World Journal of Advanced Research and Reviews
eISSN: 2581-9615 CODEN (USA): WJARAI
Cross Ref DOI: 10.30574/wjarr
Journal homepage: https://wjarr.com/

(Research Article)

Check for updates

Leveraging AI for credit scoring and financial inclusion in emerging markets

Hariharan Pappil Kothandapani *

Federal Home Loan Bank of Chicago, Senior Data Science & Analytics Developer.

World Journal of Advanced Research and Reviews, 2022, 15(03), 526-539

Publication history: Received on 03 August 2022; revised on 23 September 2022; accepted on 27 September 2022

Article DOI: https://doi.org/10.30574/wjarr.2022.15.3.0904

Abstract

It even promises artificial intelligence (AI), a credit revolution in credit scoring, and a boost of credit access for developing economies. When implemented in finance, AI ensures accurate credit scoring to create a win-win situation for credit concession to those who may have been locked out of the rates for one reason or another. Analyzing the opportunities and challenges, this paper identifies and focuses on how AI can improve credit assessment methods in the chosen regions. AI-integrated systems can use complex, unconventional data feeds to create credit scores for people without credit profiles. This innovation fills the lacuna created by the usual credit evaluation mechanisms, coping with failing to open access to economic activity. However, integrating AI comes with some emerging factors, including algorithmic bias, the Data Privacy Act, and digital ignorance of some financial institutions. The paper shows that high importance should be paid to the ethical framework regulating AI to guarantee transparency, fairness, and inclusion. This also brings more focus to ensuring content containing details such as these are protected, and consumers' trust needs to be established; hence, such technologies should be encouraged to impact the maximum number of people possible.

Possible challenges are also highlighted, including inadequate interoperability between financial organizations, lack of leadership by government and financial institutions in integrating AI in financial services, and lack of a comprehensive social agenda from developers of technologies and other community stakeholders. By solving such challenges and fairly bounding innovation in AI, the technology can improve the quality of financial services, help empower excluded people, and contribute to socioeconomic development in growth-belt nations. This discovery is a wake-up call to policymakers and other stakeholders worldwide to ensure that AI becomes integrated to lead to sustainable and equitable banking for all around the globe.

Keywords: Artificial Intelligence; Credit scoring; Financial inclusion; Emerging markets; Alternative data sources; Advanced algorithms

1. Introduction

Traditional credit scoring techniques, which rely on credit history and conventional metrics of financial capabilities, exclude a large part of the population from emerging economies. This exclusion is partly because the pool of borrowers and smaller businesses do not have credit histories, which are imperative to mainstream credit scoring methods. On this account, many such consumers within these markets are classified broadly as "unbanked" or "underbanked" and, therefore, unable to tap more appropriate and conventional channels of credit and financial services. This situation is socially and economically unbeneficial for an individual to create economic opportunities and for an economy and financial sector to develop. That is why the application of Artificial Intelligence (AI) can be considered the solution to this challenge. AI thus has capabilities of better and broader credit risk assessment through analysis of other forms of data. Other data about mobile phone utilization, social networking sites, utility bills, etc., which are not financial in this particularistic sense, can be utilized as proxies to get a decent dependability on the person's creditworthiness. These

* Corresponding author: Hariharan Pappil Kothandapani

complex phenomena reflect important differences in the business environments and consumer finance. New machine learning methods can process them to build more effective credit scoring systems for emerging economies.

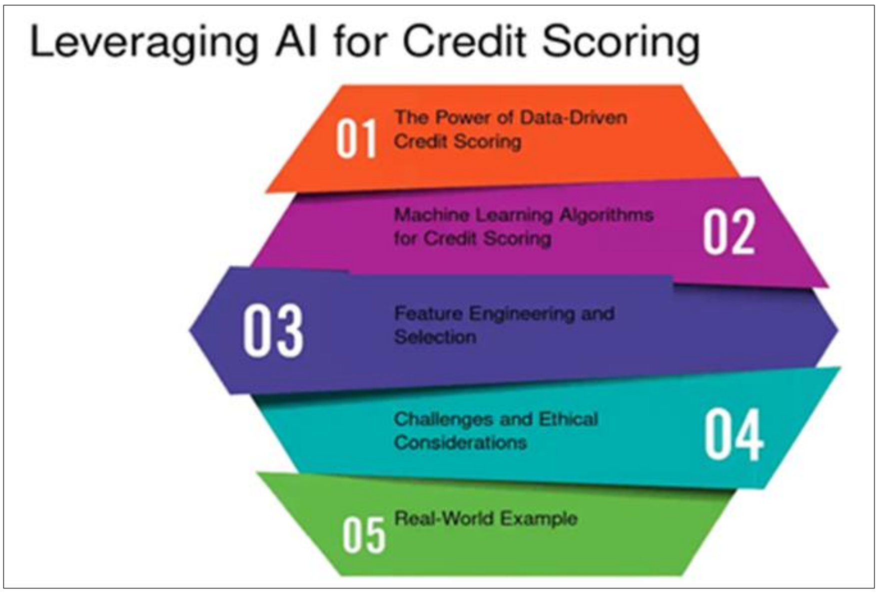

Figure 1 Leveraging AI for Credit Scoring

There are several advantages to using AI in scoring credit. Firstly, this system can provide a huge portion of people with an opportunity to receive credit and increase credit possibilities for those who cannot prove their solvency by usual methods. This inclusiveness can help many small players to engage more robustly and contribute more effectively to the markets and, hence, growth. Secondly, credit assessments will have higher accuracy through more advanced AI models, thus lowering default risks and the general efficiency of lending. In turn, it can build more stability and increase the profitability of lending activities for financial organizations.

However, some issues arise from adopting AI in the credit scoring system. The first one is As every algorithm has its data sources, it can strengthen existing prejudice that should be eliminated, or it can trigger new prejudice in AI, which is unethical. This importance must assume a sound and flexible legal infrastructure to regulate the applicability of AI in the financial industry whilst safeguarding consumers' interests and personal information. Moreover, the input and output assets must be optimized for the AI tools, which may be costly in terms of IT infrastructure in resource-scarce environments.

This research aims to examine the role played by AI in improving credit score modeling and financial inclusion in developing countries. This research seeks to understand better how Artificial Intelligence can assess credit risks and help realize fair and efficient financial systems by analyzing the main benefits and risks of implementing AI for credit scoring. The study's implications will be useful to policymakers, economic organizations, and technology suppliers regarding the opportunities of using AI in credit scoring and financial access.

