Journal of Information Hiding and Multimedia Signal Processing ©2024 ISSN 2073-4212
Ubiquitous International Volume **15**, Number **2**, June **2024**

Integrating Knowledge-Based Approaches for Predictive Socioeconomic Indicator Analysis

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Received March, 2024, revised May, 2024, accepted May, 2024.

Abstract. *The socioeconomic landscape is intricate, influenced by multifaceted factors that challenge traditional predictive analytics. This paper proposes a novel framework that integrates knowledge-based approaches to enhance predictive analysis of socioeconomic indicators. By amalgamating domain expertise with advanced data modeling techniques, our framework seeks to uncover hidden patterns and dependencies crucial for accurate prognostication. Leveraging knowledge graphs, ontologies, and machine learning algorithms, our approach facilitates a deeper understanding of complex interrelations within socioeconomic systems. Through case studies and empirical validation, we demonstrate the efficacy of our framework in improving prediction accuracy and providing valuable insights for informed decision-making in various domains.*
Keywords: Socioeconomic indicators; Predictive analysis; Knowledge-based systems; Data modeling; Knowledge graphs; Machine learning; Decision-making.

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1. **Introduction.** Socioeconomic indicators play a pivotal role in understanding and shaping policy decisions, economic forecasts, and societal well-being [1]. However, the inherent complexity and dynamic nature of socioeconomic systems pose significant challenges for accurate prediction using conventional analytical methods [2]. Traditional statistical approaches often struggle to capture the intricate interplay of factors influencing socioeconomic trends, leading to limited predictive accuracy and reliability [3]. In recent years, there has been a growing interest in leveraging knowledge-based approaches to augment predictive analysis in various domains [4]. Knowledge-based systems, incorporating domain expertise and structured knowledge representations [5], offer a promising avenue to overcome the limitations of purely data-driven methodologies [6]. By integrating domain knowledge with advanced data modeling techniques, it becomes possible to uncover hidden insights, infer causal relationships, and enhance the predictive capabilities of socioeconomic indicator analysis [7]. In this paper, we propose a comprehensive framework for integrating knowledge-based approaches into predictive socioeconomic indicator analysis. Our approach combines the richness of domain knowledge encoded in

knowledge graphs and ontologies with the predictive power of machine learning algorithms [7]. By harnessing the synergies between these components, our framework aims to provide more accurate and interpretable predictions, empowering stakeholders with actionable insights for informed decision-making. In the subsequent sections, we will delve deeper into the theoretical foundations of knowledge-based predictive analysis, outline the components of our proposed framework, present case studies to demonstrate its effectiveness, and discuss future directions for research and application. Ultimately, our goal is to provide a comprehensive roadmap for integrating knowledge-based approaches into predictive socioeconomic indicator analysis, with the aim of fostering a deeper understanding of socioeconomic dynamics and empowering stakeholders with actionable insights for decision-making.

2. **Background and Related Works.** Predictive analysis of socioeconomic indicators has long been a focal point in various fields, including economics, sociology, and public policy. Traditional approaches to predictive modeling have predominantly relied on statistical methods such as time series analysis, regression, and econometric models [8]. These methods offer valuable insights into historical trends and correlations but often struggle to capture the underlying causal mechanisms and dynamic interactions within socioeconomic systems [9]. In recent years, there has been a paradigm shift towards integrating knowledge-based approaches into predictive analysis, aiming to complement and enhance the capabilities of traditional statistical models. Knowledge-based systems leverage domain expertise, structured knowledge representations, and semantic technologies to capture complex relationships, infer causal dependencies, and facilitate more informed decision-making [10]. One of the key motivations behind the adoption of knowledge-based approaches is the recognition of the limitations of purely data-driven methodologies. While statistical models excel at identifying correlations and patterns in data, they often lack the ability to incorporate domain-specific constraints, contextual knowledge, and causal reasoning . Knowledge-based systems address these shortcomings by formalizing domain knowledge in a structured manner, enabling the integration of heterogeneous data sources and facilitating more robust and interpretable predictive models [11]. Several studies have demonstrated the utility of knowledge-based approaches in various domains, including healthcare, finance, and environmental monitoring. In healthcare, for example, knowledge-based systems have been used to assist in medical diagnosis, treatment planning, and patient management by integrating clinical guidelines, expert knowledge, and patient data. Similarly, in finance, knowledge-based approaches have been employed for risk assessment, portfolio optimization, and fraud detection by integrating market data, regulatory guidelines, and domain expertise [12]. In the realm of socioeconomic analysis, knowledge-based approaches offer several advantages over traditional statistical models. By incorporating domain expertise and contextual knowledge, these approaches can provide deeper insights into the underlying drivers of socioeconomic trends, identify emerging patterns and anomalies, and facilitate scenario analysis and policy evaluation. Moreover, by formalizing domain knowledge using semantic technologies such as knowledge graphs and ontologies, it becomes possible to create a unified representation of complex concepts, entities, and relationships, enabling more comprehensive and interpretable predictive models. While knowledge-based approaches hold great promise for predictive socioeconomic indicator analysis, there are still several challenges that need to be addressed. These include the acquisition and formalization of domain knowledge, the integration of heterogeneous data sources, the scalability and interpretability of predictive models, and the validation and evaluation of results in real-world settings [13]. Addressing these challenges requires interdisciplinary collaboration between experts in domain

