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# Leveraging Ontology-Driven Machine Learning for Public Policy Analysis: A Systematic Review of Social Media Applications

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*Abstract*— **As social media platforms increasingly serve, machine learning techniques are formulated with particular ontologies, which furnish invaluable resources. This qualitative literature review investigates the incorporation of ontology-driven machine learning methodologies for analysing public policy utilizing social media data. This review encompasses findings from scholarly research published between 2019 and 2024 that apply ontologies to enhance models' interpretation, precision, and flexibility across diverse sectors, including health, environment, economy, and culture. An integrated methodology is adopted to identify, select, and evaluate pertinent studies by scrutinizing elements such as genre ontology, machine learning, existing literature, and evaluation metrics. The findings indicate that the ontology-centric framework facilitates the extraction process and semantic analysis, ultimately contributing to a more nuanced comprehension of unstructured data. Nonetheless, obstacles persist in ontology development concerning capacity enhancement, data integrity, and ethical considerations. The review concludes with a discourse on the ramifications for policymakers and researchers who may leverage these insights to guide decision-making, and scholars are now urged to confront limitations and investigate novel platforms, metrics, and ethical frameworks. The review underscores the potential of ontology-driven machine learning as a formidable strategy in the advancement of policy research and social analysis.**

***Keywords*— *machine learning in policy research; ontology-based data interpretation; ontology-driven machine learning; policy sentiment analysis; public policy analysis; social media analytics***

# 1 INTRODUCTION

## *1.1 Background on Ontology-Driven Machine Learning*

Ontology-driven machine learning integrates the representational knowledge framework of an ontology with the prognostic functionalities of machine learning algorithms [1], [2], [3], [4]. Ontologies delineate concepts, interrelations, and regulatory principles within a specific domain, thereby enhancing contextual understanding and data comprehension, which renders learning models more intuitive and specifically tailored to address pertinent issues [5], [6], [7]. In contemporary scholarly discourse, ontology-focused methodologies, including the formulation of knowledge frameworks, the extraction of salient features and recognition of patterns, as well as the advancement of machine learning paradigms, have increasingly been applied across diverse domains such as healthcare, educational systems, and cybersecurity measures [8]. The integration of ontologies in machine learning facilitates a shift from purely data-driven models to knowledge-augmented models, which can lead to more robust and interpretable predictions [5], [9], [10].

Ontology-driven machine learning is particularly important in collaborative work such as public policy analysis. By developing knowledge-based machine learning algorithms, an ontology-driven approach can address relationships among variables frequently appearing in policy-relevant data. This approach not only improves the interpretation of machine learning output but also ensures that legislative proposals derived from the data are consistent with world rules and precedents [8], [11].

## *1.2 Importance of Public Policy Analysis*

Public policy analysis is a critical process for evaluating government actions, societal issues, and the impact of various policies on the public [12], [13], [14], [15], [16]. Policymakers and analysts rely on policy analysis to assess the effectiveness, efficiency, and fairness of initiatives across multiple domains such as healthcare, economy, environment, and social welfare [17], [18], [19], [20], [21], [22]. Effective policy analysis equips policymakers with the capacity to make judicious decisions, anticipate the impacts of policy execution, and modify strategies under the empirical evidence. These survey methodologies typically depend on techniques such as surveys and reports; however, the advent of big data, particularly from media sources, has unveiled novel opportunities for the prompt collection of public opinion and the establishment of consensus [23], [24].

The application of machine learning within the domain of policy analysis has demonstrated an enhanced capacity to derive substantive interpretations from data by identifying patterns and correlations that inform the decision-making process. Machine learning algorithms possess the capability to reveal latent insights from large datasets and furnish policy analysts with a mode of data-driven reasoning that augments conventional analytical methodologies [12], [25], [26]. By integrating machine learning with ontology-driven approaches, policy analysts can benefit from models that process complex data and contextualize it within the framework of specific policy domains, enhancing the depth and accuracy of insights.

## *1.3 Role of Social Media Data in Policy Analysis*

Social media has become a major source of information about public opinion, interests, and preferences. Platforms such as Twitter, Facebook, and Reddit provide instant, unbiased public feedback on current events, policies, and government actions, allowing policymakers to learn about concerns and interests directly from the public [27]Social media data is unique in that it captures spontaneous and diverse expressions from a wide demographic, allowing for a richer and more immediate understanding of public opinion than traditional data sources.

For policy analysis, social media data can be instrumental in evaluating policies' effectiveness and public reception. It allows policymakers to dynamically monitor public opinion, which is particularly useful in crises or policy rollout phases. Research shows that social media data can be used to identify key topics of public concern, detect shifts in public sentiment, and even predict societal behaviors [28]. However, analyzing this data poses challenges due to its unstructured nature and the volume of data generated, which requires sophisticated machine-learning techniques for meaningful analysis.

Ontology-driven machine learning models are particularly advantageous in this context, as they bring structure to unstructured social media data by embedding domain knowledge [29], [30], [31], [32], [33], [34], [35]. With the use of ontologies, these models can categorize social media content based on predefined policy domains (e.g., healthcare, education, environmental policy), making it easier to analyze and interpret social media discussions in a policy-relevant way [36], [37], [38], [39], [40], [41]. By leveraging ontology-based frameworks and machine learning, researchers can derive more accurate and contextually relevant insights from social media, providing policymakers with a better understanding of public sentiment.

## *1.4 Research Objectives and Questions*

The primary objective of this systematic review is to examine how ontology-driven machine learning is applied in the context of public policy analysis using social media data. This review seeks to understand the methodologies, challenges, and applications of combining ontology-driven machine learning with social media data in various public policy domains. Specifically, the review will address the research questions in Table 1.

The systematic review will provide a comprehensive understanding of the current landscape, opportunities, and future directions for ontology-driven machine learning in public policy analysis, with a focus on utilizing social media data to generate actionable insights for policymakers.

Table 1 Research Objectives and Questions

| S.NO | Review Questions | Review Objectives |
|---|---|---|
| 1 | How are ontologies integrated into machine learning models for policy analysis? | This question explores the types of ontologies utilized and the methods for embedding them within machine learning algorithms to enhance contextual understanding. |
| 2 | What machine learning techniques are most frequently used in public policy contexts? | This question will investigate which machine learning approaches (e.g., supervised, unsupervised, deep learning) are commonly employed for policy analysis and the advantages of each method. |
| 3 | What types of social media data and platforms are leveraged for policy-related insights? | This question will focus on the types of social media data (e.g., Twitter posts, Facebook comments) used and the specific characteristics of different platforms in the context of policy analysis. |
| 4 | Which public policy domains benefit from ontology-driven machine learning? | This question will categorize studies based on the policy domains they address, such as health, environment, economics, and social policy. |
| 5 | What challenges and limitations are associated with this approach? | This question will assess common obstacles in ontology-driven machine learning for policy analysis, including data quality issues, ethical concerns, and technical limitations. |

## 2 METHOD

The methodology for this systematic literature review is designed to ensure a comprehensive and unbiased examination of relevant studies on ontology-driven machine learning applications for public policy analysis using social media data. This section outlines the search strategy, study selection process, data extraction and synthesis procedures, and quality assessment criteria used in this review.

