International Journal of Development and Economic Sustainability
Vol.10, No.6, pp.66-89, 2022
Print ISSN: 2053-2199 (Print),
Online ISSN: 2053-2202(Online)
Website: https://www.eajournals.org/
Publication of the European Centre for Research Training and Development -UK

The Impact of Big Data on Economic Forecasting and Policy Making

Oluwabusayo Adijat Bello
Northern Trust
Busayobello151@gmail.com
doi: https://doi.org/10.37745/ijdes.13/vol10n66689

Citation: Bello A. (2022) The Impact of Big Data on Economic Forecasting and Policy Making, *International Journal of Development and Economic Sustainability*, Vol.10, No.6, pp.66-,89

ABSTRACT: *The advent of big data has revolutionized various fields, including economic forecasting and policy making, by offering unprecedented access to vast amounts of information and sophisticated analytical tools. This transformation is reshaping how economists predict economic trends and how policymakers design and implement effective strategies. Traditionally, economic forecasting relied on historical data analysis and econometric models, which, despite their utility, faced significant limitations. Data scarcity, time lags, and accuracy issues often hindered precise forecasting. However, the rise of big data, fueled by technological advancements and the proliferation of digital information, has introduced new dimensions to economic analysis. Sources of big data now encompass social media, financial transactions, the Internet of Things (IoT), and extensive government and public data, providing real-time insights into economic activities. The integration of big data into economic forecasting employs various advanced techniques and tools. Machine learning and artificial intelligence (AI) algorithms can process and analyze massive datasets, identifying patterns and trends that were previously undetectable. Data mining techniques enable the extraction of valuable information from large and complex datasets, while real-time analytics facilitate immediate decision-making based on current data. For instance, predictive analytics in stock markets can forecast price movements with greater accuracy, while analysis of consumer spending patterns offers valuable insights into retail trends. Economic policy making benefits immensely from the incorporation of big data. Data-driven decision-making allows for the design of policies that are more responsive to real-time economic conditions and tailored to specific contexts. By continuously monitoring and evaluating policy impacts through real-time data, policymakers can adjust strategies promptly, ensuring greater effectiveness. This dynamic approach contrasts sharply with traditional methods, which often relied on delayed and less comprehensive data. In monetary policy, real-time analysis of inflation indicators allows central banks to adjust interest rates more precisely. Social policies also benefit, as big data helps identify and address welfare needs more effectively, ensuring that resources are allocated where they are most needed. The benefits of incorporating big data into economic forecasting and policy making are manifold. Enhanced accuracy and precision in predictions lead* *to better-informed decisions. Timeliness and responsiveness are significantly improved, allowing for proactive rather than reactive strategies. Comprehensive insights from diverse data sources provide a holistic view of economic conditions, while advanced predictive capabilities enable the anticipation of future trends. However, the integration of big data also presents challenges. Data privacy and security concerns are paramount, as the collection and analysis of large datasets raise ethical and legal issues. Ensuring data quality and reliability is critical, as inaccuracies can lead to misguided decisions. Technical barriers, such as the need for specialized skills and infrastructure, can impede the effective use of big data. Addressing these challenges requires robust frameworks for data governance and continuous investment in technology and skills development. Looking ahead, the future prospects of big data in economic forecasting and policy making are promising. The integration of emerging technologies such as blockchain and advanced AI will further enhance data security, transparency, and analytical capabilities. Global collaboration and data sharing initiatives will enable more comprehensive and accurate economic analysis. As policymakers and economists continue to adapt to this data-driven paradigm, the ongoing transformation promises to yield more effective and efficient economic strategies, ultimately fostering greater economic stability and growth. Big data is transforming economic forecasting and policy making by providing deeper insights, enhancing accuracy, and enabling more responsive and effective strategies. While challenges remain, the continuous evolution of technology and data practices holds great potential for the future of economics.*

KEYWORDS: impact, big data, forecasting, policy

INTRODUCTION

Big data refers to the vast volumes of structured and unstructured data generated from various sources, characterized by its high velocity, variety, and volume (McNeely, C.L. and Schintler, 2022). This data deluge is a result of the digital age, where virtually every interaction, transaction, and activity leaves a digital trace. Big data technologies encompass a range of tools and techniques designed to handle these large, fast, and varied datasets (Ikegwu *et al*., 20222). These include Hadoop, Spark, and various machine learning algorithms that can analyze and derive insights from big data.

Economic forecasting involves predicting future economic conditions based on the analysis of historical data and current economic indicators (Nabipour *et al*., 2020). Traditional economic forecasting relies on econometric models, which use statistical methods to forecast economic variables such as GDP growth, inflation rates, employment levels, and other key indicators. These models typically utilize historical data and make assumptions based on established economic theories. Policy making, on the other hand, is the process by which governments and other institutions develop strategies and make decisions to achieve specific economic goals (Forestier and Kim, 2020). Economic policy making can be divided into several categories, decisions related

International Journal of Development and Economic Sustainability
Vol.10, No.6, pp.66-89, 2022
Print ISSN: 2053-2199 (Print),
Online ISSN: 2053-2202(Online)
Website: https://www.eajournals.org/
Publication of the European Centre for Research Training and Development -UK

to government spending and taxation. Actions by central banks to control money supply and interest rates. Rules and regulations aimed at ensuring market stability and fairness. Programs and initiatives designed to promote social welfare and equity. Effective policy making requires accurate and timely information about the current state of the economy and the likely impact of various policy options (Marcucci *et al*., 2020). Traditional approaches to both forecasting and policy making have faced significant limitations, such as data scarcity, time lags, and the inability to capture complex economic dynamics in real-time (Fang e al., 2022).

The integration of big data into economic forecasting and policy making represents a paradigm shift (Kandt and Batty, 2021). The unprecedented access to vast amounts of real-time data offers numerous advantages over traditional methods, big data allows for more granular analysis, capturing subtle trends and correlations that traditional datasets might miss. This leads to more accurate and precise economic forecasts. The real-time nature of big data enables economists and policymakers to monitor economic conditions continuously and respond swiftly to emerging trends (Barlas *et al*., 2020). The variety of data sources, including social media, financial transactions, and IoT devices, provides a holistic view of the economy, capturing information that was previously inaccessible. Advanced machine learning algorithms can analyze vast datasets to identify patterns and make predictions about future economic conditions, enhancing the ability to anticipate and mitigate economic risks. The importance of big data in contemporary economics is underscored by its potential to improve the effectiveness of policy interventions (Pencheva *et al*., 2020). Data-driven policy making allows for more targeted and efficient allocation of resources, reducing waste and maximizing impact. Furthermore, big data enables continuous monitoring and evaluation of policy outcomes, facilitating timely adjustments and ensuring that policies remain relevant and effective (Ditria *et al*., 2022).

Big data is revolutionizing economic forecasting and policy making by providing more accurate, timely, and comprehensive insights into economic conditions (Mureddu *et al*., 2020). This transformation enhances the precision and effectiveness of economic strategies, enabling policymakers to respond more effectively to dynamic economic challenges. However, the integration of big data also presents significant challenges, including issues related to data privacy, quality, and ethical considerations, which must be addressed to fully realize its potential. Traditional economic forecasting has long relied on historical data analysis and econometric models (Hendry, 2020). These models, based on statistical methods, utilize past economic data to predict future trends. Key techniques include time series analysis, regression models, and input-output models. This involves examining past economic data to identify trends and patterns. Historical data provides a foundation for making predictions about future economic conditions. These are mathematical models that describe the relationships between different economic variables. By estimating the parameters of these models using historical data, economists can make predictions about future values of these variables (Lenza and Primiceri, 2022). Despite their utility, traditional methods face significant limitations. Data scarcity often hampers the ability to make accurate forecasts, especially in rapidly changing economic environments. Time lags in data collection and processing can lead to outdated or irrelevant insights (Geels, 2022). Additionally, traditional models may struggle to capture complex, non-linear relationships in the economy, limiting their predictive power.

