2022.

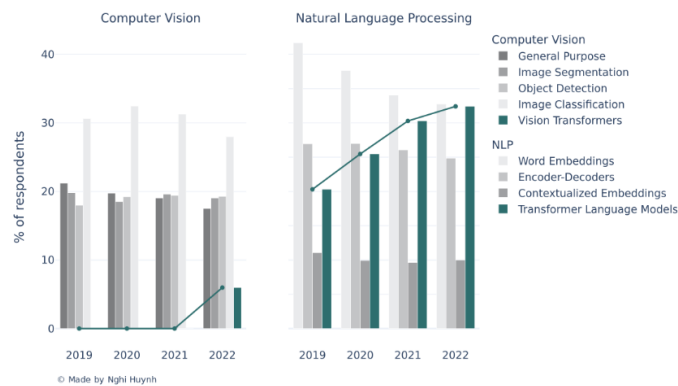


Figure 26 Computer Vision and Natural language processing

A vertical bubble chart is used in Figure 26 to visually represent certain data relationships. Each row in this diagram denotes a certain action, and each column a specific role. This visualisation can be interpreted as follows:

- Greyish-hued bubbles represent the proportion of respondents who said they engaged in a specific activity at a rate of less than 17%.
- Greenish-hued bubbles represent the proportion of respondents who said they engaged in a specific activity at a rate equal to or higher than 17%.
- The size of the bubbles is based on the actual percentage numbers, emphasising the differences in each role's principal activity visually.

The survey's findings show that research scientists, data scientists, and machine learning engineers prioritise a variety of jobs that are relatively different from one another. Importantly, their primary focus across all of their positions is creating prototypes to investigate the use of machine learning in novel and unexplored domains.

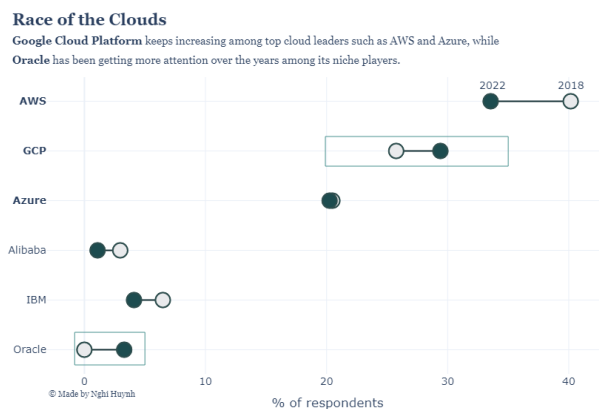


Figure 27 Race of clouds

Figure 27 shows the rapid development of both cloud and edge computing, which is shown by a staggering 136 billion investment in 2021, securing their positions as major technological developments in 2022. A multibillion dollar economy has been created as a result of this upsurge, earning a noteworthy adoption score of 4 out of 5 from McKinsey. Consequently, a large number of cloud service providers are aggressively competing for a piece of the growing cloud industry. These service providers can be divided into two categories: the market leaders, which include Amazon Web Service (AWS), Google Cloud Platform (GCP), and Microsoft Azure, and the niche players, which include Oracle, IBM Cloud, and Alibaba Cloud. In particular, data from the Kaggle Survey in 2022 show dynamic patterns. The proportion of respondents using GCP has increased significantly since 2018, in contrast to the user bases of other top cloud providers like AWS and Microsoft Azure, which have seen a minor fall in 2022. Contrarily, Oracle users have showed a growth trajectory and have been steadily catching up to IBM users since 2018, despite a slight decline in Alibaba Cloud users.

**Mitigate towards Ethical AI**

The involvement in ethical AI is evenly distributed across industries, indicating fairness and transparency in AI have been implemented.

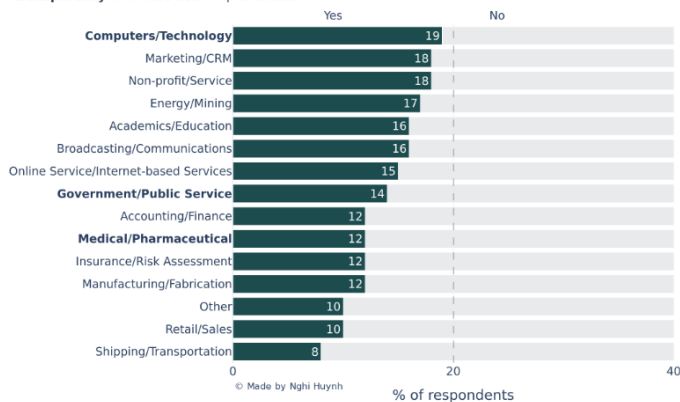


Figure 28 Mitigate to Ethical AI

With 19% of respondents acknowledging the use of ethical AI, Figure 28 shows a clear pattern where the computers/technology sector emerges as the leader. In contrast, just 12% and 14%, respectively, of the medical/pharmaceutical and government/public service industries mentioned the incorporation of ethical AI practises. This disparity between industries draws attention to an interesting finding: despite the growing interest and activity in the field of AI ethics, there is still a noticeable gap between theoretical research and its practical application, underscoring the need for further advancement in ensuring the ethical deployment of artificial intelligence across a range of domains.

