Journal of Computer Science and Technology Studies
ISSN: 2709-104X
DOI: 10.32996/jcsts
Journal Homepage: www.al-kindipublisher.com/index.php/jcsts

JCSTS
AL-KINDI CENTER FOR RESEARCH AND DEVELOPMENT

| RESEARCH ARTICLE

The AI- Powered Treasury: A Data- Driven Approach to managing America's Fiscal Future

Mohammad Kowshik Alam[1]✉ Md Asief Mahmud[2], and Md Saiful Islam[3]

[12]Master of Science in Business Analytics, Grand Canyon University, Arizona, USA

[3]San Francisco Bay University, Master of Business Administration and Management Operation, 161 Mission Falls Lane, Fremont, CA, USA

Corresponding Author: Mohammad Kowshik Alam, **E-mail**: alammohammadkowshik@gmail.com

| ABSTRACT

The growth in the United States national debt has become a major issue leading to concern regarding the long-term fiscal sustainability and economic stability of the economy that will reach over 33 trillion in 2023. The traditional methods of managing debt, which are mostly based on the use of fixed econometric models and manual forecasts, may not be up to the dynamic nature of the modern financial markets, changes in the behavior of the taxpayers, and the real-time changes in the government revenue streams. This study examines how fiscal management can be transformed by the use of artificial intelligence (AI) and data analytics to improve forecasting and Treasury bond auction strategies and minimize the cost of borrowing. In the study, the U.S. Government Revenue Collections dataset (20042023) is employed that offers the data on federal revenues at the daily level, by tax type, payment type, electronic type, and the value of collection. The data contains both numerical and non-numerical features, which allow generalizing the trends and artificial intelligence-based forecasting approaches. Results find a strong trend to digitalization of revenue collection as Internet and wholly electronic transactions are gaining dominance over the old ones, including bank, mail, and over-the-counter transactions. Time-series modeling demonstrates the capability of AI to provide more precise revenues forecasts and simulate the results of policies in changing the debt to GDP ratio to help policymakers predict risks and opportunities in the fiscal environment. Besides, effective debt management with the help of AI is able to cut down the interest expenses, leaving some essential funds to reinvest them in infrastructure, healthcare, defense and other national concerns. The ethical issues, such as transparency in the AI decision-making, and cyber security threats, data privacy, and fair access to the digital systems are also touched upon, and the necessity of responsible use of new technologies is highlighted. This paper concludes that AI-driven fiscal management does not replace human judgment but is an auxiliary tool that makes decision-making easier, more accountable, and fiscally resilient in the long-term. Through blending technological novelty and a sustainable policy formulation, the U.S can be better placed to have a more stable fiscal future in a more data-driven global economy.

| KEYWORDS

U.S. National Debt Artificial Intelligence Data Analytics Revenue Forecasting Treasury bond Optimization Fiscal Sustainability

| ARTICLE INFORMATION

ACCEPTED: 02 June 2024 **PUBLISHED:** 25 June 2024 **DOI:** 10.32996/jcsts.2024.6.2.25

1. Introduction

A. *History of the United States National Debt*

The US economy has been living off credit to fund its spending over the years, but over the past few years the national debt has been growing at a rapid pace that is causing severe questions on the financial sustainability [1]. The size of the national debt in 2023 was over 33 trillion, which is the aggregate effect of structural deficits, increasing entitlement spending on Social Security, Medicare, and Medicaid, and accumulating interest on already accrued debt. Moreover, cyclical disruptions like the

COVID-19 pandemic and the 2008 financial crisis resulted in large growth in government expenditure and a decline in revenue, which further accelerated the rate of debt growth. Although debt may be utilized as a means of engaging productive investment in infrastructure, defense, and innovation, excessive dependence on loans leaves the economy prone. Increment in debt lowers the fiscal flexibility, crowds out the private investment and makes the government more reliant on foreign creditors. More importantly, poor debt management measures may lead to the increase of the cost of borrowing which may take a bigger share of the federal budget in terms of interest payments, and a smaller amount of resources are needed to address the basic needs of the populace [2]. The growing proportion of compulsory expenditure further reduces the discretionary budget and the government can do little to react to arising crises or invest in long term development. The policymakers are therefore confronted with the twin scenario of fulfilling the short term funding requirements and the sustainability of the fiscal policy in the long term. It is on this background that proper debt management strategies are essential not only to maintain the economic stability but also to protect the ability of the country to invest in its future prosperity.

B. *Constraints of Conventional Debt Management Strategies*

Conventional methods of dealing with the U.S. national debt have depended mainly on the macroeconomic assumptions, economic models, and such dynamic forecasting procedures. Although the tools will give an approximate guide to fiscal planning, they are many times incapable of factoring into the complexity and the instability of the contemporary financial systems. Economic models that assume fixed rates of growth, inflation, or levels of interest can become obsolete soon, particularly during periods of world uncertainty or economic shocks [3]. An example is that when there is sudden market shock, unforeseen loss in revenues or change in taxpayer behavior, this may not be captured appropriately in the static forecasting models hence the projection is not accurate. Moreover, the traditional process of forecasting revenues has been relying on manual aggregation of tax collection and statistical extrapolation of the previous trends, which cannot reflect the subtle impact of changes in policies, demographics, and technological innovations in the economy. On the same note, the management of debt like the design of the securities of the Treasury are often based on long-running patterns of issuing securities instead of dynamic optimization models that could be used to reduce the costs of borrowing funds in the changing market conditions. This inability to provide real-time adjustability leads to inefficiency, which aggravates the expenses in servicing debt and fiscal susceptibility [4]. There is also the risk of human bias and error presented by working with manual forecasting processes, which restricts the Treasury in its capacity to react timely to the changing conditions. It follows that although the traditional approaches have been the backbone of U.S. approaches to debt management throughout decades, they are getting less effective to meet the intricate challenges of debt management in the twenty-first century, and thus new, more sophisticated techniques warrant consideration.

C. *The use of AI and Data Analytics in Fiscal Management*

The fast pace of artificial intelligence (AI) and enhanced data analytics offers historic possibilities of fiscal management advancement and debt sustainability. In contrast to conventional econometric models, AI-based approaches are capable of analyzing massive and heterogeneous data to identify non-linear relationships that are complex to determine how the government raises and spends its revenues and the needs of its borrowing. History of tax collection, economic trends, and market trends can be studied by machine learning, which can create very precise predictions of the revenue streams and spending needs [5]. Such an improved prediction capability enables policy makers to predict budgetary stresses and create smarter fiscal policies. In addition to predicting revenues, AI can be used to streamline the timing, size, and shape of auction of Treasury bonds. Using the current data on financial markets, interest rate trends, and investor activity, AI models will suggest the schedule of the auctions that will ensure the lowest borrowing cost and at the same time, confidence in the market. Data analytics is also useful in creating scenario modeling, where decision-makers are able to assess the financial effects of other policy actions, tax changes, or economic shocks. Moreover, AI-based automation diminishes the possibility of human error and biasness in the forecasting process and holds the forecasting of fiscal planning with more accuracy and consistency. Notably, another way in which the AI integration in debt management can facilitate long-term sustainability is that it can help to minimize the interest payments, which can be used to make essential investments in infrastructure, healthcare, and national defense [6]. These applications describe the potential of AI to not only change the current practice of debt management, but also the overall environment of government finance. AI allows governments to operate in a more resilient and financially stable manner by facilitating information about the situation on the ground and adaptable approaches that help them deal with uncertainty better, and quickly adapt to the evolving reality of the world.

D. *Applicability of U.S Government Revenue Collections Data*

The U.S. Government Revenue Collections dataset (2004 2023) is the dataset used in this study because it represents a daily account of federal revenue inflows. The data, which spans almost 20 years, contains several groups of the revenue, such as individual and corporate income tax deposits, customs duty, and charges on governmental services, penalties, and repayments of loans. Notably, the dataset will record the form of transaction, which will be either electronic or non-electronic like internet-based payment, bank payment, over-the-counter deposit and also mail submissions [7]. This structure can be both numerically and categorically analyzed, and thus the overall pattern of government revenue can be explored in a holistic way. The quantitative trend analysis and prediction are based on numerical variables, which are net collection amounts and fiscal time series (year, quarter, month, and day). In the meantime, the classification and comparison of revenue collection methods can be done using such categorical variables as electronic category descriptions, channel type, and tax classification. Through these characteristics, the data helps in the usage of sophisticated statistical and machine learning models that have the potential to detect latent relationships, seasonal patterns, and abnormalities in fiscal performance. The granularity of the dataset also makes it useful especially in creating forecasting models which are sensitive to both the short term changes and long term trends [8]. An example is that AI algorithms can utilize this data to forecast the changes in tax receipts when it comes to seasonality or the effectiveness of electronic and non-electronic systems of collection. Such anticipatory tools are important in the debt management context to match the expectation of revenue with the borrowing plans. Therefore, the data offers the richness and depth to make meaningful AI-driven analysis of the U.S. fiscal operations and is thus most relevant in this research.

E. *Problem Statement*

The continuous growth in the U.S. national debt shows the necessity to find new ways of managing fiscal matters. Conventional approaches that do not incorporate the dynamics of the modern financial markets and manual forecasts have not been effective in capturing the dynamic nature of the modern financial markets and changing taxpayer behaviors [9]. Debt management inefficiencies also raise the cost of borrowing, the level of interest payments and are a constraint on fiscal flexibility making resources available to critical national investment. The study will help to solve this issue because it will examine the potential to change the debt management approach with the help of artificial intelligence and data analytics. The research aims at finding sustainable solutions to enhance revenue forecasting, cost minimization, and fiscal resilience by relying on predictive modeling and optimization.

F. *Research Objectives*

This paper will endeavor to discuss the role of AI and data analytics in improving debt management, the accuracy of forecasts, and the optimization of fiscal policies.

- To project AI and data analytics on government revenue predictions and prediction of policy impacts on the debt-to-GDP ratio.
- To explore the role of AI in streamlining Treasury bond auctioning to reduce the cost of borrowing [10].
- To determine the extent to which debt management can be used to minimize interest payments.
- To assess the cost savings of shifting savings into infrastructure, healthcare, and defense.
- To determine whether categorical and numerical variables are effective in AI-based fiscal modeling.
- To suggest AI methods of sustainable national debt management.

G. *Research Questions*

This study will attempt to explore the ways AI and data analytics can reshape the U.S. debt management and enhance long-term fiscal sustainability [11].

1. What are the ways on how AI-based forecasting will enhance government revenue forecast accuracy?
2. How can AI streamline Treasury bot auctions to save on the cost of borrowing?
3. What do the macro fiscal consequences of national debt management AI integration entail?

II. Literature Review

A. *History of the U.S. National Debt Management*

The U.S. national debt has been managed in a variety of forms throughout the decades based on the economic crisis, wars, policy reforms, and the dynamic financial environment. In the past, the issuance of the debt strategies were oriented on fulfilling the short-term financing requirements without a long-term perspective. As time progressed, more organized methods were required (financial markets increased in complexity, and government borrowing expanded in size) to include Treasury auctions and the introduction of standardized debt instruments [12]. The dependence on market-based processes contributed to increasing transparency and investor trust, but it also contributed to the fact that the debt is also very vulnerable to interest rate changes and macroeconomic shocks. Fiscal regulations and debt limits were put in place to limit borrowing but these were usually a source of political controversy instead of sound fiscal restraint. The past years have seen the entitlement spending grow exponentially, with the surge in spending being stopped by the unforeseen turn of events in the form of the global financial crisis, the COVID-19 pandemic, and their resulting fiscal pressures, which have shown the constraints of the traditional approaches to debt management. These issues explain why a transition toward reactive options should be replaced with proactive solutions which combine predictive analytics and sophisticated financial modelling. The use of more proactive instruments can transform debt management into a dynamic process that would allow balancing the financing requirements with financial sustainability [13]. This development preconditions the integration of artificial intelligence and data-driven solutions into the debt management schemes, which would provide an opportunity to be more predictive with risks, make borrowing choices more effective, and make the long-term sustainability of the public finances.