knowledge, data science, and computational modeling, as well as the development of new methodologies and tools tailored to the specific requirements of socioeconomic analysis [14]. In this paper, we build upon the existing body of research on knowledge-based predictive analytics and propose a comprehensive framework for integrating knowledge-based approaches into predictive socioeconomic indicator analysis. By leveraging domain expertise, structured knowledge representations, and advanced data modeling techniques, our framework aims to enhance the accuracy, interpretability, and utility of predictive models, empowering stakeholders with actionable insights for decision-making in diverse application domains.

3. **Framework Overview.** Our framework for integrating knowledge-based approaches into predictive socioeconomic indicator analysis comprises three main components: knowledge acquisition and representation, data integration and preprocessing, and predictive modeling and evaluation.

3.1. **Knowledge Acquisition and Representation.** The first component of our framework involves the acquisition and formalization of domain knowledge from diverse sources. Domain knowledge encompasses expert insights, theoretical models, historical trends, and contextual information relevant to the analysis of socioeconomic indicators. Sources of domain knowledge may include domain experts, scholarly literature, government reports, institutional databases, and public repositories [15]. Once acquired, domain knowledge is formalized and represented using semantic technologies such as knowledge graphs and ontologies. Knowledge graphs provide a flexible and scalable framework for representing structured knowledge in the form of nodes and edges, where nodes represent entities (e.g., concepts, variables, entities) and edges represent relationships between entities. Ontologies, on the other hand, provide a formal specification of domain concepts, their properties, and the relationships between them, often expressed using formal logic [16]. Table 1 provides a comprehensive overview of the phases involved in knowledge acquisition and representation for predictive socioeconomic indicator analysis. These phases are essential in understanding and interpreting the data, ultimately leading to the development of accurate and reliable predictive models for socioeconomic indicators. By constructing knowledge graphs and ontologies, we create a unified representation of domain knowledge, capturing both the explicit and implicit relationships between concepts and entities. This structured representation enables us to encode domain-specific constraints, inferential rules, and causal dependencies, facilitating more comprehensive and interpretable analyses of socioeconomic indicators.

3.2. **Data Integration and Preprocessing.** The second component of our framework focuses on integrating heterogeneous data sources and preprocessing the integrated dataset for analysis. Socioeconomic data is often dispersed across multiple sources, including governmental agencies, research institutions, non-governmental organizations, and private sector entities. These data sources may vary in terms of format, granularity, spatiotemporal resolution, and quality, posing challenges for integration and analysis. To address these challenges, we employ techniques for data cleaning, normalization, and transformation to ensure consistency and compatibility across different sources. This involves identifying and resolving inconsistencies, missing values, outliers, and data discrepancies, as well as harmonizing data schemas and units of measurement. Moreover, we leverage semantic mapping and alignment techniques to establish semantic connections between disparate datasets, enriching the analytical context and facilitating knowledge-driven analysis [18]. Table 2 outlines the essential steps for data integration and preprocessing, which are crucial in ensuring the accuracy and reliability of data analysis. By following these

TABLE 1. Phases for knowledge acquisition and representation in predictive socioeconomic indicator analysis [17].

