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Big Data and Novel Sensors to Enhance Effectiveness of Monetary Policy in Internet of Things Era

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Sensor technologies with big data analytics provide effective solutions to monetary policy. When deriving the economic parameter indexes from historical data, policymaking cannot effectively respond to current economic situations. Therefore, near real-time transactional data is required for the prediction of energy consumption, consumer behavior, and economic parameters. By using sensor technology, data leakage, technical discrepancies, and restricted expansiveness in the prediction can be addressed. By using encryption protocols, the reliability of present and predicted data can be used for industrial development and allows for the efficiency of real-time analysis of the data. Effective decisions can also be made on economic policies to enhance economic stability in the complicated global economy.

1. Introduction

As the world economy has become unpredictable, the role of monetary policy is important for stable economic development. With the ever-increasing use of IoT technology, big data processing and sensor technologies are widely used to increase the accuracy and timeliness of monetary policy adjustments and execution.(1) This necessitates research on how monitoring and tracking transactions can revolutionize economic analysis and policy formulation based on big data analytics and sensor technology. By leveraging real-time data collection and analysis, authorities can gain insights into economic indicators, consumer behavior, and market fluctuations, enabling them to craft more effective monetary policies.

To shift from historical analysis to proactive policy implementation, financial institutions and banks are using IoT devices and advanced data analysis. This transformation helps authorities mitigate economic shocks, stabilize markets, and promote sustainable growth more efficiently than ever before. Additionally, these technologies enhance fairness in the distribution of economic benefits by providing an accurate way to categorize the diverse economic states across different regions.

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In this study, we aim to elucidate how to use sensor technologies and big data analysis for monetary policy-making. Various categories of sensors are reviewed for economic monitoring to collect data on economic activities and provide real-time information. Additionally, how to use large-scale data analysis techniques is explored for processing the vast amounts of data produced by these sensors and machine learning algorithms in predictive economic models. Such recent technologies can also be used for the decision-making process in monetary policy. The results of this study provide a reference for policymakers, researchers, and stakeholders to optimize economic policies. By comparing previous study results, the difficulties and ethical concerns about such technologies are also discussed from the economic perspective. Finally, we propose several approaches to improve the efficiency of monetary policy-making and execution.

2. Literature Review

2.1 Sensor technologies in financial transaction

The possibility of improving the effectiveness of monetary policy-making and economic governance using sensor technology has been investigated in various studies.(2–4) The effects of monetary policy on the macroeconomic scale were assessed as shown in Fig. 1.(4) Technologies based on IoT allow for real-time data gathering and processing and the determination of economic indicators. For instance, sensors are used to track consumers' spending and investment behavior, which is essential information for policymakers on the economy.(5) Automated accounting systems incorporating IoT and blockchain technology enable the efficient collection of data that is with extensible business reporting language (XBTL) (Fig 2). Such innovative technologies leverage the sensors to improve efficiency in the processes and the accuracy of data processes for efficient economic monitoring.

2.2 Real-time data-informed monetary policy

Big data analytics supports monetary policy-making and execution with sensor technologies.(6) Central banks and financial institutions make important decisions and manage risks on the basis of real-time data of the present economic environment and predicted data based on past data (Fig. 3).(7–9) For example, financial institutions can identify the patterns of economic transactions using sensor technologies to monitor and predict economic fluctuations and consumer behavior changes. Such tasks are important to prepare responsive monetary policies and address issues effectively. In addition, by integrating big data and sensors, decisions can be made to improve financial services for various groups of customers.(8)

2.3 Use of sensor technology

Few studies address the use of advanced sensor technologies and big data analytics in the financial industry and current economic systems. The issues in implementing these technologies