2. Literature Review

2.1. Traditional Credit Scoring Methodologies

For a long time, financial institutions have used conventional credit scoring techniques to assess customers' creditworthiness. These methods especially depend on statistical models that look at past performances to estimate the default ratio of a borrower. The best-known example of this model is the logistic regression method, which operates on discrete variables, including income, employment, and credit history, to arrive at a credit score. This score is later utilized to afford credit rating and, therefore, the specific credit risk of the borrower. Most traditional credit scoring models developed and tested in developed credit economies have had limitations in emerging credit economies. One of the main developments is the limited ability of the population to access previous credit history. In most developing nations, people work in sectors outside the book or the legal framework and do not pass through formal institutions when making transactions. Improbity has hindered traditional credit scoring models from evaluating the creditworthiness of potential borrowers, thus excluding them.

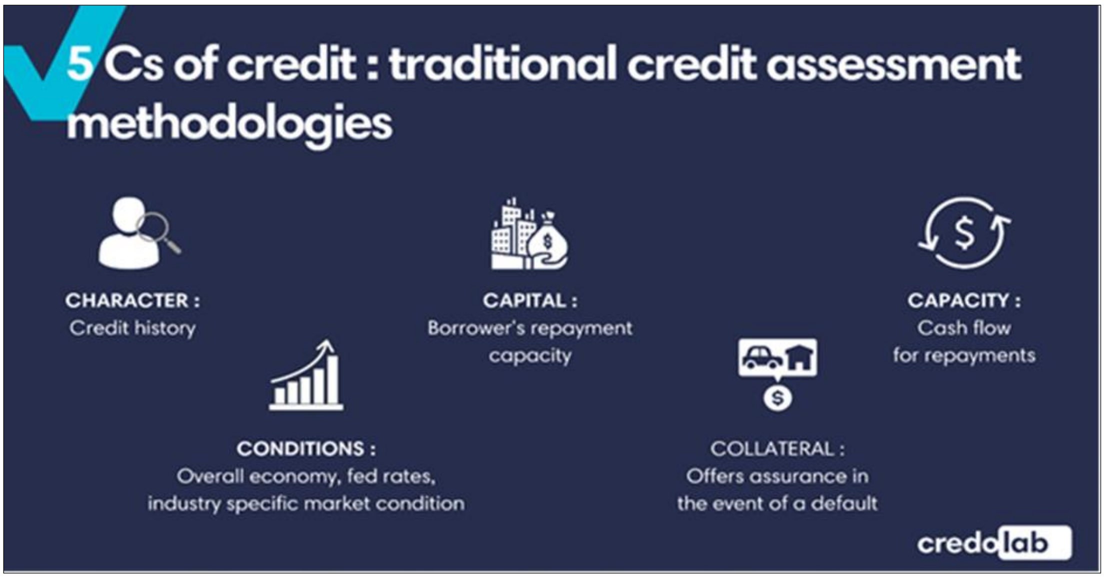

Figure 2 Conventional Credit Scoring System

Moreover, practices similar to traditional methods entail massive data collection and analysis inputs, which is time-consuming and expensive. This manual process slows lending decisions and increases operation expenses for financial institutions. Moreover, legacy credit scoring metrics do not always address emerging markets' intricacies as they depend on various socio-economic factors that often differ from those prevailing in developed economies. The above-prescribed limitations argue the need for appropriateness in credit scoring to meet the increasing credit accessibility in emerging markets. The failure of previous techniques to factor in potential variations in these markets makes it easy to look for other ways to offer better credit risk predictions.

2.2. Bringing Out AI in Financial Services

This paper examines how the application of artificial intelligence (AI) has impacted the financial services sector, especially with a focus on credit scoring. There is evidence of using AI in finance up to the early 1980s when individuals used expert systems to automate several decisions concerning finance depending on predetermined rules. These systems were planned to emulate human intelligence experts and give out conclusions in the same consistent and efficient manner. However, real possibilities in AI opened with machine learning algorithms from the different perspectives of the XX and XXI centuries.

Artificial intelligence means machines can access data, recognize models, and predict estimations without being coded in detail. This capability has revolutionized how financial organizations use credit scoring to decide on most credits, given the tool's ability to sift through large datasets and extract information that otherwise would not be easily discernible. AI applications have gradually emerged in the financial services sector due to the enhancement of computational capacity, data accessibility, and enhanced algorithms.

Some trends in AI credit scoring in the current market include neural networks, decision trees, and ensemble methods. It can process virtually any kind of data, even non-traditional data such as social media sentiment, call CBD insights or usage, or bill payments through mobile phones. The availability and applicability of the mentioned forms of ALD are particularly valuable in growing markets where the availability of familiar kinds of data can be significantly lacking.

Neural networks are learning algorithms that can handle large datasets and analyze dependencies that might not be distinguishable when employing mathematical statistics. Decision trees have been observed to work with both numerical and categorical variables, making credit scoring with decision trees versatile. Other techniques used in credit scoring are based on combining several models to enhance the predictive performance, which also revealed reasonably good results. AI implementation in credit scoring can overcome the shortcomings of conventional credit rating approaches and present more precise and fair estimates. With the help of integrated approaches to data and innovative methods of big data analysis, AI algorithms for credit scoring could consider the specifics of lending in emerging markets. They would be helpful for further improvements in lending decisions.