**Contingency Table Visualization**

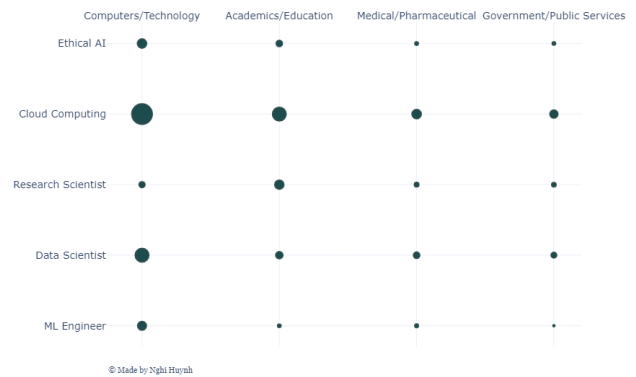


Figure 29 Contingency Table visualization

According to Figure 29, which visualises the data, the Computers/Technology sector has a higher percentage of respondents who identify as data scientists and who report using cloud computing platforms and ethical AI in conjunction with their machine learning practises than other industries. However, it becomes crucial to carefully examine the contingency table, throwing light on any correlations between these components, in order to fully identify any underlying patterns or relationships. As a result, I used a Chi-square test to carefully assess whether there is a significant relationship between the data science parameters and industry categories, hoping to clarify how these variables interact in a good statistical manner.

**Correspondence Analysis - Biplot of Data Science factors and Industries**

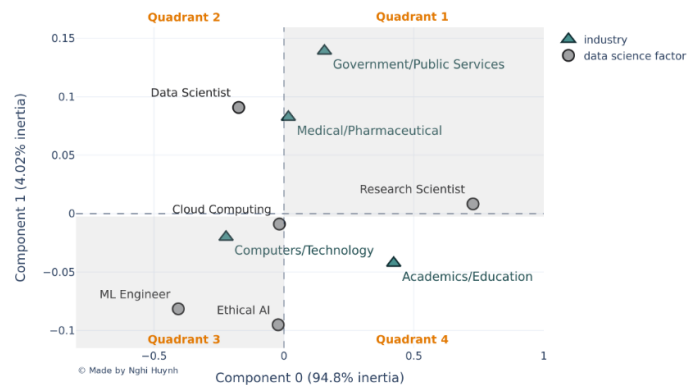


Figure 30 Biplot of Data science factors and Industries

A biplot that depicts the data science factors and how they are distributed among various sectors is shown in Figure 30. Notably, the Computer/Technology business (Quadrant 3) is where ethical AI, cloud computing, and the prevalence of ML engineers primarily cluster. Contrarily, the presence of data scientists is more evident in the government/public services and medical/pharmaceutical sectors, which correspond to Quadrants 1 and 2. This finding is intriguing since it deviates from the original impression created by the contingency table

visualisation, which suggested that the computer/technology business employed a greater proportion of data scientists. Last but not least, as shown by Quadrant 4, the Academics/Education industry emerges as a sector characterised by an equitable distribution of research scientists, the deployment of cloud computing, and moral AI practises. A deeper understanding of the connections and distributions of these crucial data science parameters across sectors is provided by this biplot analysis.

**B. Models & Algorithm**

A confidence interval is a statistical measure that is used to roughly represent the range in which a population parameter, such as the mean or proportion, is likely to lie with some degree of certainty. They are crucial for drawing conclusions from data and making decisions based on statistical analysis because they offer a range of values around a point estimate, which serves as a measure of the uncertainty associated with sample estimates. Probability Intervals of Confidence for the Difference in Two Population Proportions.

$$\hat{p}_A - \hat{p}_B \pm z_{\frac{\alpha}{2}} \sqrt{\frac{\hat{p}_c(1 - \hat{p}_c)}{n_A} + \frac{\hat{p}_c(1 - \hat{p}_c)}{n_B}}$$

Where :

The expected proportion for group A is denoted by the mathematical expression  $p_A = x_A/n_A$ .

$p_B = x_B/n_B$  can be used to calculate an estimated percentage for group B, or  $p_B$ .

The estimated pooled proportion, or  $p_c$ , is calculated using the formula  $p_c = (x_A + x_B) / (n_A + n_B)$ .

The total number of accomplishments in group A determines the significance of anything, or  $x_A$ .

The sum of all successes in group B is represented by the number  $x_B$ .

The sample size is indicated by the letters  $n_A$  and  $n_B$ , respectively.

The test statistic's score,  $z$ , is calculated using the formula  $z = (p_A - p_B) / \sqrt{p_c(1 - p_c)(1/n_A + 1/n_B)}$ .