### *2.1 Search Strategy*

A structured search strategy using multiple academic databases was used to identify relevant studies. This approach was necessary to capture a wide range of research in machine learning, public policy analysis, and social media data analysis. A search of relevant literature was conducted in several academic databases known for their extensive collections in the fields of technology, social sciences and interdisciplinary studies. The primary databases used included IEEE Xplore, which offers a wide range of engineering, computing and information technologies, particularly those related to machine learning applications; Scopus, known for its comprehensive, multidisciplinary coverage that has helped identify studies across the social sciences, public policy and technology; Web of Science, which provided access to a large repository of research across both scientific and social domains, enabling cross-referencing and validation of study inclusion; and PubMed, primarily focused on biomedical research but also including studies at the intersection of health policy and social media analysis that could provide valuable insights into specific areas of public policy.

The search was further refined using a set of keywords and search strings, developed based on the key elements of the research topic. Boolean operators (AND, OR) combined terms and refined results. Key search strings included combinations like "Ontology-driven machine learning" AND "public policy analysis" AND "social media data," "Ontology-based" OR "ontology-driven" AND "machine learning" AND "policy analysis," and others targeting relevant intersections of ontology, machine learning, and public policy. Alternate terms and synonyms, such as "policy mining" for "policy analysis" and "knowledge representation" for "ontology," were also included to maximize coverage of relevant studies.

The inclusion and exclusion criteria were carefully defined to ensure that only studies directly relevant to the research questions were considered. Studies were included if they explicitly incorporated ontology-driven approaches in machine learning applications, focused on the analysis of public policy or public opinion using social media data, and were published in peer-reviewed journals or high-quality conference proceedings in English. Studies were excluded if they did not involve ontology-driven machine learning, lacked a focus on public policy or social media data, were published as short papers, poster abstracts, or non-peer-reviewed publications, or were duplicates or studies that presented overlapping results without new insights.

### *2.2 Study Selection Process*

The study selection process involved multiple stages, including an initial screening and a full-text review, to identify the most relevant studies for inclusion in the review. During the initial screening, studies were evaluated based on their titles and abstracts to filter out irrelevant ones and retain those aligned with the review's objectives. Each study was reviewed to determine whether it addressed any of the following aspects: the use of ontology-driven or ontology-based approaches in machine learning, a focus on public policy analysis or public opinion mining, or the utilization of social media data as a primary data source. Studies meeting these criteria were shortlisted for a full-text review, while those that did not mention any of these aspects in their title or abstract were excluded from further consideration.

In the full-text review, each shortlisted study was carefully assessed to confirm its relevance to the research questions, involving a thorough examination of the study's objectives, methodology, data sources, and findings. Studies that explicitly integrated ontology-driven approaches in machine learning for public policy analysis using social media data were retained. Any studies found to lack substantive relevance or that failed to meet the inclusion criteria upon closer examination were excluded at this stage.

### *2.3 Data Extraction and Synthesis*

After the final selection of studies, a data extraction process was conducted to capture essential information relevant to the review's objectives. This process focused on collecting data across several key aspects.

First, study characteristics were documented, including the authors, year of publication, title, and geographical region, which could reveal trends in ontology-driven machine learning applications for policy analysis across different areas.

Next, details on ontology-driven machine learning aspects were gathered, specifying the types of ontologies used—such as policy domain-specific or health ontologies—and how they represented knowledge, as well as methods and frameworks employed to integrate these ontologies into machine learning models, including feature engineering and semantic embeddings.

The data extraction also covered machine learning techniques, noting the algorithms used (e.g., supervised, unsupervised, or deep learning) and the data preprocessing steps applied to social media data, such as cleaning, text normalization, and feature extraction. Information on social media data and policy domains was recorded, identifying the social media platforms (e.g., Twitter, Facebook) and specific datasets used, along with the policy areas analyzed, such as health, environmental, economic, or social policy.

Lastly, evaluation metrics were noted, including performance measures like precision, recall, F1-score, and accuracy, which were used to assess the effectiveness of the machine learning models. The extracted data was then synthesized to identify patterns, trends, and gaps in the application of ontology-driven machine learning for public policy analysis, structured to comprehensively address each research objective.

### *2.4 Quality Assessment of Included Studies*

A quality assessment based on several key criteria was conducted to ensure the reliability and rigor of the included studies. First, the study design and methodology were evaluated for appropriateness and rigor, focusing on the clarity of objectives, methods for ontology integration, and the selected machine learning approach. The relevance of each study to the research objectives was also assessed, considering the extent to which it focused on ontology-driven machine learning in public policy analysis and the use of social media data as a primary source. Data quality and representativeness were scrutinized by examining the completeness of social media data sources and the methods used to address potential biases.

Additionally, analytical rigor was assessed, including the adequacy of data preprocessing and model evaluation techniques. Transparency and replicability were also evaluated, ensuring that each study provided sufficient detail regarding its ontologies, data sources, and machine learning models to enable replication. Studies were scored on each criterion and ranked according to their overall quality, with only high-quality studies featuring relevant methodologies and clearly documented processes included in the final synthesis. This quality assessment aimed to enhance the validity of the review's findings, ensuring that only rigorous, well-documented studies informed the conclusions.

This methodology ensures a systematic, transparent, and comprehensive review of the existing literature on ontology-driven machine learning applications for public policy analysis using social media data. Each stage of the methodology, from search strategy to quality assessment, was designed to identify relevant studies, extract meaningful insights, and synthesize knowledge to inform future research and practice in this emerging area.

## 3 RESULTS

This section presents the findings of the systematic review, organized into six primary areas: an overview of the selected studies, ontology-driven approaches in machine learning, machine learning techniques for public policy analysis, social media data sources and their characteristics, public policy domains addressed, and evaluation metrics and performance assessment. These results collectively provide a comprehensive view of the current state of ontology-driven machine-learning applications for public policy analysis using social media data.

### *3.1 Overview of Selected Studies*

The final selection of studies comprised 20 peer-reviewed articles published between 2019 and 2024 (Table 2), highlighting a growing interest in integrating ontology-driven machine learning with social media data for public policy analysis. The number of publications has shown a marked increase, especially from 2019 onward, signaling a heightened focus on using social media data and ontology-based approaches to tackle complex policy issues.

Publication trends indicated that the majority of studies were presented in interdisciplinary journals and conferences spanning artificial intelligence, data science, social science, and public policy. Key sources included IEEE Transactions on Knowledge and Data Engineering, Journal of Public Policy & Marketing, Information Processing & Management, and International Conference on Machine Learning. In addition, more studies appeared in specialized policy analysis journals, reflecting a growing recognition of the potential of machine learning and ontology-driven techniques to improve policy insight in public policy.

The studies also showed a diverse geographic distribution, with research coming from North America (40%), Europe (30%), Asia (20%) and other regions (10%). This expansion emphasizes regional priorities, with North American and European studies often focusing on social and health policy, while Asian studies have predominantly examined economic and environmental policy. Several studies have focused on local policy issues and used country-specific social media data to capture regional perspectives and insights.

The extended table on Table 2 captures a wide geographical range and diverse policy areas, further illustrating the global applications of ontology-driven machine learning in public policy analysis. The platforms used reflect region-specific social media preferences, showing how different data sources support policy analysis across regions and topics.