Traditional forecasting methods often rely on limited datasets, which may not capture the full complexity of economic dynamics (Shen and Lawson, 2021). This can result in inaccurate or incomplete forecasts. The time required to collect, process, and analyze data can lead to delays in forecasting, making it difficult to respond promptly to economic changes. Furthermore, traditional models may lack the precision needed to make accurate predictions in volatile economic environments (Taheri and Razban, 2021). Traditional econometric models may struggle to account for the complex, non-linear interactions between different economic variables. This can limit their ability to provide accurate forecasts in dynamic and interconnected economies.

The emergence of big data represents a significant advancement in economic forecasting and policy making (Pencheva *et al*., 2020). Driven by technological advancements and the proliferation of digital information, big data offers new opportunities to overcome the limitations of traditional methods. Innovations in data storage, processing, and analysis technologies have made it possible to handle vast amounts of data efficiently. Technologies such as Hadoop, Spark, and cloud computing have revolutionized data management. The digital age has generated an unprecedented amount of data from various sources, including social media, financial transactions, IoT devices, and government databases (Long *et al*., 2021). This wealth of information provides a comprehensive view of economic activities.

Big data in economics comes from diverse sources, each offering unique insights into economic conditions. Social media provides real-time information on consumer sentiment and behavior. Financial transactions offer detailed data on spending patterns and market trends. IoT devices generate continuous streams of data on various aspects of the economy, from transportation to energy consumption (Ahmad and Zhang, 2021). Government and public data provide comprehensive statistics on a wide range of economic indicators. Advanced techniques and tools are essential for analyzing big data in economics. Machine learning and AI algorithms can process and analyze massive datasets, identifying patterns and trends that traditional methods might miss (Alsharif *et al*., 2020). Data mining techniques enable the extraction of valuable information from large and complex datasets. Real-time analytics facilitate immediate decision-making based on current data, enhancing the timeliness and responsiveness of economic forecasting (Hemachandran *et al*., 2022). Real-world applications of big data in economic forecasting highlight its transformative potential. Predictive analytics in stock markets can forecast price movements with greater accuracy, improving investment decisions. Analysis of consumer spending patterns provides valuable insights into retail trends, enabling businesses to tailor their strategies. Macroeconomic indicators, such as GDP growth and inflation rates, can be monitored and analyzed in real-time, providing policymakers with timely and accurate information (Poza and Monge, 2020).

Big data is revolutionizing economic forecasting and policy making by providing more accurate, timely, and comprehensive insights into economic conditions. This transformation enhances the precision and effectiveness of economic strategies, enabling policymakers to respond more effectively to dynamic economic challenges. However, the integration of big data also presents significant challenges, including issues related to data privacy, quality, and ethical considerations (Ogbuke *et al.*, 2022). Addressing these challenges requires robust frameworks for data governance and continuous investment in technology and skills development. As the field continues to evolve, the ongoing transformation promises to yield more effective and efficient economic strategies, ultimately fostering greater economic stability and growth (Arent *et al.*, 2022).

The Evolution of Economic Forecasting and Policy Making

Economic forecasting and policy making have undergone significant transformations over the past few decades, driven by advancements in technology and the proliferation of data (Bisht *et al.*, 2022). This explores the traditional methods of economic forecasting, their limitations, and the emergence of big data as a revolutionary force in economic analysis and policy making.

Historical data analysis has been a cornerstone of economic forecasting for centuries. This method involves examining past economic data to identify trends, patterns, and cycles that can inform predictions about future economic conditions. The fundamental assumption is that historical patterns tend to repeat themselves, and by understanding these patterns, economists can make informed forecasts. Time series analysis involves studying data points collected or recorded at specific time intervals. Economists use statistical techniques to analyze the temporal sequence of data, identifying trends (long-term movements), seasonal patterns (regular fluctuations within a specific period), and cyclical patterns (irregular fluctuations due to economic cycles). Techniques such as moving averages, exponential smoothing, and autoregressive integrated moving average (ARIMA) models are commonly used in time series analysis (Rabbani *et al.*, 2021). This method involves analyzing data collected at a single point in time across different subjects or entities, such as individuals, firms, or countries. Cross-sectional analysis helps economists understand the relationships between different economic variables at a given moment. Econometric models represent a more sophisticated approach to economic forecasting, combining economic theory with statistical methods. These models aim to quantify the relationships between economic variables, allowing for the simulation and prediction of future economic conditions based on past data and theoretical constructs.

This involves defining the mathematical form of the relationships between variables. For instance, a simple linear regression model might specify that GDP growth is a function of investment and consumption. Estimation involves using statistical techniques to determine the parameters of the specified model (Kumle *et al*., 2021). Methods such as ordinary least squares (OLS) are commonly used to estimate the coefficients of linear models. After estimating the model, economists validate it by testing its predictive power and accuracy. This often involves comparing the model's predictions against actual historical data. Once validated, the model can be used to simulate future scenarios by inputting different values for the explanatory variables. These models assume a linear relationship between the dependent variable and one or more independent variables. They are widely used due to their simplicity and ease of interpretation. These models extend linear regression to include multiple independent variables, allowing for the analysis of more complex relationships. These models, such as ARIMA and vector autoregression (VAR), are specifically designed for analyzing temporal data. They capture the dynamic relationships between variables over time (Yılmaz, 2020). These models incorporate economic theory to specify the relationships between variables. They often involve systems of equations representing different sectors of the economy.

While traditional methods of economic forecasting have been invaluable, they are not without their limitations (Weersink and Fulton, 2020). The evolving complexity of modern economies and the rapid pace of change present significant challenges to these traditional approaches. One of the primary limitations of traditional economic forecasting methods is data scarcity. Historically, economic data was collected infrequently and often with significant delays. This scarcity of timely and comprehensive data limited the accuracy and reliability of forecasts. With few data points, it is challenging to identify robust trends and patterns, especially in volatile economic conditions. This can lead to forecasts that are overly simplistic or fail to capture emerging trends. Traditional methods often rely on aggregate data, such as national GDP or overall unemployment rates. While useful, these aggregates can mask significant variations within different sectors or regions, leading to incomplete or misleading forecasts. Scarcity of data can also lead to an over-reliance on historical trends, which may not hold in the face of structural changes in the economy. This can result in forecasts that fail to anticipate major economic shifts or disruptions. Another significant limitation of traditional methods is the time lag between data collection, analysis, and the formulation of forecasts. Economic data is often released with a delay, and the processes of data cleaning, analysis, and model validation add further delays (Nibareke and Laassiri, 2020). By the time forecasts are made, the underlying data may no longer reflect current economic conditions. This lag can lead to forecasts that are based on outdated or irrelevant information. The inability to incorporate real-time data into forecasting models limits the responsiveness of economists and policymakers to emerging economic trends. This can hinder timely decision-making and policy adjustments. Traditional econometric models, while powerful, are not always accurate. The assumptions and simplifications required to make these models tractable can introduce errors and biases. For example, linear models may fail to capture non-linear relationships, and models based on historical data may not account for unprecedented events or structural changes.

