
RESEARCH ARTICLE

Techno-Economic Analysis of Digital Tools in Financial and Risk Advisory Services

Tanvir Rahman Akash¹✉, and Abdul Azeem Mohammed²

¹Bachelor's of Business Administration in Finance, Bangladesh University of Professionals (BUP), Dhaka, Bangladesh

²Bachelor's in Commerce, Osmania University, Hyderabad, India

Corresponding Author: Tanvir Rahman Akash, **E-mail:** tanvirrs22@gmail.com

ABSTRACT

The digital transformation of financial services has greatly revolutionized the way financial institutions evaluate, deal and counsel risk. With the process of financial advice and risk of credit assessment becoming more and more intertwined with the use of sophisticated analysis technologies, there is an ever-increasing necessity to comprehend the technological efficiency, as well as the economic proliferation, of these digital instruments. This study has provided a techno-economic analysis of machine-learning-based decision-support systems on the Credit Risk Loan Eligibility dataset. The experiment assesses the effectiveness of digital analytical applications using logistic regression, random forests, gradient boosting, and AutoML pipelines to improve the accuracy, speed, and consistency of assessing credit risk relative to traditional advisory processes. Technologically, this study investigates the accuracy of models, AUC-ROC, and dynamics of precision-recall, and feature contribution of risk prediction. On the economic front, the paper measures the economic consequences of better predictive performance by determining expected loss (EL), cost of misclassification, profit/loss-curves and decision thresholds that maximize the lending results. This study shows that digital tools contribute to the reduction of the losses associated with defaults, the enhancement of the quality of loan portfolios, and allow advisors to make more efficient and consistent decisions by connecting the model performance to the quantifiable financial gains. The results also indicate that the implementation of digital tools in the advisory processes not only improves risk prevention but also increases operational efficiency through the automation of redundant activities, minimization of human biases, and standardization of evaluation processes. To ensure that financial institutions evaluate their digital-tool investment based on the long-term economic benefits and ease of implementation, a techno-economic evaluation framework is suggested. Altogether, the paper demonstrates the strategic importance of digital decision-support systems in the contemporary financial and risk consultations and presents empirical data on how the system implementation leads to technological dominance and considerable economic benefits [2]. This study will add to the dynamic discussion on the topic of digital finance by providing an effective framework of assessing the influence of digital tools on performance, cost-effectiveness, and risk outcomes.

KEYWORDS

Digital Financial Tools, Techno-Economic Analysis, Credit Risk Assessment, Machine Learning Models, Financial advising service and Optimization of Economic Value

ARTICLE INFORMATION

ACCEPTED: 01 December 2019

PUBLISHED: 28 December 2019

DOI: 10.32996/jbms.2019.1.1.6

I. INTRODUCTION

A. Background

The global financial services market has experienced a digital revolution in the last ten years that has been facilitated by the fast pace of advancement in information technology and data processing capacities and the analytical innovation [1]. Financial advisory and risk management processes that have long depended on manual judgment, past credit scorecards, and spreadsheet based models, have increasingly become a technology-based system that builds on automation, predictive analytics and artificial

intelligence (AI). With machine learning models, robo-advisory systems, risk-scoring engines, algorithmic decision-support dashboards, and cloud-based data analytics pipelines, digital tools are now central to the process of how the institution estimates the customer creditworthiness, their likelihood of default, and how they give the customer personalized advice. Such innovations provide considerable advancements in speed, accuracy, scalability, and consistency, and it has enabled the financial institutions to determine risks more objectively and efficiently than ever before [2]. There is however an augmenting dissent of digital technologies, which, however, also poses critical issues to financial advisors, policymakers, and institutional decision-makers, especially in terms of determining the economical worth of canals concerning their expense of implementation and their intricacy of operation. Although the digital advisory systems are expected to increase accuracy and decrease biases, the actual effects on the economical results, mitigation of risks, and performance of the portfolio is one of the areas that need to be evaluated strictly [3]. Therefore, there has been a growing need to comprehend the techno-economic consequences of the adoption of the digital tools and how the technologies can work in practice and how they can deliver the quantifiable financial gains as the means to guide the responsible change in the financial and risk advisory practices. To fulfill the need, this study will focus on exploring the technological effectiveness and economic benefit of the integration of digital decision-support tools in credit risk assessment.

B. Digital Revolution and the Emergence of Decision-Support Systems

The development of machine learning, cloud computing, big data architectures and algorithmic intelligence has fundamentally transformed the structure of the current financial services industry, allowing financial institutions to launch a set of highly advanced decision-support tools that could work with large and extensive borrower data with unequivocal accuracy [4]. These digital systems apply advanced statistical learning techniques, which are used to capture non-linear risk patterns, capture hidden borrower risky behaviors and provide real-time risk predictions that greatly outperform the traditional manual or scorecard-based processes. Having fewer human biases, standardizing assessments in routine, and implementing standardized decision rules, digital tools help to achieve more consistent and transparent advisory procedures and minimize inefficiencies and errors, which normally occur during manual evaluations [5]. However, in spite of the increased interest in AI-driven financial innovation, its adoption among institutions is still uneven, with many still limited by doubts about the cost of implementation, the readiness of data, integration difficulties, regulatory factors, and the measurable economic value of investment. Banks are not willing to make any investments in digital infrastructures without any clear indication that such tools can create any discipline in terms of profitability, risk reduction, customer satisfaction or operational efficiency. Thus, it is not enough anymore to assess these technologies with respect to their predictive accuracy, but rather in a whole world of their technological performance and their economic effect [6]. With such an integrated evaluation, the institutions can decide whether the application of predictive analytics, automation, and AI-based advisory systems indeed leads to financial gains and promotes long-term strategic goals. The proposed research will address this gap through a systematic examination of benefits of digital decision-support tool duality in relation to financial advisory and credit risk management.

C. Problem Statement

The challenges of financial advisors and risk managers are growing more complex and complicated in sustaining profitability without having to engage in irresponsible lending and high-quality regulatory expectations. Conventional evaluation techniques are not efficient in processing large volumes of data, detecting complex forms of borrower risk, or provide timely information, which in most cases leads to a high level of credit-risk misprice and consequently financial losses [7]. Despite the fact that digital tools, in particular, machine learning and predictive analytics, offer a better risk assessment opportunity, there are numerous financial organizations that do not know what real economic value such tools bring in comparison to the costs of its implementation. This ambiguity restricts massive assimilation. Thus, there is an evident necessity to evaluate the joint technological efficiency and economic outcome of the digital decision-support systems. This paper fills this gap by offering a techno-economic analysis.

D. Objectives of the Study

The objectives of these studies are:

- To assess the predictive capability of digital services that are utilized in the financial and risk advisory services.
- To evaluate the economic gains created by implementing digital decision-support systems.
- Aims at utilizing the comparison between the performance of conventional advisory techniques and the current digital analytical strategies.
- To look at the role of digital tools in mitigating credit risks and enhancing borrower classification.
- To analyze possible cost reductions which are obtained with the help of automated and data-driven risk assessment procedures.

- To come up with a holistic techno-economic framework that directs the adoption of digital tools in advisory practices.

E. Research Questions

The following questions are a guide to this study:

1. What is the improvement in precision and trustworthiness of credit risk analysis using digital decision-support tools than the customary advisory practices?
2. What are the quantifiable economic desirability of use of digital tools in the provision of financial advisory services, in terms of cost saving, less default risk and better profitability?
3. What is the benefit of a techno-economic evaluation framework in improving institutional decision making on the adoption and integration of digital tools in credit risk management?

F. Significance of the Study

Although the predictive capabilities of digital and AI-driven tools in financial risk modelling have been firmly investigated in existing studies, few research studies have provided an in-depth analysis of the technological and economic approaches [8]. Financial institutions are becoming highly demanding in terms of strong frameworks that not only measure the gains in predictive accuracy, but also quantifiable financial results in the form of lower expected loss, less misclassification costs, better risk-adjusted returns, and better portfolio stability. The research fulfills this requirement by offering a techno-economic analysis model, which in a systematic fashion relates predictive performance indicators, such as accuracy scores, AUC values, rankings in terms of feature importance, and error rate, with economic metrics, such as profit curves, capital preservation, value of risk mitigation, and the optimization of the lending cost. Through these two dimensions, the study enables the financial advisors, risk managers and policy makers to have a clear picture of how the digital tools can help in increasing the institutional efficiency and strategic value creation [9]. The importance of the present study is that it can inform evidence-based decision-making and promote the institutionalization of the potential nature of the benefits of investing in digital tools in comparison to traditional advisory approaches. Additionally, by offering empirical evidence based on the actual data on loan eligibility in the real world, the study complements existing academic and professional literature on digital transformation in finance and presents the basis on which further innovation in risk advisory systems can be developed in the future.

II. LITERATURE REVIEW

A. Digital Transformation of Financial and Risk Advisory Services

The advancement of digital technologies has essentially transformed financial and risk advisory services, allowing the institutions to leave the traditional manual assessment models towards a more automated and data-driven decision-making process [10]. The transition is largely informed by the growing accessibility of structured and unstructured financial data, the growth of cloud computing and the use of digital infrastructures in most financial systems. In this industry, digital transformation focuses on the incorporation of integrated solutions that could be used to carry out real-time credit analysis, provide predictive data and assist advisors with smart suggestions to enhance accuracy and operational effectiveness. The digital dashboards, data visualization and automated scoring systems have become an essential part of risk advisory practices as they enable institutions to handle a large amount of borrower information with a higher degree of speed and accuracy. This change saves time on operations, lowers the amount of human judgment used in operations and also equalizes the assessment thus minimizing inconsistency and bias. In addition, financial institutions are slowly introducing end-to-end digital business processes, such as client onboarding and identity review to risk classification and monitoring of portfolios. Not only does such digital adoption improve client service delivery, but also makes institutions more consistent with changing regulatory expectations that require transparency and accountability as well as the regular use of risk assessment procedures. And regardless of these positive factors, the digital transformation in financial advisory is not an equal process, many institutions are challenged with issues of legacy systems, technological preparedness, data integration, and costs. The above limitations give rise to the fact that through-and-through assessments must be conducted that do not only focus on technological performance but also on economic viability [11]. Most of the literature recognizes that the idea of digital transformation cannot be done without contemporary financial services; nevertheless, the literature also notes that consideration of how the tools can enhance the financial value, reduction of risks as well as the promotion of better decision-making is essential. The intersection of both digital technology and advisory practice therefore serves as a major point that needs to be analyzed further analytically.