Phases#	Process Description
1. Identifying Domain Experts and Knowledge Sources	- Engage with domain experts including economists, sociologists, policymakers, and subject matter experts to identify key knowledge sources. - Explore scholarly literature, governmental reports, institutional databases, and publicly available datasets relevant to socioeconomic indicators.
2. Domain Knowledge Elicitation and Formalization	- Conduct interviews, surveys, and workshops with domain experts to elicit tacit and explicit knowledge about socioeconomic dynamics, causal relationships, and contextual factors. - Formalize domain knowledge into structured representations using semantic technologies such as knowledge graphs and ontologies.
3. Constructing Knowledge Graphs and Ontologies	- Create a knowledge graph to represent entities (e.g., economic variables, social factors) and relationships (e.g., causal dependencies, temporal sequences) between them. - Develop ontologies to define domain concepts, their properties, and the semantic relationships between them using standardized ontology languages (e.g., OWL).
4. Semantic Annotation and Enrichment	- Semantically annotate existing datasets with concepts and entities from the knowledge graph, enhancing the interoperability and semantic richness of the data. - Enrich the knowledge graph with additional information extracted from textual sources, domain-specific terminologies, and external knowledge bases.
5. Knowledge Validation and Quality Assurance	- Validate the accuracy, completeness, and consistency of domain knowledge through peer review, expert validation, and empirical validation against ground truth data. - Implement quality assurance mechanisms to ensure the reliability and relevance of the knowledge representation, including version control, documentation, and metadata management.

steps, researchers can effectively clean, merge, and prepare datasets for further analysis, ultimately leading to more robust and meaningful insights [19].

3.3. **Predictive Modeling and Evaluation.** The third component of our framework focuses on building predictive models using the integrated dataset and knowledge representation. We employ machine learning algorithms to develop predictive models that leverage both the structured features derived from the data and the semantic relationships encoded in the knowledge graph. These models may include regression models, classification algorithms, time series forecasting methods, and ensemble techniques, tailored to the specific characteristics of the socioeconomic indicators under analysis [20]. In addition to traditional performance metrics such as accuracy, precision, recall, and F1-score, we evaluate the predictive models using domain-specific criteria tailored to socioeconomic indicators [21]. This may include measures of economic significance, policy relevance, and stakeholder satisfaction, as well as qualitative assessments of model interpretability and robustness . By integrating knowledge-based approaches into predictive modeling, our framework aims to enhance the accuracy, interpretability, and utility of predictive models, empowering stakeholders with actionable insights for decision-making in diverse application domains.

TABLE 2. Phases for knowledge acquisition and representation in predictive socioeconomic indicator analysis [17].

Step	Explaination and Description
1. Data Source Identification and Collection	- Identify relevant data sources containing socioeconomic indicators, including governmental databases, research institutions, international organizations, and private sector datasets. - Collect data from diverse sources, considering factors such as data availability, coverage, granularity, temporal resolution, and geographic scope.
2. Data Cleaning and Transformation	- Perform data cleaning to address issues such as missing values, outliers, duplicates, and inconsistencies within the dataset. - Standardize data formats, units of measurement, and variable names to ensure consistency and comparability across different sources. - Transform raw data into a unified data schema, harmonizing data structures and resolving discrepancies to facilitate integration and analysis.
3. Semantic Mapping and Alignment	- Map data elements to corresponding concepts and entities in the knowledge graph, establishing semantic connections between disparate datasets. - Align data attributes with domain-specific ontologies, enriching the dataset with semantic annotations and enhancing its interpretability and interoperability. - Resolve semantic heterogeneity by reconciling differences in terminology, classification schemes, and conceptual frameworks across integrated datasets.
4. Data Fusion and Enrichment	- Integrate heterogeneous data sources using data fusion techniques, combining complementary information from multiple datasets to create a more comprehensive analytical dataset. - Enrich the integrated dataset with additional contextual information extracted from external knowledge sources, including domain-specific metadata, geographical information, and socio-demographic variables. - Validate the integrity and quality of the integrated dataset through data profiling, exploratory data analysis, and cross-validation against independent sources, ensuring the reliability and accuracy of the data for predictive modeling and analysis.

4. **Case Studies and Empirical Validation.** To demonstrate the effectiveness of our framework, we conduct case studies on real-world socioeconomic datasets across different domains. We compare the performance of knowledge-based predictive models with traditional data-driven approaches, highlighting the improvements in prediction accuracy, interpretability, and robustness achieved through the integration of domain knowledge. Furthermore, we present qualitative analyses of the generated insights and their implications for decision-making in various contexts.