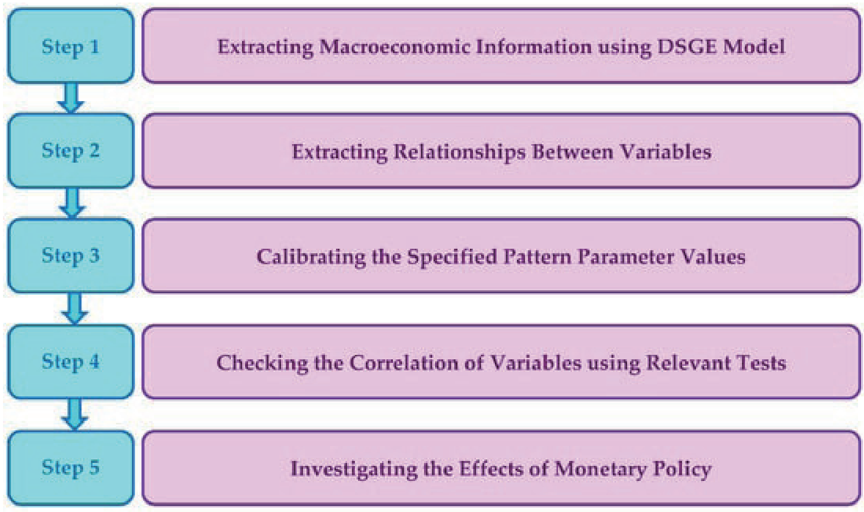

Fig. 1. (Color online) Effects of monetary policy on macroeconomic variables.[4] (DSGE: dynamic stochastic general equilibrium)

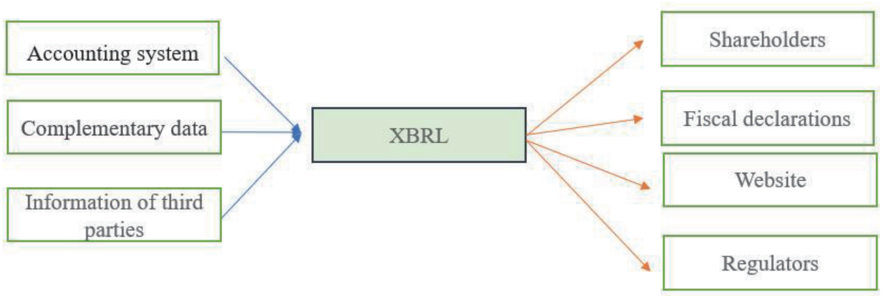

Fig. 2. (Color online) Use of XBRL model in accounting systems.

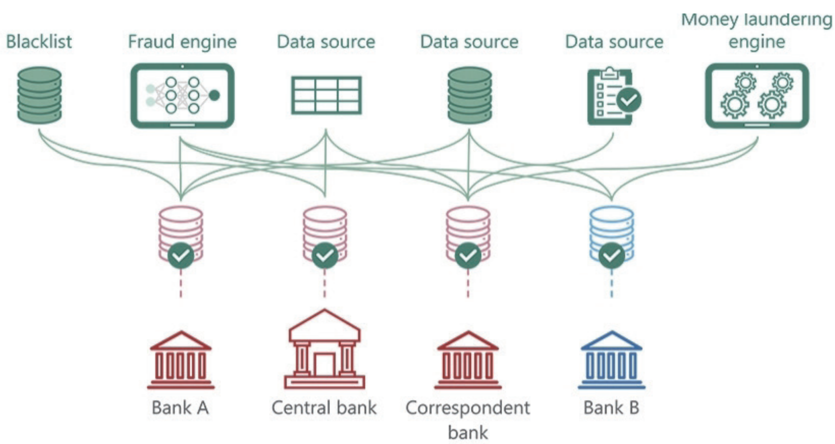

Fig. 3. (Color online) Decision-making and risk management using data and technologies.[9]

such as data privacy, security concerns, and compliance with regulations also need more research than before. Policymakers need to harness innovations for monetary policy-making and execution to enhance the development and application of domestic sensor technologies.

2.4 Ethical considerations and regulatory challenges

Ethical issues associated with real-time data collection have been addressed in previous studies. Data privacy and security of consumers' information in financial transactions must be provided using various technologies (Fig. 4). For this, existing technologies must be updated continuously with new technologies ceaselessly developed. Such updates and developments require the development of sensor technologies to build a solid foundation and framework.

3. Technical Framework

3.1 Sensor technologies

Integrating sensor technologies is crucial to improving monetary policy. For instance, timely information must be available in environmental monitoring (Fig. 5) using relevant sensors. Such sensors provide industries and governments with data on air quality, water consumption, waste production, and resource allocation. For instance, smart sensors are used to monitor volatile organic compounds (VOCs) in formulating related policies and compliance standards.[10,11] Corresponding to such policies and the growing global concerns of climate change, the sensor market and related industries can grow. These technologies also allow for the effective usage of resources, hence enhancing the efficiency of economic policy execution.