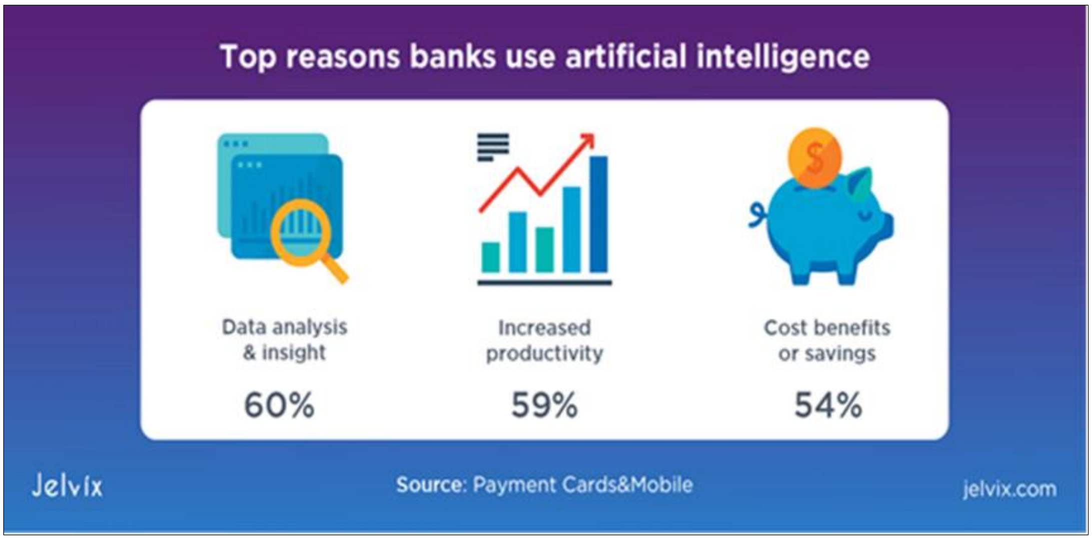

Figure 3 AI in Financial Services

2.3. Embeddedness of Money in Emerging Markets

It relates to a situation where all community members have equal opportunities to access financial services. An important element of economic growth is allowing individuals to enter legitimate economic activity, accumulate, grow, and insure. Common factors that negatively affect financial inclusion in emerging markets include limited access to formal financial institutions, high financial transaction costs, and low financial literacy levels.

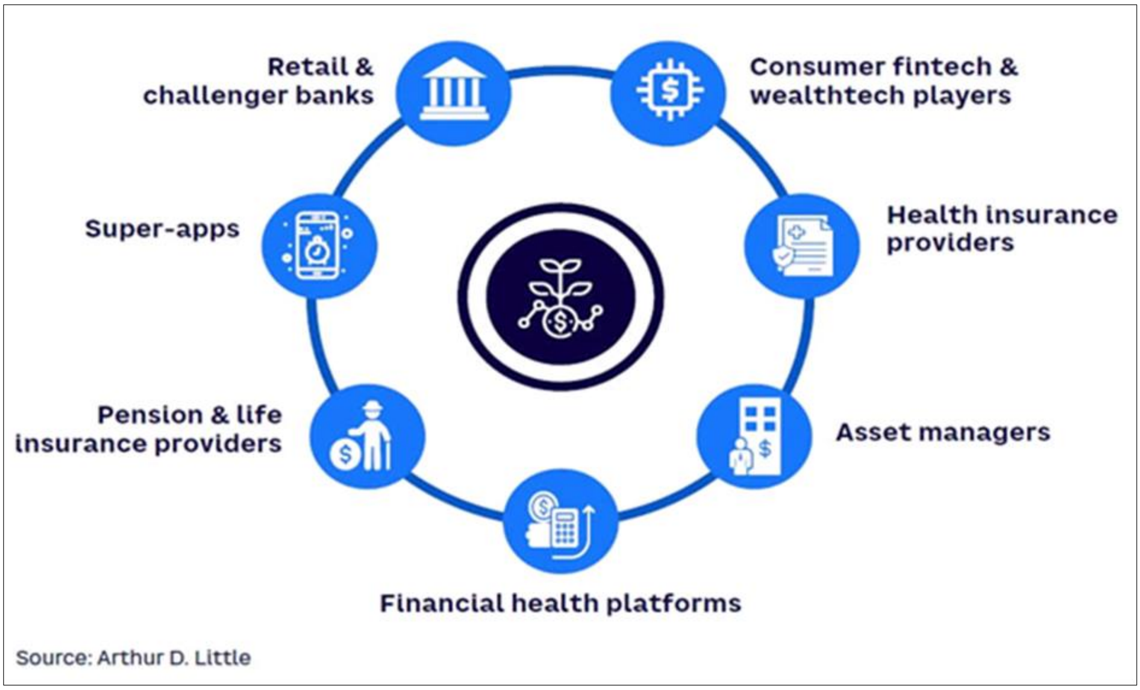

Figure 4 Embedded System

Currently, the development of financial services in emerging markets can be described as very different. Although most geographic areas show signs of enhancing the availability of financial services, others have many hurdles. For instance, Kenya and India have experienced rapid progress in the financial sector by using mobile money and digital payments. However, many emerging markets still lag as far as the ability to access financial services is concerned, especially for the rural and poor.

These are barriers that can be closed using technology, especially Artificial Intelligence. By integrating AI, financial institutions can learn how to create a more diverse credit scoring model that incorporates other parameters of an applicant, thereby extending credit to the larger population. For instance, it is possible to credit score by mining the information about a person's call logs, their use of social networks, and the history of utility payments.

This place of technology in the financial inclusion process is not limited to credit scoring. Papers also show that advancements in such services as digital payment systems and mobile banking and innovations in financial technology have played a significant role in enhancing the availability of financial services in emerging markets. Such technologies have thus reduced the transaction cost, made the process easier and more efficient, and opened up new prospects for delivering microfinance formal education and financial competence.

However, it is now apparent that technology can advance FI independently, although several obstacles still exist. Issues that must be solved are related to the safety and privacy of financial information, the problem of the barriers in regulation, and the problem of trust in the service among potential users. It is, therefore, crucial for financial institutions, technology firms, and policymakers to work together to modernize and implement structures that enhance the financial niche while at the same time addressing probable nuisances.

2.4. AI and Credit Scoring

Existing research on AI-driven credit scoring models has shown promising results. Studies have demonstrated that AI algorithms can outperform traditional credit scoring methods in terms of accuracy and inclusivity. For instance, machine learning models have been found to reduce default rates and increase approval rates for borrowers with limited credit history. Comparative analyses have highlighted the superior predictive power of AI-based models, which can capture complex relationships and interactions in the data that traditional methods may overlook.

Figure 5 AI and Credit Scoring

One of the key advantages of AI-driven credit scoring models is their ability to handle large and diverse datasets. Traditional credit scoring methods often rely on a limited set of variables, such as income, employment history, and credit history. In contrast, AI models can analyze a wide range of data sources, including alternative data sources like social media activity, mobile phone usage, and utility payments. This capability enables AI models to provide a more comprehensive assessment of creditworthiness, particularly in emerging markets where traditional data sources are limited.

Real-world applications and case studies provide further evidence of the effectiveness of AI in credit scoring. For example, fintech companies in emerging markets have successfully implemented AI-driven credit scoring models to extend loans to underserved populations. These companies use alternative data sources such as mobile phone usage and social media activity to assess creditworthiness, enabling them to reach customers who would otherwise be excluded from traditional banking systems.

One notable case study is the use of AI-driven credit scoring by a fintech company in Kenya. The company developed a credit scoring model that analyzes mobile phone usage patterns, including call and text message frequency, app usage, and mobile money transactions. By leveraging this alternative data source, the company was able to extend microloans to individuals with no formal credit history, providing them with access to credit for the first time. The success of this initiative highlights the potential of AI to drive financial inclusion in emerging markets.