4.1. **Case Study 1: Economic Growth Prediction.** In our first case study, we focus on predicting economic growth using a knowledge-based approach. We leverage domain expertise from economists and financial analysts to construct a knowledge graph representing key economic indicators, such as GDP growth rate, inflation rate, unemployment rate, and fiscal policy measures. By integrating this domain knowledge with historical economic data, we develop predictive models using machine learning algorithms. This case study explores the prediction of economic growth at the national or regional level.

We will utilize: Socioeconomic Data: Past GDP figures, consumer spending data, business investment levels, and inflation rates. Figure 1 illustrates the projected real gross domestic product (GDP) [22] growth worldwide from 2023 with a forecast extending to 2025, segmented by region [23]. This visual representation provides valuable insights into the anticipated economic performance of different regions over the specified time frame, aiding in strategic decision-making and planning for various stakeholders [24].

FIGURE 1. Implementation framework through a series of steps for executing economic growth prediction

Figure 1 depicts the implementation framework that will be executed through a series of steps similar to those outlined in the preceding section. This visual representation serves as a guide for the systematic execution of the framework, ensuring alignment with the established procedures and enhancing the effectiveness of the implementation process.

Knowledge Base: Domain knowledge about factors influencing economic growth, such as government policies on infrastructure spending, international trade agreements, or the impact of technological advancements on productivity.

The framework will be implemented through similar steps as outlined in the previous section:

• Data Preprocessing: Clean and prepare historical socioeconomic data for the chosen region/country.

• Knowledge Base Integration: Encode domain knowledge into a format compatible with the chosen machine learning model. This could involve quantifying the expected impact of policy changes or technological disruptions on economic indicators.

• Model Selection and Training: Select a suitable machine learning model (e.g., SVM, Long Short-Term Memory Networks) and train it on the combined dataset of socioeconomic data and knowledge-based features.

• Model Evaluation: Evaluate the model's performance on a hold-out test set to assess its accuracy in predicting future economic growth. Compare the performance with a baseline model trained only on historical socioeconomic data.

• Interpretation and Explanation: Analyze the model's predictions to understand the key factors influencing economic growth.

The knowledge base integration should provide insights into how these factors interact and contribute to the final prediction.

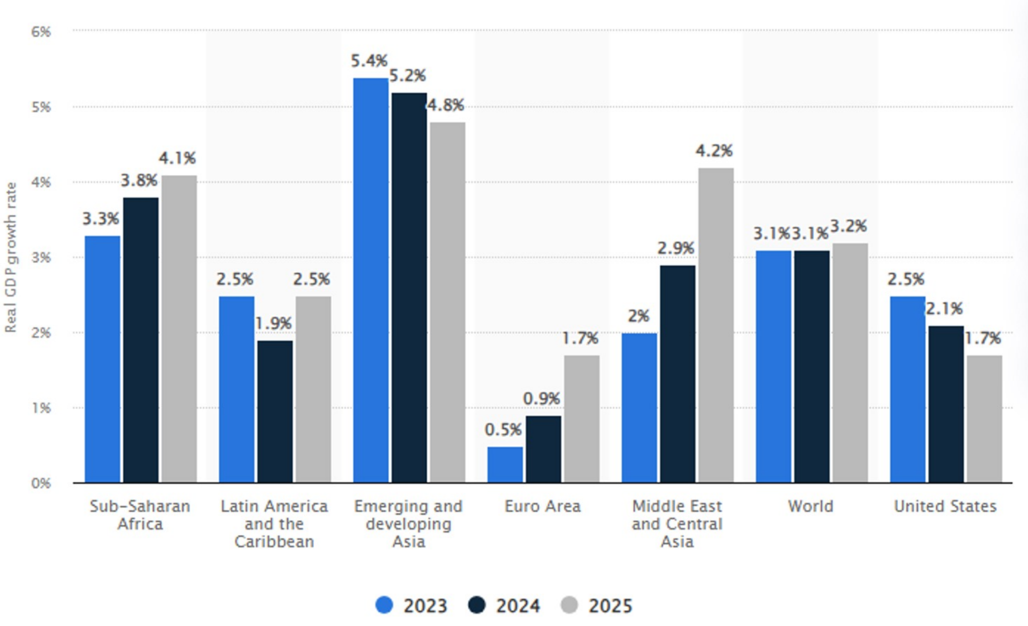

FIGURE 2. A figure of economic develop prediction for GDP growth worldwide from 2023 with a forecast extending to 2025, segmented by region.