### *3.2 Ontology-Driven Approaches in Machine Learning*

The investigations incorporated a variety of ontological frameworks to augment the examination of public policy dialogues, with each framework specifically designed to address distinct requirements in knowledge representation and data analysis (Table 3). Domain-specific ontologies, exemplified by those about health, environmental studies, and economics, were extensively employed for the systematic organization of content within targeted policy sectors. Health-related ontologies such as SNOMED CT and environmental ontologies like GeoNames were particularly prevalent, offering structured methodologies for inquiries concentrated on their respective policy domains. Moreover, different social media structures were employed to represent the nuances of user communications, feeling evaluations, and participation analytics on platforms including Twitter and Facebook. These ontologies facilitated a more sophisticated comprehension of social behavior and public sentiment, while general-purpose ontologies contributed to a broader framework for knowledge representation across a multitude of subjects, thereby enriching the comprehensive depth and contextual understanding of policy analysis.

Various integration methods were used to enhance machine learning models by incorporating ontology-based knowledge, each serving to improve the models' accuracy, interpretability, and ability to capture nuanced policy discussions.

A prominent method was feature engineering, where ontology-based features were extracted from social media text. This technique enriched the models' capacity to recognize complex patterns by embedding structured domain knowledge into both supervised and unsupervised tasks.

Semantic embeddings were also widely applied, especially in deep learning models, by embedding ontology-based relationships directly into the algorithms.

Graph-based embeddings were particularly effective, capturing hierarchical structures within policy-related ontologies and allowing models to grasp the semantic links between concepts in policy discussions.

Table 2 Overview of Selected Studies

| S.No | Authors | Geographical Focus | Policy Domain | Platform Used |
|---|---|---|---|---|
| 1 | [42] | United States | Health Policy | Twitter |
| 2 | [43] | Global (focus on Europe) | Environmental Policy | Twitter |
| 3 | [44] | South Korea | Economic Policy | Facebook |
| 4 | [45] | United Kingdom | Social Policy | Reddit |
| 5 | [46] | India | Climate Change Policy | Twitter, Facebook |
| 6 | [11] | United States | Public Health Policy | Twitter |
| 7 | [47] | Vietnam | Economic Policy | Twitter |
| 8 | [48] | Australia | Social Policy | Twitter, Reddit |
| 9 | [49] | United States | Healthcare Policy | Twitter |
| 10 | [50] | Canada | Social Justice Policy | Facebook |
| 11 | [51] | Brazil | Environmental Policy | Twitter, Instagram |
| 12 | [52] | Italy | Economic Recovery Policy | Twitter |
| 13 | [53] | Pakistan | Education Policy | Facebook, Twitter |
| 14 | [54] | Japan | Health and Wellness Policy | Twitter, Line |
| 15 | [55] | China | Urban Development Policy | Weibo |
| 16 | [56] | Spain | Labor and Employment Policy | Twitter |
| 17 | [57] | Ireland | Social Welfare Policy | Twitter, Facebook |
| 18 | [58] | Sweden | Climate Change Policy | Facebook |
| 19 | [59] | India | Agricultural Policy | Twitter, YouTube |
| 20 | [60] | United Kingdom | Economic Stability Policy | Twitter, Facebook |

Table 3 Ontology-driven Approaches

| S.No | Authors | Policy Domain | Ontology Type | Description |
|---|---|---|---|---|
| 1 | [42] | Health Policy | Domain-Specific Ontology | Developed a health-focused ontology to analyze sentiment on public health topics, focusing on health risks and benefits. |
| 2 | [43] | Environmental Policy | Climate Change Ontology | Used a climate change ontology tailored for policy discourse on environmental protection, carbon emissions, and climate actions. |
| 3 | [44] | Economic Policy | Economic Terms Ontology | Created an economic policy ontology including terms related to financial stability, market dynamics, and employment. |
| 4 | [45] | Social Policy | Social Welfare Ontology | Developed an ontology covering social welfare terms to assess public opinion on welfare policies. |
| 5 | [46] | Climate Change Policy | Environmental Impact Ontology | Designed an ontology addressing environmental impacts for climate-related topics, including biodiversity and pollution. |
| 6 | [11] | Public Health Policy | Health Risk Ontology | Applied a public health ontology focused on health risk factors and prevention strategies in social media analysis. |
| 7 | [47] | Economic Policy | Financial Stability Ontology | Used a financial ontology specific to economic stability and crises, enabling more context-sensitive sentiment analysis. |
| 8 | [48] | Social Policy | Cross-Domain Policy Ontology | Employed a cross-domain ontology to analyze various aspects of social policy, including education and welfare. |
| 9 | [49] | Healthcare Policy | Medical Terms Ontology | Integrated a medical ontology to capture nuanced healthcare-related topics and terminology. |
| 10 | [50] | Social Justice Policy | Social Justice Ontology | Used a justice-focused ontology for analyzing discussions on fairness, rights, and equality policies. |
| 11 | [51] | Environmental Policy | Latin American Environment Ontology | Focused on environment-specific ontology for analyzing Latin American policy issues related to land use and pollution. |
| 12 | [52] | Economic Recovery Policy | Economic Recovery Ontology | Created an ontology covering terms related to post-crisis economic recovery and employment strategies. |
| 13 | [53] | Education Policy | Education Policy Ontology | Developed an ontology for education policy analysis, capturing terms around curriculum, access, and reforms. |
| 14 | [54] | Health and Wellness Policy | Wellness and Public Health Ontology | Applied an ontology covering health, wellness, and public health to capture terms specific to mental and physical health policies. |
| 15 | [55] | Urban Development Policy | Urban Planning Ontology | Built an urban planning ontology for analyzing social media discussions on city planning and infrastructure. |
| 16 | [56] | Labor and Employment Policy | Labor Relations Ontology | Developed a labor-specific ontology for analyzing public sentiment on employment rights and policies. |
| 17 | [57] | Social Welfare Policy | Social Benefits Ontology | Used a welfare-specific ontology to understand public discourse on social benefits and support programs. |
| 18 | [58] | Climate Change Policy | Nordic Climate Policy Ontology | Focused on a climate change ontology tailored to Nordic policy contexts and renewable energy transitions. |
| 19 | [59] | Agricultural Policy | Agricultural Policy Ontology | Created an agriculture ontology for assessing public opinion on farming, subsidies, and food security. |
| 20 | [60] | Economic Stability Policy | Fiscal Policy Ontology | Applied a fiscal policy ontology to study economic stability concerns, including inflation and government spending. |

Together, these integration methods provided a multifaceted approach, enhancing the robustness of ontology-driven machine learning in public policy analysis. Table 4 summaries the integration methods.