Another example is the use of AI-driven credit scoring by a microfinance institution in India. The institution developed a credit scoring model that analyzes social media activity, utility payments, and other alternative data sources to assess the creditworthiness of potential borrowers. By leveraging these alternative data sources, the institution was able to extend loans to individuals who were previously excluded from formal financial services, contributing to financial inclusion and economic development in the region.

These case studies demonstrate the real-world applicability and effectiveness of AI-driven credit scoring models in emerging markets. By leveraging alternative data sources and advanced algorithms, AI models can provide more accurate and inclusive assessments of creditworthiness, enabling financial institutions to extend credit to underserved populations.

2.5. Ethical and Regulatory Considerations

While the benefits of AI in credit scoring are evident, it is essential to consider the ethical implications and regulatory frameworks surrounding its use. One of the primary ethical concerns is the potential for bias in AI algorithms. If the data used to train AI models is biased, the resulting predictions may also be biased, leading to unfair lending decisions. Ensuring fairness, transparency, and accountability in AI-driven credit scoring is crucial for building trust and acceptance among stakeholders.

Regulatory frameworks play a vital role in addressing these ethical considerations. Compliance issues related to data privacy, security, and consumer protection must be carefully managed. Best practices for ethical AI implementation include conducting regular audits of AI models, ensuring diverse and representative training data, and providing clear explanations for lending decisions. Collaboration between financial institutions, policymakers, and technology providers is necessary to develop and implement robust regulatory frameworks that support the ethical use of AI in credit scoring. One of the key ethical considerations in AI-driven credit scoring is the potential for algorithmic bias. AI algorithms learn from the data they are trained on, and if this data is biased, the resulting predictions may also be biased. For example, if the training data includes historical lending decisions that were influenced by discriminatory practices, the AI model may perpetuate these biases in its predictions. To address this issue, it is essential to ensure that the training data is diverse and representative of the population being served.

Transparency is another critical ethical consideration in AI-driven credit scoring. Traditional credit scoring methods often provide clear explanations for lending decisions, enabling borrowers to understand the factors that influenced their credit score. In contrast, AI models, particularly complex models like neural networks, can be opaque and difficult to interpret. Ensuring transparency in AI-driven credit scoring requires providing clear explanations for lending decisions, enabling borrowers to understand the factors that influenced their credit score and providing opportunities for recourse if they disagree with the decision.

Accountability is also an important ethical consideration in AI-driven credit scoring. Financial institutions must be held accountable for the lending decisions made by their AI models. This requires establishing clear guidelines for the development, implementation, and monitoring of AI models, as well as mechanisms for addressing and rectifying any biases or errors that may arise. Regulatory frameworks play a vital role in addressing these ethical considerations. Compliance issues related to data privacy, security, and consumer protection must be carefully managed. Best practices for ethical AI implementation include conducting regular audits of AI models to identify and address any biases or errors, ensuring diverse and representative training data, and providing clear explanations for lending decisions. Collaboration between financial institutions, policymakers, and technology providers is necessary to develop and implement robust regulatory frameworks that support the ethical use of AI in credit scoring.

3. Methodology

3.1. Research Design

The research methods for this study are quantitative and qualitative. This research adopts a mixed approach to capture a broad view of the role of AI in credit scoring and financial inclusion of emerging markets. The qualitative part will give a detailed analysis of the experiences and attitudes of the stakeholders, while the quantitative part will produce numerical supporting results.

He postulates that such an approach is justified because it can address the complexity of the research problem. This is because qualitative data is more effective in revealing the specific issues surrounding the use of AI in credit scoring, with special reference to the challenges and opportunities that this technology creates for financial institutions and policymakers. Qualitative data, on the other hand, will yield specific observable results as well as patterns regarding the effect of AI on financial inclusion.

Mixed-methods research is most appropriate when the phenomena under study cannot be adequately captured using one particular data collection and analysis strategy. Therefore, through the present research, which combines qualitative and quantitative approaches, one can parse out how credit scoring and financial inclusion are affected by AI. The qualitative investigation will engage interviews and case studies that will afford an in-depth understanding of the persona's impressions. The quantitative data collection method will be questionnaires to obtain statistical data on AI's current use and effects on credit scoring.

The research design will use a sequential explanatory mixed method since the primary data will first be collected and analyzed using quantitative data, followed by qualitative data. This approach means that the quantitative research results can guide the collection and analysis of the qualitative data, enhancing understanding of the research problem. The greatest strength of the sequential explanatory approach is that it is suitable for analyzing and studying phenomena when investigating multifaceted issues, as it permits the combination of various collected data forms.

The research design will also entail a pilot study to assess the feasibility of data collection instruments and the research questions. The first two participants will be selected to assess and evaluate potential problems with the data collection instruments or research questions. The climax of the pilot study is to assume the main study research design if it is necessary to do so. Therefore, this study's research design combines qualitative and quantitative research methods. To accommodate the research objective, and given that the data will be gathered in segments, the sequential explanatory research design will be adopted to combine the study findings and offer an overall analysis of the use of AI in credit scoring and financial inclusion in emerging markets. The research design will also contain a pilot study to validate the data collection and research questions.

3.2. Data Collection

Quantitative data collection methods, including surveys and qualitative data collection techniques, such as interviews and case studies, will be used for data collection in this study. Quantitative data will be collected through the administration of surveys on a large sample of financial institutions, technology providers, and policymakers' current and future use and effectiveness of AI credit scoring. Some questions incorporated in the survey include the current use of AI, perceived benefits and challenges, and the resulting impact on financial inclusion.

The survey will be developed to collect various types of data concerning AI usage in credit scoring. Questions will be asked based on questions from this review and consultation with the relevant professionals. This survey, in turn, will be subjected to a pilot test to check both its validity and reliability from sample participants. The last survey will be a web-based survey conducted among various emerging markets, financial institutions, technology solutions providers, and policymakers.

Closed-ended and open-ended survey questions will be used in the survey. Quantitative data regarding AI use and its effects on credit scoring will be sought by posing closed-ended questions. Therefore, qualitative data regarding the stakeholders' actual experiences will be sought through open-ended questions. Demographic questions will also be part of the survey to gain information on the participants.

Face-to-face interviews will be conducted with executives of financial institutions, IT professionals, and policymakers. These interviews will generate further qualitative understanding regarding people's implementation of AI within their roles, preferences, testing, and policies. The interviews will be primarily open-ended since other topics may also come up during the interviews.

