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Review

From Digital Data to Electoral Forecasts: A Systematic Review and Taxonomy of Computational Approaches

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Abstract. The increasing use of digital data in electoral prediction has motivated a growing body of computational research, yet the field remains methodologically diverse and lacks consolidated comparative frameworks. This article presents a systematic review of computational approaches for electoral outcome prediction using digital data between 2020 and 2025. Following rigorous systematic methodology, searches were conducted across three scientific databases, resulting in 80 primary studies analyzed after applying explicit quality criteria. The review proposes a taxonomy classifying studies by data integration and predictive complexity, enabling systematic identification of methodological patterns. Results reveal geographic concentration in few countries, with Twitter as the dominant platform and sentiment analysis as the most frequent technique. Vote percentage prediction and winner identification represent the primary objectives, evaluated mainly through regression and classification metrics. The field demonstrates numerical expansion with modest geographic diversification, yet persistent challenges remain regarding sample representativeness, cross-context generalization, and absence of standardized validation protocols. Findings indicate the need for broader geographic coverage, reduced platform dependency, and establishment of uniform evaluation criteria to advance methodological maturity in computational electoral prediction.

Keywords: Electoral Forecasting, Systematic Literature Review, Social Networks

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1 Introduction

For decades, the relationship between politicians and voters was mediated by journalistic institutions that selected information, defined frameworks, and controlled access to the public sphere. Television, radio, and press acted as filters that organized message flow and determined which content would reach the public.

The transition to digital tools in electoral campaigns gained momentum during the 2008 United States presidential election, when the internet became essential infrastructure for mobilizing voters and social networks began to occupy an important role in political communication. Smith [2009] documented that 55% of American adults used the internet to follow the electoral process, compared to 37% in 2004, with the internet surpassing print newspapers as the primary information source.

With social network spread, a direct communication format emerged where political actors can speak to the electorate without traditional intermediaries. As Broersma and Graham [2012] emphasize, digital platforms expand politicians' control over content, timing, and message format. This reconfiguration established a hybrid environment where politicians can simultaneously bypass and activate journalistic outlets, creating continuous interaction between digital communication and mediated coverage [Chadwick, 2017]. This transformation manifested globally, from Modi's 2014 digital strategy in India [Pal *et al.*, 2016] to Bolsonaro's social media-centered 2018 campaign in Brazil, where user interaction showed stronger association with electoral performance than publication volume [Brito *et al.*, 2019].

By 2024, the digital ecosystem reveals platform specialization. McClain *et al.* [2024] demonstrated that X (formerly Twitter) consolidated as the most politicized network (59% usage for politics, 74% content exposure), contrasting with Facebook (26%, 52%), TikTok (36%, 45%), and Instagram (26%, 36%). This indicates functional differentiation: X concentrates political debates, TikTok facilitates viral mobilization, while Facebook and Instagram integrate political communication with personal connections.

This social network incorporation as political infrastructure articulates with broader digital expansion, creating new informational infrastructure where behavioral, opinion, and social relationship data are generated continuously and publicly. As Shah *et al.* [2015] argue, digital platform interactions enable investigation of public opinion dynamics, political behaviors, and social mobilizations, configuring significant computational social science opportunities. For electoral prediction, this environment offers advantages such as real-time availability, temporal and spatial granularity, and spontaneous preference recording without structured instruments [Gayo-Avello, 2013].

However, the electoral prediction field's methodological diversity presents challenges for systematic result synthesis and consolidated pattern identification. Previous systematic reviews present temporal and methodological gaps. Gayo-Avello [2013] concentrated exclusively on Twitter data, restricting multi-platform understanding. Chauhan *et al.* [2021] focused on sentiment analysis with less systematic selection criteria. Skoric *et al.* [2020] emphasized theoretical aspects with limited computational methodological exploration. Brito *et al.* [2021], following rigorous Kitchenham *et al.* [2009] protocol, covered 2008-2019, not encompassing subsequent developments.

The present systematic review addresses these gaps through three contributions. First, it updates temporal scope to 2020-2025, incorporating recent methodological developments. Second, it proposes bidimensional taxonomy for systematic study classification according to data integration and methodological complexity. Third, it investigates computational approaches, predicted electoral results, and validation metrics, enabling cross-methodology and cross-context analysis. The rigorous adoption of Kitchenham *et al.* [2009] methodology with explicit criteria enables methodological pattern identification, establishing an updated panorama that complements previous contributions and offers structured analytical framework for future research.

2 Related Work

Electoral outcome prediction represents a research field that has transformed from traditional statistical methods based on opinion polling to computational approaches exploring digital data sources. This transformation reflects technological advances and changes in political communication patterns in digitally connected societies.

Electoral prediction through computational methods has consolidated as an interdisciplinary field combining data science, machine learning, natural language processing (NLP), and social network analysis. The increasing availability of digital data and advances in processing techniques enable near real-time analysis of large information volumes. Social media platforms such as X (formerly Twitter), Facebook, and Instagram have become relevant sources for capturing spontaneous political opinion, enabling new approaches to infer electoral preferences [Brito *et al.*, 2021; Chauhan *et al.*, 2021; Alvi *et al.*, 2023].