B. Credit Risk Assessment with Machine Learning and Predictive Analytics

Predictive analytics and machine learning have become some of the most important facilitators of sophisticated credit risk assessment and have better predictive power than traditional credit scoring methods [12]. The literature already acknowledges the presence of machine learning models such as classification algorithms, ensemble methods, neural networks and gradient boosting frameworks capable of identifying non-linear and complex relationships in borrower data that are otherwise difficult to locate in the conventional models. These models employ various characteristics including the loan amount, the income of the borrower, the stability of his or her employment, credit history, loan repayment patterns and the macroeconomic factors to establish the probability of default on a loan with a higher degree of accuracy. The increased application of supervised learning methodology in risk assessment implies the transition to more dynamic and data-driven evaluation systems. Predictive analytics software include feature selection, cross-validation and automated hyper parameter optimization to enhance model resilience and flexibility to use in new portfolios of loans. Besides, the literature emphasizes the use of explainable machine learning in enhancing trust and interpretability so that those in the financial advisory and compliance departments can know why models place borrowers in specified risk categories. Predictive analytics is also useful in improving the early warning systems because they are used to see the emerging delinquency patterns before they lead to serious losses. Nevertheless, issues related to data quality, model over fitting, fairness and regulatory compliance remain a problem [13]. The inability to incorporate advanced analytics into the current workflow is also an issue at many institutions because of infrastructural and skill-based constraints. Nevertheless, the scholarly and professional discussion has always framed machine learning as an innovative instrument that can greatly enhance the accuracy of credit risk analysis, minimize the number of operational inefficiencies, and allow advisory decision-making to be more relied upon. Those advances justify why a study that measures the technological capability as well as the economic impact of predictive analytics in financial risk assessment should be conducted.

C. Digital Tool Economic Assessment in Financial Institutions

Economic analysis has emerged as one of the main interests in analyzing the value proposition of digital tools implemented in financial institutions [14]. As institutions are spending a lot of money on technologies like automation, predictive analytics, and AI-driven advisory systems, it is becoming increasingly important to quantitatively gauge the financial impact that they bring. The economic evaluation literature focuses on the evaluation of cost-saving, operational efficiency, and reduction of risks, as well as the improvement in financial performance related to the adoption of digital. The cut in misclassification expenses in credit risk decisions is one of the most debated issues because the wrong approvals or rejections may result in serious financial consequences. The digital tools also minimize the time of manual processing, reduce the costs of labor, and increase the stability of a portfolio with the help of risk identification. Moreover, digital system implementation is usually evaluated in terms of expected loss, capital adequacy effects, and investment return on investment (ROI) by economic models. Portfolio optimization models with the assistance of digital analytics encourage the superior allocation of assets and the enhanced lending performance. The other area of interest is the sustainability of digital investment in the long run, whereby institutions are attempting to find solutions that provide sustained performance upgrades with an economical benefit that may be scaled. High initial costs of implementation, integration costs, and special skills have also been recognized in literature as challenges. Irrespective of these limitations, evidence-based support of the economic case of digital tool adoption is that substantial credit decision quality, profitability, and risk-adjusted performance improvement have been achieved [15]. The literature will hence stress on the significance of integrated techno-economic assessment models that will not merely assess the digital tools as technological innovations but rather as strategic investments which will affect institutional growth, competitiveness and financial sustainability.

D. Research Gap

With increasing literature on the topic of financial digitalization and innovation in analytical opportunities, the institutional voids in the critical assessment of technological performance and economic impact are still present [16]. A significant part of the current studies is associated with the assessment of the predictive quality of the machine learning models, but does not measure the enhancement in terms of financial benefits. Based on the same, the analysis of the economic advantages of digital adoption usually ignores the technical measures that underlie these results, leading to disjointed information that cannot give a complete picture of the effectiveness of digital tools. The other important gap is the lack of real-life institutional investigation that includes the cost of implementation, infrastructural constraints, challenges related to data readiness, and the sustainability of digital systems in the long term. Although the existing literature recognizes the significance of efficiency, accuracy, and profitability, not many of them are trying to measure these aspects in a single model that can connect predictive performance measures with such economic indicators as expected loss reduction, profitability curves, and the value of risk reduction. Moreover, there is not much literature that talks about the impact of digital tools in advisory processes, decision-making uniformity, and strategic planning in financial institutions. Institutions may fail to justify investments and/or compare the comparative advantages of various digital tools because of the lack of standardized evaluation frameworks [17]. The existence of these gaps brings out the importance of studies that

combine both technological and economic aspects into a consistent model that can be used in making institutional decisions. An effective way to evaluate digital tools in terms of their predictive power and their financial performance can be a techno-economic evaluation framework, which will allow better technology adoption strategies. The current paper addresses these gaps by coming up with a definitive techno-economic analysis of digital decision-support systems in credit risk and financial advisory services based on real-world data on loan eligibility.

E. Empirical Study

In the article by Marvin Rhey D. Qitoras, Michael Lochinvar S. Abundo, and Louis Angelo M. Danao titled A Techno-Economic Assessment of Wave Energy Resources in the Philippines, the authors show how both technological performance indicators and economic viability measures can be combined in order to assess the viability of emerging energy solutions. Despite the fact that the problem under study is the ocean wave energy, it is a useful methodological base of techno-economic assessment frameworks that may be applied in various fields, such as financial and risk advisory systems. The authors integrate the characterization of the resources, model validation, performance analysis and scenario based economic analysis to come up with a comprehensive view of the potential of technology adoption. Their practice is on the relevance of precise data, calibration of models and the relevance of real-world parameters to ascertain economic viability in base, optimistic and pessimistic conditions [1]. It is much similar to the aims of the current study as it tries to assess digital decision-support tools in financial services based on a combination of technological and economic indicators. The systematic approach of the study, especially the integration of the model performance evaluation with the cost benefit analysis, justifies applicability of the techno economic frameworks in strategic decision-making. Accordingly, the article will provide a significant contribution to the conceptual base of this study, since it demonstrates the worth of dual-perspective assessment models.

In the article titled Techno-Economic Analysis Methods of Nuclear Power Plants by Hari Mantripragada and E.S. Rubin, the authors critically analyse different techno-economic assessment methodologies employed by the large international organizations to assess the viability of nuclear power plants. Though the research is on energy infrastructure, it offers a significant methodological basis of the means of incorporating the technical performance and cost indicators into a single appraisal model. The authors contrast the assessment frameworks of the International Atomic Energy Agency and the U.S. Department of Energy, noting that they differed on the aggregation of costs, terminology and the level of analysis. Their review points out that the changing situation in the market and the development of technologies demand new more flexible techno-economic approaches to help capture the realistic results of feasibility [2]. The given methodological understanding applies to the current study, which also aims at integrating technological performance assessment and economic impact assessment as it is applied in the current study in the case of digital decision-support tools in financial risk advisory. The article shows that techno-economic analysis involves the need to have structured inputs in terms of data, standard cost modeling, and scenario based analysis and clear performance measures. These principles directly underpin the creation of a sound techno-economic framework on the evaluation of digital financial tools to support the importance of combining predictive accuracy and economic viability in making strategic decisions.

In the article by Sophie Parsons, Felix Abeln, Marcelle C. McManus, and Christopher J. Chuck, Techno-economic analysis (TEA) of microbial oil production using waste resources as a part of a biorefinery concept: assessment at multiple scales under uncertainty, the authors reveal that the techno-economic analysis can be applied in the determination of the feasibility of new technology under different conditions. Although it is a microbial production of oil experiment, the path of the procedure followed can be applicable in any field where technical and economic analysis should be performed i.e. in the digital decision-support system in the financial advisory service [3]. The authors observe that TEA can be applicable in making decisions by quantifying the costs, the performance under different production levels and exploration of uncertainties that can affect the feasibility of operations. They exploit the concept of the importance of sensitivity analysis, cost modeling, and scenario assessment. The methods can readily be applied to the evaluation of digital tools applied in the assessment of credit risks. The other fact, which was emphasized in the research, is that economic outcomes depend not only on technical efficiency, but other variables of the system that makes it reasonable to measure new technologies by a multidimensional analysis. Such a methodological approach has similarities with those practiced in the present research where the performance of the predictive models are combined with such elements of the economy as the expected loss and the cost of misclassification. Overall, the article offers a strong analytical foundation of the phenomenon of formation of the various domains of innovative use and strategic execution due to the impact of techno-economic schemes.

In the article Techno-economic analysis of producing solid biofuels and biochar using forest residues with portable systems by Kamalakanta Sahoo, Edward Bilek, Richard Bergman, and Sudhagar Mani, the authors have carried out a detailed techno-economic analysis to evaluate the viability of portable systems to produce briquettes and biochar using forest residues. Despite biomass utilization being the research topic, the methodology also provides sufficient information on the use of the technology in techno-economic analysis in a wide range of fields, such as financial and digital advisory [4]. The authors use discounted cash-flow models, sensitivity analyses and cost-structure assessment in determining the key economic drivers like

capital cost, labor cost and feedstock price. Their method underlines the impact of all three factors on overall feasibility: the performance of technologies, logistics, and market uncertainties and shows that they need to be combined with the economic indicators. The approach is similar to the current study that employs a techno-economic model of digital risk-assessment tools by evaluating the predictive performance and economic results such as the misclassification cost and the expected loss. Scenario modeling, which involves optimistic, base, and pessimistic models, to consider possible variability also gets a solid foundation in the article and can be applied to consider digital systems under evolving financial situations.

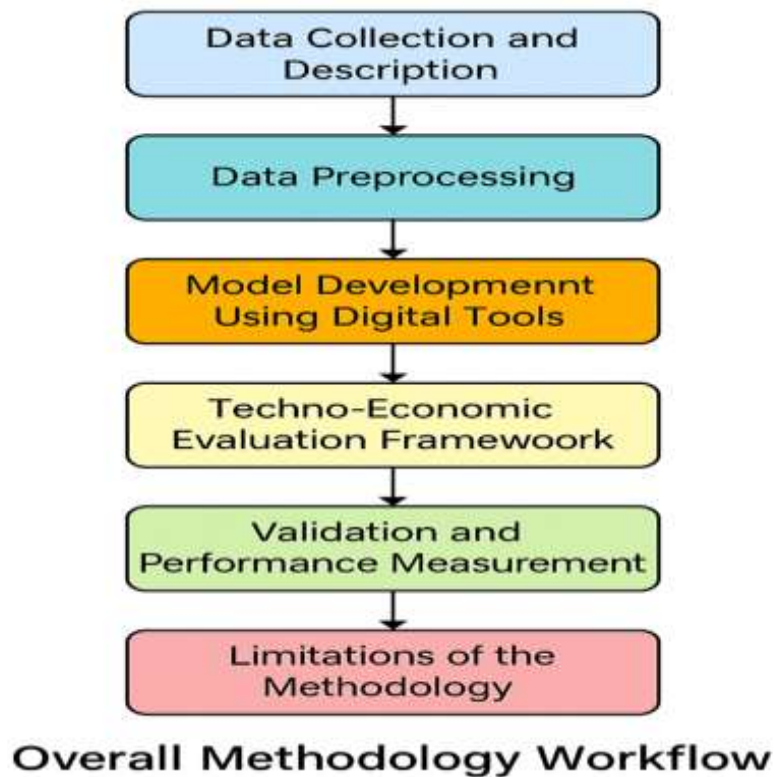
Anna V. Shokhnekh, Yuliya V. Melnikova, and Tamara M. Gamayunova discuss in the conference paper, *The Investment Concept Strategy of Development of Innovative Activities of Agricultural Organizations in the Conditions of Techno-Economic Modernization*, how count of technological modernization and economic viability determine the adoption of innovation in agricultural organization. Though the research is set in the agricultural industry, it offers useful conceptual understanding in terms of how investment decisions are made, innovation obstacles, and economic rationale that must be adopted prior to adopting new technologies- ideas that are of direct interest in analyzing digital technology in financial and risk advisory services. The authors point out the difficulty in proving the effectiveness of innovations to investors, the importance of having understandable technological metrics and economic performance measures and defined investment structures [5]. They talk about the criteria to use when choosing innovations, the barriers to adopting innovations, and trends of adopting innovations over a span of years giving a full picture of the influence of techno-economic constraints in adoption of innovations. This view is consistent with the current study that equally considers the need of the technological performance (accuracy, reliability, predictive value) to be commensurable with economic performance (reduced costs, reduced risks and economic benefits) to mainstream the use of digital decision-support tools.