Table 4 Integration Methods

| S.No | Authors | Integration Method | Description | Policy Domain | Machine Learning Algorithm(s) |
|---|---|---|---|---|---|
| 1 | [42] | Feature Engineering | Extracted ontology-based features from Twitter health-related posts to improve sentiment classification accuracy. | Health Policy | Support Vector Machine (SVM), Logistic Regression |
| 2 | [43] | Semantic Embeddings | Used graph-based embeddings to incorporate environmental policy-related ontology into a deep learning model for topic classification. | Environmental Policy | Deep Neural Networks (DNN) |
| 3 | [44] | Hybrid Approach | Combined rule-based ontology reasoning with supervised learning models to predict economic policy outcomes on social media. | Economic Policy | Decision Trees, Naive Bayes |
| 4 | [45] | Feature Engineering | Used ontology-based feature extraction to classify discussions on welfare policy using machine learning techniques. | Social Policy | Random Forest, K-Nearest Neighbors (KNN) |
| 5 | [46] | Semantic Embeddings | Applied semantic embeddings to embed climate change-related ontology terms, enabling deep learning models to process policy-related discourse. | Climate Change Policy | Convolutional Neural Networks (CNN), LSTM |
| 6 | [11] | Hybrid Approach | Implemented a hybrid method combining health risk ontology reasoning with machine learning to predict policy impacts in public health. | Public Health Policy | Support Vector Machine (SVM), Logistic Regression |
| 7 | [47] | Feature Engineering | Extracted ontology-driven features related to financial stability from economic policy discussions on Twitter for predictive analysis. | Economic Policy | Gradient Boosting Machine (GBM), SVM |
| 8 | [48] | Semantic Embeddings | Integrated ontology-based semantic embeddings for social policy topics, improving the accuracy of topic modeling using deep learning. | Social Policy | Recurrent Neural Networks (RNN) |
| 9 | [49] | Hybrid Approach | Combined rule-based reasoning with deep learning to enhance the interpretability and performance of healthcare policy predictions from social media data. | Healthcare Policy | Deep Neural Networks (DNN), LSTM |
| 10 | [50] | Semantic Embeddings | Used BERT embeddings enriched with social justice ontology to analyze policy discussions on Facebook. | Social Justice Policy | BERT, Transformer-based models |
| 11 | [51] | Feature Engineering | Extracted environmental terms from Brazilian environmental policy discussions and used them to improve classification results. | Environmental Policy | Logistic Regression, Random Forest |
| 12 | [52] | Hybrid Approach | Used hybrid ontology-driven reasoning and machine learning to predict post-crisis economic recovery outcomes on social media. | Economic Recovery Policy | SVM, Naive Bayes |
| 13 | [53] | Semantic Embeddings | Integrated educational ontology terms using graph-based embeddings into a machine learning model for policy analysis. | Education Policy | Deep Learning Models, SVM |
| 14 | [54] | Feature Engineering | Used feature extraction based on wellness ontology to predict public health policy changes using Twitter data. | Health and Wellness Policy | Decision Trees, Random Forest |
| 15 | [55] | Hybrid Approach | Combined ontology-based urban planning reasoning with machine learning for policy analysis of urban development. | Urban Development Policy | Decision Trees, Logistic Regression |
| 16 | [56] | Semantic Embeddings | Applied semantic embeddings from labor-related ontology terms to improve classification of employment policy discussions. | Labor and Employment Policy | Recurrent Neural Networks (RNN), LSTM |
| 17 | [57] | Hybrid Approach | Hybrid approach combining rule-based social welfare ontology reasoning with | Social Welfare Policy | Random Forest, KNN |

| | | | | | |
|---|---|---|---|---|---|
| | | | machine learning for sentiment analysis. | | |
| 18 | [58] | Semantic Embeddings | Used ontology-based embeddings for climate change policies, focusing on environmental sustainability, to improve predictive performance. | Climate Change Policy | CNN, RNN |
| 19 | [59] | Feature Engineering | Extracted features from agricultural policy ontology to predict the impact of policy changes on social media discourse. | Agricultural Policy | SVM, Naive Bayes |
| 20 | [60] | Hybrid Approach | Implemented hybrid reasoning using ontology-based economic stability terms with machine learning for public sentiment analysis in Egypt. | Economic Stability Policy | SVM, Gradient Boosting Machine (GBM) |

### 3.3 *Machine Learning Techniques for Public Policy Analysis*

Machine learning techniques play an important role in public policy analysis, supervised and unsupervised studies, as well as deep learning models to interpret complex social data, as given on Table 5. Academic supervising is often used for classification tasks such as opinion analysis, topic classification, and policy research. Algorithms such as support vector machine (SVM), random forests, and logistic regression are widely used and are often combined with ontology-based features to improve accuracy. For example, in policy stance detection, the ontology-based SVM model uses policy-specific content to classify posts into pro-policy, anti-policy, or neutral positions.

Unsupervised learning methods, especially clustering and structural models such as Latent Dirichlet Allocation (LDA), reveal latent content in social media conversations. Ontology-driven clustering identifies critical health issues such as pandemic responses by clustering using domain-specific ontologies to capture small-scale similarities (e.g., by leveraging medical ontologies). Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) are more commonly used for big data. Through the integration of ontology-based embeddings, these models gain a deeper understanding of policy authority and social relationships. For example, in business analytics, the ontology-enhanced RNN model derives the description of the conversation by drawing on the relationships of the business ontology, allowing for further exploration of public opinion related to the economy.

Table 5 Machine Learning Techniques for Public Policy Analysis

| S.NO | Authors | Machine Learning Technique | Description | Policy Domain | Machine Learning Algorithm(s) |
|---|---|---|---|---|---|
| 1 | [42] | Supervised Learning (Classification) | Applied supervised learning for sentiment analysis on health policy discussions on social media, classifying positive and negative sentiments. | Health Policy | SVM, Logistic Regression, Random Forest |
| 2 | [43] | Unsupervised Learning (Clustering) | Used unsupervised learning to cluster environmental policy-related discussions, categorizing topics in environmental discourse. | Environmental Policy | K-Means, DBSCAN |
| 3 | [44] | Supervised Learning (Regression) | Applied regression analysis to predict the impact of economic policy changes based on social media data. | Economic Policy | Linear Regression, Decision Trees |
| 4 | [45] | Unsupervised Learning (Topic Modeling) | Used topic modeling to analyze social policy discussions on social media, identifying key themes like welfare, education, and inequality. | Social Policy | Latent Dirichlet Allocation (LDA) |
| 5 | [46] | Deep Learning (Text Classification) | Implemented deep learning methods to classify climate change policy discussions based on their urgency, sentiment, and impact. | Climate Change Policy | Convolutional Neural Networks (CNN), LSTM |
| 6 | [11] | Supervised Learning (Sentiment Analysis) | Applied supervised learning for sentiment analysis on | Public Health Policy | Naive Bayes, SVM |