The field's empirical foundations were established by O'Connor *et al.* [2010] and Tumasjan *et al.* [2010], who introduced two influential methodological approaches. O'Connor *et al.* [2010] investigated correlations between Twitter sentiment analysis and traditional polls during the 2008 U.S. presidential elections, employing the OpinionFinder lexicon (1,600 positive and 1,200 negative terms) on 1 billion tweets. Results demonstrated up to 80% correlation with opinion polls, with textual sentiment serving as a leading indicator. Concurrently, Tumasjan *et al.* [2010] established volumetric analysis by examining 2009 German elections, where party mention volume corresponded to electoral results with 1.65% average absolute error.

These optimistic results were challenged by Gayo-Avello [2013], who analyzed the 2008 U.S. election using four sentiment analysis methods across 250,000 tweets from eight states. Simple methods presented substantial errors (13.10% average), revealing persistent problems: sampling bias and analytical limitations. The author compared this to the 1936 *Literary Digest* poll failure, which used telephone directories and automobile registrations, inadequately representing lower-income voters.

These foundational studies established four main methodological approaches: volumetric analysis, sentiment analysis, social network analysis, and hybrid methods [Chauhan *et al.*, 2021]. Each methodology evolved by incorporating sophisticated machine learning techniques and expanding to diverse global electoral contexts.

Previous systematic reviews present methodological and temporal limitations that justify a new investigation. Gayo-Avello [2013] restricted analysis to Twitter, limiting understanding of multi-platform possibilities. Chauhan *et al.* [2021] focused on sentiment analysis with less systematic selection criteria. Skoric *et al.* [2020] applied meta-analysis but concentrated on theoretical aspects with limited exploration of recent computational advances. Brito *et al.* [2021] followed rigorous systematic methodology per Kitchenham *et al.* [2009] protocol but covered only 2008-2019, missing recent developments. Khan *et al.* [2021] conducted comprehensive systematic mapping restricted to Twitter. Alvi *et al.* [2023] extended temporal scope to 2023 but based selection on first search pages prioritizing citations, without backward reference searches or formal quality assessment, maintaining Twitter-exclusive focus. Gaur and Yadav [2025] reviewed 50 studies (2009-2022) across multiple platforms but without rigorous systematic protocol or explicit quality assessment procedures.

These gaps indicate the need for a systematic review following established guidelines [Kitchenham *et al.*, 2009], covering recent period (2020-2025), incorporating multiple platforms, and applying rigorous quality criteria to identify current methodological trends and propose comprehensive taxonomies for the field.

3 Methodology

This section presents the methodological process employed to conduct the systematic review on electoral results prediction. The method rigorously follows the guidelines established by Kitchenham *et al.* [2009] for systematic reviews in computing, ensuring transparency, reproducibility, and scientific rigor in the identification, selection, and analysis of primary studies. A systematic review differs from a traditional literature review by following a predefined and explicit protocol, minimizing biases and allowing other researchers to reproduce the process.

3.1 Research Questions

To define the research questions for this study, the primary objective was established as conducting a comprehensive survey of the state of the art in electoral results prediction within the computing field. The questions were formulated to identify the main methodological advances, knowledge gaps, and research opportunities during the period from 2020 to 2025.

The following research questions were developed:

- Q1. In what electoral contexts are studies conducted?
  This question examines the application scenarios of studies, considering aspects such as country, year, election type, and electoral level, providing a comprehensive view of the geographic and temporal distribution of research.
- Q2. What data sources are employed in electoral prediction studies?
  This question investigates the different origins of data used, such as social networks, electoral polls, historical election data, and other information sources relevant to

the predictive context.

- Q3. What computational approaches have been used to perform electoral results prediction?
  This question seeks to identify and classify the main methodologies employed in the literature, including machine learning techniques, sentiment analysis, volumetric approaches, and hybrid methods.
- Q4. How are electoral prediction models methodologically characterized in terms of the types of predicted results and the performance metrics employed to evaluate them?
  This question investigates the methodological characterization of predictive validation in the analyzed studies, recognizing that the type of predicted electoral result and the performance metrics used constitute interdependent dimensions of model evaluation.
- Q5. What are the main challenges reported in the literature for predicting electoral results?
  This question identifies the limitations and difficulties reported by researchers, contributing to understanding the existing gaps in the field.

3.2 Search Strategy

The search process was structured to ensure comprehensive and systematic coverage of relevant literature on electoral prediction with digital data. Search strategies in systematic reviews constitute a fundamental methodological element that determines the quality and completeness of the analyzed corpus, requiring a balance between sensitivity (ability to retrieve relevant studies) and specificity (ability to exclude irrelevant studies).

The selection of bibliographic databases considered criteria of disciplinary relevance, adequate temporal coverage for the analysis period, and quality of indexing mechanisms. The ACM Digital Library was selected as the main repository for publications in computer science, offering access to conference and journal papers. IEEE Xplore was included for its comprehensiveness in electrical engineering, electronics, and computing, with a strong presence of research in artificial intelligence, machine learning, and information systems. Scopus was incorporated for its multidisciplinary nature and broad geographic and temporal coverage, allowing identification of works published in venues that combine computing with social and political sciences.