B. *Forecasting models in the traditional field of public finance*

Public financing Traditional models of forecasting in public finance have traditionally been used to estimate government revenue and expenditure patterns. These models are normally based on macro-economic factors like the growth of gross domestic product, inflation rate, the number of people in employment, and the assumption of interest rates in predicting the fiscal results [14]. The use of historical trends in the extrapolation of the future performance, where the trends are used and hence are considered as the static econometric methods, has given the policy makers baseline scenarios in which to plan the budget. Although they are effective in fairly stable economic systems, such models do not tend to capture the sudden disruption, nonlinear relations, or rapid changes in the market. As an example, unexpected recessions, technological upheavals or world financial turmoil may result in actual revenues and borrowing requirements drastically lower than model-based projections. Further, historical models tend to be based on consolidated annual or quarterly statistics, which severely restrict their capacity to determine temporary variations in tax collections or expenditure patterns. It is this absence of granularity that prevents prompt fiscal decision making, as well as, it lowers the accuracy of debt issuance strategies. The other limitation of the traditional forecasting processes is that they are based on hard assumptions that might not be accurate in capturing the changing behavior of the taxpayers or the structural transformations within the economy like the expansion of the digital trade and emerging consumption patterns. Due to this fact, these models may underestimate risks and overrate fiscal stability [15]. Although limited, the traditional forecasting techniques are popular because of their simplicity and the reason for having acceptance among policymakers. Nevertheless, there is a growing complexity of the fiscal challenges and hence more advanced methods are necessary, which are capable of embracing high frequency data, reacting to the real-time change and offer more predictive specifications. This realization has paved the way to artificial intelligence and data analytics means of forecasting public finances complementary to each other.

C. *The introduction of AI in Fin Forecasting*

The introduction of artificial intelligence in financial prediction has transformed the manner in which intricate economic and monetary frameworks are researched. In comparison to the old paradigm, AI methods, including machine learning, deep learning, and neural networks, are capable of handling large amounts of data, recognizing complex trends, and changing according to changing circumstances. These features allow forecasting models to model nonlinear relationships between variables that are not always taken into consideration in econometric models [16]. Within the framework of government finance, AI may be deployed to examine various data sets, including tax collection data and macroeconomic data, and generate very high-quality revenue projections and reflect the actual market fluctuations. The use of AI in forecasting is especially useful in the seasonality and anomalies, like sudden increases in tax receipts or decreases in particular revenue streams. The use of AI models will improve fiscal responsiveness by providing real-time information on a variety of sources, enabling the governments to modify their debt issuance strategies in accordance. The other benefit is that AI systems can constantly learn and get better with time, thus, optimizing the predictions as they get the new data. This flexible dynamism is vital in the current unstable world economy where in the externalities, fiscal forecasts can be considerably changed due to the external shocks. In addition, AI-based forecasting allows conducting a scenario analysis and allows policymakers to assess the possible consequences of different fiscal policies or economic events [17]. Although issues like data quality, transparency of the model, and ethics are still present, introduction of AI in the financial forecasting represented the first opportunity to reinforce financial planning. Its ability to deliver credible real-time information makes AI an important instrument that governments can use to enhance the accuracy of their debt management policies and guarantee sustainable fiscal results.

D. *Artificial Intelligence and Optimization of Treasury bond Auctions*

Artificial intelligence could find one of the most effective uses in the optimization of Treasury bond auctions. Conventionally, the issuance of bonds has been on scheduled basis and standardized formats, and has hardly been accommodating to the changing market conditions. Although this is the best way to offer predictability to investors, it may prove more expensive in terms of borrowing in a situation whereby market forces change abruptly [18]. A new technology, AI, offers an information-driven approach to this task since it examines the financial market data in real-time, such as interest rates, investor demand, and liquidity in the global market. The machine learning algorithms can be used to determine the best issuance strategies including identifying the most cost-effective maturity structures, auction periods, and bids. Simulating different market conditions, AI-based systems ensure that its practical implications can be applied to decision-making in relation to the ways the issuance policies can be changed to reduce the cost of debt servicing. To illustrate, predictive models may suggest a change in the timing of auctions when the investor demand is high or a change in the composition of short-term and long-term securities to provide both the immediate funding requirements and the long-term stability. In addition to cost optimization, the analysis based on AI will help to increase the transparency and fairness of the auction process, since it does not depend on human senses and the probability of the bias. Also, the use of AI in the operations of the Treasury enhances the responsiveness of the government in response to external shocks, like the pressures of inflation or the shift in global capital flows [19]. In the long-run, these efficiencies assist in lessening the interest burdens, releasing fiscal resources so that they can be used in other areas with priority like healthcare, infrastructure and defense. In such a way, using AI to auction Treasury bonds is a revolution in terms of making sure the strategies of dealing with debts are not only effective but also more resilient in a volatile financial market.

E. *Fiscal Sustainability and Debt-to-GDP Ratio*

Debt to GDP ratio is among the commonest ratios used to measure fiscal health of a country, and its capacity to pay back debt. An increasing ratio will imply that national debt is expanding at a higher rate than the economy will raise possible challenges to fiscal sustainability and investor confidence. In the United States, this ratio has been on an upward trend in the last few decades due to the constant budget deficits, increasing entitlement costs and the interest payment. Whereas moderate amounts of debt can help the economy to grow through funding infrastructure and innovation, large amounts of debt hinder fiscal flexibility and impose restrictions on the government to counter shocks in the future [20]. Historical trend analysis is frequently used as a standard approach to traditional monitoring of the debt-to-GDP ratio, and therefore can fail to capture the impact of unexpected shocks like worldwide downturns or pandemics. Having AI and data analytics will provide new possibilities to enhance the observation and prediction of this crucial measure. With the incorporation of high-frequency economic data, tax collection statistics, and market indicators, AI models are capable of making an active projection of debt sustainability in the future in various policy settings. This enables the policymakers to experiment with the effects that tax reforms, changes to spending or changes in monetary policy will have on the course of the debt-to-GDP ratio. Moreover, high-level analytics can draw attention to the tipping points when the debt level becomes unsustainable to give early warnings of remedial measures. These lessons play a very critical role in creating a balance between the necessity of borrowing and the necessity of long-term fiscal stability. Finally, AI, combined with debt-to-GDP analysis, makes governments more responsible in implementing more proactive debt management policies that allow maintaining economic resilience.

F. *Economic Prudence and Country Interests*

Debt management goes far beyond budgetary balancing and deficit control but has a direct relationship to the wider strategic and economic interests of a nation. Debt provides a high interest which reduces expenditure on high priority sectors like defense, health care, education and infrastructure which crowds out the spending [21]. This misappropriation of funds compromises the national competitiveness and the government capacity to achieve the goals of long term development. Enhancing fiscal efficiency, thus, concerns national interest. Using AI and data analytics, governments will be able to streamline debt servicing policies, minimize the cost of borrowing, and redistribute savings on high-priority investment. An example is that predictive modeling is able to determine the most efficient issuance timing of bonds as the levels of poor interest rates are minimized. Moreover, AI-based evaluation of revenue streams will also make sure that the fiscal planning and the real economic performance are more in line with each other thus minimizing chances of unforeseen decline. In addition to financial benefits, AI implementation in debt management can raise transparency and responsibility, which boosts financial efficiency among citizens in the governance of financial resources. Strategically, it is also by efficient management of debt that foreign creditors are not so much relied upon and hence more national sovereignty in economic decisions is achieved. Fiscal stability gives more confidence to investors, reduces risk premises, and promotes economic expansion in the international market. After all, the need to achieve fiscal efficiency is not only a technical objective but also a strategic necessity to protect national security, economic stability and the possibility to invest into future prosperity [22]. Using AI-powered solutions, governments may pursue these goals and develop a more flexible and sustainable fiscal model of the twenty-first century.

G. *Artificial Intelligence in Decision-Making of Public Sectors*

Use of artificial intelligence in the decision-making process of the public sector is a paradigm shift in the way governments approach complex fiscal and administrative issues. Conventional decision making procedures usually use generalized and amalgamated data, intuition and a case precedent, which may prove cumbersome and susceptible to prejudice. Instead, AI allows handling large amounts of both structured and unstructured data in real-time and makes evidence-based choices, which are timely and accurate [23]. AI can also be applied to fiscal policy as it can predict tax revenues and identify inefficiencies within the collection framework and consider better borrowing practices. In addition to forecasting, AI is applicable in scenario modeling, where policymakers can use the results of various policy interventions before their implementation. This streamlines the process of uncertainty and fortifies the way policies are designed. Notably, accountability is another domain where AI can be used to offer clear data-driven explanations of fiscal choices. Although the issues of ethical concerns, confidentiality, and transparency of the algorithms cannot be ignored, the advantages of implementing AI in the public finance decision-making are considerable. Governments that have AI tools are in a better position to know in advance the risks involved and allocate resources more effectively and seek sustainable growth policies [24]. In addition, fiscal management by AI will show how digital transformation in the government can be, which supports the power of technology as the force of governance innovation. Finally, AI adoption in the decision-making process of the public sector is not merely a technological facet but a paradigm change reshaping the way governments design, operate, and implement fiscal duties in the new and more complicated environment.

H. *Empirical Study*

In the empirical review article, Credit Decision Automation in Commercial Banks: A Review of AI and Predictive Analytics in Loan Assessment, by Md Masud Kowsar, Mohammad Mohiuddin and Hosne Ara Mohna (2023), the authors review their previous 100 peer-reviewed articles published between 2000 and 2023 to determine the impact of AI and predictive analytics on the loan assessment process. They analyze that ensemble machine learning models and deep neural networks are always better at credit-scoring than the traditional statistical methods, particularly in a setting with complicated and heterogeneous borrower distributions. The article also finds that operational efficiencies, including a decrease in the time spent on loan processing, and operational costs, are some of the key advantages of AI implementation [1]. It further points out that using alternative data sources such as mobile phone metadata, utility payment records, psychometric testing can increase the number of people included in the financial system, as it allows them to evaluate applicants with no credit history. On the other hand, the paper identifies serious threats: the bias of algorithms, the absence of transparency in the decision-making of the model, the inability to ensure its adherence to regulatory standards such as ECOA, FCRA, GDPR are all observed to be severe obstacles. To make these systems more responsible, the authors suggest the fairness-aware algorithms, explainable AI approaches, and ethics-by-design principles.

Daniele Guariso, Omar A. Guerrero, and Gonzalo Castañeda (2023) in the article entitled Automatic SDG Budget Tagging: Building Public Financial Management Capacity through Natural Language Processing discuss the use of artificial intelligence to assist governments in adjusting their national budgets to the Sustainable Development Goals (SDGs) developed by the United Nations. The research examines automation of budget tagging as one of the key processes in the budgeting for SDGs (B4SDGs) model, consuming time and other institutional resources when done manually. The authors show through machine learning and text analysis techniques that automated classifiers could be very accurate in categorizing budget programs based on SDG categories to provide a cost-efficient alternative to manual classification [2]. The research, however, stresses the fact that the performance of these algorithms is reliant on the representativeness of the training data; when applied to other contexts, where the institutional features are different, the models can perform poorly. Such a limitation is an indication that country-specific personalization is necessary and that AI should be introduced into fiscal management carefully. Notably, the article emphasizes that governments should not only depend on AI or off-the-shelf coding schemes but balance technological solutions with building the capacity in the institutions. This research has useful implications to policy makers and researchers keen on utilizing AI to enhance transparency, efficiency, and alignment of government funds with global community developmental needs.