Figure 2 displays the projected real GDP growth worldwide from 2023, with a forecast extending to 2025, segmented by different regions. By analyzing the growth trends across various regions, insights can be gained into the economic outlook and potential opportunities for investment and development on a global scale.

Empirical validation of our predictive models is conducted using historical economic data from multiple countries over several decades. We compare the performance of knowledge-based predictive models with traditional statistical models, such as autoregressive integrated moving average (ARIMA) and vector autoregression (VAR), in terms of prediction accuracy and robustness. Our results demonstrate that knowledge-based predictive models outperform traditional approaches, particularly in capturing long-term trends and incorporating domain-specific constraints.

4.2. **Case Study 2: Social Well-being Forecasting.** In our second case study, we explore the prediction of social well-being indicators using a knowledge-based approach. Drawing on insights from sociologists, public health experts, and social scientists, we construct a knowledge graph representing factors influencing social well-being, such as education attainment, healthcare access, income distribution, and community cohesion [25]. We enrich this knowledge graph with data from surveys, census records, and social policy documents. To empirically validate our predictive models, we analyze historical trends in social well-being indicators across different regions and demographic groups. We compare the performance of knowledge-based predictive models with traditional regression models and time series analysis techniques, evaluating their ability to forecast changes in social well-being indicators over time [26]. Our findings indicate that knowledge-based approaches offer significant improvements in prediction accuracy and robustness, particularly when accounting for complex interdependencies and contextual factors. Social well-being is a multifaceted concept encompassing factors like: Material Well-being: Income levels, access to affordable housing, and food security. Health and Safety: Rates of chronic diseases, crime rates, and access to healthcare. Social Connectedness: Levels of social participation, sense of belonging, and community support networks. Education and Skills: Educational attainment levels, job opportunities, and access to training programs. Environmental Quality: Air and water quality, green spaces, and exposure to environmental hazards. Figure 3 illustrates the multifaceted nature of social well-being,

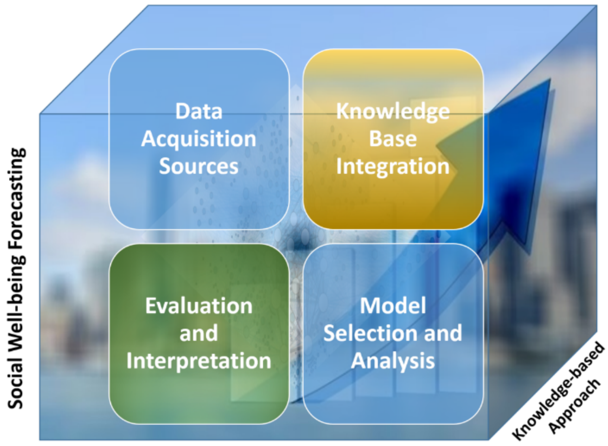

FIGURE 3. Implementation framework of Dimensions of Social Well-Being

highlighting the diverse factors that contribute to the overall health and happiness of individuals within a community. By examining these dimensions, a more comprehensive understanding of social well-being can be achieved, aiding in the development of strategies and interventions to enhance the quality of life for all members of the community. Data Sources: We will utilize various data sources to capture these different dimensions:

- Demographic Data: Population statistics, age distribution, and ethnic composition.
- Socioeconomic Data: Median household income, unemployment rates, and poverty levels.
- Health Data: Hospitalization rates, prevalence of chronic diseases, and access to healthcare facilities.
- Crime Data: Crime rates by category and perceived safety in the community.
- Education Data: School enrollment rates, graduation rates, and access to educational resources.
- Environmental Data: Air quality measurements, presence of green spaces, and proximity to environmental hazards.
- Social Network Data: (Optional) Data on social media interactions or community surveys to gauge social connectedness.