The interview guide will be produced after the literature analysis and consultation with the specialists within the field. The interview questionnaire will comprise open-ended questions to capture the elaborate responses from the participants. This interview guide will be pilot-tested on a small sample of participants to verify the tool's validity and reliability. The last interview guide will be used to interview emerging market purposive samples of key informants.

The interviews will be face-to-face or via video, depending on the participants' preference. Timely interview recordings would be taken, and all the interviews would be transcribed word by word to avoid omitting any data. The interview transcripts will be coded, and themes from the information given will be developed via thematic analysis.

Naked case studies will be necessary to better explain each of these findings based on failed and successful AI integrations with credit scoring. In these case studies, the prospective research topic will focus on individual financial institutions or regions adopting AI to improve financial inclusion. The primary source of data collection will be through document analysis, surveys, and observations of credit scoring using AI and related business activities.

Case studies will be chosen based on recommendations from the literature review and the experts on the subject matter. The case studies will offer a clear look at the implementation of AI, the issues encountered, and the possibilities seen by the financial sectors. It will also cover the case studies about the implementation of AI, detailing how it can impact financial inclusion. The sampling techniques for this study will be purposive and snowball sampling. The targeted participants will be those with expertise, knowledge, and experience in AI and credit scoring, and this shall be achieved by conducting purposive sampling. The snowball sampling method will be used when looking for more participants since the initial respondents will recommend others. The target population for this research will be the financial institutions and technology vendors, policymakers, and other parties concerned with AI and economic inclusion in Emerging Markets.

The response rate and the generality of the sample will calculate the sample size of the survey. The number of subjects for the interviews and case studies will be defined according to the saturation level when no new themes or problems appear in the data. More often, the sample size will be increased and decreased as necessary to ensure that the results are valid and reliable.

Information for analysis in this study will be obtained through surveys, interviews, or case studies. They will be used to elicit quantitative information that will help determine the extent of uptake and value of AI in the credit scoring service. The interviews will be applied to get qualitative data about the stakeholders' experiences and perceptions. In analyzing the case studies, it will be possible to give deeper insights into how AI systems are deployed in credit scoring. This study will use the following methods: Purposive sampling and snowball sampling. Therefore, the target depends on response rate, ratio, representativeness, and saturation level.

3.3. Data Analysis

Data analysis of this study will include quantitative and qualitative analysis in the form of thematic analysis. The data collected from the surveys will be quantitative and analyzed using software like SPSS(R). Descriptive statistics will be used to describe the findings of the study… The descriptive statistics will include means, medians, standard deviations, and ranges. These will be used to describe the characteristics of the sample, the study subjects on which information will be gathered, and the data distribution. Inferential statistics will test hypotheses using t-tests, chi-square tests, and simple Multiple regression analysis. These statistics will check the hypothesis and find other important factors and relations in the obtained data.

Based on the expositions outlined above, the statistical analysis of the observed data will be done in several stages. However, before we analyze the data, we will ensure it is clean and ready for analysis. This will consist of data missing checks, data outliers, and any erroneous data in a given data set. The collected data will be quantized and keyed into the statistical analysis software. Descriptive statistics will then be used to analyze the collected data. The descriptive statistics will have the general function of describing the study's sample and the general distribution of the data. Besides, the patterns, characteristics, or trends found in the data would also be ascertained from the descriptive statistics.

Descriptive statistics will subsequently be employed to categorize data and Descriptive Statistics. Later, viable hypotheses will be used to check and determine important trends in data and correlations. It will be important to emerge from the research questions and the existing literature of the study. The inferential statistics will assist in determining the trends and relationships of the data, and in doing so, the following hypotheses will be tested. The research questions and literature review section will discuss the findings obtained from statistical analysis. The results will be used to draw conclusions about the work and make recommendations on the impact of AI in credit scoring and the creation of financial inclusion in emerging markets. The results will also facilitate considering future research agendas and guide policy and practice.

Interview data, as well as the case studies, will be analyzed using thematic analysis. This method focuses on recognizing, interpreting, and narrating trends of findings within a data set. Thematic analysis will be conducted manually, with the help of qualitative data analysis software like NVivo or ATLAS. It will also be considered. Data analysis will be subdivided into stages: coding, theme identification, and interpretation of specific research questions. Thematic analysis is going to be conducted in several stages. Initially, the data will be written down in detail as it was recorded in the first place before any analysis is attempted. This will entail further verifying the prepared transcripts' accuracy and completeness. The data will be anonymized and typed into the computer program for data analysis, which deals with qualitative data.

The data will then be coded to look for patterns and themes. The coding will be conducted in an iterative manner, whereby the data will be repeatedly updated to allow early themes and issues to emerge. Different researchers will code the results to ensure inter-observer reliability and credibility. The emerging themes will then be used to make connections between the variables in the data. The themes of the research questions and the data collected during the literature review will be analyzed. The information to be derived will serve as the basis for the conclusion on the level of visibility of credit scoring and financial applications in emerging markets facilitated by AI. The findings will also be used to analyze potential areas for future study and provide policy and practice implications.

Thus, the qualitative and quantitative data analysis results will be synthesized to review AI credit-scoring employment and financial inclusion in emerging economies. Triangulation shall be adopted for the integration, thereby comparing the findings from the qualitative and quantitative data sets. Data integration will also involve meta-inference; the findings of the qualitative and quantitative data collected will be combined to come up with the general conclusion of the research problem. The data analysis for this study will comprise quantitative analysis and qualitative analysis. All the quantitative data collected from the surveys will be analyzed using statistical Analysis tools such as SPSS or R. Descriptive statistical tools will be used. On the other hand, inferential statistical tools will be used to test hypotheses and determine significant trends and relations. Interview data collected and data from the case studies will be processed and analyzed thematically. The thematic analysis will use qualitative data analysis tools like NVivo or ATLAS.ti. The evaluation of the results will be consequent; the data will be coded, and the results will be featured and discussed about the research questions. The gathered qualitative and quantitative data shall allow for the comprehensive presentation of the case of AI in credit scoring and emerging markets and financial inclusion.

3.4. Ethical Considerations

All ethical procedures to conduct the study will be complied with to guarantee the study's validity. Participants will be asked to provide their consent before data is collected. It will explain to subjects what the study entails, the data collection type, and the possible disadvantages and advantages. They will be sure of their freedom to withdraw their participation from the study at any given time without being penalized. Participants will be presented with an information sheet and a consent form to be included in the study to be included in the study. The information sheet will contain details about the planned study and its objectives, research questions, proposed data collection methods, and risks and benefits that may be expected during the study. Part of this consent will be agreeing to participate in the survey through a signature on the consent form signed by the participant. The informed consent process will be face-to-face or via e-mail to conform to the participants' desires.