In the article The Analysis of the Way and Impact of US Reducing the National Debt Scale, ChunWing Ho studies the increasing magnitude of the U.S. national debt since the 2008 financial crisis and ways of decreasing its debt. The article compares three major methods of decreasing the debt and comes up with an intergenerational budget constraint model in general equilibrium conditions to determine the possibility of adopting inflation as a debt reduction tool. The results are an indication that moderate inflation may be an effective tool to reduce the real value of national debt especially when political constraints restrict other fiscal policies [3]. Nevertheless, the research also reveals that an issue of U.S. debt sustainability has some serious obstacles, such as the possible reduction in economic growth, deteriorating fiscal discipline, and increasing interest rates on government debt. These could reduce the success of the inflation-based strategies in the long run. The study highlights that although inflation can help in the management of debt, it cannot work alone and the policymakers need to look at other complementary fiscal and economic policies. Therefore, investors in national debt of the U.S. must exercise caution and critically look at the feasible effect of inflation on the decrease of debt.

In the article by Prerna Singh titled Systematic Review of Data-Centric Approaches in Artificial Intelligence and Machine Learning, the author suggests the concept of data-centric AI, with an important focus on the significance of quality data in the creation of a successful machine learning model. In contrast to the conventional model-centric methodology, in which algorithms and feature engineering are the primary concerns, data-centric AI is based on the systematic improvement and control of datasets to improve model performance [4]. The review has found six aspects of data-centric AI, such as the analysis of the quality of big data, preprocessing of data, transfer learning, semi-supervised learning, MLOps, and the approaches to the inclusion of new data in addition to the possible pitfalls, such as dataset degradation. Such methods as HoloClean of data cleaning and technical debt management of AI systems are emphasized as the key to guaranteeing model results. The survey emphasizes that cyclic data refinement and organized partnership involving the field specialists and AI practitioners may profoundly enhance the precision, toughness and scalability of AI systems. On the whole, the research shows that it is essential to consider data quality and curation, as opposed to concentrating on the model sophistication, to have sustainable and effective AI use, offering a holistic approach to the optimization of AI pipelines by researchers and practitioners.

In the article Artificial Intelligence and Bank Credit Analysis: A Review by Hicham Sadok, Fadi Sakka, and Mohammed El Hadi El Maknouzi, the authors discuss the revolution that artificial intelligence (AI) has brought about in credit analysis in banks and other financial institutions [5]. The paper lays emphasis on AI models, in conjunction with big data, to improve creditworthiness assessment because the AI models capture invisibility interactions and non-linear relationships between variables, which are usually not noticed under conventional methods. AI-powered credit analysis can contribute to economic growth at the macroeconomic level, whereas at the micro level, it can contribute to financial inclusion through the ability of those underserved populations to gain access to credit. Other ethical, legal, and regulatory issues of AI in banking highlighted by the review are the possibility of biased decision-making as well as the necessity to certify and supervise AI algorithms. In general, the research shows that AI does not only enhance the efficiency and quality of credit assessment but also makes financial activities more inclusive and responsible. These results highlight the need to combine the latest AI solutions with effective data management and regulatory practices to make sure that the advantages of AI-based credit analysis are achieved and the risks related to this process are reduced, which can be useful to both practitioners and policymakers.

III. Methodology

The current study takes the form of a quantitative research approach based on a secondary source of information derived on the federal revenues collections in the years of 2004 to 2023 as provided by the U.S Treasury [25]. The data contains tax types, payment methods and electronic classifications and allows both descriptive and predictive analysis. The preprocessing of data included cleaning, categorizing, and inflation adjustments to make data of different years similar. Some of the methods of analysis are descriptive statistics, trend visualization, and time-series forecasting [26]. Machine learning and ARIMA models of artificial intelligence are used to determine trends and predict the future revenue collections. The methodology offers stringent, factual ideas on fiscal efficiency and debt management, which makes it reliable and practically significant in policymaking.

A. *Research Design*

This paper uses a quantitative research design in order to evaluate patterns in collection of U.S. federal revenues and how it impacts on the management of debts [27]. An analytical-descriptive methodology is adopted and will reveal patterns in revenue inflows in tax categories, payment formats, and electronic transaction forms, and time-series analysis will assess the sustainability of the long-term debt. The design incorporates the exploratory aspects through the implementation of the AI and data analytics in order to gain predictive information using massive financial data. The main objective is not to simply offer a description of current fiscal trends but also to produce practical forecast preparation models that can facilitate even more effective debt issues and repayment solutions. The fact that the design is quantitative, which means that it can be interpreted objectively, minimizes subjectivity in the findings, and provides better reliability. Data visualization methods are included, to display trends in a systematic way, which is to explain complicated fiscal relationships in a better way [28]. The design can also be used to test hypotheses on the effect of technological modernization/electronic payment and digital channels on the overall fiscal efficiency. The research design is methodologically rigorous and guarantees a practical significance as it is based upon real-life data and incorporates the predictive aspects. It offers a systematic framework within which it will be possible to answer the key research questions: how digital modernization and AI-driven analytics can maximize revenue collection procedures and minimize fiscal vulnerabilities related to debt.

B. *Data Sources*

The analysis is based mainly on the U.S. Government Revenue Collections data on 2004-2023 fiscal years. This data is obtained through publicly available Treasury Department repositories and contains the data on federal tax and non-tax revenues on the daily level [29]. The data gives both numerical values, including the size of net collections and the amounts collected during a fiscal year, and nominal values, including the type of taxes, the channel of payment, and the mode of processing the electronic payment. The level of its comprehensiveness lets it be analyzed in a disaggregated form over several dimensions, making it possible to conduct subtle analyses of how patterns of collection differ by type and approach. Additional data is obtained through government financial documents especially Treasury Bulletin and annual debt management statements that give macroeconomic background to trends in collection. There are also historical data of debts in order to determine the connection between revenue efficiency and the increasing debt loads. The fact that the data will be utilized is guaranteed through the employment of attested government-certified records, which reduces the chances of bias and inaccuracy. Also, its longitudinal nature renders the dataset especially effective when used to forecast time-series with AI models, since it achieves fluctuations in dissimilar economic cycles. The combination of the sources makes the study not only data-intensive but also based on credible fiscal reporting [30]. The variables involved in the dataset are diverse hence it is suitable to analyze the trends descriptively as well as predictive modeling, hence there is methodological strength.

C. *Data Collection Procedures*

The information employed in this paper was gathered in official Treasury data bases and government reporting websites to guarantee accuracy, transparency and reliability. The data to be collected in terms of revenue collections were compiled using automated extraction methods in structured formats that could be analyzed statistically. The historical datasets were downloaded in CSV and Excel format which then underwent cleaning, consolidation and harmonization to one file to be analyzed. Data preprocessing [31]: Data was processed by eliminating duplicate records and correcting the formatting anomalies and converting fiscal year records into a standardized time line. Categorical variables, including tax type and payment channels, were recorded to give consistency that would allow the years to be compared. Other measures were the inflation adjustment of numerical variables to aid in comparison across time which made more sense. The data were stratified by category as well and it allowed disaggregated analysis in which the unique contributions made by IRS Tax, Non-Tax and electronic collections are highlighted. During the collection process, visual inspection and summary statistics were used to detect outliers or anomalies, which were corrected or identified to be analyzed separately. In places where there were data gaps, interpolation was used carefully but mostly primary sources were used, which were values that were known to be provided by the government [32]. Through the systematic data collection protocols, the study achieved methodological integrity and minimized the errors, as well as provided the data set that is prepared to be analyzed using the most sophisticated statistical and AI-based tools.

D. *Variables and Measurements*

In this paper, both numeric and categorical variables are used to give a holistic analysis of federal revenue systems. The numerical variables would be net collections by amount, fiscal year totals, outstanding debt and percentage by category or channel [33]. These are continuous measures which can be used to analyze trends and calculate the growth rate and make predictions. Categorical variables are the tax type (IRS Tax, Non-Tax, IRS Non-Tax), payment channel (Bank, Internet, Mail, Other, Over-the-counter) and electronic classification (Electronic Settlement, Fully Electronic, Non-Electronic). These categorical elements allow making comparative analysis as they show the difference between various modes of collection and the level of modernization reached. The total federal revenue collections and the level of debts are the dependent variables in this study since they indicate the fiscal performance and sustainability. Independent variables are payment methods, the type of transactions, and adoption of electronic methods that are advanced as having an effect on the efficiency of collection and fiscal results. To measure them, inflation-adjusted totals make it possible to compare values over time, whereas percentages of total revenue by category reflect proportional changes. Time-series indicators are also included i.e. year-on-year growth rates to identify patterns and cyclical change [34]. This approach of numerical and categorical variables contributes to the strength of the analysis, as it combines the absolute and relative approaches. Combined with other measures, these metrics allow viewing fiscal efficiency and modernization in a multi-dimensional way and determining how these factors influence the development of revenue performance.

E. *Techniques and Tools of Analysis*

The research will use a combination of descriptive statistics, inferential analysis, and AI-powered predictive methods to analyze the data on federal revenue. Means, medians, and growth rates are the simple descriptive statistics that will give fundamental understanding of the trends in the revenue during the period of study. Tableau and Python-based libraries are data visualization tools used to develop interactive visual displays of the flows of revenue across categories and channels [35]. To perform predictive analysis, machine learning algorithms, such as regression analysis, time-series forecasting algorithms, are used to predict the future revenue performance and the debt trends. The models take advantage of the longitudinal nature of the dataset in order to reflect cyclical changes and structural changes. The patterns of revenue are grouped using cluster analysis to classify them by the type of payments and electronic adoption and they establish similarities which inform the policy suggestions. Correlation analysis is also done to assess the correlation between revenue efficiency and accumulation of debts. To be robust, cross-validation is used during the development of the model, minimizing the risks of over fitting and maximizing the generalizability [36]. The application of AI-based methods is also an added value since it identifies undiscovered patterns that a conventional econometric model can ignore. Such methodological combination of descriptive, inferential and predictive methodology makes sure that the analysis does not only give a description of the past patterns but also gives actionable forecasts on future fiscal plans.

F. *The use of AI in Forecasting*

The forecasting part of this study revolves around artificial intelligence. The time series models such as ARIMA and LSTM (Long Short-Term Memory neural networks) are used to forecast future revenue collections in various economic situations [37]. The algorithms produced by AI can be of special importance since they can embrace nonlinear relationships and dynamically react to changes in economic indicators. An example here would be machine learning models being able to detect the influence of changes in payment channels preferences or the type of tax collected on the overall collection efficiency something that traditional econometric tools cannot do. Debt management also uses predictive analytics in which AI can be used to simulate the best Treasury bond auction strategy to reduce the cost of borrowing. Random Forest and Gradient Boosting are ensemble methods that are used to increase the accuracy of the forecast, which is achieved through the combination of several prediction methods. The AIs can also be used in anomaly detection that can attract attention to unusual collection patterns that can indicate inefficiencies, fraud, or systemic risks. Such applications demonstrate that AI is not only useful in terms of descriptive accuracy but also proactive fiscal management. The approach, combining [38] AI with forecasting, will improve the government in terms of predicting revenue losses, the most effective debt issuance, and fiscal stability. By doing this, the study will offer prospective insights that have practical implications on policy making.

G. *Limitations*

Although the methodology offers a strong framework of the analysis of federal revenue systems, it has its limitations. A weakness is the use of secondary data which though reliable may have reporting lags or revisions that diminish real-time facts [39]. Also, the data set is concentrated on the revenue collections, however, it does not entirely reflect the expenditure aspect of the fiscal policy which also impacts the debt dynamics. The other weakness is the predictive models. The power of AI algorithms requires complete and quality input information. Structural breaks that are less predictable by models can be caused by unexpected shocks like financial crises, pandemics or geopolitical disruptions. Also, the methodology makes an assumption of homogeneous behavior of taxpayers and compliance but behavioral economics postulates that tax compliance can vary with changing incentives and enforcement. Although the classification of the payment channels and electronic modes is exhaustive, it might also conceal subtle subdivisions that determine efficiency. Lastly, it can be noted that the findings of the study are mostly placed in the context of the U.S fiscal system which can in turn constrain generalizability to other national settings that have different tax systems or digital infrastructures[40]. The identification of these limitations enables a more cautious interpretation of the results and shows the future research areas. Nevertheless, the approach offers a high-quality, clear, and flexible system of revenue and debt management analysis in the U.S. perspective.