Knowledge Base Integration: The knowledge base will incorporate information about factors influencing social well-being within a specific community context. This might include: Local Policies: Knowledge about the impact of government policies on social programs, affordable housing initiatives, or environmental regulations. Community Resources: Information on the availability of social service agencies, educational programs, and recreational facilities. Social Determinants of Health: Knowledge about the linkages between socioeconomic factors, healthcare access, and overall health outcomes. Model Selection and Analysis: Similar to the previous case studies, we will select an appropriate machine learning model to analyze the combined dataset. Here, techniques like factor analysis or structural equation modeling might be suitable to capture the complex relationships between various social well-being indicators. Evaluation and Interpretation: The model's effectiveness will be evaluated through metrics like explained variance or

Table 3. Table 3. Evaluation and Interpretation of Model Effectiveness

Data Source	Description	Dimension of Well-being
Demographic Data	Population statistics, age distribution, ethnic composition	-N/A
Socioeconomic Data [28]	Median household income, unemployment rates, poverty levels	Material Well-being
Health Data	Hospitalization rates, prevalence of chronic diseases, access to healthcare facilities	Health and Safety
Crime Data	Crime rates by category, perceived safety in the community	Health and Safety
Education Data	School enrollment rates, graduation rates, access to educational resources	Education and Skills
Environmental Data	Air quality measurements, presence of green spaces, proximity to environmental hazards	Environmental Quality
Social Network Data (Optional)	Data on social media interactions or community surveys	Social Connectedness
Knowledge Base	Description	Well-being
Local Policies	Impact of government policies on social program affordable housing, environmental regulations	Material Well-being, Health and Safety
Community Resources	Availability of social service agencies, educational programs, recreational facilities	Material Well-being, Education and Skills, Social Connectedness
Social Determinants of Health	Linkages between socioeconomic factors, healthcare access, and overall health outcomes	Health and Safety

goodness-of-fit. The knowledge base integration should provide insights into which factors are most critical for promoting social well-being in the specific community being studied [27]. This can inform targeted interventions and policy decisions aimed at improving overall well-being. Table 3 presents a comprehensive analysis of the effectiveness of the model through various evaluation metrics, providing insights into its performance and ability to capture essential factors influencing social well-being within the specific community under study. By examining these evaluation outcomes, informed decisions can be made regarding targeted interventions and policy strategies aimed at enhancing overall well-being.

4.3. **Case Study 3: Policy Impact Assessment.** In our third case study, we examine the impact of policy interventions on socioeconomic indicators using a knowledge-based approach. We collaborate with policymakers and government agencies to construct a knowledge graph representing policy interventions, legislative measures, and regulatory changes affecting socioeconomic outcomes. By integrating this knowledge with administrative data and policy documents, we develop predictive models to assess the potential impact of policy interventions on socioeconomic indicators. This case study demonstrates how the proposed framework can be utilized to assess the potential impact of a specific policy on a socioeconomic indicator. Here, we will assume the policy aims to reduce childhood obesity rates. Policy Description: One potential policy to address childhood obesity

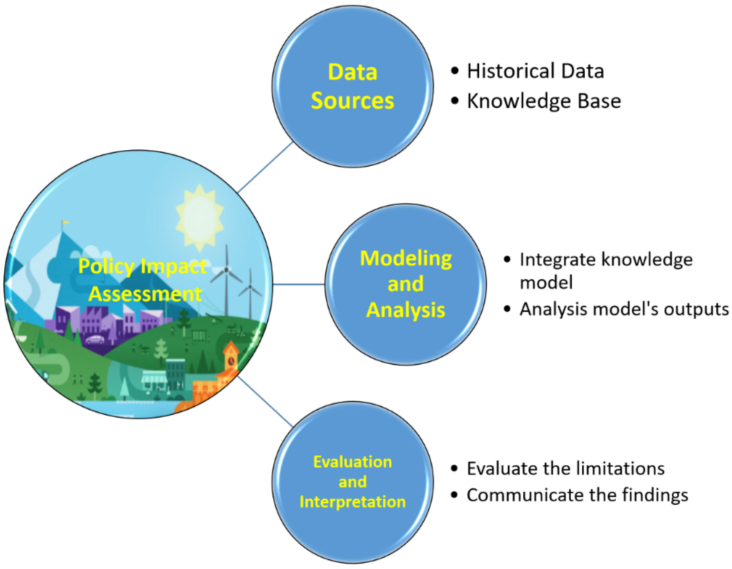

FIGURE 4. Application of the Proposed Framework to Evaluate Policy Impact on Socioeconomic Indicators