Besides environmental sensors, tracking sensors such as RF identification (RFID) are revolutionizing the way to trace consumer behavior. These sensors are used to gather data on purchases of goods and stock trading. RFID tags are used in the retail industry. From the collected information, central banks and policymakers can monitor economic activities and respond to unexpected fluctuations. Through the real-time monitoring of transactions,

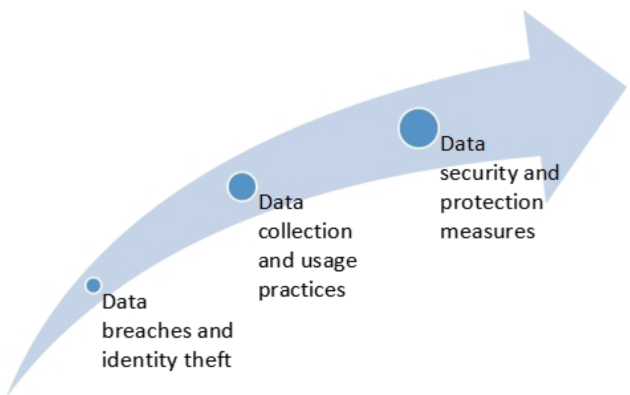

Fig. 4. (Color online) Data privacy and security at different levels.

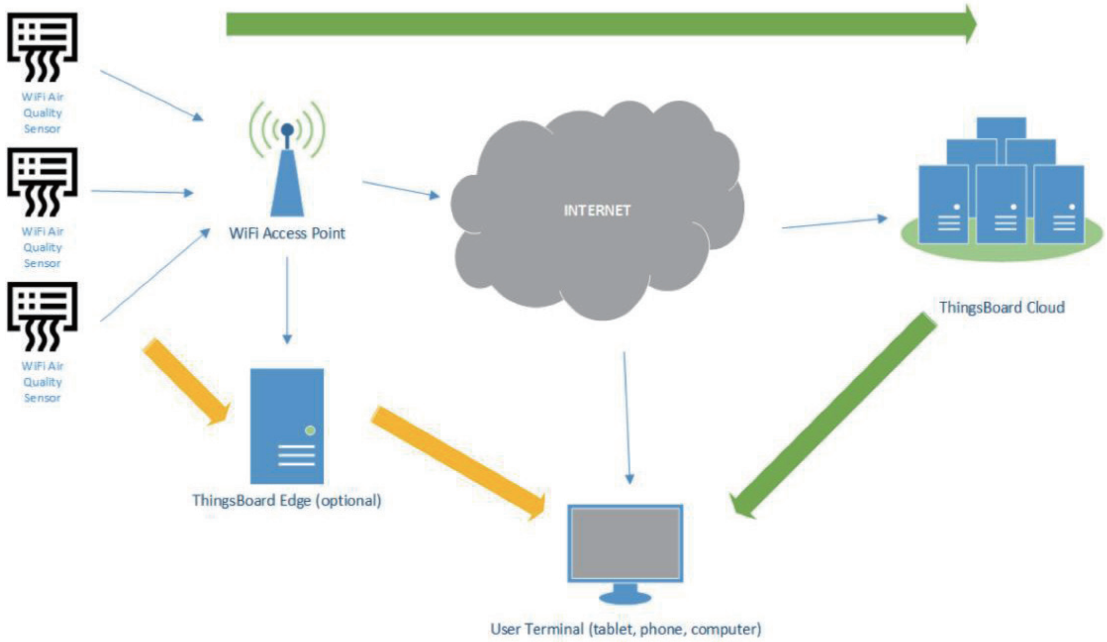

Fig. 5. (Color online) Air quality monitoring system.[11,12]

consumers' confidence levels can be increased, which helps formulate related policies.[13] The tracking sensor data can be used with big data analytics for establishing prediction models and refining monetary policy systems.