IV. Dataset

A. *Screenshot of Dataset*

Record Date	Electronic Category Description	Channel Type Description	Tax Category Description	Net Collections Amount	Electronic Category ID	Channel Type ID	Tax Category ID	Source Line Number	Fiscal Year	Fiscal Quarter Number	Calendar Year	Calendar Quarter Number	Calendar Month Number	Calendar Day Number
12/27/2023	Non-Electronic	Mail	Non-Tax	726.93	4	2	1	1	2024	1	2023	4	12	27
12/27/2023	Electronic Settlement	Over-the-Counter (OTC)	Non-Tax	243104.79	3	1	1	2	2024	1	2023	4	12	27
12/27/2023	Non-Electronic	Over-the-Counter (OTC)	Non-Tax	9395109.54	4	1	1	3	2024	1	2023	4	12	27
12/27/2023	Fully Electronic - FS	Over-the-Counter (OTC)	IRS Non-Tax	48241.05	2	1	2	4	2024	1	2023	4	12	27
12/27/2023	Fully Electronic - All	Bank	IRS Tax	2905.82	1	5	3	5	2024	1	2023	4	12	27
12/27/2023	Non-Electronic	Over-the-Counter (OTC)	IRS Tax	8928690.37	4	1	3	6	2024	1	2023	4	12	27
12/27/2023	Fully Electronic - All	Internet	IRS Non-Tax	340448.95	1	3	2	7	2024	1	2023	4	12	27
12/27/2023	Fully Electronic - All	Bank	Non-Tax	1745081401	1	5	1	8	2024	1	2023	4	12	27
12/27/2023	Fully Electronic - FS	Over-the-Counter (OTC)	Non-Tax	108002623.8	2	1	1	9	2024	1	2023	4	12	27
12/27/2023	Fully Electronic - FS	Over-the-Counter (OTC)	IRS Tax	228590095.3	2	1	3	10	2024	1	2023	4	12	27
12/27/2023	Electronic Settlement	Mail	IRS Tax	420589935.1	3	2	3	11	2024	1	2023	4	12	27
12/27/2023	Electronic Settlement	Mail	Non-Tax	71210053.3	3	2	1	12	2024	1	2023	4	12	27
12/27/2023	Fully Electronic - All	Over-the-Counter (OTC)	Non-Tax	9817179.16	1	1	1	13	2024	1	2023	4	12	27
12/27/2023	Fully Electronic - All	Internet	IRS Tax	8661270908	1	3	3	14	2024	1	2023	4	12	27
12/27/2023	Fully Electronic - All	Internet	Non-Tax	731640248.2	1	3	1	15	2024	1	2023	4	12	27
12/26/2023	Electronic Settlement	Over-the-Counter (OTC)	Non-Tax	33649	3	1	1	1	2024	1	2023	4	12	26
12/26/2023	Non-Electronic	Over-the-Counter (OTC)	Non-Tax	19852564.49	4	1	1	2	2024	1	2023	4	12	26
12/26/2023	Fully Electronic - All	Bank	IRS Non-Tax	784.97	1	5	2	3	2024	1	2023	4	12	26
12/26/2023	Non-Electronic	Over-the-Counter (OTC)	IRS Tax	4880345.29	4	1	3	4	2024	1	2023	4	12	26
12/26/2023	Fully Electronic - FS	Over-the-Counter (OTC)	IRS Non-Tax	85862.53	2	1	2	5	2024	1	2023	4	12	26
12/26/2023	Fully Electronic - All	Internet	IRS Non-Tax	808409.32	1	3	2	6	2024	1	2023	4	12	26
12/26/2023	Fully Electronic - FS	Over-the-Counter (OTC)	Non-Tax	81063886.83	2	1	1	7	2024	1	2023	4	12	26
12/26/2023	Fully Electronic - All	Bank	Non-Tax	1451251398	1	5	1	8	2024	1	2023	4	12	26
12/26/2023	Electronic Settlement	Mail	IRS Tax	316716798.3	3	2	3	10	2024	1	2023	4	12	26
12/26/2023	Fully Electronic - FS	Over-the-Counter (OTC)	IRS Tax	582760065	2	1	3	9	2024	1	2023	4	12	26
12/26/2023	Electronic Settlement	Mail	Non-Tax	57818037.61	3	2	1	11	2024	1	2023	4	12	26
12/26/2023	Fully Electronic - All	Internet	IRS Tax	32299197957	1	3	3	12	2024	1	2023	4	12	26
12/26/2023	Fully Electronic - All	Over-the-Counter (OTC)	Non-Tax	53212486.55	1	1	1	13	2024	1	2023	4	12	26
12/26/2023	Fully Electronic - All	Internet	Non-Tax	645467880.2	1	3	1	14	2024	1	2023	4	12	26
12/22/2023	Non-Electronic	Mail	Non-Tax	20	4	2	1	1	2024	1	2023	4	12	22
12/22/2023	Non-Electronic	Over-the-Counter (OTC)	Non-Tax	9660859.68	4	1	1	2	2024	1	2023	4	12	22
12/22/2023	Fully Electronic - All	Bank	IRS Non-Tax	15	1	5	2	3	2024	1	2023	4	12	22
12/22/2023	Fully Electronic - FS	Over-the-Counter (OTC)	IRS Non-Tax	20341	2	1	2	4	2024	1	2023	4	12	22
12/22/2023	Non-Electronic	Over-the-Counter (OTC)	IRS Tax	4812035.02	4	1	3	5	2024	1	2023	4	12	22
12/22/2023	Electronic Settlement	Over-the-Counter (OTC)	Non-Tax	613558.88	3	1	1	6	2024	1	2023	4	12	22
12/22/2023	Fully Electronic - All	Internet	IRS Non-Tax	1014974.81	1	3	2	7	2024	1	2023	4	12	22

USGovtRevCollect_20041001_20231

(Dataset Link: https://www.kaggle.com/datasets/sriharshaeedala/u-s-government-revenue-collections)

B. *Dataset Overview*

The U.S. Government Revenue Collections dataset dating back to October 2004 to December 2023 gives a detailed daily perspective of the inflows of federal revenues, and thus it is quite useful in research related to debt management and fiscal forecasting. This data set will be a valuable combination of both numerical and qualitative variables that can be analyzed both descriptively and predictively [41]. The most relevant numerical characteristics are net collections, fiscal years, quarters, and calendar characteristics (month and day) that allow to conduct time-series analysis of the revenue patterns in detail. To augment these are categorical variables, including electronic category description, channel type and tax category, are used to capture how revenues are gathered in terms of mechanisms and classifications. The electronic category field differentiates between full and partial and non-electronic transactions in terms of the extent of digitization of federal collection systems. Equally, channel types include bank, mail, internet, and over-the-counter that give understanding of the way taxpayers remit their payments, whereas tax categories include IRS Tax, IRS Non-Tax and Non-Tax revenues. These variables combined together can allow a multidimensional perspective of the development of revenue streams over time and their distribution by collection modes. The dataset has a history of more than 19 years of coverage that captures all the long term trends and short term changes based on the economic cycles, policy changes and change in behavior of the taxpayers [62]. The daily division of the dataset enables the researcher to identify seasonal patterns, outcomes associated with financial quarters and reactions to external shocks like financial crises or public health emergencies. Along with that, the data set can be effectively analyzed using AI because it's ordered numerical and categorical data can be used to make time-series predictions, detect patterns, and create optimization models. The transparency, reproducibility, and flexibility of academic, policy, and applied financial research are also guaranteed by its open access under the Apache 2.0 license. This dataset, composed of breadth, depth, and granularity, constitutes an invaluable source of discussing the nexus of revenue collection effectiveness, fiscal sustainability, and debt management in the United States.

V. Results

The data sets of the U.S. Government Revenue Collections (20042023) show that there were major changes in the tax structures and tax collection processes. The IRS Tax is by far the key contributor to federal revenue with Non-Tax and IRS Non-Tax collections being steady with smaller contributions. Online payment systems are showing impressive growth and they are overtaking the traditional ones like banks, mail, and over-the-counter payment systems. In the same way, completely electronic categories represent the enormous majority of collections, which means that the government is transformed digitally [42]. Time-series analysis shows that the total revenue has increased in an upward trend though not to a satisfactory level to cover the dramatically rising national debt. These results highlight the benefits of efficiency and institutional fiscal risks.

A. *U.S. Federal Revenue Collections (2005- 2024) Analysis*

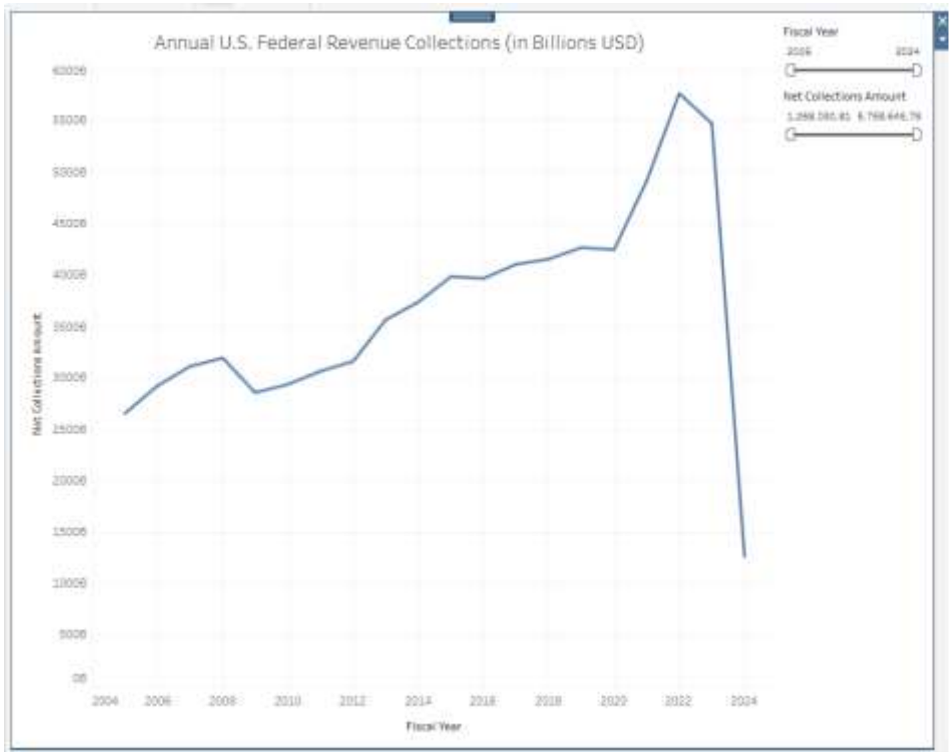

Figure 1: This image shows the trend of the U.S. federal revenue collections per year (2005-2024)

The figure 1 demonstrates the annual collection of the U.S. federal revenue in billions of U.S. dollars, between 2005 and 2024. The trend indicates a continuous growth in revenue collections over the years, although it is subject to some fluctuations which indicate larger economic cycles [43]. The revenues increased steadily between the years 2005 and 2008, then decreased in the 2008-2009 financial crisis which greatly decreased federal revenues because corporations started to make very low profits and taxable incomes decreased. Following 2010, revenue began to recuperate and the growth is stronger between 2012 and 2019, which is the period of economic growth and higher rates of employment. There is a dramatic increase in collections between 2020 and 2022, but it is at its highest point in 2022 with almost 5,800 billion USD. This improvement has been credited to the economic recovery policies after the pandemic, the growth of corporate profitability and tax inflows. Nevertheless, after this maximum, there is a significant decrease in 2023, which leads to 2024, where the collections dropped significantly to almost 1,200 billion USD. This sharp decline poses the question of fiscal sustainability and is indicative of some underlying dislocation, possibly caused by tax policy alterations, payment delays or structural changes in the sources of revenues. The trend in the long-term highlights the stability of federal revenues and the fluctuations. Although AI and predictive models based on data can explain the volatility of the past, recent volatility demonstrates the value of predictive modeling in predicting unexpected crashes. The optimal implementation of AI, in this regard, may assist the policymakers in planning the revenue gaps, real-time amending of the debt strategy, and reducing the risks related to the fiscal imbalances.