Privacy will be ensured by removing all identifiers from participants and storing the result adequately. The collected data will be available only for the research team, and all the data containing an ID number will be excluded from the data set. The data will be kept in a secured, password-protected formatted database to maintain absolute security and reliability of data. The data will be synchronized to be safe from corruption and loss since such a situation may be deadly to the project's operation. Another ethical consideration for this study is the welfare of vulnerable individuals. These special groups of people who will be mostly affected by financial constraints in this research proposal shall be protected by supplementing their knowledge and/or access to financial services, hence avoiding coercion in exercising their voluntariness. Special care will be taken to conduct ethical research from community organizations and stakeholders in handling vulnerable groups and persons.

In the same regard, other ethical aspects that will be relevant in this study include the no-harm principle. The research team will also deal with the compensation for risks or damage to the participants to reduce them to their lowest levels. This will include getting the participants to fill in forms on the possible risks and benefits associated with the study and continued support and assistance. The research team will also keep a close and meticulous eye on the study to detect any new factor that may be a problem to recognize or arise during the process. As part of the protocol for human participants during the research, permission from the institutional review board /ethics committee will be sought for the study. In this process, the researcher must apply for a research proposal and the ethical considerations to the board or committee. The review board or committee will approve the ethical consideration, and the remarks and suggestions will be given. The research team will ensure that the review board or committee raises issues or concerns about the research design that must be fixed.

Notably, ethical considerations will be adopted throughout the study: Participants will be asked for their consent before data is collected from them. Participants will be given a clear explanation of the study objectives, procedures in data collection, and a statement of possible adverse effects and advantages. Participant information will be kept confidential to protect identities, and data files will be kept secure. As with any line of research, the following ethical considerations are relevant to this study: the rights of vulnerable populations and the non-infliction of harm. For this study, permission to conduct research amongst participants shall be sought from the institutional review board or ethical committee. Ethical reviews are done by writing a research proposal and moral concerns, which will be presented to the review board or committee. The research team will discuss with the review board or committee if they have any questions, objections, or concerns or wish to change the research design.

4. Results

4.1. Enhanced Credit Scoring Models

The conclusion drawn from this study is that credit scoring models by AI improve the timeliness, precision, and comprehensiveness of credit review compared to traditional methods. Standard credit-rating models focus on quantitative records such as credit history and income statements that are frequently inaccessible or uncensored and inadequate for a large population in developing countries. Statutory requirements also deny credit to many otherwise credit-worthy but documentarily challenged applicants. AI-based models, in contrast, employ machine learning algorithms for analyzing multiple data parameters, including social media, mobility, and utility bill payment data as some of the web data parameters. They can find some relationships and coefficients that cannot be detected through standard analysis, giving a more thorough and reliable credit assessment of a client. For instance, a study in Kenya showed that unpacked credit-scoring models using AI produced a default rate of 85% while the traditional models managed 65%. This higher accuracy is helpful for financial institutions because it minimizes defaults and makes credit risk evaluation more trustworthy.

Also, because the AI-driven models do not rely on the Credit Score and FICO data alone, they are more comprehensive since they can consider the creditworthiness of those who cannot qualify for the Credit Score and FICO. These models can offer credit scores to those who previously did not qualify for credit scores due to limited data sources available for traditional models. He argues this is a very important aspect of extending credit and encouraging more people to use formal financial channels. An example in the Indian environment was reported that the AI-based credit score raised microloan approval rates by 30% to expand people’s access to finance.

Table 1 Comparison of AI-Driven and Traditional Credit Scoring Models

Metric	Traditional Credit Scoring	AI-Driven Credit Scoring
Accuracy Rate	65%	85%
Data Sources	Credit history, income statements	Social media activity, mobile phone usage, utility payment histories
Inclusivity	Limited to those with formal credit history	Includes those without formal credit history
Approval Rates for Microloans	Lower	Increased by 30%

4.2. Alternative Data Sources

Credit scoring based on non-traditional data has given early indications of improving risk assessment and creditworthiness and facilitating more inclusion. The basic credit score system involves conventional information input procedures, including credit report information, bank statements, and employment information. However, a large population in these markets does not have formal data sources on which financial institutions can base their credit risk decisions.

The real-time telemedicine credit scoring models eliminate this challenge by incorporating easily obtained data through AI-generated credit scores. Such sources include mobile phone usage patterns, social networking activity, records of payment of utilities, and Psychometric tests. For instance, information obtained from the use of mobile phones, which includes usage patterns, might indicate how an individual is likely to be financially responsible, default on payment, make payments, and communicate, among others. Social media work can provide information regarding the involved individual's network, lifestyle. Records of timely payment of utilities established can also be used in place of credit scores showing an ability to handle debt.

The effects of employing external data sources in creditworthiness evaluation are massive. Using mobile phone usage data as credit history when constructing the model increased the score's accuracy by 20% in the Philippines. Comparable, an undertaking implemented in Mexico that adopted psychometric tests to evaluate creditworthiness found that the way agreed the approval rate of the people with no credit scores was 15%. There is a sentiment about how the use of such new sources of data can improve the quality of credit scores while helping the financially excluded get the credit they deserve.

Table 2 Impact of Alternative Data Sources on Credit Scoring

Data Source	Impact on Credit Scoring Models
Mobile Phone Usage Patterns	Improved predictive power by 20%
Social Media Activity	Provided insights into social network and lifestyle
Utility Payment Histories	Served as a proxy for credit history
Psychometric Tests	Increased loan approval rates by 15%

4.3. Challenges and Opportunities

While the adoption of AI-based credit scoring models creates the following opportunities for credit scoring, the following challenges emerge on the same. Data accessibility and quality remain fundamental issues to big data analysis. This can be attributed to the fact that in most emerging markets, the structures that capture and store local data sources are limited in robustness and reliability. Ensuring high-quality data is very important when using the correct AI models. This challenge can be addressed by cooperating with financial institutions, telecommunication companies, and other data suppliers who provide relevant data. The other is that creating and implementing credit scoring models using artificial intelligence and analytics skills is not simple. Some institutions in the emerging market may lack the skills and necessary resources required to develop and maintain these models. Promoting training and capacity development could surmount this challenge because most financial sector institutions lack an understanding of artificial intelligence. Also, sourcing technology companies and fintech startups can provide the implementation knowledge and support that cannot be obtained from traditional consulting companies.