3.2 Big data analytics

Big data analytics has revolutionized the ways of processing and utilizing sensor data in the economy. Various techniques are used to process numerous data collected from sensors. Through data cleaning, merging, and converting, the data becomes more reliable for accurate information retrieval.[14] Such data preprocessing is vital for policy-makers to make the right decisions. Sophisticated analysis technologies also enable stakeholders to predict future trends and prepare for market changes. Artificial neural networks (ANNs) are the essence of big data analysis in the prediction of future trends.[15] The algorithms are created on the basis of data collected from sensors and forecast future economic parameters. For instance, machine learning models are established to predict consumer spending using the data on transactions collected from RFID sensors and demographic data. Using such algorithms, central banks can decide on economic policy changes appropriately. Machine learning's predictive capability has evolved, providing policymakers with efficient and updated models that show the improved accuracy of economic forecasts for appropriate monetary policies.

3.3 Integration of sensor technology and big data analytics into economic models

By applying real-time sensor data to existing economic models, the monetary policy-making system can be improved most effectively. The data can be integrated into traditional economic forecasting models using various methods. The current model can adopt indexes or parameters representing real-time economic activities, which are determined on the basis of sensor data.[2] For example, by correlating the data obtained from the environmental sensors with consumer behavior, the air quality can be predicted and its impact on the economy can be estimated. Then, the consequences on economic performance and public health can also be predicted. New econometric models can be established on the basis of various sensor data using state-of-the-art statistical tools to predict economic growth rates or inflation.[16] When real-time data is used in the models, accurate predictions can be made, which induces synergies of various policies.[16]

Using real-time sensor data integrated into economic models, engineers, economists, policymakers, and stakeholders can collaborate to formulate policies in consideration of the dynamic structure of economic structures.[17] Such collaboration is crucial for managing modern economies and monetary policies for sustainable development. Therefore, sensor technologies and big data analytics must be used to improve monetary policies. The improvement allows for well-defined operations of the economic and data acquisition systems. The application of such advanced technologies improves the predictability of economic trends and the soundness of economic systems.

4. Case Studies

4.1 Sensor data application

Sensor technologies can improve efficiency in the execution of policies.[18,19] For instance, smart meters are used to monitor real-time energy use, which is used to realize the usage patterns that can be used for demand and supply control. Data obtained from smart meters can be used to improve the management of energy grids, mitigate peak load issues, and decide on how to charge.[20] Through the process, efficient resource allocation is enabled, and consumer behavior is understood for making appropriate charging and sustainable energy consumption. Smart meters provide various sensor data to optimize and stabilize the energy market while also protecting the environment by controlling energy consumption.

Smart sensors are installed to monitor weather conditions and the degree of pollution. Large cities such as Los Angeles and Beijing have installed a network of sensors to measure and report air quality standards. The data gathered help residents monitor air quality and enable policymakers to implement necessary measures to control pollutant emissions. With the aid of sensor technology, policies for environmental sustainability can be made.[21] Such uses of sensors illustrate how they contribute to economic development and related policy-making in modern society (Fig. 6).

4.2 Implementations of sensors

Stakeholders must invest more in the implementation of sensor networks to increase the volume of collected data. It is also necessary to share the data with companies and authorities to use them effectively.[22] Stakeholders must cooperate to ensure new perspectives on the delivery of diverse services and develop innovative technology. The technical issues related to sensor

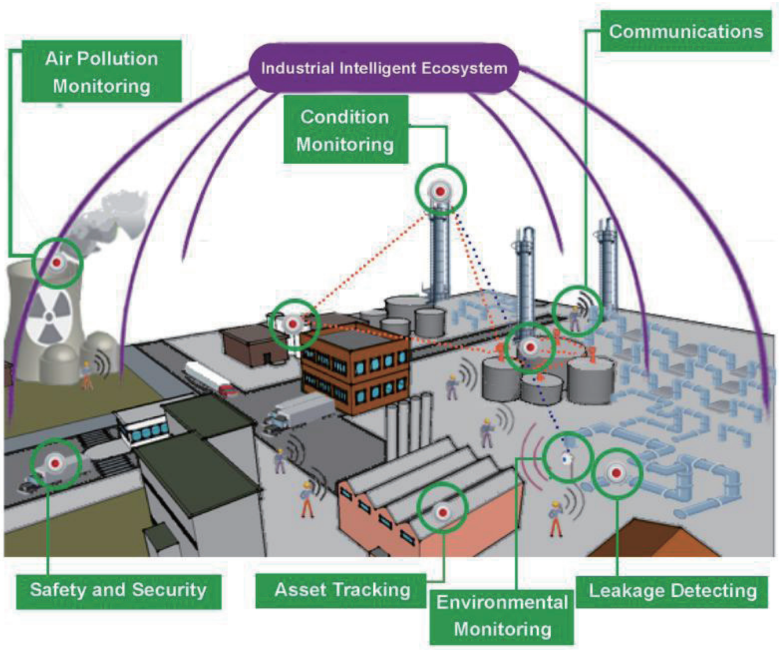

Fig. 6. (Color online) Environmental monitoring using sensors and their networks.