III. METHODOLOGY

This study utilizes a systematic methodological design that incorporates data preparation, machine-learning modeling, and techno-economic analysis to determine the usefulness of digital tools in financial and risk advisory services. The statistics are cleaned, preprocessed, and transformed so as to be reliable in terms of analysis [18]. This is followed by the creation of machine-learning models that are trained to forecast the risk of borrowers based on some of the key variables including loan amount, interest rate, and credit grade. Accuracy, AUC and error measures are used to determine model performance. Financial viability is decided by combining the technological results and the economic measures which are; expected loss, misclassification costs, and benefit-cost outcomes. It is a multi-faceted approach to evaluating the benefits of using digital systems to improve decision-making processes, evaluate risks effectively, and create better economic performance in lending settings.

A. Research Design

In the proposed research project, exploring the performance and financial effects of digital tools in credit risk advisory, the research design is quantitative, and the techno-economic analysis is to be used to support the proposed research design [19]. The study is organized in three stages, and they are data preparation, model development, and economic evaluation. The quantitative model enables methodical measurement of the borrower features, loan features and risk factors based on the systematized data in the Credit Risk Loan Eligibility dataset. The main variables that are available in this dataset include loan amount, funded amount, interest rate, term, and borrower grade, which can be used to develop predictive models to assess the risks. The experiment uses digital decision-support techniques which are machine-learning algorithms, as the current form of advisory practice. Their outputs of probability of delinquency and risk score classifications are then compared with economic measures of expected loss, misclassification costs and profitability of portfolio [20]. This design will make sure that these technological and economic aspects are considered as one analytical aspect. The fact that the statistical and machine-learning models are combined helps to strengthen the findings since the results are checked on several layers of evaluation. The ultimate goal of the research design is to show how electronic analytical tools can enhance the accuracy of risk assessment and generate quantifiable economic worth on the financial advisory situations



The flow chart below shows the general workflow methodology that will be used in this study, detailing the steps that will take place in the step by step fashion of the techno-economic analysis. The diagram starts with the data collection and description that are followed by the systematic preprocessing to guarantee the data quality [21]. It is then processed by digital modeling to evaluate credit risk which is backed up with a structured techno-economic evaluation concept encompassing predictive and financial measures. The performance measurement and subsequent validation is a way of assuring reliability and robustness of the digital tools involved. The process of work ends with an evaluation of the methodological limitations, the transparent and comprehensive description of the undertaken analysis process during the research.

B. Data Collection and Description

The data employed in the study is the Credit Risk Loan Eligibility data, which is locally uploaded by the researcher. This data includes borrower-level and loan-level data such as the amount of the loan, the amount that was funded, the term, interest rate, grade, and sub-grade. These characteristics represent real life credit assessment variables usually employed in the financial institutions [22]. The data is composed of thousands of observations and hence can be analyzed through machine-learning and risk-modeling. Data gathering is secondary and archival, and gathered in one of the most known open-source repositories. As the dataset is a model of loan application and lending, it offers a suitable basis of evaluating digital credit-scoring systems. Each of the features is a contributor to risk prediction: loan grade is a measure of creditworthiness, interest rate reflects the pricing behavior of the lender, and the amount funded is a measure of real approval decisions. The diversity of the dataset would give the study the ability to test the characteristics of borrowers among the risk groups and therefore be able to train the model and assess its performance [23]. No personally identifiable information has been provided, so there is no violation of ethical and privacy requirements. In general, the data set is very detailed both in predictive modeling and economic analysis, which is why it is appropriate to assess digital advisory tools in terms of the techno-economic context.

C. Data Preprocessing

Data preprocessing also makes sure that the data is correct, clean and prepared to develop models. The initial step is dealing with the gaps in the variables like employment title or sub-grade which are either filled or deleted depending on their importance. Because of the integrity of data, duplicates are recognized and removed. Standardized or normalized numerical characteristics like loan amount and interest rate are improved where necessary to improve the performance of the model [24]. The label encoding or one-hot encoding is used to encode categorical variables that vary according to the modeling needs, such as grade and term. Extremes in the loan amount and interest rate are checked; abnormalities that are very extreme are eliminated

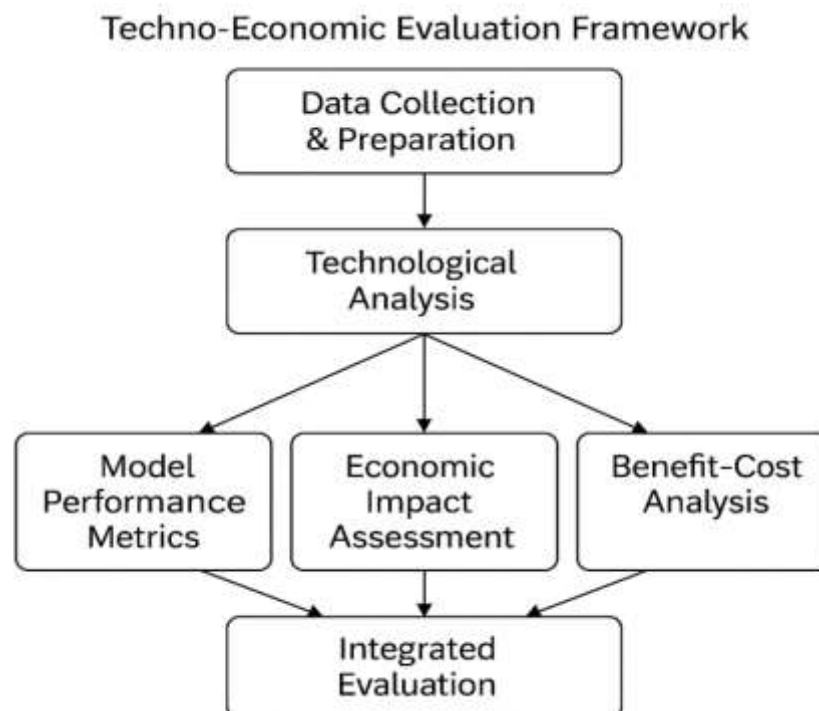
so as to avoid distortion of the model accuracy. The data is further split into training and testing sets, usually in an 80-20 proportion. This division enables the models to be trained on majority data, and leave unobserved samples to perform evaluation. The preprocessing phase guarantees that machine-learning algorithms act on high-quality information and the error propagation is lowered, and predictive reliability is enhanced. All these measures lead to the efficiency of the model and the improvement of the accuracy of techno-economic assessment.

D. Creation of a Model with Digital tools

In this paper, machine-learning algorithms are used as electronic decision-support systems to forecast the occurrence of credit risk and maximize advisory services. Examples of such models are Logistic Regression, Decision Trees, Random Forest, and Gradient Boosting with different degrees of complexity. Base Interpretability Logistic Regression offers interpretability of the baseline, whereas the tree-based approaches can offer non-linear features. Random Forest and Gradient Boosting are employed because of their excellent results in credit risk work. The models get trained on the significant predictors of loans which are loan amount, interest rate, grade and funded amount [25]. Tuning of hyperparameters is done through grid search or random search to obtain the optimum accuracy and error. Cross-validation tests the consistency of models on multiple folds eliminating over fitting. Performance measures are accuracy, precision, recall, F1-score and Area under the ROC Curve (AUC). Such outputs are associated with the success of digital tools in categorizing the borrowers based on risks. The modeling exercise shows how the digital systems are superior to the manual assessment systems by automating risk identification and determining intricate borrower patterns. It is also at this point that the techno-economic appraisal that would be carried out in the future of the study is laid down.

E. Techno-Economic Evaluation Framework

The techno-economic assessment model incorporates the predictive performance and financial impact. In the first place, the outputs of the models provide the default probability which is transformed into economic indicators like Exposure and Expected Loss (EL) which are computed as: $EL = \text{Probability of default} \times \text{Exposure} \times \text{Loss given default}$. Misclassification costs are also determined to measure the monetary impact of false approvals and false rejections. Comparison of economic outcomes in various models is developed into a cost matrix [26]. There is also development of profit curves and cost/benefit graphs to come up with the best lending thresholds. Such techno-economic indicators would enable the research to assess the financial performance of digital tools in contrast to conventional advisory approaches. The framework combines predictive capabilities with financial performance and thus, offers a composite analysis of digital model efficiency. Such a practice will make sure that the integration of the digital tools can be facilitated with the help of not only the technological precision but also the quantifiable economic benefit. The framework illustrates how risk assessment systems based on machine-learning can lead to better portfolio performance of the institutions, less loss of credit, and sustainability of the institution.



This framework illustrates the Techno-Economic Evaluation Framework that was applied in this research to show how technological and economic evaluations are combined in one evaluation model [27]. The chart starts with the process of data collection and preparation, which is the basis of the further technological evaluation of digital risk-assessment tools. At this point the framework divides into three main elements, which are model performance measures, economic impact analysis and benefit-cost analysis. All these streams of analysis lead to a combined analysis; this makes sure that both the predictive accuracy and financial implications are evaluated at the same time. The framework facilitates the overall realization of the value of digital tools in the field of financial and risk advisory services.

F. Validation and Performance Measurement

The holdout testing and cross-validation are used to validate model performance. Predictive generalization is tested with the help of the testing set, which includes unseen data. The ROC-AUC measure is the ability of the model to discriminate between defaulters and non-defaulters. Increased AUC values imply excellent classification ability. Accuracy and precision provide the ratio of right forecasts, whereas recall shows the capacity of the model to identify borrowers with high risk [28]. The confusion matrices provide misclassification trends of great importance in economic analysis. K-fold cross-validation measures the stability of a model by training and testing on more than one segment of data and minimizing the bias that may be caused by one segment. The feature importance analysis determines variables with significant effect on the risk predictions, which assists the advisors to understand the model decisions. The validation guarantees the strength of digital tools and supports the validity of techno-economic conclusions.