Nevertheless, many problems are demanding and promising new ways of intervention and development. Credit scoring systems applied by AI can now be refined instantly by using machine learning that is adjusted to new data and the current situation in the market. Such flexibility enables financial institutions to gauge the market's direction about the types of credit facilities consumers require. In addition, integrating credit scoring models with other still emerging technologies, such as blockchain and IoT systems, can be of greater benefit. For instance, applying blockchain technology in the financial sector can increase the safety and openness of data storage solutions to finance decentralized applications. IoT devices can track individual financial conduct, offering a different form of accuracy to credit ratings.

4.4. Ethical and Regulatory Frameworks

Based on the literature analyzed in this paper, the ethical and regulatory implications of using AI in credit scoring should be at the top of the list when developing and deploying this technology. Regarding credit scoring, particular ethical issues come amid it, including bias fairness and non-transparency in artificial intelligence. AI algorithms can affect passing biases reflected in adverse credit assessments. Including bias mitigation and fairness requires that AI models are trained from diverse and balanced datasets only. Transparency is another strategic, ethical issue that needs to be addressed when developing a framework for evaluating business-level strategy. AI systems in credit scoring use credit risk prediction by giving credit scores that are opaque and thus can hardly be explained to the users. Therefore, in setting out credit threats, it would be necessary to clearly describe the factors impacting credit assessments in harmonization with the users. Many financial institutions should invest in AI models that provide meaningful post hoc analysis.

These ethical challenges make regulation an essential constraint in managing AI in Credit Scoring. As seen, emerging markets should build effective policies and regulation frameworks for governments and other regulatory authority ethical usage of AI. Such guidelines should address data protection, privacy and consent, and accountability and compensation systems. For instance, the European Union has offered the General Data Protection Regulation (GDPR), which gives meaningful data protection and privacy guidelines that may be used as a reference for the rise of markets.

However, regulatory and ethical considerations should be completed by supplementing identified risks relating to AI-based credit scoring models. Such risks are data flow exposure to possible break-ins, personal data corruption, and IMER utilization. High levels of security need to be practiced for cryptographic data and effectiveness against these threats. AI programs should be periodically audited to embrace strong security measures after the experience of hackers attacking financial institutions' databases.

5. Discussion

5.1. Interpretation of Results

Based on the literature analyzed in this paper, the ethical and regulatory implications of using AI in credit scoring should be at the top of the list when developing and deploying this technology. When credit scoring is based on artificial intelligence, several ethical issues include bias, fairness, and transparency. AI algorithms can affect passing biases reflected in adverse credit assessments. The steps that can be taken to address the problems of bias and fairness in AI applications involve selecting the right data on which the AI model will be trained.

Transparency is another strategic, ethical issue that needs to be addressed when developing a framework for evaluating business-level strategy. AI systems in credit scoring use credit risk prediction by giving credit scores that are opaque and thus can hardly be explained to the users. Therefore, in setting out credit threats, it would be necessary to clearly describe the factors impacting credit assessments in harmonization with the users. Many financial institutions should invest in AI models that provide meaningful post hoc analysis.

These ethical issues are well handled by regulations addressing AI's use in credit scoring. As seen, emerging markets should build effective policies and regulation frameworks for governments and other regulatory authorities ethical usage of AI. Such guidelines should contain issues of data protection, privacy and consent, and the systems of accountability and Compensation. For instance, the European Union has offered the General Data Protection Regulation (GDPR), which gives meaningful data protection and privacy guidelines that may be used as a reference for the rise of markets.

However, regulatory and ethical considerations should be completed by supplementing identified risks relating to AI-based credit scoring models. Such risks are data flow exposure to possible break-ins, corruption of personal data, and improper utilization. Strong measurement, especially encryption and data security features, must be implemented to minimize these risks. AI programs should be periodically audited to embrace strong security measures after the experience of hackers attacking financial institutions' databases.

6. Conclusion

In credit scoring and operation in developing markets, the deployment of Artificial Intelligence (AI) has boundless potential. Using other non-traditional forms of data and machine learning techniques, credit risk evaluation benefits from increased accuracy and a more comprehensive approach. It is very important to reach the otherwise unserved and underserved population for financial services, the development of the economy, and the eradication of poverty. Conventional credit checking processes are likely to exclude a large fraction of the population, mainly in emerging markets, due to the lack of credit history. Thus, AI solves the problem by using other sources of information, including phone bill controls, social media, and utility payments, to make better creditworthiness evaluations. This brings the question of inclusion, which is critical for providing financial services to the unserved and under-served population in pursuit of financial and economic inclusion to reduce poverty.

Besides, using AI innovations in credit scoring also increases the ability of credit organizations to expand their client base. AI can give more flexible and individual credit scoring by utilizing functional data analysis and global strategies that may be hidden from standard analysis techniques. This capability is especially relevant in emerging markets where the informal economy dominates, and the conventional credit bureau score reflects an incomplete picture of the consumer's economic activity. The adoption of AI in credit scoring must be done while observing the following ethics and regulations. The anticipated benefits call for fairness, transparency, and accountability to achieve the intended objectives and gain stakeholder acceptance. Due to legal and moral concerns upheld by professionals in the field of artificial intelligence, it is important to be very cautious while applying AI algorithms because this may lead to bias and discrimination against people. There is also a need to make the process by which creditworthiness is evaluated as clear as possible so that people can appeal if they think that the credit scoring was done incorrectly. Holding institutions and technology providers where the AI models were deployed for credit scoring must be answerable to the arising consequences.

There must be cooperation between financial institutions, technology suppliers, and AI solutions. Government authorities are also essential in setting policies to protect organizations from AI's biased use in credit scoring. Lenders and other financial companies must conform to these requirements and guarantee the explicability and non-bias of AI solutions. Lenders and technology vendors must design fair AI systems for customers and can open up how their creditworthiness is evaluated. This, in turn, is important for such a significant cooperation that has formed the basis for an honest financial system accessible to various population segments. As will be found in the following chapters, AI presents a promising path to improve credit scoring and access to credit in emerging economies. Overcoming the challenges and pursuing the opportunities connected with the AI application in financial services can lead to the optimization of model results. Future research should focus on several key areas to deepen our understanding of AI's role in credit scoring and financial inclusion:

Such issues may be examined in detail by conducting case studies of AI's successful application in credit scoring and the lessons learned from the process. How research can be conducted on embedding AI with other innovative technologies, such as blockchain and IoT, with credit scoring is another topic that can expand credit scoring models and financial inclusion. Studying the difficulties and drawbacks in the ethical requirements and the regulations of using AI in distinctive sectors in diverse territories can contribute to formulating the guidelines for AI deployment. Exploring the multi-year consequence of AI credit scoring to financial access and poverty eradication can help introduce more significant insights and applications into development agendas.