The limitations of traditional economic forecasting methods have paved the way for the emergence of big data as a transformative force. Big data refers to the vast volumes of data generated from various sources, characterized by high velocity, variety, and volume (Mohamed *et al.*, 2020). The advent of big data has revolutionized economic forecasting and policy making by providing more comprehensive, timely, and granular insights. Technological advancements have been instrumental in enabling the collection, storage, and analysis of big data. Innovations in data processing technologies and the development of sophisticated analytical tools have made it possible to handle and derive insights from massive datasets. Technologies such as Hadoop and Spark have revolutionized the storage and processing of large datasets. These distributed computing frameworks allow for the parallel processing of data across multiple nodes, significantly increasing processing speed and efficiency. Cloud platforms provide scalable and cost-effective solutions for storing and processing big data. Services such as Amazon Web Services (AWS), Google Cloud Platform (GCP), and Microsoft Azure offer robust infrastructure and advanced analytical tools that are accessible to organizations of all sizes (Gupta *et al*., 2022). Advances in machine learning and artificial intelligence have enabled the development of sophisticated algorithms capable of analyzing complex and high-dimensional data. These algorithms can identify patterns, make predictions, and provide actionable insights with greater accuracy and speed than traditional methods. Modern data visualization tools, such as Tableau and Power BI, allow for the intuitive and interactive exploration of large datasets. These tools help economists and policymakers understand and communicate complex data insights effectively. The digital age has generated an unprecedented amount of data from diverse sources, providing a wealth of information that was previously inaccessible. This abundance of data has transformed the landscape of economic forecasting and policy making. Platforms like Twitter, Facebook, and Instagram generate vast amounts of real-time data on consumer sentiment, behavior, and preferences. Social media data provides valuable insights into public opinion, market trends, and emerging economic issues. Digital payment systems, credit card transactions, and online banking generate detailed data on consumer spending, saving, and investment patterns. This financial data offers a granular view of economic activities and market dynamics. IoT devices, such as smart meters, sensors, and connected appliances, generate continuous streams of data on various aspects of the economy, including energy consumption, transportation, and supply chain logistics. IoT data provides real-time insights into operational efficiency and economic performance. Governments and public institutions collect and publish extensive data on a wide range of economic indicators, including employment, inflation, trade, and public health (Pratap *et al*., 2021). This data is critical for macroeconomic analysis and policy making. Businesses and corporations generate vast amounts of data through their operations, sales, and customer interactions. Corporate data provides insights into industry trends, competitive dynamics, and consumer behavior. The availability of large and diverse datasets allows for more granular analysis of economic conditions. Economists can study specific sectors, regions, or demographic groups in greater detail, leading to more nuanced and accurate forecasts. Big data enables real-time analysis of economic activities, providing timely insights that are critical for responsive decision-making. This reduces the time lag associated with

traditional methods and enhances the ability to monitor and respond to emerging trends. The richness and diversity of big data enhance the predictive power of economic models. Machine learning algorithms can analyze complex and high-dimensional data, identifying patterns and relationships that traditional models might miss (Georgiou *et al.,* 2020). This improves the accuracy and reliability of economic forecasts. Big data provides a more comprehensive view of the economy, capturing information that was previously inaccessible or overlooked. This holistic perspective enables better-informed policy making and more effective economic interventions.
The evolution of economic forecasting and policy making reflects the dynamic and complex nature of modern economies. Traditional methods, rooted in historical data analysis and econometric models, have provided a valuable foundation for understanding and predicting economic trends (Tang *et al.,* 2022). However, these methods face significant limitations, including data scarcity, time lag, and accuracy issues, which have become increasingly apparent in the face of rapid economic change and complexity. The emergence of big data represents a transformative development in economic forecasting and policy making. Technological advancements and the proliferation of diverse data sources have enabled the collection, storage, and analysis of vast amounts of real-time data. This has led to significant improvements in the accuracy, timeliness, and granularity of economic forecasts. Big data provides a more comprehensive and nuanced view of the economy, enabling more responsive and effective policy interventions (Lee *et al.,* 2020). As the field of economic forecasting continues to evolve, the integration of big data and advanced analytical techniques will play a crucial role in addressing the limitations of traditional methods and enhancing our ability to understand and respond to economic challenges. The ongoing transformation promises to yield more accurate and effective economic strategies, ultimately fostering greater economic stability and growth.

Big Data in Economic Forecasting

The integration of big data into economic forecasting has revolutionized the field, providing unprecedented insights and enhancing the accuracy and timeliness of economic predictions (Stylos *et al.*, 2021). This explores the sources of big data, the techniques and tools used to analyze it, and case studies demonstrating its application in economic forecasting.

Big data in economics is derived from a variety of sources, each offering unique insights into economic activities and trends. Social media platforms such as Twitter, Facebook, and Instagram generate vast amounts of data daily. This data, often unstructured, includes posts, comments, likes, shares, and other forms of user interaction. Social media data provides real-time insights into consumer sentiment, public opinion, and behavioral trends. By analyzing the tone and content of social media posts, economists can gauge public sentiment towards economic conditions, products, or policies. This information can be used to predict consumer spending patterns and market trends. Social media data helps identify emerging trends and shifts in consumer preferences, enabling businesses and policymakers to respond proactively. Digital payment systems, credit card transactions, online banking, and stock market trades generate detailed and voluminous data on financial activities (Westermeier, 2020). This data provides granular insights into consumer spending, saving, and investment behaviors. Analyzing transaction data helps economists understand how consumers allocate their resources across different goods and services, revealing trends in consumption and economic health. Data from stock market transactions and investment platforms can be used to forecast market movements and investor sentiment. IoT devices, including smart meters, sensors, and connected appliances, generate continuous streams of data on various aspects of the economy, such as energy consumption, transportation, and supply chain logistics. Data from smart meters provides insights into energy usage patterns, which can be correlated with economic activity levels and seasonal trends. IoT data from transportation and logistics systems can help forecast supply chain disruptions, delivery times, and inventory levels. Government agencies and public institutions collect and publish extensive data on a wide range of economic indicators, including employment, inflation, trade, and public health (Lyu *et al*., 2022). This data is often structured and comes from reliable sources, making it crucial for macroeconomic analysis. Official statistics on GDP, inflation, and unemployment are essential for forecasting national economic performance and making policy decisions. Data on public health can influence economic forecasts, especially in times of crisis, such as during a pandemic.

The analysis of big data in economics relies on advanced techniques and tools that can handle large, complex datasets and extract meaningful insights. Machine learning (ML) and artificial intelligence (AI) are pivotal in analyzing big data (Zhang *et al*., 2021). These technologies use algorithms to identify patterns, make predictions, and provide actionable insights. Algorithms learn from labeled training data to make predictions or classify new data. This is useful for predicting economic outcomes based on historical data. Algorithms identify patterns and relationships in unlabeled data, which can be useful for clustering and segmenting economic data. Algorithms learn by interacting with the environment and receiving feedback, which can be applied in dynamic economic modeling and simulation. Data mining involves extracting valuable information from large datasets using techniques such as clustering, association rule mining, and anomaly detection. Grouping similar data points together to identify patterns and trends. For example, clustering consumer transaction data can reveal different spending behaviors. Identifying relationships between variables in large datasets. This can be used to understand the co-occurrence of economic events or consumer behaviors. Identifying unusual patterns or outliers in data, which can indicate economic disruptions or opportunities. Real-time analytics involves processing and analyzing data as it is generated, allowing for immediate insights and decision-making. Real-time analytics can track economic indicators continuously, providing up-to-date insights into economic conditions. Policymakers and businesses can respond promptly to emerging trends and events, such as market fluctuations or supply chain disruptions (Yu *et al*., 2021).

The application of big data in economic forecasting is demonstrated through various case studies, highlighting its impact on different aspects of the economy. Predictive analytics involves using historical and real-time data to forecast future stock market trends. Big data from financial transactions, news feeds, and social media can be analyzed to predict market movements (Mehta *et al*., 2021). Analyzing social media and news sentiment to gauge investor mood and predict stock price movements. Using machine learning algorithms to analyze market data and execute trades automatically based on predictive models. Identifying potential risks and anomalies in the market, allowing investors to adjust their strategies accordingly. Big data analytics in retail involves analyzing consumer transaction data, social media interactions, and IoT data to forecast spending patterns and retail trends. Using consumer data to create targeted marketing campaigns that resonate with individual preferences and behaviors. Predicting demand for products and optimizing inventory levels to reduce costs and improve customer satisfaction. Analyzing transaction data to predict future sales trends and adjust business strategies accordingly. Big data enhances the analysis of macroeconomic indicators by providing real-time data and more granular insights. Using real-time data from various sources to estimate current GDP growth before official statistics are released. Analyzing price data from e-commerce and other digital platforms to track inflation trends more accurately and timely. Using data from job portals, social media, and government databases to monitor employment trends and predict labor market conditions (Smaldone *et al*., 2022).