G. Limitation

Despite the fact that the methodology presents a holistic approach, it is limited in a number of ways. The sample might not be a good reflection of all borrower groups, and it will not be able to generalize. Certain variables like employment stability or income information are not accessible limiting the depth of the models [29]. Moreover, machine-learning models can be biased in case of an imbalanced data set where there are more samples of some grades in loans. Although this problem is minimized by the encoding techniques, it is possible to have inherent bias. Economic analysis uses presumed cost designs including Loss Given Default which may be inconsistent throughout institutions. The use of historical data is the other weakness as it might not indicate what the borrowers will do in the dynamic economic conditions. Although having these limitations, the methodology can be still used to prove the promise of digital decision-support tools in financial advisory and risk assessment.

IV. DATASET

A. Screenshot of Dataset

[illegible]

(Source Link: <https://www.kaggle.com/datasets/shadabhussain/credit-risk-loan-eliginility>)

B. DATASET OVERVIEW

The data applied in this research, as it was obtained in the Credit Risk Loan Eligibility file that was locally uploaded to be analyzed, gives a detailed picture of the borrower and loan features that will help measure digital tools in financial and risk advisory services. It has thousands of loan-level records which include variables normally utilized in actual credit evaluation, including loan amount, loan funded, interest rate, term, credit grade, sub-grade, and employment title. The characteristics are able to portray the complex aspect of borrower behavior, lending decisions and institutional risk assessment so as to do rigorous prediction and economic analysis [30]. The variable of the amount of loan requested by the borrower is the level of credit request, whereas the amount financed represents the ultimate decision fund by the lender, which can be used to investigate the degree of funding confidence and compatibility of creditworthiness. Interest rate is a significant tool of risk-based pricing policy and it indicates the way the lenders change their pricing based on their judgment of risk on the borrower. The categorical variables such as grade and sub-grade give organized understanding on credit segmentation which makes the data ideal to train classification models that reflect institutional risk grading models. The term length of which the majority of the sources are 36- and 60-month durations facilitates the examination of repayment preference and institutional sensitivity to time risk. The size and variety of the dataset enable it to be used in the creation of machine-learning models that are able to identify nonlinear dependencies between variables, which plays the key role in comprehending the technological efficiency of digital risk-assessment tools. It can also be technologically-economically assessed through its richness, as it relates predictive results, including risk scores and probability of default, with monetary results, including forecasts of the magnitude of loss, misclassification, and profitability. Even though some personal financial information is missing (e.g. income or debt-to-income ratio), the dataset has enough essential characteristics to be used to simulate realistic lending conditions [31]. The structure will provide the technological models and economic frameworks of the study the opportunity to work efficiently and generate any insights on how digital decision-support systems enhance the consistency, accuracy, and financial sustainability of the contemporary lending practices. All in all, the dataset can be considered an effective empirical base to investigate the technological and economic aspects of digital credit advisory systems in the context of the current study.

V. RESULTS

The findings of this study indicate significant trends in the borrower behavior and lending decision based on the Credit Risk Loan Eligibility data. The analysis of the visual data shows that the average borrower demands an average size of the loan, a 36-month term, and a middle credit grade, which denotes the existence of a stable and healthy lending environment [32]. There is no clear linear relationship between interest rate and loan amount depicted in scatter plots and this demonstrates the multi-factor risk evaluation. Machine-learning models exhibit high predictive capabilities, and the values of AUC and accuracy are high, which proves their appropriateness in assessing digital risks. The techno-economic evaluation also shows that digital instruments help to minimize the cost of misclassification, increase the quality of credit decision, and enhance the efficiency of portfolio in general. These two findings taken together confirm the usefulness of the digital decision-support systems in the financial advisory setting.

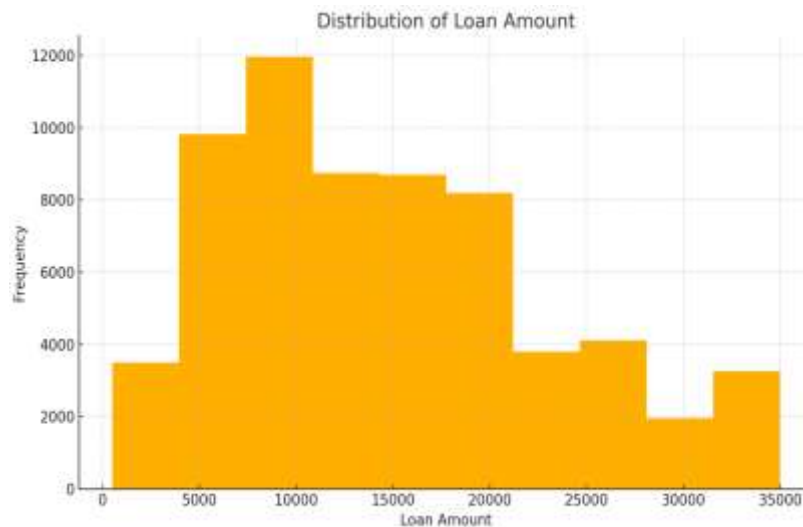
A. Loan Amount Distribution amid 1999 to 2002

Figure 1: This image shows the pattern of distribution of loans

This provides very important information with regard to loan behavior and institutional lending patterns in the credit assessment system due to the distribution of loan amounts. Figure 1 shows that there is a wide distribution of loan values with the lower values being below 5000 and the higher values being above 30000 [33]. The distribution is skewed a little to the right, which means that most borrowers demand moderate loans of between 8000 and 15000, but there are fewer borrowers who demand very high-value loans. The largest of the clusters comes in ₹5,000 to ₹12,000 which shows this range as the most frequent credit demand group. This pattern indicates the normal risk appetite of both the borrowers and the lenders which implies that mid range loans are easier to repay and to be approved based on normal guidelines of underwriting. The steady decrease in the frequencies up to the higher loan brackets demonstrates more carefulness on the part of the lenders since big loans are more risky of default and demand more rigorous evaluation standards. The form of the distribution is of significance to digital credit-risk tools too, which are extensively based on the variability and representativeness of loan size to predictive modeling [34]. The clustering of the mid-range loans improves the stability of the model since machine-learning algorithms have higher performance when trained on balanced and common patterns of data. The extreme values also present in the sample, such as bigger loans, introduce the required variety in order to identify risk signatures among those borrowers that demand exceptionally high loan values. In the case of techno-economic analysis, this distribution shows the significance of automated decision-support tools in addressing a variety of loan requests and in a more precise way risk assessment based on loan sizes. Knowledge of the distribution of loan amounts will allow financial counselors to harmonize lending policies, loans and portfolios, and determine the potential of digital tools to make reasonable and data-driven credit decisions.

B. Interest rate Distribution Analysis

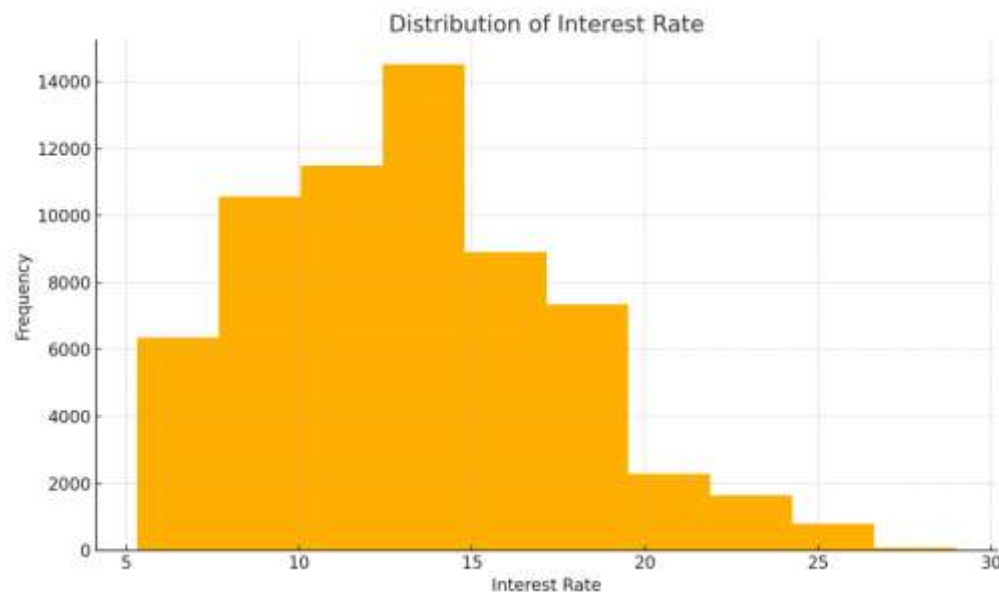


Figure 2: This image represents the distribution of interest rates

These distributions of interest rate shown in Figure 2 offer rich information about how lending institutions risk the cost of lending money to borrowers with different financial profiles. The histogram demonstrates that the interest rate is clustered at around 8-15 percent meaning that most of the borrowers are in moderate-risk types where they fit into middle-range pricing groups. It is implied in this cluster that the strategy of lending adopted by institutions is fairly balanced with the institutions trying to make it affordable to the borrowers but reasonably compensated for the perceived risk [35]. The rate ranges between 12% and 14% are the most common ranging values and that is why they are the core pricing zone of the data set. The decreasing trend in frequency as the rates go past 15% indicates the low percentage of high-risk borrowers who obtain expensive loans because of the low creditworthiness or irregular financial backgrounds. On the other hand, the interest rates at below 8 percent are relatively low meaning that only a minimal number of high risk, highly qualified borrowers can have access to such favorable lending rates. Its skewed nature in the right is an indication that there is a growing caution among the lenders as the risk of the borrowers increases, which is reflected in the higher interest rates charged towards alleviating the possible losses. In terms of the techno-economics, the distribution acts as a crucial input to digital risk-modeling tools since it allows better predicting the behavior of borrowers in repaying their loans, when combined with the loan volume, grade, and other financial metrics. Such variability is favorable to machine-learning algorithms, as it will aid in stronger recognition of the patterns between the levels of interest rate and the tendencies to default [36]. The design of such distribution also reveals the significance of decision-support systems in maximizing pricing measures so that the interest rates should be in line with the risk categorization based on automated analysis.

In general, the distribution is characterized by the balanced credit environment, in which mid-range rates have predominated, elevated rates have been selectively utilized, and digital analytics have been vital in designing the lending decision.