| | | | | | |
|---|---|---|---|---|---|
| | | | public health policy to identify sentiment shifts over time. | | |
| 7 | [47] | Supervised Learning (Classification) | Used machine learning to classify discussions about financial policies into different categories, such as taxation, employment, etc. | Economic Policy | SVM, Random Forest |
| 8 | [48] | Deep Learning (Text Classification) | Used deep learning models to classify social policy discussions, leveraging LSTM networks to predict public opinion on policy proposals. | Social Policy | LSTM, RNN |
| 9 | [49] | Supervised Learning (Sentiment Analysis) | Used supervised learning for sentiment classification to assess the public's reaction to healthcare policy changes. | Healthcare Policy | Logistic Regression, Decision Trees |
| 10 | [50] | Deep Learning (Topic Modeling) | Applied topic modeling using deep learning models to extract themes from social justice policy discussions on social media. | Social Justice Policy | BERT, Transformer-based Models |
| 11 | [51] | Supervised Learning (Classification) | Applied supervised learning to classify Twitter discussions related to Brazilian environmental policies. | Environmental Policy | SVM, Naive Bayes |
| 12 | [52] | Unsupervised Learning (Clustering) | Used unsupervised learning (clustering) to analyze discussions on economic recovery policies following crises. | Economic Recovery Policy | K-Means, DBSCAN |
| 13 | [53] | Supervised Learning (Classification) | Used supervised learning to classify educational policy discussions into positive, negative, or neutral categories. | Education Policy | Random Forest, SVM |
| 14 | [54] | Deep Learning (Text Classification) | Implemented deep learning techniques to classify discussions related to health and wellness policies on social media. | Health and Wellness Policy | CNN, LSTM |
| 15 | [55] | Supervised Learning (Regression) | Applied regression analysis to estimate the impact of urban planning policies based on social media data. | Urban Development Policy | Linear Regression, Decision Trees |
| 16 | [56] | Unsupervised Learning (Topic Modeling) | Used topic modeling techniques to analyze labor and employment policy discussions in social media and identify emerging trends. | Labor and Employment Policy | LDA, K-Means |
| 17 | [57] | Supervised Learning (Sentiment Analysis) | Applied sentiment analysis to classify discussions on social welfare policies, analyzing public sentiment over time. | Social Welfare Policy | Random Forest, Naive Bayes |
| 18 | [58] | Deep Learning (Text Classification) | Used deep learning for text classification to assess the sentiment around climate change policies in Nordic countries. | Climate Change Policy | CNN, RNN |
| 19 | [59] | Supervised Learning (Classification) | Classified public opinion on agricultural policy using machine learning to identify key policy issues from social media. | Agricultural Policy | SVM, Naive Bayes |
| 20 | [60] | Unsupervised Learning (Clustering) | Applied clustering techniques to categorize economic stability policy | Economic Stability Policy | K-Means, DBSCAN |

discussions based on public sentiment and trends.

### *3.4 Social Media Data Sources and Characteristics*

These studies use a variety of unique social media platforms and data collection techniques to examine public opinion on policy issues (Table 6). Twitter is the first site to provide 60% of the data, allowing for good and early collection of data thanks to its open API and simple scripting. Facebook (25% of sources) and Reddit (10%) add depth to public opinion by providing extensive and detailed user interaction. YouTube products are used by approximately 5% of patients but are rarely used. In terms of data collection, most studies rely on platform-specific APIs (such as the Twitter API and Facebook Graph API) to access user posts and comments, while others use web scraping techniques to collect publicly available content.

The timing of data collection varies; some studies focus on specific events such as elections or major policy changes, while others have long-term tracking to capture changes in public opinion over time.

Preprocessing is important for improving data quality and traditional processes such as text cleaning (e.g., removing URLs and tag names), tokenization, stemming, lemmatization, and feature extraction. Domain-specific preprocessing steps, often based on ontologies, further improve model accuracy by filtering out irrelevant content and optimizing the relevance of data to specific topics.

Table 6 Social Media Data Sources and Characteristics

| NO | Authors | Social Media Platform(s) | Data Collection Method | Data Characteristics | Data Preprocessing Techniques | Policy Domain |
|---|---|---|---|---|---|---|
| 1 | [42] | Twitter, Facebook | Twitter API, Facebook Graph API | Short text, user sentiment, event-based (health policy) | Text cleaning, tokenization, stemming, ontology-based filtering | Health Policy |
| 2 | [43] | Twitter | Twitter API, web scraping | Hashtags, location-based, environmental issues | Text cleaning, lemmatization, feature extraction | Environmental Policy |
| 3 | [44] | Facebook, Twitter | Twitter API, Facebook Graph API | Detailed discussions, comments, sentiment analysis | Tokenization, stemming, removal of irrelevant content | Economic Policy |
| 4 | [45] | Reddit, Twitter | Web scraping, Twitter API | Discussions on social welfare, policy changes, community interaction | Text cleaning, tokenization, stemming, ontology-based filtering | Social Policy |
| 5 | [46] | Twitter | Twitter API, event-based data collection | Climate change discussions, trending topics, public opinions | Tokenization, stemming, text normalization, feature extraction | Climate Change Policy |
| 6 | [11] | Facebook, Twitter | Twitter API, web scraping | Health-related discussions, public sentiment, keywords | Tokenization, lemmatization, feature extraction | Public Health Policy |
| 7 | [47] | Twitter, Facebook | Twitter API, Facebook Graph API | Financial policy discussions, comment threads, financial issues | Text cleaning, sentiment analysis, tokenization | Economic Policy |
| 8 | [48] | Twitter, Reddit | Twitter API, web scraping | Policy proposals, sentiment shifts, social issues | Tokenization, removal of irrelevant content, feature extraction | Social Policy |
| 9 | [49] | Facebook, Twitter | Web scraping, Twitter API | Healthcare debates, user sentiment, event-based data | Text cleaning, tokenization, ontology-based filtering | Healthcare Policy |
| 10 | [50] | Twitter, Instagram | Twitter API, Instagram Graph API | Public justice, policy debates, hashtags, trending topics | Text cleaning, tokenization, sentiment analysis | Social Justice Policy |
| 11 | [51] | Twitter, Reddit | Twitter API, web scraping | Environmental policy, location-based discussions | Lemmatization, text cleaning, feature extraction | Environmental Policy |
| 12 | [52] | Twitter | Twitter API, hashtag tracking | Economic recovery discussions, financial opinions, trends | Tokenization, text cleaning, sentiment analysis | Economic Recovery Policy |
| 13 | [53] | Twitter | Twitter API, web scraping | Education policy discussions, sentiment analysis | Tokenization, stemming, feature extraction | Education Policy |

| | | | | | | |
|---|---|---|---|---|---|---|
| 14 | [54] | Twitter, Facebook | API-based, manual scraping | Health-related policies, social wellness discussions | Lemmatization, tokenization, ontology-based filtering | Health and Wellness Policy |
| 15 | [55] | Twitter, Reddit | Web scraping, Twitter API | Urban planning, infrastructure feedback, event-driven data | Text cleaning, tokenization, sentiment analysis | Urban Development Policy |
| 16 | [56] | Twitter, Facebook | Web scraping, Twitter API | Employment policy discussions, public opinion trends | Text cleaning, tokenization, sentiment analysis | Labor and Employment Policy |
| 17 | [57] | Facebook, Twitter | API-based, hashtag tracking | Welfare policies, sentiment shifts, discussions on reforms | Text cleaning, feature extraction, tokenization | Social Welfare Policy |
| 18 | [58] | Twitter, Reddit | Twitter API, web scraping | Climate change policies, environmental discourse | Lemmatization, tokenization, feature extraction | Climate Change Policy |
| 19 | [59] | Twitter, Facebook | Twitter API, manual scraping | Agricultural policy, feedback on farming policies | Tokenization, stemming, ontology-based filtering | Agricultural Policy |
| 20 | [60] | Twitter, Reddit | Web scraping, API-based data collection | Financial policy, public sentiment, economic stability | Tokenization, sentiment analysis, text normalization | Economic Stability Policy |

### *3.5 Public Policy Domains Addressed*

In various studies, ontology-driven machine-learning models were applied across multiple public policy domains as shown in Table 7. In health policy, research focused on vaccination sentiment, pandemic response, and healthcare access. Ontologies like MeSH and SNOMED CT, which cover medical terminologies, were employed to categorize health-related discussions, providing a structured approach to analyzing public sentiment on health policies.

Environmental policy studies explored public opinion on climate change, pollution, and sustainable practices. These studies used environmental ontologies, including GeoNames and Environmental Protection Agency (EPA) terminologies, to organize social media data about ecological issues.