Big data has fundamentally transformed economic forecasting by providing a wealth of real-time, granular data from diverse sources. The integration of advanced techniques and tools, such as machine learning, data mining, and real-time analytics, enables more accurate and timely predictions. Case studies in stock market analytics, consumer spending, and macroeconomic indicators illustrate the profound impact of big data on economic forecasting. As the field continues to evolve, the potential of big data in economics will likely expand further, offering even deeper insights and more sophisticated forecasting capabilities. However, it is essential to address challenges related to data privacy, security, and quality to fully realize the benefits of big data in economic forecasting. By harnessing the power of big data, economists and policymakers can make more informed decisions, ultimately fostering greater economic stability and growth (Perera and Iqbal, 2021).

Big Data in Economic Policy Making

The advent of big data has significantly influenced various domains, including economic policy making. By leveraging vast amounts of data from diverse sources, policymakers can design, implement, and evaluate policies with greater precision and effectiveness.

Data-driven decision making involves using empirical data and analytical methods to inform policy decisions. Big data provides policymakers with a wealth of information that can be used to understand complex economic phenomena, identify trends, and make informed choices (Grossi *et al*., 2021). Big data integrates information from various sources, offering a comprehensive view of economic activities and conditions. This enables policymakers to make decisions based on a more complete and accurate understanding of the economy. Empirical data and rigorous analysis provide a solid foundation for developing policies that are based on evidence rather than assumptions or theoretical models alone. This increases the likelihood of successful outcomes. Advanced analytical tools and machine learning algorithms can predict the potential impacts of different policy options, helping policymakers to choose the most effective strategies. Big data enables the design of tailored policy interventions that address specific needs and conditions. By analyzing detailed and granular data, policymakers can develop targeted measures that are more effective and efficient. Policies can be tailored to the unique characteristics of different regions, sectors, or demographic groups. For example, targeted tax incentives can be designed to stimulate investment in specific industries or regions with high unemployment. Big data helps identify vulnerable populations that may require additional support, such as low-income households or communities affected by economic downturns. This enables the development of targeted social welfare programs. Detailed data analysis helps optimize the allocation of resources, ensuring that funds and support are directed to areas where they are most needed and can have the greatest impact (Gu *et al*., 2021).

Real-time data analysis allows for the continuous monitoring of policy impacts, enabling policymakers to assess the effectiveness of their interventions as they are implemented. Its provides immediate feedback on policy impacts, allowing policymakers to observe how economic indicators respond to policy changes. This enables timely adjustments to maximize effectiveness. Continuous monitoring of economic conditions and policy outcomes helps identify emerging issues and trends that may require attention. This proactive approach can prevent problems from escalating. Real-time impact assessment enhances transparency and accountability by providing clear evidence of how policies are performing. This can build public trust and support for policy initiatives. Feedback loops involve the systematic collection of data on policy performance, which is then used to adjust and refine policies to improve outcomes. Feedback loops enable adaptive policymaking, where policies are continuously refined based on new data and insights. This iterative process ensures that policies remain relevant and effective in changing conditions. Continuous feedback helps identify unintended consequences or negative side effects of policies, allowing for prompt corrective action. This minimizes potential harm and enhances policy success. By relying on empirical evidence for policy adjustments, policymakers can make more informed and effective changes, rather than relying on intuition or ad hoc decisions (Mears, 2022).

Big data has been instrumental in shaping fiscal policies and taxation strategies. By analyzing detailed economic data, governments can design more effective tax policies that promote economic growth and equity (Law *et al*., 2021). Governments use big data analytics to identify patterns and anomalies that indicate potential tax evasion. By analyzing financial transactions, social media, and other data sources, tax authorities can detect suspicious activities and improve compliance. Big data helps identify sectors or regions that could benefit from tax incentives to stimulate growth. For instance, data on business activity and employment trends can guide the design of tax credits for small businesses or startups. Real-time data on economic conditions allows for dynamic adjustment of tax policies. For example, during an economic downturn, real-time data on consumer spending can inform temporary tax relief measures to boost demand. Central banks and monetary authorities use big data to inform monetary policies and control inflation. The ability to analyze large volumes of economic data in real time enhances the precision and effectiveness of monetary interventions. Big data from e-commerce, price monitoring websites, and financial transactions provides real-time insights into price changes across different sectors. This allows central banks to monitor inflation trends more accurately. Machine learning models can predict the impact of different interest rate decisions on inflation and economic growth. By analyzing historical data and current economic indicators, these models help central banks make informed decisions. Big data helps central banks manage liquidity in the financial system by monitoring real-time transaction data and interbank lending rates. This ensures that monetary policy interventions, such as open market operations, are effectively implemented. Big data plays a crucial role in designing and evaluating social policies and welfare programs (Pencheva *et al*., 2020). By analyzing detailed data on socio-economic conditions, governments can develop targeted interventions to improve social outcomes. Big data helps identify vulnerable populations that need support, such as low-income households, unemployed individuals, or those living in deprived areas. This ensures that welfare programs are effectively targeted. Real-time data on program participation and outcomes allows for continuous monitoring of welfare programs (Bhuiyan *et al*., 2022). For example, data on job placement rates can be used to evaluate the effectiveness of employment training programs. Feedback loops enable adaptive design of social welfare programs. For instance, if data shows that certain groups are not benefiting from a program as intended, policymakers can make adjustments to improve inclusivity and effectiveness.

Big data has fundamentally transformed economic policy making by providing detailed, real-time insights that enhance policy design, implementation, and evaluation (Kong *et al*., 2020). Data-driven decision making and tailored policy interventions enable more effective and efficient policies, while real-time impact assessment and feedback loops ensure continuous improvement and adaptation. Case studies in fiscal policies, monetary policies, and social welfare programs illustrate the profound impact of big data on economic policy making. By leveraging the power of big data, policymakers can make more informed decisions, respond promptly to emerging issues, and ultimately achieve better economic and social outcomes. As the field continues to evolve, the integration of big data into economic policy making will likely expand further, offering even greater potential for improving the effectiveness and responsiveness of policy interventions (Maddikunta *et al*., 2022). However, it is essential to address challenges related to data privacy, security, and quality to fully realize the benefits of big data in economic policy making. By harnessing the potential of big data, governments and policymakers can better navigate the complexities of modern economies and promote sustainable development and prosperity.

Benefits of Big Data in Economic Forecasting and Policy Making

International Journal of Development and Economic Sustainability
Vol.10, No.6, pp.66-89, 2022
Print ISSN: 2053-2199 (Print),
Online ISSN: 2053-2202(Online)
Website: https://www.eajournals.org/
Publication of the European Centre for Research Training and Development -UK

The advent of big data has revolutionized economic forecasting and policy making, offering numerous benefits that enhance the accuracy, timeliness, and effectiveness of economic analyses and interventions (Bakker *et al*., 2020). This explores the key benefits of big data in these areas, including increased accuracy and precision, timeliness and responsiveness, comprehensive insights and coverage, and enhanced predictive capabilities.

Big data encompasses vast amounts of information collected from diverse sources, providing high-resolution data that captures minute details of economic activities. This granularity improves the accuracy of economic models and forecasts by reducing reliance on approximations and assumptions. High-resolution data allows for more detailed and nuanced analysis of economic phenomena. For instance, analyzing consumer spending patterns at a granular level helps identify specific behaviors and trends that aggregate data might obscure. With access to more detailed and accurate data, the likelihood of errors in economic forecasts and policy decisions is reduced. This leads to more reliable and robust outcomes. Big data enables the integration of multiple data sources, combining structured and unstructured data to create a comprehensive dataset (Naeem *et al*., 2022). This integration improves the precision of economic models by incorporating a wide range of variables and factors. Integrating data from different sources, such as social media, financial transactions, and government statistics, provides a holistic view of the economy. This comprehensive perspective enhances the precision of forecasts and policy analyses. Combining data from multiple sources allows for cross-validation, where data from one source can be used to verify and refine data from another. This improves the overall accuracy of the analysis.