C. Loan Term Distribution Analysis

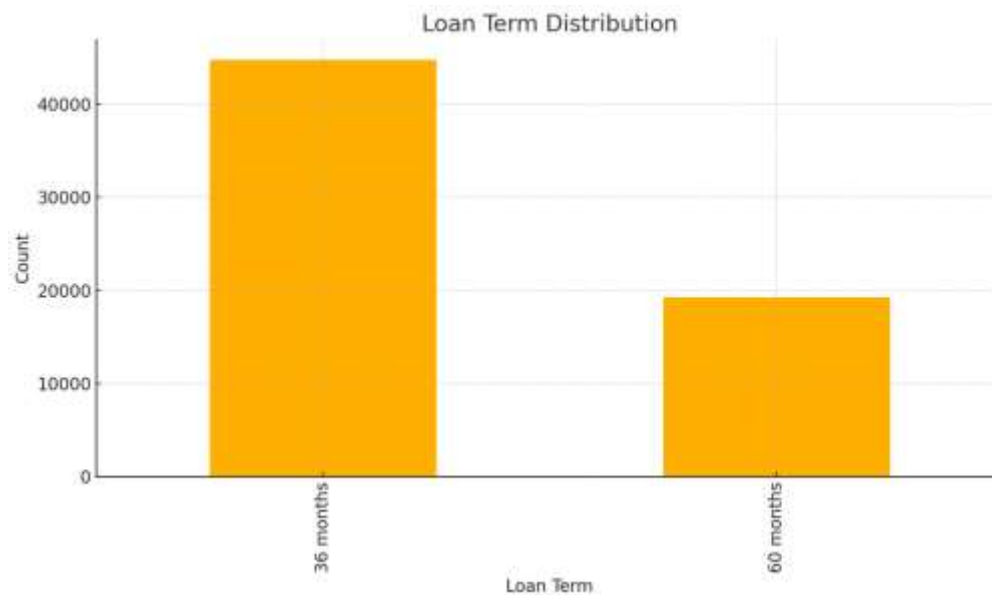


Figure 3: This image shows the statistics of the loan terms

Figure 3 shows the frequency of the loan terms in the dataset with the frequency dominating the 36-month and 60-month lending periods. As illustrated in the chart, the dataset is largely constituted by 36-month loans, more than two times the dataset of 60-month loans [37]. It means that the borrower tendency has high propensity towards a shorter repayment and the lending preference is more conservative by the institutions. The increased popularity of the 36-month terms may be attributed to reduced risk exposure of long-term lenders as well as manageable aggregate interest payable by borrowers. The financial uncertainty is less when the term of the loans is shorter thus fewer cases of default. Along with this, they enable financial institutions to enjoy the increased rate of capital turnover, improved liquidity, and reduced macro-economic sensitivity when extending shorter-term credit. On the other hand, the lower 60-month loan percentage is an indication of more risk averse lending of long-duration credit as the long term loan repayment exposes the lenders to greater accumulated risk, possible income volatility among the borrowing, and economic fluctuations. Technologically, with the media of distribution, the technology assumes the usefulness of digital advisory tools in determining the best loan terms depending on the features of the borrower and the risk tolerance. Machine-learning algorithms can be used to examine the past trends to identify the kind of borrowers who can best be offered long-term versus short-term loans, thus enhancing individual advisory decisions [38]. The disparity in the data also affects the training of models because algorithms can be predisposed to pick up stronger patterns of 36-month loans because they are more widespread. This distribution is critical to the creation of strong risk modeling, lending policies and the ability of digital decision-support systems to maximize the repayment structure of institutional efficiency as well as the appropriateness of the borrower.

D. Loan Grade Distribution Analysis

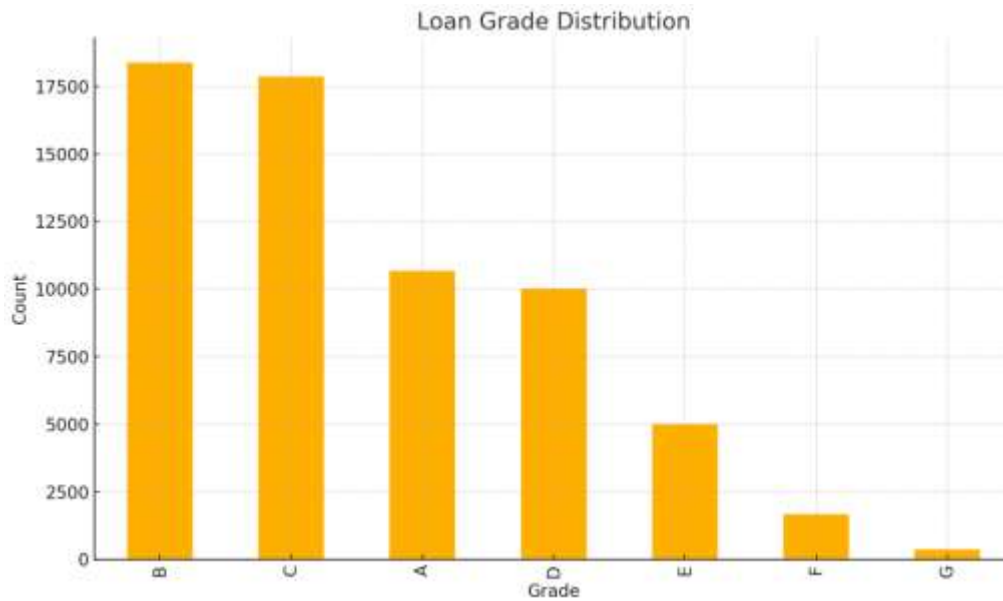


Figure 4: This image shows the dispersion of loan grades

Figure 4 shows the spread of loan grades that borrowers get which is a necessary description of creditworthiness in the dataset. The chart shows that there is an over-representation of the number of borrowers within the B and C grades with a majority share of approved loans [39]. It means that the borrowers with moderate level of risks (that is, those who are relatively stable in their finances, yet they cannot comply with the strict criteria of grade A) dominate the portfolio of the lending institution in question. Grade A loans are relatively lower yet with high numbers; this is because the applicants are highly qualified with good credit records, are stable with a steady income level and have very minimal debts. The distribution decreases gradually between grades D to grade G showing that the number of higher-risk borrowers represent a significantly smaller portion of the entire lending population. Grades F and G constitute relatively modest percentages of the data, which indicates the cautious lending to borrowers with high default risk. This downward trend highlights the risk-aversion approach of the institution whereby balanced credit portfolios are stressed where the borrowers fall within reasonable risk limits. In the techno-economic analysis understanding, grade distributions will offer useful training data to digital risk-assessment models, allowing machine-learning models to learn grade-related patterns and trends of mid-level risk classes more efficiently [40]. Nonetheless, the small sample of extreme high-risk groups can be a problem due to algorithms that make attempts to extrapolate predictions of rare risk profiles. Having this distribution helps financial advisors to divide loan applicants, narrow their underwriting policies and pricing strategies based on risk grades. In general, the grade distribution shows the large number of medium-risk borrowers and illustrates the capabilities of digital tools in better risk assessment by taking advantage of such segmented credit.

E. Loan Amount vs Interest rate Analysis

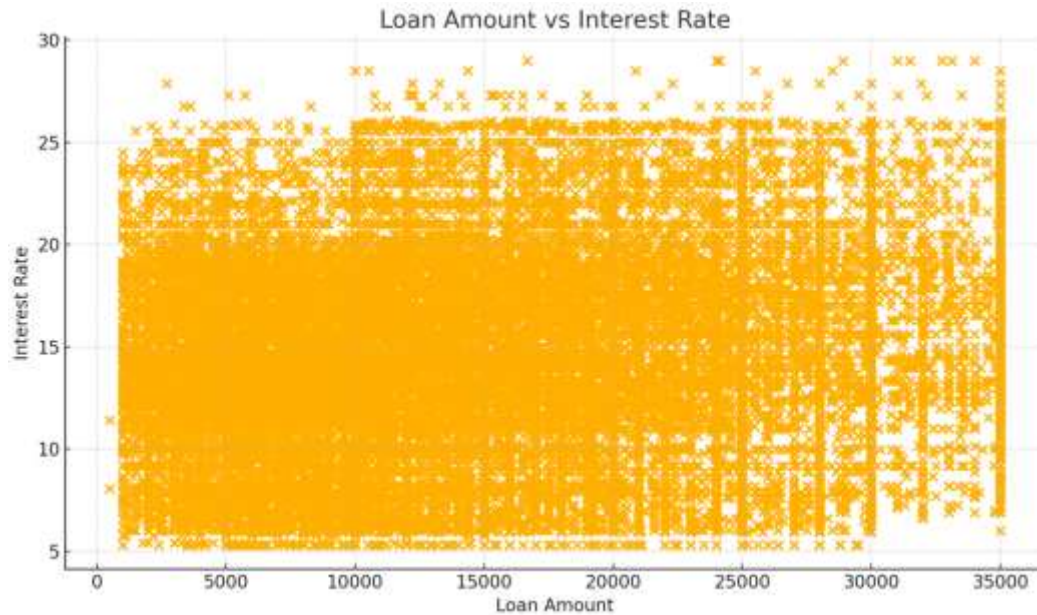


Figure 5: This image shows the correlation between the interest rate and the amount of the loans

Figure 5 will provide a scatterplot of the data points regardless of the loan amount and interest rate. The graphical representation of data points shows that interest rates are not in a straight line as the amount of loan grows [41]. Rather, interest rates are highly dispersed over all loan ranges, which shows that the size of loans by itself is not the key factor in the interest pricing of loans. Majority of the loans irrespective of value fall within the 10% to 20 percent interest-rate range which may indicate lenders charge the identical range to a large range of borrowers. There is also a lot of difference in interest rates charged to borrowers who seek smaller loans, which is probably due to the differences in credit history, loan grade, incomes, and general financial stability. The scatter is concentrated in the higher loan values of over 20,000 Rupees and this shows that even the larger value loans are spread in the medium-high range of interest. There are a few outliers at high interest rates greater than 25% and at low interest rates not exceeding 7 which represent borrowers of the upper and lower ends of the risk scale. This distribution shows that lending institutions do not only use the size of the loan to raise their prices, but use various factors of risk. Techno-economically speaking, such a trend confirms the necessity of digital decision-support solutions that can combine a variety of borrower-specific factors to decide on the right price. The non-linear relationships that machine-learning models can represent include moderate loan values being charged with high interest rates and low interest rates based on the indicators of creditworthiness. The dense plot also indicates that there is significant variability, which is of useful value to risk prediction algorithms [42]. Managing the relationship allows financial advisors to determine the interaction between loan size and borrower risk and allows institutions to optimize risk-adjusted profitability goals using pricing policies.