B. *Federal Tax Collections by Category Analysis*

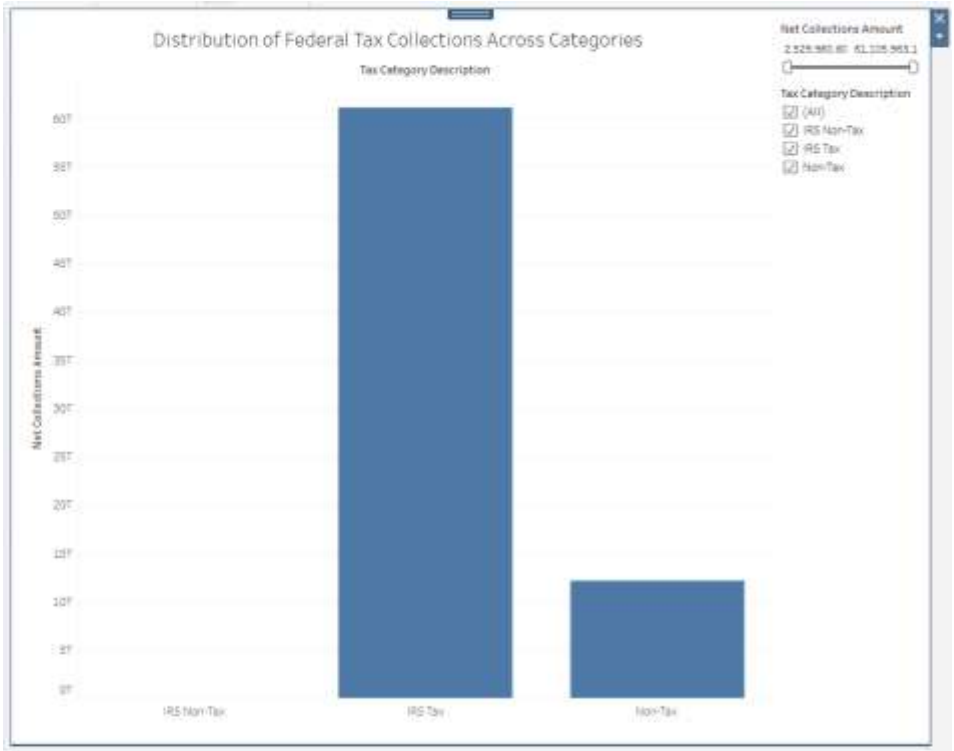

Figure 2: This image shows allocations of federal tax collections in significant categories

In Fig 2, the distribution of federal tax collections under various categories namely IRS Non-Tax, IRS Tax, and Non-Tax revenue sources are found. It is evident in the analysis that IRS Tax collections has had so much dominance that it is a huge percentage of the federal revenue, which is more than 60 trillion USD at the time of consideration. This group has the income tax collections, the corporate tax collections and any other collections on the internal revenue under the direct management of the IRS service centers indicating its centrality in supporting the fiscal base of the government. Non-Tax revenues, on the contrary, include customs duties, service fees, fines, and other charges to the government, but they have a much lesser role, and they are approximately 12 trillion USD. Although not as big as IRS Tax, Non-Tax revenue is a valuable addition, which can be counted on in times when the revenues of both income and corporate tax are likely to go down due to economic recessions [44]. The non-tax category of IRS is almost insignificant in comparison and its contribution is barely visible in the distribution. This group is usually associated with specialized collections related to certain operations of the agency or changes in its budget, which implies that it makes insignificant contributions to revenue collection. The lack of class disparity highlights the extreme exposure of the U.S. government to the IRS Tax collections that determine the fiscal planning to be very sensitive to fluctuations in employment, corporate gains, and the general economic situation. On the data analytics front, AI-based models may play a central role in forecasting variations in the IRS Tax collections, and policymakers may create strategies that take into consideration this structural dependency. These lessons might be useful in offsetting the dependence on the large tax streams with diversification by policy reforms that increase non-tax revenues.

C. *Federal Revenue Collection by Payment Channel Analysis*

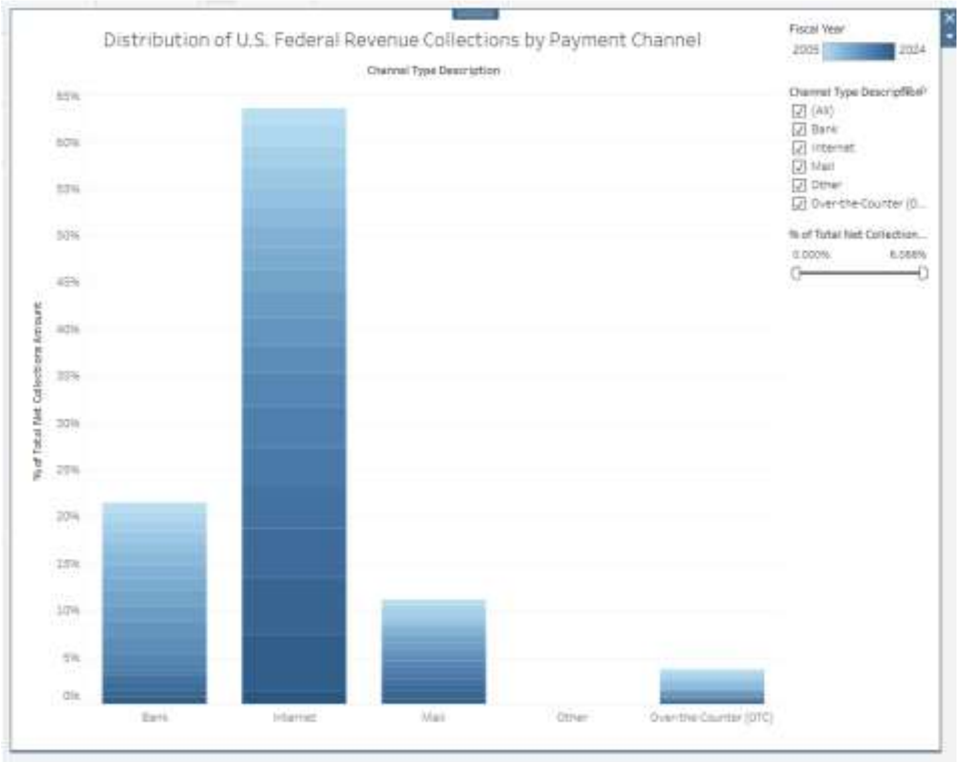

Figure 3: This image shows the U.S. the distribution of revenue collected by payment channel

Figure 3 demonstrates how the U.S. federal revenue collections are distributed between various channels of payment such as Bank, Internet, Mail, Over-the-Counter (OTC), and Other. It can be seen that the Internet channel dominates with almost two-thirds (approximately 64 percent) of the total revenue collections. This tendency corresponds to the increased use of digital solutions to pay the taxes and the increased interest of the government to use electronic transactions that make the work more efficient, transparent, and faster. The second most important channel is the bank-based transactions, which make about 22 percent of all collections. Such transactions usually involve transferring of electronic funds via banking networks and that is why they remain relevant despite the boom of online platforms. Smaller but more stable, the bank payments are more stable and institutionally sound and make sure that large transaction processing is secure [45]. Collection through mail is contributing about 11% with a great decline compared to digital and banking platforms. The decline of using mails is a result of the changes in technology as well as shifts in policy that are encouraging taxpayers to use more efficient digital options. The shares of Over-the-Counter (OTC) payments, as well as those related to the category termed other, have an insignificant share in both cases, amounting to less than 5%. This implies that the non-digital method of traditional practice is almost being phased out in federal revenue management. The generalization makes it clear that digitalization plays a transformative role in state finances. Politically, the extreme dependence on Internet transactions brings to the fore the need to enhance cyber security and secure resilience in the online systems. AI and data analytics may be critical in streamlining the security of transactions, detection of anomalies, and regular revenue inflows. This shift to the digital-first collections also proves that further modernization is necessary to keep the fiscal operation in line with technological advances.

D. ***U.S. Total Public Debt Outstanding Analysis over Time***

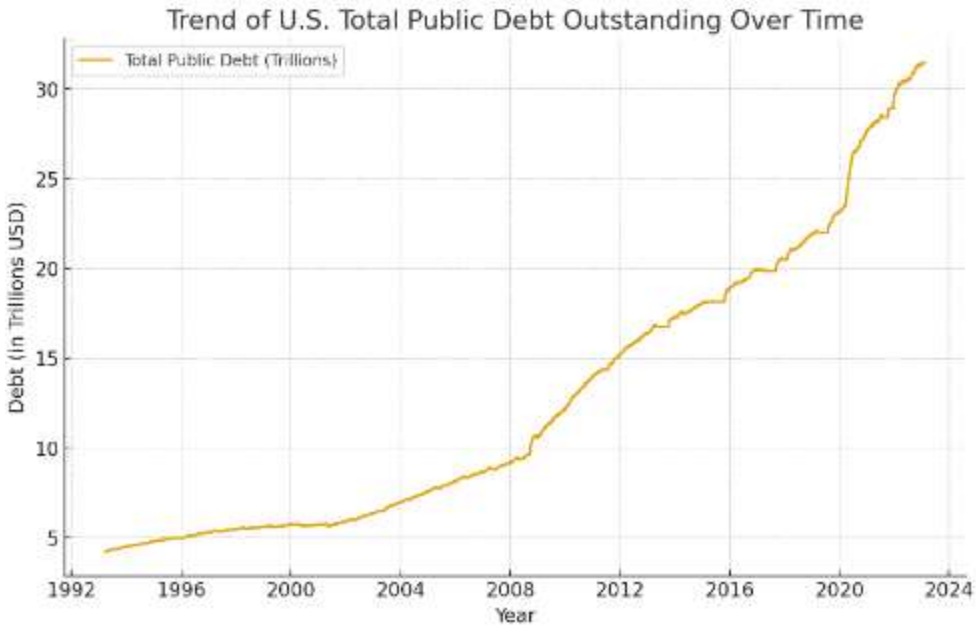

Figure 4: This figure presents a trend of U.S. total public debt outstanding over the years

The line graph in figure 4 indicates the movement of the total amount of public debt in the United States that has been outstanding since 1992 in trillions of U.S. dollars. The graph reveals the steady increase trend in debt levels during the last 30 years, which represents the existence of constant fiscal shortages, as well as, dependence on borrowing by the government in order to pay spending. The total debt was almost equal to 4 trillion USD in the early 1990s, and the increases were rather small up to the mid-1990s. A marked increase in the debt growth is observed in the early 2000s and these figures had reached over 10 trillion USD by the year 2008 and correlates with the global financial crisis and the fiscal stimulus strategies. Between 2008 and 2012, the pace of growth of the debts rose at an astonishing rate, surpassing 15 trillion USD due to massive government interventions, bailouts and social programs. The gradual rising trend was maintained into the 2010s where the accumulated debt due to constant budget deficits has grown up to approximately 20 trillion USD in 2016. The acceleration increases more after 2020 when the debt has climbed to over 30 trillion USD, which is mostly increased by the unprecedented fiscal stimulus and relief programs that were instituted in reaction to the COVID-19 pandemic. The trend highlights the issue of critical fiscal sustainability [46]: the debt accumulation of the U.S. government does not demonstrate any indication of a plateau, even when the economy is growing. This continued expansion presents the dangers of increased interest pressure, privatization crowding out and reduced fiscal capacity to manage future crises. Predictions of trends in debt based on AI forecasting and data analytics can be more accurate and reflect the impact of policy options, which gives policymakers empirical approaches to stabilizing the long-term debt trend.