network installation and the use of the sensor data must be addressed. Such issues include data accuracy, privacy, and security, the compatibility of sensor systems, and big data analytics. Addressing the related problems requires appropriate investment to enhance knowledge of sensor technologies and big data analytics, as well as the formulation of standard procedures for data collection and system compatibility. These solutions can improve sensor performance and diversify their efficient use.

4.3 Data privacy and security

While sensor technologies are evolving fast, data privacy and security pose a serious challenge. Personal data requires effective measures to prevent information leaks or cyberattacks.(23) For example, smart meters gather usage data containing personal information. Without encryption standards and corresponding compliance, the information can be leaked easily.(24) Additionally, public trust in collecting, using, and sharing the data can deteriorate. Therefore, the data must be protected for the personal privacy of people.(25) Sometimes, algorithms can be altered to interpret the data to reinforce misinformation and exert inequalities. By formulating ethical standards for the use of sensor data, we can facilitate balanced and non-discriminatory economic growth while respecting individuals' rights.

4.4 Future research

The use of sensor technology coupled with AI improves its predictive capability considerably.(26) For instance, AI algorithms accurately predict future energy usage or the surrounding environmental conditions based on the collected data from smart meters. Such predictive power enables policymakers to take preventive measures to prevent potential problems. By integrating IoT into sensor technology, stakeholders effectively cooperate to address common issues and make appropriate policies and decisions.(27) For example, agronomic sensors in the environmental control system enhance resource usage, reduce pollution, and make the right decisions from a combined viewpoint.

5. Comparative Study

5.1 Conventional methods

To improve the effectiveness of monetary policy-making, economic indicators are used. They are obtained from economic data including gross domestic product (GDP), growth rate, unemployment rate, and inflation/deflation rate. Such indicators are the basic data for policymakers to diagnose the status of the economy and design strategies. However, these indicators restrain monetary policy execution as they are determined on the basis of past data. Therefore, they cannot be used to diagnose and predict the economic status in such fast-changing markets. Consumer confidence index (CCI) and purchasing managers' index (PMI) are also used as information to perceive and forecast consumer behavior and purchasing power.(28) Surveys are also used to determine them. However, the indicators and the gathered survey data are often subjective and affected by short-term situations not capturing the correct economic situations for real-time decision-making.(28)

5.2 Sensor-based and conventional methods

Several advantages are found in using sensor-based methods. First, sensor technology enables the real-time monitoring of current economic conditions, facilitating the formulation of policies tailored to present and near-future scenarios. Moreover, sensor-based methods allow decision-makers to have a better and more diverse picture of the current economy to solve current problems even considering the future effects. Big data analytics and AI algorithms process enormous volumes of sensor data quickly to determine current patterns and future trends so that policymakers take timely actions immediately. Therefore, the efficiency of monetary policy-making is improved and mitigates drawbacks such as a lack of speed, specificity, and accuracy in forecasting with traditional methods. The sensor-based method provides a realistic approach to monetary policy-making and execution.

6. Results and Discussion

The implication of sensor technology and big data analytics on the functionality of policies must be considered. Descriptive, predictive, and prescriptive methods are required to improve policy-making and its implementation. The dataset provides monthly observations on particulate (PM) 2.5 levels, noise levels, population density, health expenditures, economic activity, energy consumption, smart meter accuracy, and retail spending. Table 1 shows the data on air quality and energy obtained from sensors and smart meters. Table 2 shows the descriptive statistics of the data in Table 1 including means, standard deviations, and skewnesses. The data included environmental and economic indicators and their monthly trends in a year. The mean value of PM2.5 is 35.52 μg/m^3 with the highest value of 40.13 μg/m^3 in November. This coincided with increased health expenditures of USD189.32 in November, suggesting a potential relationship between air quality and public health costs. Noise levels fluctuated throughout the months with a mean of 63.67 dB and a standard deviation of 8.38. Energy consumption demonstrated seasonal variation, peaking in October at 284.27 kWh, which aligned with the higher retail spending of USD1812.57. These descriptive statistics underscore the interconnectedness of environmental factors and economic activities, highlighting the need for integrated monitoring systems.