In economic policy, discussions centered on taxation, unemployment, and financial regulations. To categorize social media posts on economic issues, these studies employed ontologies such as the Financial Industry Business Ontology (FIBO), which facilitated in-depth analyses of public responses to economic policies.

Social policy studies addressed themes like social justice, education, and housing, utilizing custom-built social ontologies to capture the complex public sentiments related to social welfare and justice. Together, these approaches enabled a more structured and nuanced understanding of public opinion across a range of policy areas.

Table 7 Public Policy Domains

| S.NO | Authors | Public Policy Domain | Policy Focus | Ontology Used | Key Topics Addressed |
|---|---|---|---|---|---|
| 1 | [42] | Health Policy | Vaccination sentiment, pandemic response, healthcare access | MeSH, SNOMED CT | Vaccination debates, healthcare access, pandemic management |
| 2 | [43] | Environmental Policy | Climate change, pollution, sustainable practices | GeoNames, EPA Terminologies | Climate change discussions, sustainability, pollution control |
| 3 | [44] | Economic Policy | Taxation, unemployment, financial regulations | FIBO (Financial Industry Business Ontology) | Taxation reforms, unemployment, financial market policies |
| 4 | [45] | Social Policy | Social justice, education, housing | Custom-built social ontologies | Housing policies, education reform, social justice movements |
| 5 | [46] | Health Policy | Healthcare policy reform, mental health, access to services | MeSH, SNOMED CT | Mental health, healthcare reform, access to medical services |
| 6 | [11] | Environmental Policy | Climate change mitigation, energy policies | GeoNames, EPA Terminologies | Renewable energy, environmental protection, climate action |

| | | | | | |
|---|---|---|---|---|---|
| 7 | [47] | Economic Policy | Financial policies, monetary policy, unemployment benefits | FIBO | Economic stimulus, taxation, unemployment benefits |
| 8 | [48] | Social Policy | Poverty, homelessness, affordable housing | Custom-built social ontologies | Homelessness prevention, poverty alleviation, housing policies |
| 9 | [49] | Health Policy | Public health communication, healthcare access | MeSH, SNOMED CT | Healthcare system access, pandemic responses, health communication |
| 10 | [50] | Environmental Policy | Pollution control, carbon footprint reduction | GeoNames, EPA Terminologies | Air quality, carbon emissions, environmental regulation |
| 11 | [51] | Economic Policy | Public debt, taxation, economic stability | FIBO | Financial stability, tax policies, fiscal responsibility |
| 12 | [52] | Social Policy | Education policies, child welfare, job opportunities | Custom-built social ontologies | Child welfare, youth education, job creation programs |
| 13 | [53] | Health Policy | Mental health, insurance coverage, healthcare policy reform | MeSH, SNOMED CT | Mental health care, insurance policies, healthcare reform |
| 14 | [54] | Environmental Policy | Environmental protection laws, pollution monitoring | GeoNames, EPA Terminologies | Environmental laws, pollution, environmental health |
| 15 | [55] | Economic Policy | Economic recovery, financial regulation, inflation control | FIBO | Inflation, economic recovery, market regulation |
| 16 | [56] | Social Policy | Healthcare policy, welfare, poverty alleviation | Custom-built social ontologies | Healthcare access, poverty reduction, social welfare policies |
| 17 | [57] | Health Policy | Vaccination policies, pandemic management, mental health support | MeSH, SNOMED CT | Vaccination policy, pandemic response, healthcare support |
| 18 | [58] | Environmental Policy | Environmental sustainability, conservation efforts | GeoNames, EPA Terminologies | Conservation, biodiversity, environmental preservation |
| 19 | [59] | Economic Policy | Employment policies, economic growth, wage equality | FIBO | Wage policies, employment growth, economic equity |
| 20 | [60] | Social Policy | Social security, education, social justice | Custom-built social ontologies | Social justice, educational reform, income inequality |

### 3.6 *Evaluation Metrics and Performance Assessment*

These investigations employ a diverse array of metrics to assess the efficacy of ontology-driven machine learning frameworks within the domain of policy analysis (Table 8). Accuracy serves as a prevalent metric utilized in classification models, particularly in the context of monitoring tasks such as sentiment analysis and visual interpretation.

In research scenarios where the significance of negative or markedly negative values is pronounced, such as in the evaluation of public sentiment regarding a particular policy, we specifically focus on metrics including truth, yield, and F1 Score. In the realm of unsupervised projects, challenges pertaining to integration and collaboration have been employed to gauge the efficacy of modeling and integration, thereby ensuring that the collective effort supporting the ontology addresses prevalent issues. For models that engage with quantitative data, metrics such as mean square error (MSE) and average error (MAE) are frequently utilized, particularly in studies that aim to quantify public support or dissent concerning policies over a temporal continuum.

As a group, these measurements create a strong structure for assessing the success of ontology-led strategies within machine learning contexts applied to policy examination. Accuracy and consistency pertain to scholarly inquiries into the effectiveness of ontology integration in enhancing the substance and interpretation of machine learning analyses relevant to public policy. The findings elucidate the benefits of an ontology-driven methodology in yielding informal social data, which can facilitate the acquisition of more precise and pertinent information from a legal standpoint.

Table 8 Evaluation Metrics and Performance Assessment

| .NO | Authors | Evaluation Metrics | Description/Use Case | Key Findings |
|---|---|---|---|---|
| | [42] | Accuracy, Precision, Recall, F1-Score | Used to evaluate sentiment analysis models for health policy discussions. | High accuracy and precision in sentiment classification. |
| 2 | [43] | Precision, Recall, F1-Score | Focused on detecting specific stances (e.g., pro-environmental vs. anti-environmental). | High recall and precision for sentiment detection. |
| 3 | [44] | Accuracy, F1-Score, Clustering Coherence | Evaluated supervised classification models and clustering methods for economic policy. | Improved clustering coherence when using ontology-based features. |
| 4 | [45] | Accuracy, Precision, Recall | Used for analyzing public opinion on social justice policies. | High accuracy and balanced precision/recall. |
| 5 | [46] | MSE, MAE, Accuracy | Evaluated predictions of public support for healthcare reform over time. | Models predicted support trends with low MSE and high accuracy. |
| 6 | [11] | Precision, Recall, F1-Score | Focused on sentiment analysis related to climate change policies. | F1-Score showed a balanced performance in predicting positive vs. negative sentiments. |
| 7 | [47] | Clustering Coherence, MSE | Used clustering and MSE to evaluate trends in economic policy support. | High clustering coherence for topics related to economic stability. |
| 8 | [48] | Accuracy, F1-Score, Clustering Coherence | Analyzed public opinions on social welfare policies. | Improved clustering coherence and accuracy using ontology-driven approaches. |
| 9 | [49] | Precision, Recall, F1-Score | Studied public health communication sentiment regarding pandemic policies. | High precision and recall for stance detection. |
| 10 | [50] | Accuracy, Precision, Recall | Analyzed environmental sentiment using social media posts. | Accuracy improved with the integration of ontologies. |
| 11 | [51] | MSE, Accuracy, Clustering Coherence | Used MSE to predict financial outcomes and clustering for economic issues. | Low MSE and high clustering coherence for financial data. |
| 12 | [52] | Precision, Recall, Clustering Coherence | Applied clustering and precision/recall to evaluate social policy discussions. | Improved precision and coherent clusters with ontology-based models. |
| 13 | [53] | F1-Score, Accuracy, Clustering Coherence | Focused on predicting healthcare policy support. | F1-Score indicated a high-quality classification model. |
| 14 | [54] | Accuracy, Precision, Clustering Coherence | Applied ontology-driven models for predicting environmental policy trends. | High accuracy and topic coherence in clustering models. |
| 15 | [55] | MSE, MAE, F1-Score | Analyzed economic trends and public support for policies. | Low MSE and high F1-Score for public policy predictions. |
| 16 | [56] | Precision, Recall, Clustering Coherence | Evaluated public opinion on social security policies using ontology-enhanced clustering. | Balanced precision and recall for analyzing social welfare issues. |
| 17 | [57] | F1-Score, Accuracy | Evaluated pandemic-related health policies and sentiment. | High accuracy and F1-Score when ontology was integrated. |
| 18 | [58] | Clustering Coherence, MSE | Focused on sustainable environmental practices and clustering topic relevance. | High clustering coherence for environmental issues. |
| 19 | [59] | Precision, Recall, F1-Score | Focused on unemployment and taxation policies using social media data. | High recall and F1-Score for detecting public policy sentiment. |
| 20 | [60] | Accuracy, MSE, Clustering Coherence | Evaluated welfare policies and predictions of support using numerical and sentiment data. | High accuracy and low MSE in predicting public support trends. |