E. ***Revenue by Electronic Category Analysis***

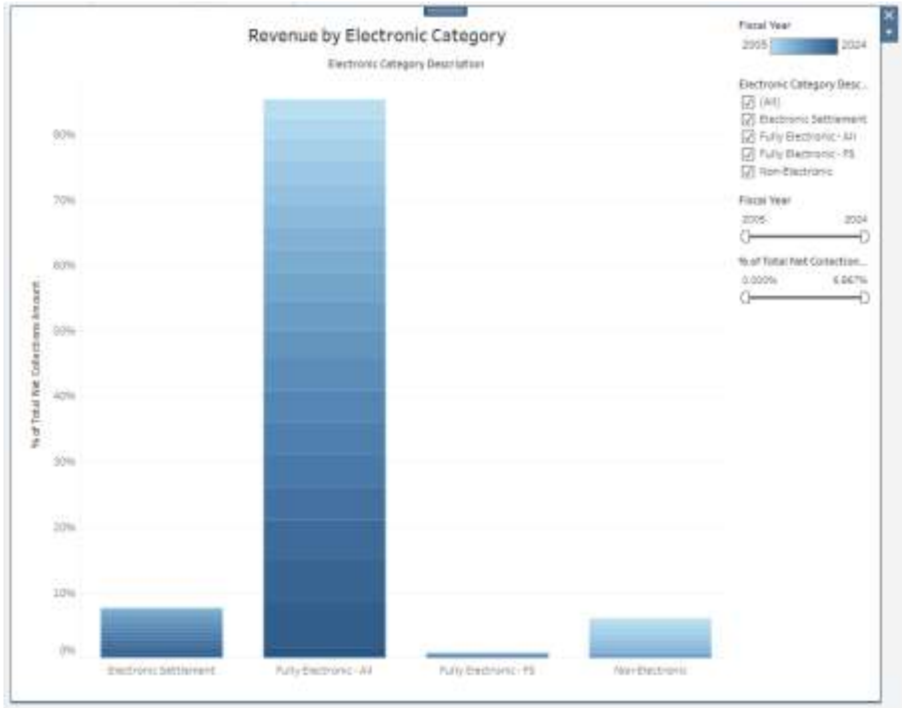

Figure 5: This image shows the U.S federal revenue distribution by category of electronic payments

In Figure 5, the revenue collections in the various electronic and non-electronic categories between 2005 and 2024 have been distributed. The chart illustrates that there is a high prevalence of an all-electronic payment mode especially under the Fully Electronic -All classification that represents over 80% of the total net collections. This shows that the U.S. government is highly transitioning to digitized revenue collection systems, and this is an indication of the progress in financial technology and increased adoption of electronic payment systems by people [47]. The electronic settlement methods are also a smaller yet significant amount in revenue collections with less than 10 percent. This category reflects on transitional-based mechanisms that can have some little to no manual processes and are driven mostly by electronic channels. Conversely, the percentage of the collections in Fully Electronic -FS is extremely small, which indicates that there are still no electronic subcategories that have taken on a broad scope of application. The percentage of non-electronic payments, which is less than 10 percent of the total collections, also proves the decreasing use of the traditional channels like the paper check or the physical transactions. The low marginal proportion of non-electronic payments highlight the efficacy of policy measures and technological framework in promoting the adoption of electronics. This allocation is indicative of more general fiscal modernization initiatives, in which electronic platforms can not only increase efficiency but also transparency, security and reduce costs in the collection of federal revenue. Concentration of revenue using fully electronic systems implies that, in most cases, digital-first strategies constitute the default position of most taxpayers and institutions. Going later, the use of artificial intelligence and automation should further streamline the process of electronic revenues, minimizing the risk of fraud, increasing the effectiveness of transactions verification, and increasing real-time monitoring of inflows.

F. *Trend Analysis in the U.S. Federal Revenue Collections in terms of Type and Method of payment*

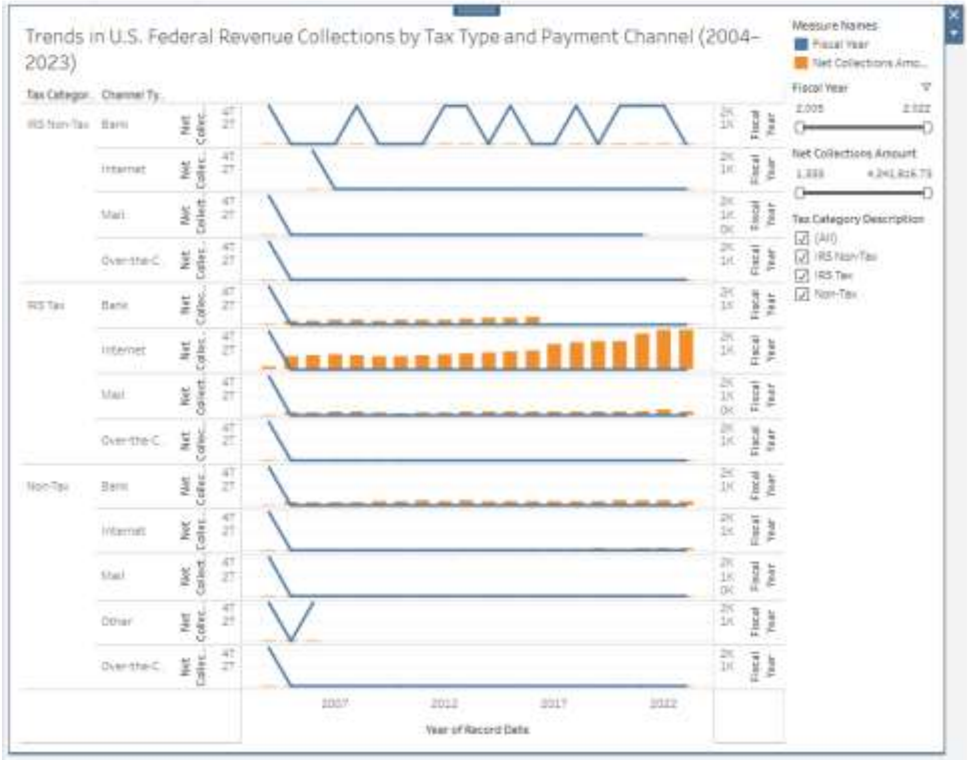

Figure 6: This image shows the U.S revenue trends by tax type and routes of payment

The trends of U.S. federal revenue collections by type of taxes (IRS Tax, IRS Non-Tax and Non-Tax) and payment channels (Bank, Internet, Mail, Over-the-Counter and Other) are presented in Figure 6 between 2004 and 2023. The visualization indicates that there are evident trends to the prevalence of specific channels, with the most significant increase in the count of the Internet-based payments, particularly, in the IRS tax collections. This indicates the robust transition of the federal government to the digital channel of revenue collection as it tries to keep the fiscal processes kept abreast with the current times [48]. In the case of IRS Tax, Internet channels kept on increasing with time meaning that they are increasingly being embraced by the taxpayers. Traditional channels on the other hand like Mail and Over-the-counter transactions remained rather flat with minimal contributions to total collections. The stability in terms of bank-based transactions to the IRS Tax was also noted but no drastic increase was realized in the case of Internet payments. IRS Non-Tax collections which consist of payments other than conventional taxation had a lower variation across channels with Bank and Internet channels having minimal but a steady contribution. On the same note, Non-Tax collections in channels like Mail and Other continued to be on the lower side indicating that non-tax revenues did not concentrate much on the channel distributions as compared to tax revenues. The chart underlines the effectiveness and scalability of online payment systems, with Internet-based transactions evidently defeating legacy systems. This trend is an indication of an ever-growing dependence on the automated and technology-driven mechanisms to augment the government fiscal operations. Such findings support the possible use of artificial intelligence in maximizing digital revenues, forecasting taxpayer activity, and maintaining the effective operation of federal inflows.

VI. Discussion and Analysis

A. *Changes in Federal Revenue Collection Trends*

The findings demonstrate significant changes in federal revenues collection trends, which indicate economic as well as fiscal policy changes [49]. It is evident that the IRS Tax collections continue to be the biggest contributor to the federal revenue base, by far, as compared to other items like IRS Non-Tax and Non-Tax revenues. This hegemony highlights the importance of the tax policies that are linked to income earned by both an individual and a company critical in supporting the operations of the government. But it also shows a structural dependence which may cause vulnerabilities. Since the revenues of the IRS Tax are strongly related to the fluctuations of the business cycle, decreases in employment rates, household consumption, or the profitability of companies may introduce significant fiscal undertrains. Non-Tax Revenues in contrast like custom duties, fees and fines give smaller though more consistent inflows that are not directly related to macroeconomic performance. These sources serve as cushioning agents whenever the economy is contracting and the revenue streams are not fully reliant on the level of fluctuation in revenues or profits. In addition, the revenue distribution that is observed indicates that there is a form of diversification, although it is not much. The great dependence on IRS Tax revenues implies that fiscal stability can be disrupted by external shocks like recessions or world crises. This indicates the need to embrace policies which reinforce revenue diversity, such as the strategic growth of non-tax sources, enhanced application of existing collection policies, and the search of new revenue sources such as taxation of digital services [50]. The capability of the government to have a balance in the portfolio of the revenue sources will not only be critical in managing the debt but also responding efficiently to the unexpected challenges without affecting service delivery and the confidence of the population.

B. *Diversisoglu: The Digitalization of Revenue Collection*

When we examine the channels of payment, there is a revolutionary digitalization of the collection of federal revenue. Internet based payments are in most cases the largest portion of what the channels collect, which is way beyond the previous methods of collection that include bank, mail, or over the counter payments. This shift is an indication of the effectiveness of the modernization policies which promote the use of electronic payments, especially by secure online portals that make it easy to pay taxes to the government both as an individual and as a corporation. The trend is consistent with the rest of the world trends in which digital financial ecosystems have become the focus of the private and government. The advantages of this move are obvious, the administrative expenses decrease, the processing of transactions is accelerated, and the efficiency of data management rises. Utilizing digital platforms more, the federal government can also better track the flow of revenues in real-time thereby facilitating superior fiscal projections and policy changes. But such excessive dependence on Internet-channels also brings about fresh dangers which cannot be disregarded [51]. The efficiency and reliability of revenue collection can be disrupted by the cyber security threats that may be viewed as phishing activities, as well as large-scale breaches. More so, such a change can pose a challenge to those populations which are not digitally literate or have little access to dependable internet infrastructure, and it will raise the issue of equity in the way government services are delivered. In general, although digitalization obviously enhances efficiency and transparency, it should be supported by the investments in cyber security resilience, strong contingency plans, and digital inclusion. The way forward in the future policy formulations should be to strike a balance between efficiency and inclusivity where modernization should not unintentionally create accessibility disparities. The success of this transformation will be based on the completion of a secure, equitable, and resilient digital collection system, which will be able to adjust to the changes in technology and the society of the future.