Correlation analysis was conducted to identify relationships between environmental conditions and economic metrics. PM2.5 levels showed a moderate positive correlation with health expenditures (r = 0.486), indicating that deteriorating air quality directly impacted public

Table 1
Data of air quality and energy consumption.

Month	PM2.5	Noise (dB)	Population density	Health expenditure (USD)	Economic activity index	Energy consumption (kWh)	Smart meter accuracy (%)	Spending (USD)
January	36.96	77	924	205.99	5.24	264.39	98.01	1775.56
February	36.63	56	590	109.28	6.99	239.16	97.5	1462.63
March	32.96	52	1293	125.01	6.9	271.86	98.99	1645.47
April	34.94	63	862	208.93	7.11	235.57	97.89	1782.97
May	34.08	61	1275	111.22	5.59	240.5	98.7	1734.53
June	38.52	56	693	249.16	7.16	204.87	97.03	1396.53
July	37.84	63	1071	176.92	7.96	226.71	97.76	1640.32
August	26.29	66	1147	123.79	6.26	220.04	97.05	1654.76
September	35.48	55	1277	138.68	6.86	250.15	97.28	1471.93
October	37.49	68	1283	145.27	7.92	284.27	97.26	1812.57
November	40.13	78	1033	189.32	5.62	251.53	97.46	1443.92
December	34.95	69	817	201.15	5.03	240.4	97.7	1507.64

Table 2
Descriptive statistics of data in Table 1.

	Number of data	Mean	Standard deviation	Skewness	
				Value	Standard error
PM2.5	12	35.5225	3.53301	−1.628	0.637
Noise	12	63.67	8.381	0.445	0.637
Population density	12	1022.08	245.104	−0.426	0.637
Health expenditure (USD)	12	165.3933	45.83362	0.337	0.637
Economic activity index	12	6.5533	0.99361	−0.183	0.637
Energy consumption (kWh)	12	244.1208	22.22168	0.144	0.637
Smart meter accuracy (%)	12	97.7192	0.61308	1.036	0.637
Spending (USD)	12	1610.7358	148.46373	−0.054	0.637
Number of data	12				

health costs. Noise levels were moderately correlated with retail spending (r = 0.244), suggesting that urban noise pollution affected consumer behavior (Table 3). Energy consumption was an essential factor affecting economic performance, and a direct relationship with the economic activity index was established (r = 0.451). Optimal energy utilization was related to increased

Table 3
Correlation analysis results.

		PM2.5	Noise (dB)	Population density	Health expenditure (USD)	Economic activity index	Energy consumption (kWh)	Smart meter accuracy (%)	Spending (USD)
PM2.5	Pearson Correlation	1	0.217	−0.309	0.486	0.150	0.165	−0.103	−0.274
	Two-tailed significance		0.498	0.329	0.109	0.641	0.609	0.750	0.389
	N	12	12	12	12	12	12	12	12
Noise (dB)	Pearson Correlation	0.217	1	−0.042	0.352	−0.515	0.227	−0.182	0.244
	Two-tailed significance	0.498		0.896	0.261	0.086	0.479	0.571	0.444
	N	12	12	12	12	12	12	12	12
Population density	Pearson Correlation	−0.309	−0.042	1	−0.507	0.101	0.501	0.330	0.437
	Two-tailed significance	0.329	0.896		0.092	0.755	0.097	0.295	0.155
	N	12	12	12	12	12	12	12	12
Health expenditure (USD)	Pearson Correlation	0.486	0.352	−0.507	1	−0.097	−0.322	−0.286	−0.175
	Two-tailed significance	0.109	0.261	0.092		0.764	0.308	0.368	0.587
	N	12	12	12	12	12	12	12	12
Economic activity index	Pearson Correlation	0.150	−0.515	0.101	−0.097	1	−0.026	−0.230	0.094
	Two-tailed significance	0.641	0.086	0.755	0.764		0.937	0.472	0.772
	N	12	12	12	12	12	12	12	12
Energy consumption (kWh)	Pearson Correlation	0.165	0.227	0.501	−0.322	−0.026	1	0.379	0.451
	Two-tailed significance	0.609	0.479	0.097	0.308	0.937		0.225	0.141
	N	12	12	12	12	12	12	12	12
Smart meter accuracy (%)	Pearson Correlation	−0.103	−0.182	0.330	−0.286	−0.230	0.379	1	0.408
	Two-tailed significance	0.750	0.571	0.295	0.368	0.472	0.225		0.188
	N	12	12	12	12	12	12	12	12
Spending (USD)	Pearson Correlation	−0.274	0.244	0.437	−0.175	0.094	0.451	0.408	1
	Two-tailed significance	0.389	0.444	0.155	0.587	0.772	0.141	0.188	
	N	12	12	12	12	12	12	12	12