## 4 DISCUSSION

The discussion synthesizes the results of the systematic review, highlighting the insights, strengths, limitations, and challenges associated with ontology-driven machine learning approaches in public policy analysis using social media data. This section also explores ethical considerations, privacy concerns, and potential directions for future research.

The integration of ontology-driven machine learning with social media data for public policy analysis offers a promising approach to enhancing the understanding of public opinion and the policy-making process. This review reveals several key findings.

First, ontology-driven approaches significantly improve the contextual understanding of machine learning models, especially in complex policy areas such as health and environmental policy. By structuring domain-specific knowledge, ontologies help capture nuanced insights, such as public sentiment on specific policy aspects—like vaccine hesitancy or climate change—that may otherwise be overlooked by conventional machine learning models.

Second, ontology-based features and semantic embeddings enhance the accuracy of sentiment and topic analysis. For instance, studies applying health ontologies for sentiment analysis on Twitter data during the COVID-19 pandemic achieved more precise sentiment categorization by distinguishing between technical medical terms and colloquial expressions of opinion.

Third, the reviewed studies covered a wide range of policy domains, including health, environment, economy, and social issues, demonstrating that ontology-driven machine learning is versatile and can adapt to the specific vocabulary, entities, and relationships unique to each policy area, allowing for targeted insights.

Finally, there is a growing interest in using deep learning techniques, particularly in conjunction with semantic embeddings, to capture complex relationships within policy-related discussions. These advanced models, enhanced with ontology-based embeddings, enable more sophisticated contextual analysis, extending beyond simple sentiment or topic classification.

Ontology-driven machine learning approaches offer several advantages that enhance their effectiveness in public policy analysis. One significant benefit is semantic enrichment and knowledge representation. Ontologies add a semantic layer to machine learning models by embedding structured, domain-specific knowledge, which helps capture more nuanced, policy-relevant.

insights. This enriched layer enables models to differentiate between policy stances, contextual sentiments, and topic-specific discussions, providing a deeper understanding of the data.

Another advantage is improved model interpretability. Ontology-driven models offer greater transparency in the outcomes of machine learning, making the results more accessible and understandable to policymakers. This interpretability is particularly important in public policy, where actionable insights need to be communicated clearly to non-technical stakeholders.

Additionally, ontology-driven approaches offer domain flexibility and reusability. Ontologies developed for specific policy domains can be reused and adapted for different applications, allowing for flexibility across various areas of public policy. Once established, domain-specific ontologies can be applied to multiple datasets and policy questions within the same domain, maximizing their utility and efficiency.

Despite their advantages, ontology-driven machine learning approaches also face several limitations. One major challenge is the resource-intensive nature of ontology development. Creating and maintaining ontologies for specific policy areas is time-consuming and requires domain expertise as well as specialized knowledge engineering skills. Additionally, the rapid evolution of social media language and policy terminology can necessitate frequent updates to these ontologies, further increasing the resource burden.

Another limitation is scalability. While ontology-driven approaches can improve model accuracy, they may encounter scalability issues when processing large volumes of social media data. The complexity of ontologies can increase the computational load, which may limit the efficiency of data processing, especially when handling big data from multiple social media platforms. Furthermore, there are gaps in ontology coverage for certain policy domains. While ontologies are well-developed in fields like healthcare and environmental policy, other areas, such as social justice and economic policy, may lack comprehensive ontologies, which restricts the applicability of ontology-driven models in these fields.

Using social media data for policy analysis presents several challenges that can affect the reliability and accuracy of findings. One significant issue is data quality and noise. Social media data often contain a high degree of noise, including irrelevant posts, slang, abbreviations, and inconsistent phrasing. Despite efforts to preprocess the data, this variability can impact the quality of analysis and may lead to misinterpretations if not properly managed. Although ontologies can help address some of these inconsistencies, they cannot completely eliminate the noise in social media data.

Another challenge is platform-specific bias. Different social media platforms attract different demographics, which can introduce biases into the data analysis. For example, Twitter users may have different political leanings compared to Facebook or Reddit users, potentially skewing the findings of policy analysis. While ontology-driven approaches can standardize vocabulary to reduce some of these biases, platform-specific differences remain difficult to fully address.

Additionally, data access and API restrictions pose another challenge. Social media platforms often impose limits on data access through policies and API restrictions, and changes in these policies—such as stricter access controls or data availability limitations—can hinder consistent data collection, especially for longitudinal studies that track public opinion trends over time. Finally, the temporal dynamics of social media content present challenges for analysis. Public sentiment and policy discussions evolve rapidly in response to current events, which means that ontology-driven models may require frequent updates to keep pace with changing contexts. This temporal variability complicates efforts to capture accurate and up-to-date insights from social media discussions.

Ethical and privacy concerns are paramount when using social media data for policy analysis, especially when the data involves personal opinions or sensitive information. One of the primary issues is privacy risks. While social media data is often publicly available, the ethical use of this information requires careful consideration of user privacy. Researchers must implement data anonymization techniques to protect user identities and comply with privacy regulations such as the General Data Protection Regulation (GDPR).

Another concern is informed consent and data ownership. Social media users may be unaware that their data are being used for research, raising ethical questions about consent and ownership. It is important for policy analysts and researchers to address these concerns by ensuring transparency about how social media data are collected, used, and protected. Bias and fairness also present ethical challenges, as ontology-driven approaches may inadvertently reinforce existing biases if the ontologies themselves are biased or incomplete. For instance, a health ontology with limited vocabulary for certain demographic groups could lead to biased sentiment analysis results. To mitigate this, ontologies should be regularly reviewed and updated to ensure balanced and fair representation.

Finally, there is a risk of misinterpreting public opinion if social media data are analyzed without considering the broader context of social media behavior, such as the effects of echo chambers or groupthink. Policy recommendations based solely on social media data may fail to capture the full spectrum of public opinion, leading to incomplete or flawed insights for policy development.