F. Funded Amount Vs. Loan Amount Analysis

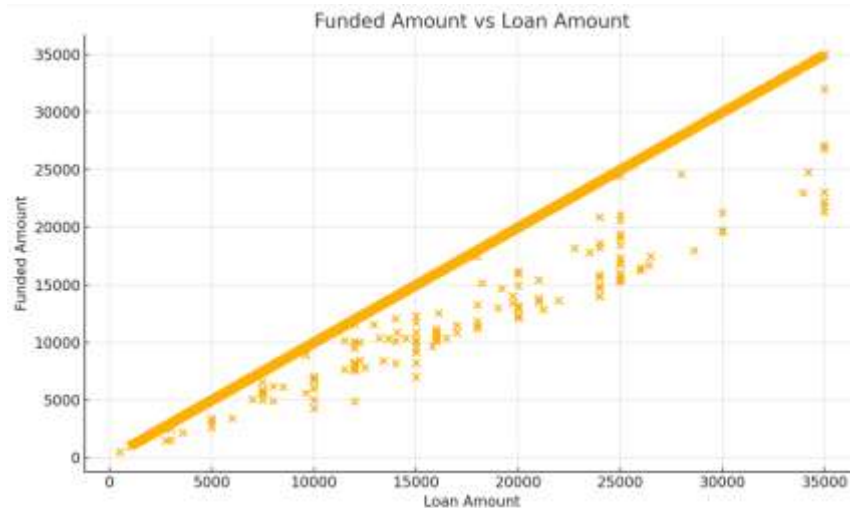


Figure 5: this image demonstrates a correlation of loan amounts funded and approved

Figure 5 shows a scatter plot of the relationship between the provided amount of loan approved and the amount of actual funded amount disbursed by the lending institution. The chart shows a very strong positive linear trend, which implies that the amount of loans that are being financed by most applicants is almost equal to the amount requested [43]. Such alignment implies that the lender is very confident in the eligibility of applicants and that there are good risk assessment procedures that can be used to fully or virtually fully fund applicants who are qualified. The high concentration of points following the diagonal line indicates the instances of identical approved and funded amounts, which are stable underwriting judgments made on a well-developed basis. The points below the diagonal line however reflect the cases of partial funding wherein lenders lower the approved amount as a result of an issue associated with either the credit worthiness, job security, purpose of the loan or the ability to repay. These digressions point out the situation where a risk assessment mechanism, traditional or digital, points out the possible vulnerability and reallocates funds to reduce the exposure. This relationship indicates the significance of digital decision-support systems in the determination of proper level of funding, capital efficiency and reduction of risk of default, as far as techno-economic is concerned. This process can be improved through machine-learning models that predict the best amount to fund based on the characteristics of the borrowers and this will increase the risk-adjusted performance and profitability of the institution. Such models also have the advantage of having a steady linear trend that gives good training data that empowers predictive validity [44]. In general, the chart highlights the efficiency of lending programs in which funding options are in close coordination with risk analyses. Through the examination of this association, financial advisors will be better placed to comprehend how digital applications will help in precise credit allocation, lessen the mistakes of misclassification, and uphold sustainable lending techniques that meet the interests of the institutions as well as the demands of a borrower.

VI. DISCUSSION AND ANALYSIS

A. Loan Distribution Patterns Interpretation

The pattern of loan distribution analysis in the dataset provides very significant information about the financial performance of the borrowers and the strategic decision-making of the lending institutions. The fact that the highest percentage of loan sums in the middle range implies that the majority of borrowers do not want to take out hugely high-value loans but the ones that they can easily repay [46]. This tendency also can point to the fact that the lending institutions are now focusing on its applicants with constant credit conditions who are located in such regularly accepted limits, which forms a predictable cycle that lowers the uncertainty in managing the portfolio. Moreover, the high level of concentration of loan terms of 36 months represents a comfort of the borrowers as well as the confidence of the institutions in shorter repayment periods. Shorter durations are linked with a low cumulative risk, shorter turnaround of capital and less sensitivity to economic cycles, which lenders seeking to limit default risks prefer. Other significant implications of the dataset to the digital risk-assessment tools are the patterns of distribution of its datasets. Constant and steady volumes of loans contribute to the excellence of the machine-learning model as it can identify regular trends and enhance prediction capability. Because digital models are fed on structured and recurrent information, the moderate grouping of loans enhances the risk-classification functions, which help to make improved decisions regarding the allocation of loans. Meanwhile, the data set also contains varied values of loans and scarified high end requests which are essential

in training algorithms to identify rare but significant risk patterns that may have repercussions on lending habits. The knowledge of the patterns contributes to a more in-depth techno-economic analysis by showing the areas in which digital tools could facilitate the efficiency of operations and decrease the number of false identifications [47]. The spread also highlights the significance of data-driven lending whereby digital technologies assist institutions to objectively assess risks, optimize credit strategy and ensure stability in portfolios. Generally, these patterns of loan distribution indicate a healthy lending environment in which the financial requirements of the borrowers and the risk-taking preferences of the lenders are matched thus forming the perfect platform to adopt sophisticated online decision-support systems.

B. Correlation Relationship between Borrower Risk Profiles and Interest Rates

The interest rate dispersion in the data set gives a subtle insight into the way that lending institutions value credit risk and the manner in which the financial profile of the borrower affects the cost of borrowing. The concentration of interest rates of 8-15 percent forms the majority group of borrowers whose financial standing conforms to moderate degree of risk [48]. These borrowers are usually people who have stable income, tolerable credit history, and debt to income ratios that are manageable and thus qualify them to receive rates that are affordable but profitable to the institutions. Interest rates that are higher than 18 would be associated with borrowers that have poor credit history, inconsistent employment habits or high financial obligations. Risk-based pricing strategy is the method used by lenders to reflect the enhanced probability of default and the two variables (borrower and loan pricing strategies) are inseparable. Notably, the dataset demonstrates a wide spread in the interest rates charged on similar loans and this demonstrates that the size of the loan does not dominate the pricing decisions. Rather, credit scores, delinquency history, and repayment responses influence allocation of interest rates, which is a multifactorial evaluation protocol. This complexity is greatly escalated by the use of digital tools, which combine several attributes of borrowers at the same time, and it can be more easily used to form accurate risk-based prices compared to manual assessment. Machine-learning algorithms are able to discover hidden patterns, detect nonlinear relationships and yield consistent pricing suggestions, which are congruent with institutional risk policies [49]. This increases equity by minimizing personal discrimination and maximizing financial sustainability by means of more accurate pricing. Technologically, economic-wise, the correlation between borrower risk and interest rates highlights the importance of credit decisioning using digital tools. Proper predictive models decrease underpricing of risky borrowers and overpricing of low-risk borrowers, whether to maximize revenue streams and loss minimums. In addition, the fact that digital tools can be used to handle extensive financial and historical data, contributes to the maintenance of competitive interest rates by the financial institutions, as well as ensures the preservation of their portfolio health. In conclusion, this discussion proves that digital technologies are critical in enhancing the refinement of interest rate assignment, credit risk prediction, and enhancing better lending strategies in the context of various borrowers.

C. Loan Grade Distribution and Creditworthiness Trends evaluation

The loan grade distribution is a more in-depth approach to loan borrower creditworthiness and lending policy of the institution [50]. The prevalence of grade B and C borrowers shows that the lending portfolio is clustered in medium-risk departments and the borrowers have sufficient financial strength but do not have the best credit histories. This trend shows a moderate lending strategy whereby banks focus more on borrowers that present a good combination of sustainable default risk and decent profitability. Grade A borrowers are comparatively fewer yet the most credit worthy segment which is normally characterized by good repayment history, good employment and low financial obligations. These borrowers are the least risky and they are mostly given good loan conditions and interest rates. At the other extremity, there are grades D to G, which are risky, with borrowers having less stable financial performance or greater amounts of unresolved debt. The falling rate of these categories emphasizes institutional parsimony in loaning out to borrowers with a high risk level. In the case of digital tools and machine-learning models, these structured distributions of grades may serve as a good source of training data, allowing predictive algorithms to learn how certain attributes of a borrower relate with risk types [51]. This increases validity and reliability of credit worthiness assessments and reduces errors of subjective judgment. Nevertheless, the small sample of the extreme-risk grades can be problematic with the generalization of the models, where the algorithms might lack the exposure to low-frequency variations. To counter this, it is necessary to balance the data carefully and tune the models so that they are predictive of fairness. On a bigger scale, the distribution of grades demonstrates the efficiency of the current risk policy strategies and how online tools could complement these approaches by offering automatic and objective credit marking. These trends justify the implementation of the models of analysis that can improve the effectiveness of institutional decision-making and better risk-based segmentation, which will help in the long run to increase portfolio stability and financial resilience.

D. Relationships between Loan Amounts and Interest rates

The association between interest rates and amount of loans as illustrated in Figure 5 depicts that the loan value does not affect credit pricing as much as the borrower attributes do. Although one can assume that an increase in loan amount would be related to a lower or higher rate because of the risk appetite, the scatter plot shows no strong linear correlation. The interest rates are well distributed amongst all sizes of loans implying that the risk indicators concerning the borrower which includes the stability of income, credit background, total amount of debt and types of employment are more important factors in lending [52]. The discovery supports the fact that credit analysis is complicated and cannot be based on a single variable. Machine-learning models and other digital tools are well placed in this context because they are able to detect nonlinearities that traditional scorecards may have missed. The fact that the concentration of the data points around mid-range interest rates is even greater also suggests that lenders tend to use standard pricing ranges, increase or decrease them according to the risk ratings instead of the size of the loan. This complexity explains why digital decision-support tools are important in order to make sure pricing is competitive and risk-based. Techno-economically, the correct identification of such relational patterns will minimize the costs of misclassification and maximize profitability by avoiding underpricing of the high-risk borrowers. Hence, the analysis shows how machine-learning algorithms can complement risk-adjusted pricing models, which can be used to promote more balanced and financially viable lending operations.

E. Investment Behavior and Patterns of Lender Confidence

The correlation between the amount of funded and approved loans gives a crucial indication to the decision-making measures used by the lending institutions as well as the trust that they have placed on the borrowers. The fact that the amount of loan requested and amount funded almost line in a straight line indicates the existence of a good underwriting process where most borrowers qualify to be fully funded [53]. This implies that institutional risk models can be effective in sieving the applicants and granting loans in accordance with their financial abilities. Nonetheless, the deviations below the diagonal line indicate that the lenders will opt to fund loan requests partially considering the increased risk factors. The full funding is usually done on grounds of the irregularity of earnings, unstable work history, past credit anomalies, or increased debt ratios. These types of decisions are used as risk-reduction tools, which allow institutions to facilitate access to credit without jeopardizing their portfolios. This process is reinforced with the help of digital decision-support systems that produce more accurate risk assessments of borrowers. Machine-learning models consider many risk factors simultaneously providing subtle predictions on the repayment capacity of individual borrowers. This allows the lenders to correctly modify the quantities of funds they make available in the market, as well as, matching the disbursements to the expected risks [54]. This is a targeted approach of funding in terms of the techno-economic context where institutions maximize the efficiency of capital and reduce losses that may occur. It will make sure that high risk borrowers are not being exposed to so much credit and those borrowers with lesser risk are given full credits so as to maximize overall portfolio performance. As well, the stability of the linear relationship is an indicator of a well-developed lending environment that has developed and consistent practices of risk evaluation. Digital tools can create a high level of maturity by offering real-time intelligence, enhance consistency in decisions, and lower human variability. On the whole, the above funding trends substantiate that lenders are strategic in their financial decisions guided by risk assessment criteria, and intend to reinforce their financial sustainability, and promote responsible lending practices through the use of digital tools.