productivity and resource depletion minimization. The results showed that real-time data can be used for identifying and managing challenges in economics and environments.

The results also confirmed the importance of environmental and energy data in forming economic policy. For instance, a positive relationship between PM2.5 and health expenditures indicated the cost incurred from poor air quality and a need for policies to control pollution and its financial consequences. A high dependence on energy consumption and activity ratio confirmed that the effective management of resources is necessary to enhance productivity and economic growth.

These findings are consistent with previous study results that stress a significant relationship between smart meter accuracy and health expenditure (Fig. 7). The interpretation of the sensor data aids policymakers in executing preemptive actions through which the efficiency of monetary policy-making and execution is increased while uncertainty is minimized.

Real-time data can also be used for policy assessment. For example, debit card transaction data can be used to improve the consumption prediction accuracy. Aastveit *et al.* used data to nowcast household consumption and enhance the accuracy of GDP growth forecasts by over 60% compared with conventional models based on past data and showed that efficiency is important in developing sensitive monetary policies (Table 4).[29] Smart meter data and analytics

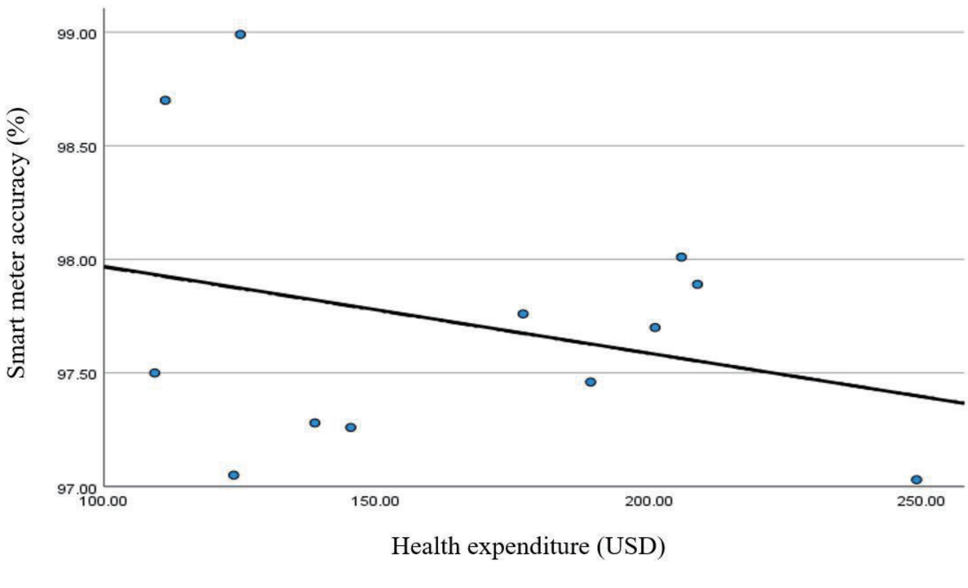

Fig. 7. (Color online) Linear relationship between smart meter accuracy and health expenditure in this study.

Table 4
Accuracies of traditional and real-time data-based models.