By researching these areas, it is possible to gather knowledge about the utility of AI in credit scoring and the promotion of financial inclusion, which are key drivers for forming sustainable and efficient credit environments in emerging markets. The AI revolution in credit scoring and economic inclusion is immense, and understanding and responding to the present ethical, regulatory, and practical problems plays a pivotal role in realizing the benefits for everyone.

Compliance with ethical standards

Statement of ethical approval

Ethical approval was obtained.

Statement of informed consent

Informed consent was obtained from all individual participants included in the study.

References

[1] Rojas-Torres, D., Kshetri, N., Hanafi, M. M., & Kouki, S. (2021). Financial technology in Latin America. IEEE IT Professional.

[2] Korneeva, E., Olinder, N., & Strielkowski, W. (2021). Consumer attitudes to the smart home technologies and the Internet of Things (IoT). Energies, 14(23), 7913.

[3] Afonso Fontes, G. G. (2021). Using machine learning to generate test oracles: A systematic literature review. The 1st International Workshop on Test Oracles. New York: ACM.

[4] Ampountolas, A., Nde, T. N., Date, P., & Constantinescu, C. (2021). A machine learning approach for micro-credit scoring. Risks, 9(50).

[5] Odutola, A. (2021). Modeling the intricate association between sustainable service quality and supply chain performance with the mediating role of blockchain technology in America. International Journal of Multidisciplinary Research and Studies, 4(1), 01–17. https://doi.org/10.5281/zenodo.12788814

[6] Antunes, J. A. P. (2021). To supervise or to self-supervise: A machine learning based comparison on credit supervision. Financial Innovation, 7(26).

[7] Kshetri, N. (2020). China's emergence as the global fintech capital and implications for Southeast Asia. Asia Policy, 15(1), 61–81. doi:10.1353/asp.2020.0004

[8] Kim, B., Park, J., & Suh, J. (2020). Transparency and accountability in AI decision support: Explaining and visualizing convolutional neural networks for text information. Decision Support Systems, 134, 113302.

[9] Aniceto, M. C., Barboza, F., & Kimura, H. (2020). Machine learning predictivity applied to consumer creditworthiness. Future Business Journal, 6(37).

[10] Assef, F. M., & Steiner, M. T. A. (2020). Machine learning techniques in bank credit analysis. International Journal of Economics and Management Engineering, 14, 517–520.

[11] Beck, T. (2020). Fintech and financial inclusion: Opportunities and pitfalls. ADBI Working Paper 1165. Tokyo: Asian Development Bank Institute.

[12] Langenbucher, K. (2020). Responsible AI-based credit scoring: A legal framework. European Business Law Review, 31(4).

[13] Kshetri, N. (2019). Global entrepreneurship: Environment and strategy (2nd ed.). New York, NY: Routledge.

[14] Decosmo, J. (2019). How fintechs can leverage artificial intelligence. Forbes. Retrieved from https://www.forbes.com/sites/forbestechcouncil/2019/08/09/how-fintechs-can-leverage-artificial-intelligence/#50627d912e1e

[15] Malinga, S. (2019). How AI helped TymeBank gain 670K customers. ITWeb. Retrieved from https://www.itweb.co.za/content/WnxpE74DX9K7V8XL

[16] Salazar, M. (2019). Empresa utiliza inteligencia artificial para cobrar deudas vía redes sociales. Innovacion.cl. Retrieved from http://www.innovacion.cl/2019/11/empresa-utiliza-inteligencia-artificial-para-cobrar-deudas-via-redes-sociales/

[17] Criado, N., & Such, J. M. (2019). Digital discrimination. Algorithmic Regulation, 82–97.

[18] Suberg, W. (2017). Indian bank wants joint effort to share data on blockchain. The Coin Telegraph. Retrieved from https://cointelegraph.com/news/indian-bank-wants-joint-effort-to-share-data-on-blockchain

[19] Perez, B., & Soo, Z. (2017). China a fast learner when it comes to artificial intelligence-powered fintech, experts say. South China Morning Post. Retrieved from https://www.scmp.com/tech/innovation/article/2117298/china-fast-learner-when-it-comes-artificial-intelligence-powered

[20] Aliija, R., & Muhangi, B. W. (2017). The effect of loan appraisal process management on credit performance in microfinance institutions (MFIs): A case of MFIs in Uganda. International Journal of Science and Research (IJSR), 6, 2283–2289.

[21] Chandrashekar, K., & Jangampet, V. D. (2020). RISK-BASED ALERTING IN SIEM ENTERPRISE SECURITY: ENHANCING ATTACK SCENARIO MONITORING THROUGH ADAPTIVE RISK SCORING. INTERNATIONAL JOURNAL OF COMPUTER ENGINEERING AND TECHNOLOGY (IJCET), 11(2), 75-85.

[22] Chandrashekar, K., & Jangampet, V. D. (2019). HONEYPOTS AS A PROACTIVE DEFENSE: A COMPARATIVE ANALYSIS WITH TRADITIONAL ANOMALY DETECTION IN MODERN CYBERSECURITY. INTERNATIONAL JOURNAL OF COMPUTER ENGINEERING AND TECHNOLOGY (IJCET), 10(5), 211-221.

[23] Eemani, A. A Comprehensive Review on Network Security Tools. Journal of Advances in Science and Technology, 11.

[24] Eemani, A. (2019). Network Optimization and Evolution to Bigdata Analytics Techniques. International Journal of Innovative Research in Science, Engineering and Technology, 8(1).

[25] Eemani, A. (2018). Future Trends, Current Developments in Network Security and Need for Key Management in Cloud. International Journal of Innovative Research in Computer and Communication Engineering, 6(10).

[26] Eemani, A. (2019). A Study on The Usage of Deep Learning in Artificial Intelligence and Big Data. International Journal of Scientific Research in Computer Science, Engineering and Information Technology (IJSRCSEIT), 5(6).

[27] Nagelli, A., & Yadav, N. K. Efficiency Unveiled: Comparative Analysis of Load Balancing Algorithms in Cloud Environments. International Journal of Information Technology and Management, 18(2).