A rough normal distribution, abbreviated as  $p_A - p_B$ , can be found for the products A and B. --  $[0, p_c(1 - p_c)(1/n_A + 1/n_B)]$

**IV. RESULT & DISCUSSION**

Performance evaluation involves the systematic assessment of the effectiveness and efficiency of a system, process, or entity. It typically entails the measurement of key performance indicators (KPIs) to gauge how well objectives are being met, resources are being utilized, and outcomes are being achieved.

The evaluation process can encompass a range of techniques, including data analysis, benchmarking, feedback, and various metrics, to enable informed decision-making, identify areas for improvement, and ensure alignment with organizational goals and standards.

**Table.1 Performance Evaluation of Industry**

Industry	$x_1 (n_1 = 16,316)$	$x_2 (n_2 = 9,094)$	95% CI
Computers/Technology	5584	2321	[0.075, 0.099]
Government/Public Services	636	500	[-0.021, -0.011]
Medical/Pharmaceutical	751	509	[-0.016, -0.004]

Table.1 Computing and technology have a 95% confidence interval of [0.075, 0.099]. For the total population of all respondents in all industries in 2018 and 2022, may conclude that the number of Computers/Technology respondents in 2022 will be between 7.5% and 9.9% lower than the number of Computers/Technology respondents in 2018. Government/public service percentages have a 95% confidence interval of [-0.021, -0.011]. There is a 95% chance that there will be more Government/Public Services respondents in 2022 than in 2018, and that increase will be between 1.1% and 2.1% of the total population of all respondents across industries in both years. Medical/pharmaceutical ratios have a 95% confidence interval of [-0.016, -0.004]. Conclusion: Between 0.4% and 1.6% more Medical/Pharmaceutical respondents will be polled in 2022 compared to 2018 among the total population of all respondents across industries (95% confidence interval).

**Table.2 Performance Evaluation of Job Title**

Job Title	$x_1 (n_1 = 4,932)$	$x_2 (n_2 = 3,065)$	95% CI
Data Scientist	2676	1913	[-0.104, -0.059]

The 95% confidence interval for the proportion of Data Scientists is [-0.104, -0.059], as shown in Table.2. It can be concluded with 95% confidence that the number of Data Scientist respondents in 2022 is between 5.9% and 10.4% higher than the number of Data Scientist respondents in 2020, based on the entire population of respondents across all three job titles in 2020 and 2022.

**Table.3 Performance Evaluation of Cloud Platform**

Cloud platform	$x_1 (n_1 = 18,577)$	$x_2 (n_2 = 6,993)$	95% CI
GCP	4783	2056	[-0.0487, -0.0244]
Oracle	0	230	[-0.0355, -0.0303]

Table 3 displays the Performance Evaluation of Cloud Platform, presenting 95% confidence intervals for proportions within Google Cloud Platform (GCP) and Oracle. For GCP, the confidence interval is [-0.0487, -0.0244], indicating with 95% confidence that the count of GCP respondents in 2022, concerning the entire population of respondents across various cloud platform providers in 2018 and 2022, is between 2.44% and 4.87% higher than the count of GCP respondents in 2018.

Similarly, for Oracle, the 95% confidence interval for proportions is [-0.0355, -0.0303], signifying with 95% confidence that the number of Oracle respondents in 2022, within the same population context, surpasses the count in 2018 by a range of 3.03% to 3.55%.

#### V. CONCLUSION

In Conclusion, this study has provided valuable insights into the diverse applications and significant economic implications of cutting-edge technologies. Through a comprehensive examination across various application domains, it is evident that machine learning and blockchain technologies offer substantial opportunities to improve efficiency, strengthen security, and drive innovation within cloud environments. The concrete economic impact, observed as cost-effectiveness, revenue enhancement, and optimized resource allocation, underscores their potential to bring about substantial changes across industries, especially in finance and healthcare. This research emphasizes the pivotal role of technology adoption in shaping the trajectory of cloud computing and the broader economic landscape, enabling well-informed decision-making and strategic planning in the digital era. During the watershed year of 2022, characterized by significant innovation and investments in Applied AI and Cloud Computing, there was a proliferation of cloud services catering to both individuals and businesses. This expansion unlocked immense potential and facilitated competition based on expertise rather than mere scale. The emergence of Machine Learning Engineers, alongside Research Scientists and Data Scientists, has expedited the transition of AI research from theoretical concepts to practical applications. However, Data Scientists continue to hold significant influence, particularly in the Medical/Pharmaceutical and Government/Public Services sectors. From a technical performance viewpoint, the rise of Vision Transformers has paved the way for new advancements in Computer Vision, promising exciting technological milestones in the coming years. Nonetheless, a comprehensive analysis indicates that the narrative of AI adoption in India is still in its early stages, with a few cities leading in the development of AI strategies while much of the country lags behind. Similarly, cloud computing, a pivotal aspect of the Fourth Industrial Revolution, is still in its initial phases of adoption across the continent. Despite AI's potential to revolutionize various enterprises and industries, its progress in India is hindered by a prevailing lack of trust. The absence of a mature risk awareness framework and essential controls has impeded the practical application of AI, resulting in minimal progress beyond proof-of-concept and isolated solutions.

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