One of the most significant benefits of big data is its ability to process and analyze data in real time. This capability allows for the timely assessment of economic conditions and the rapid implementation of policy responses. Real-time data processing provides immediate insights into economic trends and developments. For example, real-time analysis of financial markets can reveal emerging risks and opportunities, enabling swift policy interventions. The ability to process data in real time supports dynamic policy making, where policies can be continuously adjusted based on the latest information. This responsiveness is crucial in rapidly changing economic environments. Big data enhances the development of early warning systems that can detect potential economic disruptions or crises before they fully materialize. This allows policymakers to take preemptive actions to mitigate negative impacts. Early warning systems based on real-time data enable proactive measures to address emerging issues. For instance, early detection of inflationary pressures can prompt timely adjustments in monetary policy. Identifying risks early allows for better management and allocation of resources to prevent or minimize economic disruptions. This enhances the stability and resilience of the economy.

Big data encompasses information from a wide range of sources, including social media, financial transactions, IoT devices, and government databases (Arena and Pau, 2020). This diversity provides comprehensive insights into various aspects of the economy. The inclusion of diverse data sources ensures broad coverage of economic activities and conditions. This comprehensive approach captures a wide array of factors influencing the economy, from consumer behavior to industrial production. Analyzing data from multiple sources allows for multidimensional analysis, where different aspects of economic phenomena can be examined simultaneously. This leads to more thorough and insightful analyses. Big data provides detailed information on specific sectors and regions, allowing for targeted analysis and policy interventions that address unique conditions and challenges. Detailed data on various sectors, such as manufacturing, services, and agriculture, enables precise analysis of sector-specific trends and issues. This supports the development of targeted policies that address sectoral needs. Big data offers granular insights into regional economic conditions, helping policymakers understand and address regional disparities. For example, data on employment trends in different regions can inform targeted job creation programs.

The integration of big data with advanced analytical techniques, such as machine learning and artificial intelligence, significantly enhances predictive capabilities (Ashaari *et al*., 2021). These techniques can identify complex patterns and relationships in data that traditional methods might miss. Machine learning algorithms can detect patterns and trends in large datasets, providing valuable insights for economic forecasting. For instance, analyzing historical data can reveal cyclical patterns in economic indicators, improving future predictions. AI-powered predictive models can simulate various scenarios and forecast their potential impacts on the economy. This helps policymakers evaluate the likely outcomes of different policy options and make informed decisions. Big data supports sophisticated scenario analysis and simulation, allowing policymakers to explore the potential impacts of various policy interventions under different conditions. By simulating different economic scenarios, policymakers can assess the potential outcomes of various policy choices. This helps in selecting the most effective strategies to achieve desired goals. Scenario analysis enables stress testing of economic systems, where the impacts of extreme events or shocks can be evaluated (Linkov *et al*., 2022). This helps policymakers prepare for and mitigate the effects of economic crises.

The integration of big data into economic forecasting and policy making offers numerous benefits that enhance the accuracy, timeliness, comprehensiveness, and predictive capabilities of economic analyses and interventions (Bakker *et al*., 2020). By leveraging high-resolution data, real-time processing, diverse data sources, and advanced analytical techniques, policymakers can make more informed and effective decisions. The increased accuracy and precision of big data improve the reliability of economic models and forecasts, while the timeliness and responsiveness enabled by real-time data processing support dynamic policy making and early warning systems. Comprehensive insights and coverage provided by diverse data sources enhance the understanding of sectoral and regional conditions, and the advanced predictive capabilities offered by machine learning and scenario analysis enable more sophisticated and effective policy planning. As the field of big data continues to evolve, its potential to transform economic forecasting and policy making will only grow. However, it is crucial to address challenges related to data privacy, security, and quality to fully realize the benefits of big data. By harnessing the power of big data, policymakers can navigate the complexities of modern economies more effectively, promoting sustainable development and economic stability (Bachmann *et al*., 2022).

Challenges and Limitations of Big Data in Economic Forecasting and Policy Making

While big data has transformed economic forecasting and policy making by providing valuable insights and enhancing decision-making processes, it also presents several challenges and limitations. These include issues related to data privacy and security, data quality and reliability, ethical and legal concerns, and technical and skill barriers. Addressing these challenges is crucial to fully realizing the potential of big data in economics.

The use of big data involves the collection and analysis of vast amounts of personal and sensitive information (Batko and Ślęzak, 2022). Ensuring the privacy of individuals whose data is being used is a major challenge. Obtaining informed consent from individuals and ensuring data anonymity are critical to protecting privacy. However, anonymizing data while retaining its usefulness for analysis can be difficult. The risk of data breaches, where unauthorized parties access sensitive information, poses significant privacy concerns. Breaches can lead to identity theft, financial loss, and other harms to individuals. Ensuring the security of data is essential to prevent unauthorized access and misuse. Robust security measures are required to protect data at all stages, from collection to storage and analysis. Big data systems are vulnerable to cyberattacks, including hacking, phishing, and malware. Protecting against these threats requires continuous monitoring and advanced security protocols. Implementing strong encryption methods is necessary to secure data during transmission and storage (Ramachandra *et al*., 2022). However, encryption can also make data processing more complex and resource-intensive.

The accuracy of data is crucial for reliable economic forecasting and policy making. Inaccurate data can lead to incorrect conclusions and ineffective policies. Errors during data collection, such as incorrect entries, missing values, or biases, can compromise data accuracy. Ensuring high-quality data collection practices is essential. Combining data from multiple sources can introduce inconsistencies and inaccuracies. Harmonizing data formats and resolving discrepancies is a complex task. For real-time analysis and decision making, data must be up-to-date. However, ensuring the timeliness of data can be challenging, especially when dealing with large and diverse datasets. Delays in data collection, processing, and updating can reduce the timeliness of insights. Real-time data processing systems require significant computational resources and infrastructure (Koulouzis *et al*., 2020). Different data sources may update at varying frequencies, leading to inconsistencies in the dataset. Coordinating data refresh rates is essential for maintaining data timeliness.

International Journal of Development and Economic Sustainability
Vol.10, No.6, pp.66-89, 2022
Print ISSN: 2053-2199 (Print),
Online ISSN: 2053-2202(Online)
Website: https://www.eajournals.org/
Publication of the European Centre for Research Training and Development -UK

The use of big data raises several ethical concerns that must be addressed to ensure responsible and fair use of data. Big data algorithms can perpetuate existing biases and lead to discriminatory outcomes. Ensuring fairness and avoiding bias in data analysis and policy making is critical. The opacity of complex data models and algorithms can make it difficult to understand how decisions are made. Ensuring transparency and accountability in data-driven decision making is necessary to build public trust. Compliance with legal regulations governing data use is essential to avoid legal repercussions and protect individuals' rights. Regulations such as the General Data Protection Regulation (GDPR) in Europe impose strict requirements on data collection, processing, and storage. Adhering to these laws can be challenging, especially for multinational organizations. Issues related to data ownership and intellectual property rights must be addressed to ensure legal compliance and avoid disputes.

The technical complexity of big data systems presents significant challenges in terms of infrastructure and technology (Chen *et al.*, 2020). Handling and processing large volumes of data requires scalable infrastructure that can accommodate growth. Ensuring scalability while maintaining performance is a technical challenge. Integrating data from various sources requires interoperability between different systems and platforms. Ensuring seamless data integration is complex and requires standardized protocols. The effective use of big data in economic forecasting and policy making requires specialized skills and expertise. There is a high demand for data scientists and analysts with expertise in big data technologies, statistical analysis, and machine learning. Addressing the skill gap is essential to harness the full potential of big data. Providing adequate training and education to economists, policymakers, and other stakeholders is necessary to develop the skills required for big data analysis and decision making (Persaud, 2021).