Model	Data	Accuracy improvement	Key metrics
Traditional lag model	Historical GDP data	Baseline	GDP growth forecast
Real-time analytics	Debit card transactions	60%	Consumption prediction
Smart meter analytics	Electricity usage data	35%	Load forecasting

improve energy management. Smart meter data improved the forecasting accuracy by 35%. The clustering and dimensionality reduction were used to analyze consumption patterns and predict load demand to prescribe grid optimization and detect consumption anomalies and load profiling.[20] Real-time data analytics are superior to traditional monetary and energy models in terms of accuracy and speed. Real-time transaction data mitigates the time discrepancies found in models based on past data as they offer factual data on consumer behavior. Newly added data allows such models to be more accurate in predicting future trends, which facilitates the formulation of more effective policies.

7. Challenges

For the model based on real-time sensor data, technical reliability is a concern in monetary policy formulation.[19] Several sensor systems suffer from low accuracy and reliability.[30] Environmental effects, sensor elements, and data communication affect the reliability of the data gathered. For example, sensors in urban environments might have signal interferences or physical barriers, producing poor-quality signals. Different manufacturing qualities and methods lead to variations in the performance of sensors. Overcoming these technical issues is critical to developing sensor technology as inaccurate data leads to inappropriate policy decisions.

In using sensor data, regulatory and ethical issues must be considered.[25] While sensors are essential components to gather data, data privacy and security issues surface.[31] Therefore, policymakers need to protect personal data. Ethical concerns also need to be addressed to prevent potential societal gaps and discrimination.[32] Appropriate regulations are essential to ensure that the public and industries trust the technology.

The other important challenge in the effective integration of sensor technologies into monetary policy is a sound ecosystem including related industries. Only a few companies supply advanced sensors through extensive research and development. Since smaller companies cannot finance such activities, governments need to award incentives and funds, and collaborate with them for the efficient development of sensor technology.[33]

8. Recommendations

Incorporating sensor technology in monitoring the economy is important for monetary policy-making and execution. Sensors are used to collect data on consumer behavior, environmental factors, market trends, and so forth, and assist policymakers in making informed decisions.[34] For timely and accurate responses to current and expected threats such as high inflation and fluctuations in customer confidence, various sensor data need to be used. Advanced sensor technology and data analytics contribute to the improvement of monetary policy and stable economic growth.

Central banks and policymakers must fine-tune the current structures of monetary policy for the successful integration of sensor data. Re-evaluating previous economic models is mandated to introduce real-time sensor data. Instead of sensor data integration into previous models, new models need to be developed to describe the complicated relationship between various aspects of the economy.[35] Stakeholders who use real-time data must be trained to understand its implications and apply it to decision-making processes. Then, monetary authorities can effectively respond to constantly changing economic conditions for increased policy efficiency.

In the integration of sensor technology into monetary policy, the cooperation of the government, industry, and academic organizations is essential for knowledge sharing and innovation to meet economic requirements. Grants or incentives for industries for research and development with partners can boost the integration.[36] Accelerators need to play a role in supporting technology development. Through such efforts, sensor technology can be more extensively used to determine economic indicators and formulate monetary policies.

It is also necessary to develop big data analytics by designing AI models to use sensor data. Investment in machine learning and AI needs to be increased to enhance the prediction and analysis capability. Close cooperation between the government, industry, and academic organizations is also mandated to develop the models. Stakeholders need to be trained for data analysis and the application of the results to the decision-making process.

Basic research in sensor technology needs to be encouraged to develop new technologies and increase reliability. Authorities must provide grants for research projects to develop new-generation sensors and to formulate global standards for accuracy, durability, and compatibility. With standardized sensors and technologies, performance, the same technology, materials, and solutions can be used for various economic environments for further comparison and development of related data analytics. When basic research is promoted, sensor technology for the efficient monitoring of the economy and the efficacy of monetary policy can be further developed.

9. Conclusions

The results of this study show the significance of sensor technology and big data analytics to monetary policy-making and execution. The data gathered from various sensors are used for the real-time analysis and determination of economic indicators, customer behavior, and resource allocation. By using sensor data, the deficiencies of standard economic indicators can be addressed, and up-to-date information is provided to policymakers. However, data privacy protection, technological constraints, and the standardization of sensor technology need to be considered by policymakers, researchers, and industries to enhance the reliability and ethical use of sensor data. Sensor data and big data analytics are pivotal to enhancing productivity, promoting environmental sustainability, and increasing the versatility of the global economy. However, addressing the associated challenges effectively is crucial for realizing these benefits.

Acknowledgments

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