C. *Impact of Increased Public Debt*

The time-series trend of the U.S. public debt shows that the debt has been steadily growing and accelerating its growth, which is raising the urgent concerns of fiscal sustainability. Since the beginning of 1990s, when the debt levels were around $4 trillion, the total debt of the people has grown exponentially to more than 30 trillion in recent years. This spurt is not only a cyclical economic decline but also structural forces like entitlement spending, stimulus action, and interest payables. Although debt is typically required to finance government functions, its steady increase pattern is an indication of more intrinsic problems [52]. A key implication is the increasing proportion of federal revenue that is used in debt servicing in lieu of productive investments that bring about infrastructure, healthcare, or defense. The higher the ratio of interest expenses to the budget, the less the fiscal flexibility of the government, and the more difficult it becomes to act in response to an emergency or to invest in long-term growth policies. Moreover, debts could create less investor confidence, which could drive the cost of borrowing up even higher and institute a cycle of fiscal strains that feed on themselves. Of particular interest is the relation between the efficiency of debt and revenue. When the revenue collection mechanisms are streamlined by using advanced analytics and digital processes, the government may be in a position to decrease its debts, which are caused by heavy borrowing. Better prediction, such as, would enable better-informed debt issues strategies to reduce idle borrowings and low long term expenditures. Nevertheless, lack of correction of revenue collection inefficiencies risks increasing debt susceptibility and the government may have to rely on borrowing to cover gaps in the budget. On the whole, the discussion shows that an increase in the level of public debt is not only a financial indicator but also a primary concern that replenishes with efficiency in revenues, planning of policies and economic stability. The solution to this will mean a moderated approach to boost revenue-generation and at the same time stimulate fiscal discipline.

D. *The Role of Electronic Categories in Growth of Revenue*

In this review of the electronic category of revenue, it is clear that the fully electronic transactions dominate the revenue almost 90% of all the collections. The trend shows that the federal government has excelled in its use of digital infrastructure to streamline revenue systems. Promoting complete electronic settlements, policymakers have facilitated more transparent, efficient and traceable transactions at lower administrative costs and errors involved in manually processing them. The extensive use of electronic types shows that there is a high compliance rate with the modernization efforts by taxpayers implying that individuals and corporations are aware of the convenience and safety values of electronic payments. Nevertheless, although such dominance is a demonstration of progress, it also brings up the issue of endless reliance on digital infrastructure [53]. Any form of interruption, whether as a result of technical breakdowns, computer attacks or massive shutdowns may severely impact the revenue streams, weakening the financial system. More so, the continuation of non-electronic transactions, albeit minor, indicates the existence of taxpayers that do not know how to use digital tools or do not find it convenient to do so. Leaving this group aside may pose the risk of alienating some groups of people especially in rural or under banked communities. Therefore, even though complete electronic systems lead to efficiency, it is important to have alternative solutions in case of inclusivity and resilience. A second interesting implication is that it may result in data-driven insights. As the majority of transactions are done electronically, the government will be able to utilize the mass datasets to make predictive models, detect fraud, and monitor compliance. This ability would be in line with the other fiscal management goals wherein the applications of artificial intelligence can optimize the forecasting process and also enhance policy-making. Finally, although the overruling of the electronic categories can be defined as the positive force of modernization, the future strategies should be aimed at efficiency and inclusivity, as well as resilience to future risks. The efficiency of revenue systems will rely more on how the government incorporates the power of technology innovation in implementing a fair and secure practice.

E. *Channel Specific Trends in Tax and Non-Tax Revenue*

The disaggregation of revenue streams by channel gives important information as to how taxpayers interact with federal systems. The highest correlation with Internet channels is in the IRS Tax revenues, which proves the superiority of digital adoption when it comes to the primary tax collections. This shows how the digitalization of the filing and payment systems has eased the compliance and enhanced efficiency in gathering the greatest piece of revenue. In comparison, IRS Non-Tax and Non-Tax revenues are spread more evenly across the channels, with bank payments, mail and over-the-counter options continuing to be prominent. The differences imply that not all types of revenues have experienced a similar shift to digital systems. Certain types (especially ones, which relate to customs duties, fees, or fines) still rely on traditional mechanisms that could be explained by the administrative character of such collections or preferences of taxpayers [54]. These disparities in digital adoption have significant policy implications. First is that it points out the necessity of differentiating modernization strategies according to revenue type as opposed to using a one-size-fits-all approach. As an example, as much as Internet-based transactions can be attributed to tax payment, other types might need hybrid systems, which would involve the use of digital efficiency but still be familiar with the usual channel. Secondly, the results indicate that the increased digital literacy and access may promote the increased adoption of the categories [55]. The gap can be bridged by investing in taxpayer education, mobile payment platforms and simplified processes. Lastly, there is the value of flexibility that is analyzed. By maintaining various collection channels, there will be inclusivity, a variety of needs by taxpayers and redundancy in the instances of digital disruptions. Overall, the channel-specific analysis supports the relevance of the adaptive strategies to acknowledge the variation between the revenue categories and promote the modernization goals.

F. *Policy and Technology Integration Strategic Insights*

Combined, the findings offer relevant strategic information on policy, technology and fiscal sustainability interplay. The hegemony of IRS Tax revenues speaks of the traditional approach to taxation, whereas the hectic rates of the development of electronic and Internet-based channels can be interpreted as the forces of transformation through the influence of digitalization. The concurrent increase in the debt of the populace is an indicator, however, that efficiency in revenue gathering is not enough without extending fiscal reforms. It requires a two-pronged strategy to ensure the consolidation of the revenue apparatus and technological advancement as well as restraint in government expenditure and debt control. The results give a number of policy recommendations that policymakers can implement [56]. To start with, revenue forecasting, debt issuance, and compliance monitoring should be increasingly implemented with the help of AI and sophisticated data analytics. Predictive models can assist in predicting changes in the behavior of tax payers and conduct a better auction of Treasury bonds, which in turn will make it cheaper to borrow. Second, cyber security should be discussed as one of the pillars of modernization. With the growing reliance of federal systems on electronic and Internet solutions, there is a significant need to protect them against electronic threats to ensure that the systems are trusted and stable. Third, modernization strategies need to be executed in terms of inclusiveness. Although many people have adopted digital, the under banked, rural or digitally restricted populations need to have policies that will deal with the accessibility issue to avoid systemic marginalization. Lastly, fiscal discipline needs to keep it at the center stage. The most effective revenue collection systems are not able to counter unsustainable debt growth without expenditure control. Finally, the paper identifies that technology, inclusivity, and policy discipline are three areas that need to converge in order to manage sustainable fiscal management. With the harmonization of these dimensions, the federal government will be able to not only optimize revenue collection, but also enhance the fiscal resiliency and economic stability in the long term.

VII. Future Work

The future investigations on artificial intelligence and data analytics used in the management of the U.S. national debt must be extended in some aspects to build upon theoretical knowledge and practical applications. To begin with, the future work might incorporate wider datasets than revenue collections, which may include expenditure disaggregations, macroeconomic variables, fluctuations in interest rates, and macroeconomic financial shocks to give a deeper model of debt sustainability [57]. Second, more sophisticated AI applications can be considered such as deep learning, reinforcement learning, and hybrid predictive systems that can be used to optimize the Treasury bond auction plan, predict taxpayer behavior and simulate long-run fiscal effects in response to various policy options. Moreover, economic studies with elements of computer science and policy would also be useful to ensure that the results of the analyses are not in conflict with the budgetary reality and political limitations. The other emerging opportunity is the creation of explainable AI tools to improve transparency and accountability so that policymakers and the general population could gain a clearer insight into the generation of forecasts and recommendations. Cyber security should also never be left behind in future endeavors since the more people are dependent on digital sources of revenue and automated systems, the more susceptible they will be to cyber-attacks and data breaches. Moreover, future AI applications are to be anchored on ethical principles in order to protect privacy, be fair in tax treatment, and not overly dependent on algorithmic decisions, which would damage the trust of the population. The Treasury Department can use pilot projects to test these innovations and create evidence of how it will save money, enhance efficiency, and possible risks before it can be applied nationwide [58]. Lastly, the possibility of comparative research of other countries that have tried AI-driven fiscal management would be an insightful resource that would allow the United States to implement the best practices and address the distinct fiscal situation. In general, the future labor should be somewhere in the middle between technological growth and ethical protection, sound governance, and participative policymaking that would make the fullest use of AI in ensuring the financial future of America.

VIII. Conclusion

In this study, one of the key transformative opportunities is identified as artificial intelligence and data analytics that could have the potential to help resolve increasing problems related to the management of the U.S. national debt. The research exhibits the ability of the AI and data-driven model to increase the precision of revenue forecasting, optimize Treasury bonds auction strategies, and cut down on the cost of borrowing by analyzing the U.S. Government Revenue Collections dataset (20042023). The findings show that the government has been modernized as the Internet and electronic channels have become the dominant income collection methods. Simultaneously, the systematic growth of the national debt promotes the fact that new monetary policies have to be implemented that are not aimed at conventional econometrics [59]. The results indicate that despite the multiple efficiency benefits, digital transformation has emerged as an additional source of systemic risks associated with cyber security, equity of access, and transparency in algorithmic decision-making. The issue of ethical considerations, especially in the area of data privacy, inclusivity, and accountability, will be the main focus of responsible implementation of AI in fiscal governance. In addition, the national interest in general, as much as the freeing of resources to build infrastructures, health and defense, secure intergenerational equity, and a future-proof approach to debt management are all hanging on more intelligent and adaptive debt management practices. This study highlights that AI is not a substitute for human judgment; rather it is a supplementary tool that can offer an informed policymaker with sound insights to overcome intricate fiscal realities [60]. In the future, the application of advanced predictive models, increasing the explain ability of AI, and enhancing trust in the mentioned technologies by the population through transparent governance will play a significant role in achieving the potential of these technologies. To summarize, the successful implementation of AI and data analytics will be a great solution to the sustainable financial position of America, yet its success will be conditional on a balanced approach between technological improvement, ethical accountability, and policy formulation.

Funding: This research received no external funding.
Conflicts of Interest: The authors declare no conflict of interest.
Publisher's Note: All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers.

References

[1]. Kowsar, M. M., Mohiuddin, M., & Mohna, H. A. (2023). Credit decision automation in commercial banks: a review of AI and predictive analytics in loan assessment. American Journal of Interdisciplinary Studies, 4(04), 01-26.

[2]. Guariso, D., Guerrero, O. A., & Castañeda, G. (2023). Automatic SDG budget tagging: Building public financial management capacity through natural language processing. Data & Policy, 5, e31.

[3]. Ho, C. (2020, October). The Analysis of the Way and Impact of US Reducing the National Debt Scale. In 2020 2nd International Conference on Applied Machine Learning (ICAML) (pp. 146-152). IEEE.

[4]. Singh, P. (2023). Systematic review of data-centric approaches in artificial intelligence and machine learning. Data Science and Management, 6(3), 144-157.

[5]. Sadok, H., Sakka, F., & El Maknouzi, M. E. H. (2022). Artificial intelligence and bank credit analysis: A review. Cogent Economics & Finance, 10(1), 2023262.

[6]. Cordery, C. J., & Hay, D. C. (2022). Public sector audit in uncertain times. Financial accountability & management, 38(3), 426-446.

[7]. Musah, I. (2023). An empirical investigation of macroeconomic determinants of public debt in Ghana. Cogent Economics & Finance, 11(2), 2285625.

[8]. Nalbandian, L. (2022). An eye for an 'I:'a critical assessment of artificial intelligence tools in migration and asylum management. Comparative Migration Studies, 10(1), 32.

[9]. Bose, S., Dey, S. K., & Bhattacharjee, S. (2023). Big data, data analytics and artificial intelligence in accounting: An overview. Handbook of big data research methods, 32-51.

[10]. Fedyk, A., Hodson, J., Khimich, N., & Fedyk, T. (2022). Is artificial intelligence improving the audit process?. Review of Accounting Studies, 27(3), 938-985.