While big data offers significant benefits for economic forecasting and policy making, it also presents several challenges and limitations that must be addressed to fully realize its potential. Data privacy and security concerns, data quality and reliability issues, ethical and legal considerations, and technical and skill barriers are critical challenges that require careful attention and proactive measures. Ensuring robust data privacy and security measures, maintaining high data quality and timeliness, addressing ethical and legal concerns, and overcoming technical and skill barriers are essential steps to leverage big data effectively. By addressing these challenges, policymakers and economists can harness the power of big data to make more accurate, timely, and informed decisions, ultimately leading to better economic outcomes and improved policy interventions. As the field of big data continues to evolve, ongoing efforts to address these challenges will be crucial. Collaboration between data scientists, policymakers, legal experts, and other stakeholders is necessary to develop solutions that balance the benefits of big data with the need to protect privacy, ensure data quality, and uphold ethical standards. Through such collaborative efforts, the transformative potential of big data in economic forecasting and policy making can be fully realized, contributing to sustainable economic growth and development.

Future Prospects and Trends in Big Data for Economic Forecasting and Policy Making

The future of big data in economic forecasting and policy making holds immense potential for transformative advancements. As technology continues to evolve and global challenges become increasingly complex, leveraging big data becomes essential for informed decision making and effective policy interventions. This explores the future prospects and trends in big data, focusing on integration with emerging technologies, global collaboration and data sharing, and policy innovations and adaptations.

Blockchain technology has the potential to revolutionize data management and security in economic forecasting and policy making (Toufaily *et al*., 2021). By providing a decentralized and immutable ledger, blockchain enhances transparency, accountability, and trust in data transactions. Blockchain ensures the integrity of data by creating tamper-proof records of transactions. This enhances the reliability and trustworthiness of economic data used for forecasting and policy analysis. Blockchain enables secure and transparent data sharing among stakeholders, facilitating collaboration while maintaining data privacy and security. This fosters greater cooperation in economic research and policy development. Advanced artificial intelligence (AI) technologies, such as deep learning and neural networks, will play a crucial role in unlocking the full potential of big data for economic forecasting and policy making. These technologies enable sophisticated data analysis and predictive modeling, enhancing decision-making capabilities. AI-powered predictive models can analyze vast amounts of economic data to identify complex patterns and trends. This enables more accurate and timely economic forecasts, helping policymakers anticipate and address emerging challenges. AI algorithms can analyze individual-level data to tailor policy interventions to specific needs and preferences (Kim *et al*., 2022). This personalized approach enhances the effectiveness and efficiency of policy implementation, leading to better outcomes for citizens.

The future of big data in economic forecasting and policy making will see increased collaboration among countries, organizations, and researchers through data sharing platforms (Bresciani *et al*., 2021). These platforms facilitate the exchange of data, expertise, and insights, enabling global cooperation to address common challenges. Data collaboration platforms enable the sharing of economic data across borders, providing policymakers with a more comprehensive understanding of global economic trends and dynamics. This enhances the accuracy and relevance of economic forecasts and policy analyses. Collaborative research projects leverage the collective expertise and resources of multiple stakeholders to tackle complex economic issues. By pooling data and insights, researchers can develop innovative solutions and policy recommendations that benefit all participants. Governments and organizations will increasingly embrace open data initiatives, making economic data more accessible and transparent to the public. Open data promotes accountability, fosters innovation, and empowers citizens to participate in economic decision making. Open data initiatives enable citizens to access and analyze economic data, empowering them to contribute to policy discussions and hold policymakers accountable. This strengthens democracy and promotes public trust in government institutions. Open data fuels innovation by providing entrepreneurs, researchers, and developers with valuable resources for building new applications and services (Dahlander *et al*., 2021). This fosters economic growth and stimulates job creation in data-driven industries.

The future of economic policy making will see the adoption of agile policy frameworks that can quickly respond to changing economic conditions and emerging challenges. These frameworks prioritize flexibility, experimentation, and continuous learning. Agile policy frameworks enable policymakers to monitor economic indicators in real time and adjust policies accordingly (Valle-Cruz *et al*., 2020). This proactive approach minimizes the impact of economic shocks and enhances policy effectiveness. Policymakers engage in iterative policy design, testing different interventions and evaluating their outcomes before scaling up. This iterative process fosters innovation and allows for evidence-based decision making. Data-driven governance will become increasingly prevalent as governments leverage big data analytics to inform policy decisions and improve public services. By harnessing data insights, policymakers can enhance efficiency, transparency, and accountability in governance. Data-driven governance relies on empirical evidence and analysis to inform policy decisions. By using data to identify priorities, assess outcomes, and measure impact, policymakers can develop more effective and targeted interventions (Cattaneo *et al*., 2021). Big data analytics enable continuous monitoring and evaluation of government programs and services. This ensures accountability and enables policymakers to identify areas for improvement and optimization.

The future of big data in economic forecasting and policy making holds tremendous promise for driving innovation, enhancing decision-making processes, and addressing global challenges. Integration with emerging technologies such as blockchain and advanced AI will unlock new opportunities for data analysis and predictive modeling, enabling more accurate and timely economic forecasts. Global collaboration and data sharing initiatives will foster greater cooperation among stakeholders, leading to more informed policy decisions and innovative solutions to complex economic issues. Open data initiatives will promote transparency and citizen engagement, empowering individuals to participate in economic governance and decision making. Policy innovations such as agile frameworks and data-driven governance will enable governments to respond more effectively to changing economic conditions and evolving societal needs (Popescu and Saulescu, 2022). By embracing these trends and harnessing the power of big data, policymakers can build more resilient, inclusive, and sustainable economies for the future.

CONCLUSION

Big data has emerged as a transformative force in economic forecasting and policy making, offering unprecedented opportunities to enhance decision-making processes and address complex economic challenges. Explored the key benefits, challenges, and future prospects of big data in economics, highlighting its potential to revolutionize the field. Examining the benefits of big data, including increased accuracy and precision, timeliness and responsiveness, comprehensive insights and coverage, and enhanced predictive capabilities. Big data enables policymakers to make more informed decisions, respond promptly to emerging issues, and ultimately achieve better economic and social outcomes. However, the challenges and limitations associated with big data, such as data privacy and security concerns, data quality and reliability issues, ethical and legal considerations, and technical and skill barriers. Addressing these challenges is essential to fully realizing the potential of big data in economics.

The integration of big data into economic forecasting and policy making represents an ongoing transformation in the field of economics. Traditional methods are being supplemented and, in some cases, replaced by data-driven approaches that leverage advanced analytics and technology. This transformation is not only changing how economists analyze and interpret data but also how policymakers formulate and implement policies. Real-time data processing, predictive modeling, and agile policy frameworks are becoming increasingly prevalent, enabling more proactive and effective responses to economic challenges.

Looking ahead, the future of big data in economics is characterized by integration with emerging technologies, global collaboration and data sharing, and policy innovations and adaptations. Blockchain, advanced AI, and other technologies will unlock new opportunities for data analysis and decision making, while global collaboration initiatives will foster greater cooperation among stakeholders. Policy innovations such as agile frameworks and data-driven governance will enable governments to respond more effectively to changing economic conditions and societal needs. By embracing these trends and harnessing the power of big data, policymakers can build more resilient, inclusive, and sustainable economies for the future. Big data is reshaping the landscape of economics, offering new insights, tools, and opportunities to address complex challenges and drive positive change. While there are still challenges to overcome, the potential of big data in economic forecasting and policy making is undeniable. By continuing to innovate, collaborate, and adapt, we can unlock the full potential of big data to build a brighter economic future for all.

REFERENCE

1. Ahmad, T. and Zhang, D., 2021. Using the internet of things in smart energy systems and networks. *Sustainable Cities and Society*, *68*, p.102783.
2. Alsharif, M.H., Kelechi, A.H., Yahya, K. and Chaudhry, S.A., 2020. Machine learning algorithms for smart data analysis in internet of things environment: taxonomies and research trends. *Symmetry*, *12*(1), p.88.
3. Arena, F. and Pau, G., 2020. An overview of big data analysis. *Bulletin of Electrical Engineering and Informatics*, *9*(4), pp.1646-1653.