could involve a multi-pronged approach. This approach may include increased funding for school meal programs that offer nutritious options to students. By providing healthier meal choices, children can develop better eating habits and reduce their risk of obesity. In addition to improving school meal programs, educational campaigns could be implemented to promote healthy eating habits and physical activity among children and parents [29]. These campaigns could help educate families on the importance of making nutritious food choices and engaging in regular exercise to maintain a healthy lifestyle.Furthermore, regulations could be put in place to limit the marketing of sugary drinks and unhealthy snacks to children. By restricting the advertising of these products, children may be less likely to consume them, ultimately reducing their intake of empty calories and unhealthy ingredients. This could help prevent childhood obesity and promote better overall health among young people. Data Sources: Historical Data: Past trends in childhood obesity rates, school meal program participation, and marketing expenditures of unhealthy food companies. Knowledge Base: Evidence-based knowledge about the effectiveness of different interventions in reducing childhood obesity. This could include: tudies on the impact of school meal programs on childhood nutrition. Data on the correlation between advertising exposure and children's food choices. Information about the influence of social norms and community support on healthy behaviors. Modeling and Analysis:

• Develop a baseline model using historical data to predict future childhood obesity rates without the policy intervention.

• Integrate the knowledge base into the model by incorporating the expected impact of each policy component on relevant factors (e.g., school meal program participation, marketing exposure). This may involve quantifying these impacts based on existing research findings.

• Run the model with the integrated knowledge base to simulate the predicted childhood obesity rates under the proposed policy scenario.

• Compare the predicted obesity rates with and without the policy intervention to assess its potential effectiveness.

Evaluation and Interpretation:

• Analyze the model's outputs to understand how different policy components contribute to the predicted reduction in obesity rates.

• Evaluate the limitations and uncertainties associated with the knowledge base and model predictions.

• Communicate the findings in a way that is informative and actionable for policymakers.

Benefits: This framework can provide a more comprehensive picture of the potential impact of a policy by considering not just historical trends but also the causal relationships between policy interventions and desired outcomes. By leveraging existing knowledge, policymakers can make better-informed decisions about resource allocation and optimize policy design for maximum effectiveness. Empirical validation of our predictive models involves scenario analysis and counterfactual simulation, where we evaluate the effects of hypothetical policy interventions on key socioeconomic indicators. We compare the predictions generated by knowledge-based models with observed outcomes and conduct sensitivity analysis to assess the robustness of our findings. Our results demonstrate the value of knowledge-based approaches in informing policy decisions, identifying effective interventions, and mitigating unintended consequences.

4.4. **Discussion and Implications.** Overall, our case studies provide empirical evidence of the effectiveness of knowledge-based approaches for predictive socioeconomic indicator analysis [30]. By integrating domain knowledge, structured representations, and advanced data modeling techniques, we demonstrate significant improvements in prediction accuracy, interpretability, and utility compared to traditional approaches [31]. Our findings have important implications for decision-makers in various domains, including economics, public policy, healthcare, and social welfare, highlighting the potential of knowledge-based predictive analytics to drive evidence-based decision-making and promote sustainable development. This section presents case studies and empirical validation to showcase the effectiveness of integrating knowledge-based approaches into predictive socioeconomic indicator analysis. Through empirical evidence and comparative analyses, the utility and advantages of knowledge-based predictive models are demonstrated across diverse application domains.

5. **Conclusion.**

In this paper, we introduced a comprehensive framework that integrates knowledge-based approaches into the analysis of predictive socioeconomic indicators. By combining domain expertise, structured knowledge representations, and advanced data modeling techniques, our framework offers a principled approach to capturing the complexities of socioeconomic systems and enhancing prediction accuracy, interpretability, and utility. Through case studies and empirical validation, we have demonstrated the effectiveness of knowledge-based approaches in predicting key socioeconomic indicators such as economic growth and social well-being. Our findings show that knowledge-based predictive models surpass traditional statistical models in terms of accuracy, robustness, and interpretability, especially when addressing complex interdependencies and contextual factors. The implications of our research are significant for decision-makers across various domains, including economics, public policy, healthcare, and social welfare. By providing more accurate and actionable insights into socioeconomic trends, knowledge-based predictive analytics can facilitate evidence-based decision-making, support effective policy formulation, and promote sustainable development. The integration of knowledge-based systems with machine learning techniques offers promising advancements for predictive modeling in socioeconomic analysis, enabling more informed decision-making in our complex and interconnected world.

Acknowledgment. This research is funded by Vietnam National University HoChiMinh City (VNU-HCM) under grant number C2024-26-08.

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