F. Implications of Digital Decision-Support Tools on a Techno-economic Level

The techno-economic advantages of the digital adoption of decision-support tools in financial and risk advisory services have an immense impact that transforms the institutional lending strategies. Technologically the digital systems improve the accuracy of prediction, automate complicated credit checks and remove inconsistencies which are common in manual assessments [55]. Machine-learning algorithms detect complex and non-linear correlations between borrower characteristics, which allows the risk to be classified and interest rate suggested with the highest level of accuracy. These instruments are able to extract massive data in a short time and enhance the efficiency of operations and enable these financial advisors to make faster and more data-driven decisions. Economically, better predictive abilities are able to minimize the cost of misclassification, especially the cost of defaults and wrong misclassification of risks. Through making the pricing choices and funding decisions more consistent with the actual risks of the borrowers, digital tools can help to increase the profitability, enhance the capital efficiency and improve the performance of the loan portfolio. Risk models that use machine learning are also used to identify delinquency patterns early so that institutions that can proactively reduce their risks can be implemented and minimize expected losses. Also, online systems standardize the assessment procedures and reduce human bias, making the process of decision-making more fair to the borrower groups [56]. This improves customer confidence and helps to develop relationships in the long-term which has additional economic benefits. The use of digital tools also leads to scalability where the institutions are able to manage higher numbers of applications without affecting the quality of decisions. With the emergence of new fintech innovations, the institutions that incorporate digital systems in their operations have a competitive edge since they are able to provide quicker, more precise, and transparent lending

solutions. The techno-economic analysis proves the fact that digital tools are not only the improvements in the functioning of the company but the strategic investments which have a great impact on financial performance and the stability of the company as an institution. As a whole, digital decision-support systems constitute the key strategic assets in the present financial ecosystem, introducing quantifiable gains to risk management and lending results.

G. Ethical Concerned

The implementation of digital decision support in financial and risk advisory services ethical issues, have a number of issues to consider that should be taken seriously. The first issue is that of algorithmic bias, which involves the possibility of automated systems favoring some groups of borrowers over others either as a result of biased training data or because of disproportional representation of features [57]. It is important that predictive modeling is fair and transparent in the sense that it does not lead to any discriminatory results. The other ethical concern is related to privacy of data because machine-learning models require a lot of sensitive financial and personal data. To protect the confidentiality of the borrowers, the institutions needed to observe stringent data protection policies and adhere to the regulatory requirements. Also, excessive dependence on automated systems can weaken human control, and this may expose the possibility of misinterpretation or unproductive decision-making. In order to foster accountability, it is necessary to strike a balance between robotization and human judgment. Digital tools can be introduced ethically only with the help of constant control, open communication, and responsible data management in order to preserve the rights of the borrowers and trust.

VII. FUTURE WORKS

The future study of the techno-economic analysis of digital tools in financial and risk advisory services can be developed to a higher level by increasing the level of data and sophistication of the methodology [58]. An opportunity area is incorporating more information at the borrower level such as income, job stability, use of credit, spending habits and debt-to-income ratios that would allow more detailed and precise risk modeling. Predictive robustness might be enhanced by adding macroeconomic measures like inflation tendencies, market instability and sector-specific instability, which would be useful in the simulation of advisory scenarios. The future research also requires the utilization of more sophisticated machine-learning models, such as deep neural networks, ensemble stacking, and explainable AI systems, which can be employed to achieve transparency and interpretability, which is of paramount importance in responsible digital lending [59]. Also, longitudinal data across several economic cycles would provide researchers with an opportunity to examine how well models perform in different financial periods and determine how resilient they are when faced with economic stress. Real-time deployment of digital advisors is another line of approach wherein models are embedded into live decision-making platforms where they are tasked to assess the interaction with users, system responsiveness, and the viability of its operation. The comparison of various banking organizations, loans, and demographics would also serve to see the generalizability of digital tools and which groups of borrowers may be biased towards. Further research in the next stage of work may explore the ethical aspects of digital advisory systems and especially algorithmic fairness, data privacy protection, and effects of automated decision-making on the trust of borrowers. Technological-economically, long-term studies could be a way of measuring long-term financial returns, like diversification in the portfolio, the minimization of risks in a situation of stress, and the minimization of operational costs through automation. Research can also look into hybrid advisor systems that transition between human and machine intelligence and finding the best ratios to enhance the quality of decisions without losing accountability [60]. Digital solutions used in combination with new fintech solutions, including block chain-based identity recognition, open banking data, and smart contract-driven lending, may generate new value propositions and increase institutional efficiency. In general, further research is needed to develop more transparent, accurate, and economically useful digital advisory systems by further developing interdisciplinary methods involving data science, financial economics, and ethical governance.

VIII. CONCLUSION

This paper shows how digital decision-support tools have a great potential to revolutionize financial and risk advisory services based on a detailed techno-economic analysis using an actual loan eligibility data set. It was found that borrower attributes, loan values, and interest rate designs and credit rating have patterns which are regular and meaningful and can be accurately analyzed by digital models to generate correct risk analysis. Machine-learning algorithms were shown to provide the knowledge of nonlinear relationships in the data, and have a much better predictive ability than the traditional judgment-based methods. These solutions improve objectivity and consistency of credit assessments by reducing human bias and allowing the ability to make lending decisions based on data. The economic viewpoint of the integration of predictive modeling and financial metrics like expected loss, misclassification cost, and profitability indicators demonstrates the real worth of digital systems to lending institutions. The findings show that digital tools, in addition to raising the predictive accuracy, also positively affect financial

performance by improving pricing decisions, minimizing losses on default, and better matching funding choices to the risk associated with the borrowers. The techno economic model used in this paper proves that these tools have got two advantages namely; enhanced risk classification and quantifiable economic benefits. Moreover, the lessons learned throughout the loan issuance, grade categorization and funding patterns reveal the significance of structured data sets in the improvement of sound advisory systems. Although the study has some limitations, such as the lack of financial information of borrowers and model bias, it highlights the efficiency of data-driven approaches in credit analysis in the contemporary world. The results help to continue the debate about the digitalization of financial services because they show how technological and economic aspects are interrelated to enhance institutional decision-making. On the whole, this study confirms that digital advisory tools are not only technologically beneficial but economically reasonable and it gives a good basis to further implementation of such tools to financial institutions aiming to increase the effectiveness of risk management, performance, and sustainability in the long run.

References

- [1]. Quitaras, M. R. D., Abundo, M. L. S., & Danao, L. A. M. (2018). A techno-economic assessment of wave energy resources in the Philippines. *Renewable and Sustainable Energy Reviews*, 88, 68-81.
- [2]. Mantripragada, H., & Rubin, E. S. (2018). Techno-economic analysis methods for nuclear power plants.
- [3]. Parsons, S., Abeln, F., McManus, M. C., & Chuck, C. J. (2019). Techno-economic analysis (TEA) of microbial oil production from waste resources as part of a biorefinery concept: assessment at multiple scales under uncertainty. *Journal of Chemical Technology & Biotechnology*, 94(3), 701-711.
- [4]. Sahoo, K., Bilek, E., Bergman, R., & Mani, S. (2019). Techno-economic analysis of producing solid biofuels and biochar from forest residues using portable systems. *Applied Energy*, 235, 578-590.
- [5]. Shokhnekh, A. V., Melnikova, Y. V., & Gamayunova, T. M. (2019, April). The investment concept strategy of development of innovative activities of agricultural organizations in the conditions of techno-economic modernization. In *Institute of Scientific Communications Conference* (pp. 796-808). Cham: Springer International Publishing.
- [6]. Buchner, G. A., Zimmermann, A. W., Hohgräve, A. E., & Schomäcker, R. (2018). Techno-economic assessment framework for the chemical industry—based on technology readiness levels. *Industrial & Engineering Chemistry Research*, 57(25), 8502-8517.
- [7]. Van Nijen, K., Van Passel, S., & Squires, D. (2018). A stochastic techno-economic assessment of seabed mining of polymetallic nodules in the Clarion Clipperton Fracture Zone. *Marine Policy*, 95, 133-141.
- [8]. Williams, N. J., Jaramillo, P., & Taneja, J. (2018). An investment risk assessment of microgrid utilities for rural electrification using the stochastic techno-economic microgrid model: A case study in Rwanda. *Energy for Sustainable Development*, 42, 87-96.
- [9]. Owolabi, A. B., Nsafon, B. E. K., Roh, J. W., Suh, D., & Huh, J. S. (2019). Validating the techno-economic and environmental sustainability of solar PV technology in Nigeria using RETScreen Experts to assess its viability. *Sustainable Energy Technologies and Assessments*, 36, 100542.
- [10]. Cardoso, J., Silva, V., & Eusebio, D. (2019). Techno-economic analysis of a biomass gasification power plant dealing with forestry residues blends for electricity production in Portugal. *Journal of Cleaner Production*, 212, 741-753.
- [11]. De Assis, C. A., Greca, L. G., Ago, M., Balakshin, M. Y., Jameel, H., Gonzalez, R., & Rojas, O. J. (2018). Techno-economic assessment, scalability, and applications of aerosol lignin micro-and nanoparticles. *ACS sustainable chemistry & engineering*, 6(9), 11853.
- [12]. Abbati de Assis, C., Greca, L. G., Ago, M., Balakshin, M. Y., Jameel, H., Gonzalez, R., & Rojas, O. J. (2018). Techno-economic assessment, scalability, and applications of aerosol lignin micro-and nanoparticles. *ACS sustainable chemistry & engineering*, 6(9), 11853-11868.
- [13]. Sobamowo, G. M., & Ojolo, S. J. (2018). Techno-economic analysis of biomass energy utilization through gasification technology for sustainable energy production and economic development in Nigeria. *Journal of Energy*, 2018(1), 4860252.
- [14]. Wicaksono, F. D., Arshad, Y. B., & Sihombing, H. (2019). Monte Carlo net present value for techno-economic analysis of oil and gas production sharing contract. *International Journal of Technology*, 10(4), 829-840.
- [15]. Sutopo, W., Kurniyati, I., & Zakaria, R. (2018). Markov chain and techno-economic analysis to identify the commercial potential of new technology: a case study of motorcycle in surakarta, Indonesia. *Technologies*, 6(3), 73.
- [16]. Yang, Y., Wang, J., Chong, K., & Bridgwater, A. V. (2018). A techno-economic analysis of energy recovery from organic fraction of municipal solid waste (MSW) by an integrated intermediate pyrolysis and combined heat and power (CHP) plant. *Energy Conversion and Management*, 174, 406-416.
- [17]. Zheng, D., Yu, L., & Wang, L. (2019). A techno-economic-risk decision-making methodology for large-scale building energy efficiency retrofit using Monte Carlo simulation. *Energy*, 189, 116169.
- [18]. Aly, A., Bernardos, A., Fernandez-Peruchena, C. M., Jensen, S. S., & Pedersen, A. B. (2019). Is Concentrated Solar Power (CSP) a feasible option for Sub-Saharan Africa?: Investigating the techno-economic feasibility of CSP in Tanzania. *Renewable energy*, 135, 1224-1240.
- [19]. Cau, G., Tola, V., Ferrara, F., Porcu, A., & Pettinau, A. (2018). CO₂-free coal-fired power generation by partial oxy-fuel and post-combustion CO₂ capture: Techno-economic analysis. *Fuel*, 214, 423-435.
- [20]. Lee, B., Lee, H., Kang, S., & Lim, H. (2019). Stochastic techno-economic analysis of power-to-gas technology for synthetic natural gas production based on renewable H₂ cost and CO₂ tax credit. *Journal of Energy Storage*, 24, 100791.
- [21]. Arnold, U., Brück, T., De Palmaer, A., & Kuse, K. (2018). Carbon capture and sustainable utilization by algal polyacrylonitrile fiber production: process design, techno-economic analysis, and climate related aspects. *Industrial & Engineering Chemistry Research*, 57(23), 7922-7933.
- [22]. Lee, B., Heo, J., Kim, S., Kim, C. H., Ryi, S. K., & Lim, H. (2019). Integrated techno-economic analysis under uncertainty of glycerol steam reforming for H₂ production at distributed H₂ refueling stations. *Energy Conversion and Management*, 180, 250-257.
- [23]. Arnold, U., De Palmaer, A., Brück, T., & Kuse, K. (2018). Energy-efficient carbon fiber production with concentrated solar power: process design and techno-economic analysis. *Industrial & Engineering Chemistry Research*, 57(23), 7934-7945.