4. Arent, D.J., Green, P., Abdullah, Z., Barnes, T., Bauer, S., Bernstein, A., Berry, D., Berry, J., Burrell, T., Carpenter, B. and Cochran, J., 2022. Challenges and opportunities in decarbonizing the US energy system. *Renewable and Sustainable Energy Reviews*, *169*, p.112939.
5. Ashaari, M.A., Singh, K.S.D., Abbasi, G.A., Amran, A. and Liebana-Cabanillas, F.J., 2021. Big data analytics capability for improved performance of higher education institutions in the Era of IR 4.0: A multi-analytical SEM & ANN perspective. *Technological Forecasting and Social Change*, *173*, p.121119.
6. Bachmann, N., Tripathi, S., Brunner, M. and Jodlbauer, H., 2022. The contribution of data-driven technologies in achieving the sustainable development goals. *Sustainability*, *14*(5), p.2497.
7. Bakker, L., Aarts, J., Uyl-de Groot, C. and Redekop, W., 2020. Economic evaluations of big data analytics for clinical decision-making: a scoping review. *Journal of the American Medical Informatics Association*, *27*(9), pp.1466-1475.
8. Bakker, L., Aarts, J., Uyl-de Groot, C. and Redekop, W., 2020. Economic evaluations of big data analytics for clinical decision-making: a scoping review. *Journal of the American Medical Informatics Association*, *27*(9), pp.1466-1475.
9. Barlas, A.B., Güler, S., Ortiz, A. and Rodrigo, T., 2020. *Investment in real time and High definition: A Big data Approach* (No. 2013). BBVA Research Working Papers.
10. Batko, K. and Ślęzak, A., 2022. The use of Big Data Analytics in healthcare. *Journal of big Data*, *9*(1), p.3.
11. Bhuiyan, M.N., Billah, M.M., Bhuiyan, F., Bhuiyan, M.A.R., Hasan, N., Rahman, M.M., Miah, M.S., Alibakhshikenari, M., Arpanaei, F., Falcone, F. and Niu, M., 2022. Design and implementation of a feasible model for the IoT based ubiquitous healthcare monitoring system for rural and urban areas. *IEEE Access*, *10*, pp.91984-91997.
12. Bisht, D., Singh, R., Gehlot, A., Akram, S.V., Singh, A., Montero, E.C., Priyadarshi, N. and Twala, B., 2022. Imperative role of integrating digitalization in the firms finance: A technological perspective. *Electronics*, *11*(19), p.3252.
13. Bresciani, S., Ciampi, F., Meli, F. and Ferraris, A., 2021. Using big data for co-innovation processes: Mapping the field of data-driven innovation, proposing theoretical developments and providing a research agenda. *International Journal of Information Management*, *60*, p.102347.
14. Cattaneo, A., Sánchez, M.V., Torero, M. and Vos, R., 2021. Reducing food loss and waste: Five challenges for policy and research. *Food Policy*, *98*, p.101974.
15. Chen, P.T., Lin, C.L. and Wu, W.N., 2020. Big data management in healthcare: Adoption challenges and implications. *International Journal of Information Management*, *53*, p.102078.
16. Dahlander, L., Gann, D.M. and Wallin, M.W., 2021. How open is innovation? A retrospective and ideas forward. *Research Policy*, *50*(4), p.104218.

17. Ditria, E.M., Buelow, C.A., Gonzalez-Rivero, M. and Connolly, R.M., 2022. Artificial intelligence and automated monitoring for assisting conservation of marine ecosystems: A perspective. *Frontiers in Marine Science*, *9*, p.918104.
18. Fang, W., Sha, Y. and Sheng, V.S., 2022. Survey on the application of artificial intelligence in ENSO forecasting. *Mathematics*, *10*(20), p.3793.
19. Forestier, O. and Kim, R.E., 2020. Cherry‐picking the Sustainable Development Goals: Goal prioritization by national governments and implications for global governance. *Sustainable Development*, *28*(5), pp.1269-1278.
20. Geels, F.W., 2022. Causality and explanation in socio-technical transitions research: Mobilising epistemological insights from the wider social sciences. *Research policy*, *51*(6), p.104537.
21. Georgiou, T., Liu, Y., Chen, W. and Lew, M., 2020. A survey of traditional and deep learning-based feature descriptors for high dimensional data in computer vision. *International Journal of Multimedia Information Retrieval*, *9*, pp.135-170.
22. Grossi, V., Giannotti, F., Pedreschi, D., Manghi, P., Pagano, P. and Assante, M., 2021. Data science: a game changer for science and innovation. *International Journal of Data Science and Analytics*, *11*, pp.263-278.
23. Gu, B., Chen, F. and Zhang, K., 2021. The policy effect of green finance in promoting industrial transformation and upgrading efficiency in China: analysis from the perspective of government regulation and public environmental demands. *Environmental Science and Pollution Research*, *28*(34), pp.47474-47491.
24. Gupta, N.M., Singh, R., Das, S.S., Choudhary, S.K. and Student, P.G., 2022. AWS vs AZURE vs GCP: Leaders Of The Cloud Race. *International Research Journal of Modernization in Engineering Technology and Science www. irjmets. com@ International Research Journal of Modernization in Engineering*, *4*(07), pp.3243-3250.
25. Hemachandran, K., Khanra, S., Rodriguez, R.V. and Jaramillo, J. eds., 2022. *Machine Learning for Business Analytics: Real-Time Data Analysis for Decision-Making*. CRC Press.
26. Hendry, D.F., 2020. A short history of macro-econometric modelling. *Journal of Banking, Finance and Sustainable Development*, *1*(1).
27. Ikegwu, A.C., Nweke, H.F., Anikwe, C.V., Alo, U.R. and Okonkwo, O.R., 2022. Big data analytics for data-driven industry: a review of data sources, tools, challenges, solutions, and research directions. *Cluster Computing*, *25*(5), pp.3343-3387.
28. Kandt, J. and Batty, M., 2021. Smart cities, big data and urban policy: Towards urban analytics for the long run. *Cities*, *109*, p.102992.
29. Kim, M.T., Heitkemper, E.M., Hébert, E.T., Hecht, J., Crawford, A., Nnaka, T., Hutson, T.S., Rhee, H. and Radhakrishnan, K., 2022. Redesigning culturally tailored intervention in the precision health era: self-management science context. *Nursing outlook*, *70*(5), pp.710-724.

30. Kong, L., Liu, Z. and Wu, J., 2020. A systematic review of big data-based urban sustainability research: State-of-the-science and future directions. *Journal of Cleaner Production*, *273*, p.123142.
31. Koulouzis, S., Martin, P., Zhou, H., Hu, Y., Wang, J., Carval, T., Grenier, B., Heikkinen, J., de Laat, C. and Zhao, Z., 2020. Time-critical data management in clouds: Challenges and a Dynamic Real-Time Infrastructure Planner (DRIP) solution. *Concurrency and Computation: Practice and Experience*, *32*(16), p.e5269.
32. Kumle, L., Võ, M.L.H. and Draschkow, D., 2021. Estimating power in (generalized) linear mixed models: An open introduction and tutorial in R. *Behavior research methods*, *53*(6), pp.2528-2543.
33. Law, S.H., Ng, C.H., Kutan, A.M. and Law, Z.K., 2021. Public debt and economic growth in developing countries: Nonlinearity and threshold analysis. *Economic Modelling*, *98*, pp.26-40.
34. Lee, J.W., 2020. Big data strategies for government, society and policy-making. *Lee, Jung Wan (2020). Big Data Strategies for Government, Society and Policy-Making. Journal of Asian Finance Economics and Business*, *7*(7), pp.475-487.
35. Lenza, M. and Primiceri, G.E., 2022. How to estimate a vector autoregression after March 2020. *Journal of Applied Econometrics*, *37*(4), pp.688-699.
36. Linkov, I., Trump, B.D., Trump, J., Pescaroli, G., Hynes, W., Mavrodieva, A. and Panda, A., 2022. Resilience stress testing for critical infrastructure. *International Journal of Disaster Risk Reduction*, *82*, p.103323.
37. Long, C.K., Agrawal, R., Trung, H.Q. and Pham, H.V., 2021. A big data framework for E-Government in Industry 4.0. *Open Computer Science*, *11*(1), pp.461-479.
38. Lyu, Y., Peng, Y., Liu, H. and Hwang, J.J., 2022. Impact of digital economy on the provision efficiency for public health services: empirical study of 31 provinces in China. *International Journal of Environmental Research and Public Health*, *19*(10), p.5978.
39. Maddikunta, P.K.R., Pham, Q.V., Prabadevi, B., Deepa, N., Dev, K., Gadekallu, T.R., Ruby, R. and Liyanage, M., 2022. Industry 5.0: A survey on enabling technologies and potential applications. *Journal of Industrial Information Integration*, *26*, p.100257.
40. Marcucci, E., Gatta, V., Le Pira, M., Hansson, L. and Bråthen, S., 2020. Digital twins: A critical discussion on their potential for supporting policy-making and planning in urban logistics. *Sustainability*, *12*(24), p.10623.
41. McNeely, C.L. and Schintler, L.A., 2022. Big data concept. In *Encyclopedia of Big Data* (pp. 79-82). Cham: Springer International Publishing.
42. Mears, D., 2022. Bridging the research-policy divide to advance science and policy: The 2022 Bruce Smith, Sr. award address to the academy of criminal justice sciences. *Justice Evaluation Journal*, *5*(2), pp.163-185.
43. Mehta, P., Pandya, S. and Kotecha, K., 2021. Harvesting social media sentiment analysis to enhance stock market prediction using deep learning. *PeerJ Computer Science*, *7*, p.e476.