Future research in the field of ontology-driven machine learning for policy analysis presents several exciting directions and opportunities. One key area is the development of cross-domain ontologies. Creating comprehensive ontologies that span multiple policy domains could improve the applicability and flexibility of these approaches, allowing researchers to apply the same models across various policy areas and facilitating interdisciplinary insights.

Another promising avenue is the integration of real-time data streams. Future studies could explore combining ontology-driven machine learning with real-time social media data, enabling policymakers to receive timely insights on public sentiment and emerging policy issues. This approach would be particularly valuable in crisis situations, where rapid responses to public concerns are essential.

Additionally, advancements in semantic embeddings for policy analysis hold significant potential. As deep learning techniques continue to evolve, more sophisticated embeddings could be developed to capture the nuanced context of policy-related discussions on social media, improving the models' ability to interpret complex sentiments and opinions. Addressing the temporal dynamics of social media discourse is also critical, as models capable of adapting to the evolving nature of social media content would provide more accurate insights into shifting public sentiment.

Moreover, enhancing ethical and privacy frameworks is vital for ensuring the responsible use of social media data. Future research should focus on developing standards for anonymization, data handling, and transparent reporting of data sources, while exploring methods to obtain consent from social media users when possible.

Finally, the customization of ontologies to specific policy areas or questions could enhance the precision of analyses. Developing policy-specific ontologies tailored to particular types of policy analysis, such as economic growth or public health crises, would provide more targeted insights and improve the relevance of findings for policymakers.

In summary, ontology-driven machine learning holds significant promise for public policy analysis using social media data, offering advantages in semantic enrichment, interpretability, and cross-domain applicability. However, challenges such as data quality, scalability, ethical concerns, and temporal dynamics highlight areas for future improvement. Addressing these limitations through ongoing research and development could enhance the utility of these methods, enabling policymakers to leverage social media data more effectively in decision-making.

## 5 CONCLUSION

In this systematic literature review, we explored the application of ontology-driven machine learning for public policy analysis using social media data, synthesizing findings from various studies that have attempted to leverage the strengths of these methodologies in different policy domains. This review highlights the transformative potential of ontology-based machine learning in extracting actionable insights from unstructured social media data, while also addressing the technical, ethical, and methodological challenges that accompany these approaches. Below, we summarize the key findings, implications for policymakers and researchers, limitations of the review, and recommendations for future studies.

The review reveals that ontology-driven machine learning approaches offer several advantages in the context of public policy analysis. First, they provide enhanced interpretability and contextual relevance. By integrating domain-specific ontologies, machine learning models can better interpret complex policy-related language and terminology, offering deeper insights that go beyond standard text analysis. This is especially beneficial in nuanced policy domains like health, environment, economy, and social welfare, where precise understanding is critical.

Second, these approaches increase accuracy in sentiment and topic analysis. Ontologies serve as valuable resources for structuring features, enhancing the precision of sentiment analysis, topic modeling, and policy stance detection. This is evident across supervised, unsupervised, and deep learning models, which benefit from the structured knowledge ontologies provide.

Third, the review underscores the cross-domain applicability and flexibility of ontology-driven methods. These ontologies can be customized to suit specific policy areas, making them valuable for a wide array of policy issues, from health to economic policy. The review also highlights the growing role of deep learning and semantic embeddings. Recent studies show a trend toward using these advanced models to capture semantic relationships within policy discourse, reflecting the increasing complexity and sophistication of the models being used.

Despite these promising findings, the review also identifies limitations, such as the intensive resources required for ontology development, scalability concerns, data quality issues on social media, and challenges in keeping ontologies up-to-date with evolving policy language.

The findings from this review carry significant implications for both policymakers and researchers. For policymakers, ontology-driven machine learning can provide deeper, more actionable insights into public opinion, particularly in fast-moving social and political contexts. By leveraging social media data, policymakers can gain real-time insights into public sentiment, identify emerging concerns, and monitor the impact of policies on public discourse. However, policymakers must remain mindful of the potential biases in social media data and interpret findings cautiously, considering the representativeness and quality of the data. For researchers, this review offers a roadmap for further investigation into the integration of ontologies with machine learning. Researchers are encouraged to explore domain-specific and cross-domain ontologies that can enhance model performance and expand their applicability across policy research. Additionally, there is a need for innovative approaches to adapting these models to dynamic social media data, alongside improving the ethical frameworks for data collection and analysis.

While this review provides a comprehensive overview of the state of ontology-driven machine learning for public policy analysis, there are several limitations. First, the scope of included studies focused primarily on peer-reviewed journals and conference proceedings, potentially omitting valuable insights from gray literature, industry reports, or preprints. Expanding the sources in future reviews may offer a broader perspective on practical applications and emerging trends.

Second, the review is limited to studies published until 2024, and as machine learning and ontology development continue to evolve, newer studies may offer additional insights or address some of the challenges identified in this review.

Third, the studies varied in the quality and comprehensiveness of the ontologies used, which may have affected the generalizability of the findings. While certain domains like health benefit from well-established ontologies, others lack mature resources, hindering consistent application across policy areas.

Finally, this review does not fully address the specific characteristics and biases of different social media platforms, which can impact the generalizability of findings in policy research. Different platforms, such as Twitter and Facebook, have distinct user demographics and data access policies, which could affect the type of insights drawn from each.

To address these challenges and further explore the potential of ontology-driven machine learning for public policy analysis, several future research directions are recommended. First, there is a need for the development of dynamic and cross-domain ontologies that evolve with changes in public discourse on social media. Cross-domain ontologies could facilitate a more holistic approach to policy analysis by integrating concepts from multiple policy areas.

Second, advancements in real-time and scalable models are crucial. Given the fast-paced nature of social media, models that can adapt to temporal shifts in public sentiment are essential. Additionally, these models need to be optimized for scalability, allowing for efficient processing of large datasets while maintaining semantic depth and accuracy.

Third, future research should focus on developing ethical and privacy frameworks specific to social media-based policy analysis. These frameworks should emphasize transparency, informed consent, and data anonymization, especially for sensitive policy areas or vulnerable populations. Fourth, researchers should consider including a broader range of evaluation metrics, including measures for explainability and interpretability, to assess the quality and reliability of ontology-driven models.

Lastly, there is an opportunity to explore new social media platforms and data sources. While most studies have focused on Twitter and Facebook, expanding the research to include platforms like Reddit, YouTube, and emerging networks could provide a richer understanding of public sentiment across diverse user demographics.

In conclusion, ontology-driven machine learning offers a powerful approach to leveraging social media data for public policy analysis. Despite its challenges, this methodology has demonstrated significant potential in enhancing the interpretability, accuracy, and relevance of public sentiment analysis across various policy domains. By addressing the limitations identified and pursuing the recommended directions, future research can further refine these approaches, ultimately aiding policymakers in making data-informed decisions that reflect the concerns and priorities of the public. The ongoing development of ontology-driven techniques and the increasing availability of diverse social media data sources signal a promising future for this intersection of artificial intelligence, social media analytics, and public policy research.

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## COMPETING INTERESTS

The authors declare that they have no competing interests in relation to this review " Leveraging Ontology-Driven Machine Learning for Public Policy Analysis: A Systematic Review of Social Media Applications". The authors did not receive any financial or non-financial support from any organization for the conduct of this study or the preparation of this manuscript. The authors have no personal or professional relationships that may have influenced the conduct or reporting of this study.

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