[11]. Nielsen, S. (2022). Management accounting and the concepts of exploratory data analysis and unsupervised machine learning: a literature study and future directions. Journal of Accounting & Organizational Change, 18(5), 811-853.

[12]. Kannan, S. (2022). The Role Of AI And Machine Learning In Financial Services: A Neural Network-based Framework For Predictive Analytics And Customercentric Innovations. Migration Letters, 19(6), 985-1000.

[13]. Cho, W., Choi, S., & Choi, H. (2023). Human resources analytics for public personnel management: Concepts, cases, and caveats. Administrative Sciences, 13(2), 41.

[14]. De Soyres, C., Kawai, R., & Wang, M. (2022). Public debt and real GDP: Revisiting the impact. International Monetary Fund.

[15]. Ahmed, A., Xi, R., Hou, M., Shah, S. A., & Hameed, S. (2023). Harnessing big data analytics for healthcare: A comprehensive review of frameworks, implications, applications, and impacts. IEEE Access, 11, 112891-112928.

[16]. Cheng, Y., Jia, S., & Meng, H. (2022). Fiscal policy choices of local governments in China: Land finance or local government debt?. International Review of Economics & Finance, 80, 294-308.

[17]. Fahlevi, H., Irsyadillah, I., Indriani, M., & Oktari, R. S. (2022). DRG-based payment system and management accounting changes in an Indonesian public hospital: exploring potential roles of big data analytics. Journal of Accounting & Organizational Change, 18(2), 325-345.

[18]. Cao, L. (2023). AI and data science for smart emergency, crisis and disaster resilience. International journal of data science and analytics, 15(3), 231-246.

[19]. Ahmed, S., Alshater, M. M., El Ammari, A., & Hammami, H. (2022). Artificial intelligence and machine learning in finance: A bibliometric review. Research in International Business and Finance, 61, 101646.

[20]. Ragazou, K., Passas, I., Garefalakis, A., Galariotis, E., & Zopounidis, C. (2023). Big data analytics applications in information management driving operational efficiencies and decision-making: Mapping the field of knowledge with bibliometric analysis using R. Big Data and Cognitive Computing, 7(1), 13.

[21]. Yigitcanlar, T., Agdas, D., & Degirmenci, K. (2023). Artificial intelligence in local governments: perceptions of city managers on prospects, constraints and choices. Ai & Society, 38(3), 1135-1150.

[22]. Khambam, S. K. R., Kaluvakuri, V. P. K., & Peta, V. P. (2022). The Cloud as A Financial Forecast: Leveraging AI For Predictive Analytics. Available at SSRN 4927232.

[23]. Shiyyab, F. S., Alzoubi, A. B., Obidat, Q. M., & Alshurafat, H. (2023). The impact of artificial intelligence disclosure on financial performance. International Journal of Financial Studies, 11(3), 115.

Reis, R. (2022). Debt revenue and the sustainability of public debt. Journal of Economic Perspectives, 36(4), 103-124.

[24]. Newman, J., Mintrom, M., & O'Neill, D. (2022). Digital technologies, artificial intelligence, and bureaucratic transformation. Futures, 136, 102886.

[25]. Heimberger, P. (2023). Do higher public debt levels reduce economic growth?. Journal of Economic Surveys, 37(4), 1061-1089.

[26]. Salas-Pilco, S. Z., & Yang, Y. (2022). Artificial intelligence applications in Latin American higher education: a systematic review. International Journal of Educational Technology in Higher Education, 19(1), 21.

[27]. Hamilton, L., Elliott, D., Quick, A., Smith, S., & Choplin, V. (2023). Exploring the use of AI in qualitative analysis: A comparative study of guaranteed income data. International journal of qualitative methods, 22, 16094069231201504.

[28]. Klusak, P., Agarwala, M., Burke, M., Kraemer, M., & Mohaddes, K. (2023). Rising temperatures, falling ratings: The effect of climate change on sovereign creditworthiness. Management Science, 69(12), 7468-7491.

[29]. Hossain, M. Z. (2023). Emerging trends in forensic accounting: Data analytics, cyber forensic accounting, cryptocurrencies, and blockchain technology for fraud investigation and prevention. Cyber Forensic Accounting, Cryptocurrencies, and Blockchain Technology for Fraud Investigation and Prevention (May 16, 2023).

[30]. Gao, B. (2022). The use of machine learning combined with data mining technology in financial risk prevention. Computational economics, 59(4), 1385-1405.

[31]. Farooq, F. (2022). How does institutional quality moderates the impact of public debt on economic growth? Startling evidence from OIC countries. International Journal of Management Research and Emerging Sciences, 12(3).

[32]. Elumilade, O. O., Ogundeji, I. A., Achumie, G. O., Omokhoa, H. E., & Omowole, B. M. (2022). Optimizing corporate tax strategies and transfer pricing policies to improve financial efficiency and compliance. Journal of Advanced Multidisciplinary Research, 1(2), 28-38.

[33]. Zenios, S. A. (2022). The risks from climate change to sovereign debt. Climatic Change, 172(3), 30.

Altman, E. I., Balzano, M., Giannozzi, A., & Srhoj, S. (2023). Revisiting SME default predictors: The omega score. Journal of small business management, 61(6), 2383-2417.

[34]. Basiru, J. O., Ejiofor, C. L., Onukwulu, E. C., & Attah, R. (2023). Enhancing financial reporting systems: A conceptual framework for integrating data analytics in business decision-making. IRE Journals,[online], 7(4), 587-606.

[35]. Timmons, A. C., Duong, J. B., Simo Fiallo, N., Lee, T., Vo, H. P. Q., Ahle, M. W., ... & Chaspari, T. (2023). A call to action on assessing and mitigating bias in artificial intelligence applications for mental health. Perspectives on Psychological Science, 18(5), 1062-1096.
[36]. Mogaji, E., & Nguyen, N. P. (2022). Managers' understanding of artificial intelligence in relation to marketing financial services: insights from a cross-country study. International Journal of Bank Marketing, 40(6), 1272-1298.
[37]. Sazu, M. H., & Jahan, S. A. (2022). Impact of blockchain-enabled analytics as a tool to revolutionize the banking industry. Data Science in Finance and Economics, 2(3), 275-293.
[38]. Burk, S., & Miner, G. (2023). It's All Analytics, Part III: The Applications of AI, Analytics, and Data Science. Productivity Press.
[39]. Amarnadh, V., & Moparthi, N. R. (2023). Comprehensive review of different artificial intelligence-based methods for credit risk assessment in data science. Intelligent Decision Technologies, 17(4), 1265-1282.
[40]. Lăzăroiu, G., Bogdan, M., Geamănu, M., Hurloiu, L., Luminița, L., & Ștefănescu, R. (2023). Artificial intelligence algorithms and cloud computing technologies in blockchain-based fintech management. Oeconomia Copernicana, 14(3), 707-730.
[41]. Krishnan, S. R., Nallakaruppan, M. K., Chengoden, R., Koppu, S., Iyapparaja, M., Sadhasivam, J., & Sethuraman, S. (2022). Smart water resource management using Artificial Intelligence—A review. Sustainability, 14(20), 13384.
[42]. Ozili, P. K. (2023). Big data and artificial intelligence for financial inclusion: benefits and issues. In Artificial intelligence, fintech, and financial inclusion (pp. 1-10). CRC Press.
[43]. Zhang, B., Shi, H., & Wang, H. (2023). Machine learning and AI in cancer prognosis, prediction, and treatment selection: a critical approach. Journal of multidisciplinary healthcare, 1779-1791.
[44]. Tian, J., Yu, L., Xue, R., Zhuang, S., & Shan, Y. (2022). Global low-carbon energy transition in the post-COVID-19 era. Applied energy, 307, 118205.
[45]. Kaulwar, P. K., Pamisetty, A., Mashetty, S., Adusupalli, B., & Pandiri, L. (2023). Harnessing Intelligent Systems and Secure Digital Infrastructure for Optimizing Housing Finance, Risk Mitigation, and Enterprise Supply Networks. International Journal of Finance (IJFIN)-ABDC Journal Quality List, 36(6), 372-402.
[46]. Kulkarni, P. A. (2023). Advanced Analytics Driven Financial Management: An Innovative Approach to Financial Planning & Analysis. International Journal of Computer Trends and Technology, 71(6), 17-24.
[47]. Barua, P. D., Vicnesh, J., Gururajan, R., Oh, S. L., Palmer, E., Azizan, M. M., ... & Acharya, U. R. (2022). Artificial intelligence enabled personalised assistive tools to enhance education of children with neurodevelopmental disorders—a review. International Journal of Environmental Research and Public Health, 19(3), 1192.
[48]. Pham, S. T., & Sampson, P. M. (2022). The development of artificial intelligence in education: A review in context. Journal of Computer Assisted Learning, 38(5), 1408-1421.
[49]. Wahyudi, M., Meilinda, V., & Khairunnisa, A. (2022). The Digital Economy's Use of Big Data. International Transactions on Artificial Intelligence, 1(1), 62-70.
[50]. Chukwuma-Eke, E. C., Ogunsola, O. Y., & Isibor, N. J. (2022). A conceptual framework for financial optimization and budget management in large-scale energy projects. International Journal of Multidisciplinary Research and Growth Evaluation, 2(1), 823-834.
[51]. Otia, J. E., & Bracci, E. (2022). Digital transformation and the public sector auditing: The SAI's perspective. Financial Accountability & Management, 38(2), 252-280.
[52]. Schein, J., Adler, L. A., Childress, A., Cloutier, M., Gagnon-Sanschagrin, P., Davidson, M., ... & Lefebvre, P. (2022). Economic burden of attention-deficit/hyperactivity disorder among children and adolescents in the United States: a societal perspective. Journal of Medical Economics, 25(1), 193-205.
[53]. Gigante, G., & Zago, A. (2023). DARQ technologies in the financial sector: artificial intelligence applications in personalized banking. Qualitative Research in Financial Markets, 15(1), 29-57.
[54]. Machireddy, J. R. (2023). Data science and business analytics approaches to financial wellbeing: Modeling consumer habits and identifying at-risk individuals in financial services. Journal of Applied Big Data Analytics, Decision-Making, and Predictive Modelling Systems, 7(12), 1-18.
[55]. Aminzadeh, F., Temizel, C., & Hajizadeh, Y. (2022). Artificial Intelligence and Data Analytics for Energy Exploration and Production. John Wiley & Sons.
[56]. Apergis, N., Poufinas, T., & Antonopoulos, A. (2022). ESG scores and cost of debt. Energy Economics, 112, 106186.
[57]. Ajuwon, A., Adewuyi, A., Oladuji, T. J., & Akintobi, A. O. (2023). A Model for Strategic Investment in African Infrastructure: Using AI for Due Diligence and Portfolio Optimization. International Journal of Advanced Multidisciplinary Research and Studies, 3(6), 1811-1826.
[58]. Malali, N. (2022). Using Machine Learning to Optimize Life Insurance Claim Triage Processes Via Anomaly Detection in Databricks: Prioritizing High-Risk Claims for Human Review. International Journal of Engineering Technology Research & Management (IJETRM), 6(06).
[59]. Fares, O. H., Butt, I., & Lee, S. H. M. (2022). Utilization of artificial intelligence in the banking sector: a systematic literature review. Journal of Financial Services Marketing, 1.
[60]. Wu, J. S. (2023). Applying frontier approach to measure the financial efficiency of hospitals. Digital Health, 9, 20552076231162987.
[61]. Farooq, F., Zaib, A., Faheem, M., & Gardezi, M. A. (2023). Public debt and environment degradation in OIC countries: the moderating role of institutional quality. Environmental Science and Pollution Research, 30(19), 55354-55371.
[62]. Dataset Link:
https://www.kaggle.com/datasets/sriharshaeedala/u-s-government-revenue-collections