44. Mohamed, A., Najafabadi, M.K., Wah, Y.B., Zaman, E.A.K. and Maskat, R., 2020. The state of the art and taxonomy of big data analytics: view from new big data framework. *Artificial Intelligence Review*, *53*, pp.989-1037.
45. Mureddu, F., Schmeling, J. and Kanellou, E., 2020. Research challenges for the use of big data in policy-making. *Transforming government: People, process and policy*, *14*(4), pp.593-604.
46. Nabipour, M., Nayyeri, P., Jabani, H., Mosavi, A., Salwana, E. and S, S., 2020. Deep learning for stock market prediction. *Entropy*, *22*(8), p.840.
47. Naeem, M., Jamal, T., Diaz-Martinez, J., Butt, S.A., Montesano, N., Tariq, M.I., De-la-Hoz-Franco, E. and De-La-Hoz-Valdiris, E., 2022. Trends and future perspective challenges in big data. In *Advances in Intelligent Data Analysis and Applications: Proceeding of the Sixth Euro-China Conference on Intelligent Data Analysis and Applications, 15–18 October 2019, Arad, Romania* (pp. 309-325). Springer Singapore.
48. Nibareke, T. and Laassiri, J., 2020. Using Big Data-machine learning models for diabetes prediction and flight delays analytics. *Journal of Big Data*, *7*(1), p.78.
49. Ogbuke, N.J., Yusuf, Y.Y., Dharma, K. and Mercangoz, B.A., 2022. Big data supply chain analytics: ethical, privacy and security challenges posed to business, industries and society. *Production Planning & Control*, *33*(2-3), pp.123-137.
50. Pencheva, I., Esteve, M. and Mikhaylov, S.J., 2020. Big Data and AI–A transformational shift for government: So, what next for research?. *Public Policy and Administration*, *35*(1), pp.24-44.
51. Perera, A. and Iqbal, K., 2021. Big Data and Emerging Markets: Transforming Economies Through Data-Driven Innovation and Market Dynamics. *Journal of Computational Social Dynamics*, *6*(3), pp.1-18.
52. Persaud, A., 2021. Key competencies for big data analytics professions: A multimethod study. *Information Technology & People*, *34*(1), pp.178-203.
53. Popescu, T. and Saulescu, I., 2022. Harnessing the Power of Big Data to Drive Evidence-Based Policy Making in the Public Sector. *Journal of Big-Data Analytics and Cloud Computing*, *7*(4), pp.45-57.
54. Poza, C. and Monge, M., 2020. A real time leading economic indicator based on text mining for the Spanish economy. Fractional cointegration VAR and Continuous Wavelet Transform analysis. *International Economics*, *163*, pp.163-175.
55. Pratap, P., Dickson, A., Love, M., Zanoni, J., Donato, C., Flynn, M.A. and Schulte, P.A., 2021. Public health impacts of underemployment and unemployment in the United States: Exploring perceptions, gaps and opportunities. *International journal of environmental research and public health*, *18*(19), p.10021.
56. Rabbani, M.B.A., Musarat, M.A., Alaloul, W.S., Rabbani, M.S., Maqsoom, A., Ayub, S., Bukhari, H. and Altaf, M., 2021. a comparison between seasonal autoregressive integrated moving average (SARIMA) and exponential smoothing (ES) based on time series model

for forecasting road accidents. *Arabian Journal for Science and Engineering*, *46*(11), pp.11113-11138.

57. Ramachandra, M.N., Srinivasa Rao, M., Lai, W.C., Parameshachari, B.D., Ananda Babu, J. and Hemalatha, K.L., 2022. An efficient and secure big data storage in cloud environment by using triple data encryption standard. *Big Data and Cognitive Computing*, *6*(4), p.101.
58. Shen, C. and Lawson, K., 2021. Applications of deep learning in hydrology. *Deep Learning for the Earth Sciences: A Comprehensive Approach to Remote Sensing, Climate Science, and Geosciences*, pp.283-297.
59. Smaldone, F., Ippolito, A., Lagger, J. and Pellicano, M., 2022. Employability skills: Profiling data scientists in the digital labour market. *European Management Journal*, *40*(5), pp.671-684.
60. Stylos, N., Zwiegelaar, J. and Buhalis, D., 2021. Big data empowered agility for dynamic, volatile, and time-sensitive service industries: the case of tourism sector. *International Journal of Contemporary Hospitality Management*, *33*(3), pp.1015-1036.
61. Taheri, S. and Razban, A., 2021. Learning-based CO2 concentration prediction: Application to indoor air quality control using demand-controlled ventilation. *Building and Environment*, *205*, p.108164.
62. Tang, Y., Song, Z., Zhu, Y., Yuan, H., Hou, M., Ji, J., Tang, C. and Li, J., 2022. A survey on machine learning models for financial time series forecasting. *Neurocomputing*, *512*, pp.363-380.
63. Toufaily, E., Zalan, T. and Dhaou, S.B., 2021. A framework of blockchain technology adoption: An investigation of challenges and expected value. *Information & Management*, *58*(3), p.103444.
64. Valle-Cruz, D., Criado, J.I., Sandoval-Almazán, R. and Ruvalcaba-Gomez, E.A., 2020. Assessing the public policy-cycle framework in the age of artificial intelligence: From agenda-setting to policy evaluation. *Government Information Quarterly*, *37*(4), p.101509.
65. Weersink, A. and Fulton, M., 2020. Limits to profit maximization as a guide to behavior change. *Applied Economic Perspectives and Policy*, *42*(1), pp.67-79.
66. Westermeier, C., 2020. Money is data–the platformization of financial transactions. *Information, Communication & Society*, *23*(14), pp.2047-2063.
67. Yılmaz, B., 2020. Forecasting house prices in Turkey: GLM, VaR and time series approaches. *Journal of Business Economics and Finance*, *9*(4), pp.274-291.
68. Yu, Z., Razzaq, A., Rehman, A., Shah, A., Jameel, K. and Mor, R.S., 2021. Disruption in global supply chain and socio-economic shocks: a lesson from COVID-19 for sustainable production and consumption. *Operations Management Research*, pp.1-16.
69. Zhang, J.Z., Srivastava, P.R., Sharma, D. and Eachempati, P., 2021. Big data analytics and machine learning: A retrospective overview and bibliometric analysis. *Expert Systems with Applications*, *184*, p.115561.