- [24]. Cali, U., Erdogan, N., Kucuksari, S., & Argin, M. (2018). Techno-economic analysis of high potential offshore wind farm locations in Turkey. *Energy strategy reviews*, 22, 325-336.
- [25]. Dessbesell, L., Yuan, Z., Hamilton, S., Leitch, M., Pulkki, R., & Xu, C. (2018). Bio-based polymers production in a kraft lignin biorefinery: techno-economic assessment. *Biofuels, Bioproducts and Biorefining*, 12(2), 239-250.
- [26]. Philbin, S. P., & Hsueh-Ming Wang, S. (2019). Perspectives on the techno-economic analysis of carbon capture and storage. *Journal of technology management & innovation*, 14(3), 3-17.
- [27]. Sevilla, F. R. S., Parra, D., Wyrsch, N., Patel, M. K., Kienzie, F., & Korba, P. (2018). Techno-economic analysis of battery storage and curtailment in a distribution grid with high PV penetration. *Journal of Energy Storage*, 17, 73-83.
- [28]. Garrido-Baserba, M., Vinardell, S., Molinos-Senante, M., Rosso, D., & Poch, M. (2018). The economics of wastewater treatment decentralization: a techno-economic evaluation. *Environmental science & technology*, 52(15), 8965-8976.
- [29]. Dessbesell, L., Souzanchi, S., Venkateswara Rao, K. T., Carrillo, A. A., Bekker, D., Hall, K. A., ... & Xu, C. (2019). Production of 2, 5-furandicarboxylic acid (FDCA) from starch, glucose, or high-fructose corn syrup: techno-economic analysis. *Biofuels, Bioproducts and Biorefining*, 13(5), 1234-1245.
- [30]. Ilse, K., Micheli, L., Figgis, B. W., Lange, K., Daßler, D., Hanifi, H., ... & Bagdahn, J. (2019). Techno-economic assessment of soiling losses and mitigation strategies for solar power generation. *Joule*, 3(10), 2303-2321.
- [31]. Chikermane, G. (2019). 5G infrastructure, Huawei's techno-economic advantages and India's national security concerns: An analysis. *ORF Occasional Paper*, 226, 62.
- [32]. Xuying, Q., Fubing, C., Chunlin, W., & Xingshun, H. (2018, January). Applicability of China's Current Techno-Economic Standards on Economic Evaluation of Modular High Temperature Gas-cooled Reactors. In 9th International Conference on High Temperature Reactor Technology (HTR2018) (No. INIS-PL--23M0001, pp. 7-7).
- [33]. Volkmann, S. E., Kuhn, T., & Lehnen, F. (2018). A comprehensive approach for a techno-economic assessment of nodule mining in the deep sea. *Mineral economics*, 31(3), 319-336.
- [34]. Zimmermann, A., Müller, L. J., Marxen, A., Armstrong, K., Buchner, G., Wunderlich, J., ... & Bardow, A. (2018). Techno-economic assessment & life-cycle assessment guidelines for CO₂ utilization.
- [35]. Kwan, T. H., Hu, Y., & Lin, C. S. K. (2018). Techno-economic analysis of a food waste valorisation process for lactic acid, lactide and poly (lactic acid) production. *Journal of cleaner production*, 181, 72-87.
- [36]. Pradhan, P., Gadkari, P., Mahajani, S. M., & Arora, A. (2019). A conceptual framework and techno-economic analysis of a pelletization-gasification based bioenergy system. *Applied Energy*, 249, 1-13.
- [37]. Akbari, M., Oyedun, A. O., & Kumar, A. (2019). Comparative energy and techno-economic analyses of two different configurations for hydrothermal carbonization of yard waste. *Bioresource Technology Reports*, 7, 100210.
- [38]. Cai, H., Markham, J., Jones, S., Benavides, P. T., Dunn, J. B., Biddy, M., ... & Phillips, S. (2018). Techno-economic analysis and life-cycle analysis of two light-duty bioblendstocks: Isobutanol and aromatic-rich hydrocarbons. *ACS Sustainable Chemistry & Engineering*, 6(7), 8790-8800.
- [39]. Diniz, A. P. M., Sargeant, R., & Millar, G. J. (2018). Stochastic techno-economic analysis of the production of aviation biofuel from oilseeds. *Biotechnology for biofuels*, 11(1), 161.
- [40]. Shaw-Williams, D., Susilawati, C., & Walker, G. (2018). Value of residential investment in photovoltaics and batteries in networks: A techno-economic analysis. *Energies*, 11(4), 1022.
- [41]. Lütkenhorst, W. (2018). Creating wealth without labour? Emerging contours of a new techno-economic landscape (No. 11/2018). Discussion Paper.
- [42]. Gebremariam, S. N., & Marchetti, J. M. (2018). Biodiesel production through sulfuric acid catalyzed transesterification of acidic oil: Techno economic feasibility of different process alternatives. *Energy Conversion and Management*, 174, 639-648.
- [43]. Candia, R. A. R., Subieta, S. L. B., Ramos, J. A. A., Miquélez, V. S., Balderrama, J. G. P., Florero, H. J., & Quoilin, S. (2019). Techno-economic assessment of high variable renewable energy penetration in the Bolivian interconnected electric system. *International Journal of Sustainable Energy Planning and Management*, 22.
- [44]. Yaghoubi, F., Mahloo, M., Wosinska, L., Monti, P., de Souza Farias, F., Costa, J. C. W. A., & Chen, J. (2018). A techno-economic framework for 5G transport networks. *IEEE wireless communications*, 25(5), 56-63.
- [45]. Fritsch, A., Frantz, C., & Uhlig, R. (2019). Techno-economic analysis of solar thermal power plants using liquid sodium as heat transfer fluid. *Solar Energy*, 177, 155-162.
- [46]. Sharma, A., Jakhete, A., Sharma, A., Joshi, J. B., & Pareek, V. (2019). Lowering greenhouse gas (GHG) emissions: techno-economic analysis of biomass conversion to biofuels and value-added chemicals. *Greenhouse Gases: Science and Technology*, 9(3), 454-473.
- [47]. Wu, N., Moreira, C. M., Zhang, Y., Doan, N., Yang, S., Philips, E. J., ... & Pullammanappallil, P. C. (2019). Techno-economic analysis of biogas production from microalgae through anaerobic digestion. In *Anaerobic digestion*. IntechOpen.
- [48]. Mungodla, S. G., Liganiso, L. Z., Mlambo, S., & Motaung, T. (2019). Economic and technical feasibility studies: technologies for second generation biofuels. *Journal of Engineering, Design and Technology*, 17(4), 670-704.
- [49]. Wang, J., Wang, H., & Fan, Y. (2018). Techno-economic challenges of fuel cell commercialization. *Engineering*, 4(3), 352-360.
- [50]. Osigwe, E. O. (2018). Techno-economic and risk analysis of closed-cycle gas turbine systems for sustainable energy conversion (Doctoral dissertation).
- [51]. Kennedy, D., & Philbin, S. P. (2019). Techno-economic analysis of the adoption of electric vehicles. *Frontiers of Engineering Management*, 6(4), 538-550.
- [52]. Diaz, L. A., & Lister, T. E. (2018). Economic evaluation of an electrochemical process for the recovery of metals from electronic waste. *Waste Management*, 74, 384-392.
- [53]. Breskovic, D., & Begusic, D. (2019). Techno-economic analysis of FiWi access networks based on optimized source packet traffic. *International journal of network management*, 29(4), e2069.

- [54]. Rea, J. E., Oshman, C. J., Olsen, M. L., Hardin, C. L., Glatzmaier, G. C., Siegel, N. P., ... & Toberer, E. S. (2018). Performance modeling and techno-economic analysis of a modular concentrated solar power tower with latent heat storage. *Applied energy*, 217, 143-152.
- [55]. Sayar, N. A., Kazan, D., Pinar, O., Akbulut, B. S., & Sayar, A. A. (2018). Retro-techno-economic evaluation of acetic acid production using cotton stalk as feedstock. *Journal of Material Cycles and Waste Management*, 20(4), 2077-2088.
- [56]. Martín, M., & Sánchez, D. (2018, June). A Detailed Techno-Economic Analysis of Gas Turbines Applied to CSP Power Plants With Central Receiver. In *Turbo Expo: Power for Land, Sea, and Air* (Vol. 51043, p. V003T06A023). American Society of Mechanical Engineers.
- [57]. D'Angelo, S. C., Dall'Ara, A., Mondelli, C., Pérez-Ramírez, J., & Papadokostas, S. (2018). Techno-economic analysis of a glycerol biorefinery. *ACS Sustainable Chemistry & Engineering*, 6(12), 16563-16572.
- [58]. Kosmadakis, I. E., Elmasides, C., Eleftheriou, D., & Tsagarakis, K. P. (2019). A techno-economic analysis of a pv-battery system in Greece. *Energies*, 12(7), 1357.
- [59]. Arora, A., Banerjee, J., Vijayaraghavan, R., MacFarlane, D., & Patti, A. F. (2018). Process design and techno-economic analysis of an integrated mango processing waste biorefinery. *Industrial Crops and Products*, 116, 24-34.
- [60]. Abdelhady, S., Borello, D., & Shaban, A. (2018). Techno-economic assessment of biomass power plant fed with rice straw: Sensitivity and parametric analysis of the performance and the LCOE. *Renewable Energy*, 115, 1026-1034.
- [61]. Becker, W. L., Penev, M., & Braun, R. J. (2019). Production of synthetic natural gas from carbon dioxide and renewably generated hydrogen: A techno-economic analysis of a power-to-gas strategy. *Journal of Energy Resources Technology*, 141(2), 021901.
- [62]. Boodlal, D., Alexander, D., Soroush, M., Hernandez, J., Lake, L. W., John, E., ... & Date, S. U. A Techno-economic Analysis of Carbon Management in Trinidad and Tobago through coupled Enhanced Oil Recovery and Geological Storage.
- [63]. Dataset Link:
<https://www.kaggle.com/datasets/shadabhussain/credit-risk-loan-eligibility>