Search expressions were developed through an iterative process involving analysis of pre-2020 publications, extraction of recurring key terms, and validation through exploratory searches. The general structure combined two main semantic groups: electoral domain terms (election, electoral, voting, vote) and predictive terms (predict*, prediction, forecast*, forecasting), where the asterisk represents a truncation operator that retrieves morphological variations.

The queries were adapted to meet the syntactic specificities of each database. For **IEEE Xplore**, searches were conducted across document titles, author keywords, and abstracts using the appropriate field identifiers. The **ACM Digital Library** employed simplified syntax with truncation operators across title, keywords, and abstract fields. For **Scopus**, specific field identifiers (TITLE, KEY, ABS) were used. All searches combined electoral and prediction terms with Boolean operators, with abstract searches including additional result-related terms (result*, outcome*, vot*) to enhance specificity.

3.3 Selection Criteria

Inclusion and exclusion criteria were established to ensure that only relevant studies of adequate quality were included in the systematic review. These criteria were designed to focus the review on computational prediction models applied to real electoral contexts while maintaining methodological rigor and practical applicability.

3.3.1 Inclusion Criteria

The inclusion criteria define the essential characteristics that studies must possess to be considered relevant to this systematic review. These criteria ensure alignment with the research objectives and guarantee that selected studies contribute meaningfully to understanding the state of the art in electoral prediction.

- C1: Studies that propose and present computational models or techniques for predicting aggregate electoral results (percentage of votes for parties or candidates, winner projection, or seat distribution) will be included.
- C2: Research that includes model validation in real elections will be accepted, including retrospective studies that apply methodologies to historical data to evaluate the predictive effectiveness of proposed models.
- C3: Works that present clear methodology will be included.
- C4: Studies reporting predictive performance measures or comparative assessments with actual election results will be considered.

3.3.2 Exclusion Criteria

The exclusion criteria identify conditions that make studies unsuitable for inclusion in this review. These criteria help filter out works that, despite potentially appearing in search results, do not align with the specific focus on computational electoral prediction or lack sufficient methodological quality for meaningful analysis.

- E1: Publications whose full text is not available or with restricted access that prevents adequate evaluation will be excluded.
- E2: Research whose main objective is not the construction, evaluation, or application of predictive models for political elections will not be considered.
- E3: Works that use exclusively synthetic or simulated data without validation in real electoral scenarios will be excluded.
- E4: Works not written in English or Portuguese will be excluded.

3.3.3 Selection Process

The selection process was conducted in multiple stages to ensure rigor and minimize inappropriate exclusion of relevant studies. This multi-stage approach allows for systematic refinement of the corpus while maintaining transparency and consistency in decision-making throughout the review process.

- First Stage: Selection by Title and Abstract
  Initial selection was based on analysis of titles and abstracts, applying the established inclusion and exclusion criteria. This stage was conducted independently, with documentation of inclusion or exclusion decisions.
- Second Stage: Full Reading
  Studies selected in the first stage were subjected to full reading to confirm their eligibility.
- Divergence Resolution
  Cases of doubt during the selection process were documented and resolved through discussion and consensus, ensuring consistency in applying the criteria.

3.4 Conduction

The systematic search was conducted from 2020 to 2025 across three scientific databases: IEEE Xplore, ACM Digital Library, and Scopus. Search strings were applied to title, abstract, and keyword fields, using Boolean operators to combine terms related to electoral prediction, elections, and computational methods. The search in IEEE Xplore returned 198 results, ACM Digital Library yielded 45 studies, while Scopus, with filters specifically applied to Computer Science and Engineering areas, resulted in 205 publications, totaling 448 initial studies.

The selection process followed multiple refinement stages. After duplicate removal and application of inclusion and exclusion criteria during title and abstract analysis, 133 studies were selected for full reading. Methodological quality assessment resulted in the final selection of 80 primary studies that compose the corpus of this systematic review. The entire process was documented to ensure transparency and reproducibility, including the reasons for study exclusion at each stage.

4 Results

This section presents findings from the systematic review of 80 primary studies addressing electoral prediction using digital data. Extracted data from each study are systematized in Table 1. We first provide bibliometric characteristics of the analyzed corpus, followed by a structured presentation of findings addressing the five research questions established in the methodology.

4.1 Corpus Overview

The temporal distribution of publications (Figure 1) reveals irregular patterns between 2020 and 2025. The 80 primary studies comprise 46 conference papers and 34 journal articles.

Publications peaked in 2020 with 19 studies (15 conference, 4 journal), likely driven by the U.S. presidential election's prominence and data availability. This concentration aligns with traditional patterns of increased scientific interest during major electoral cycles. The year 2021 maintained 19 publications but with more balanced distribution (10 conference, 9 journal), suggesting research maturation beyond immediate electoral events.

A sharp decline occurred in 2022, with only 6 studies (5 conference, 1 journal), a 68% reduction from preceding years. Recovery began in 2023 with 14 publications, continuing through 2024 with 15 studies. During this period,

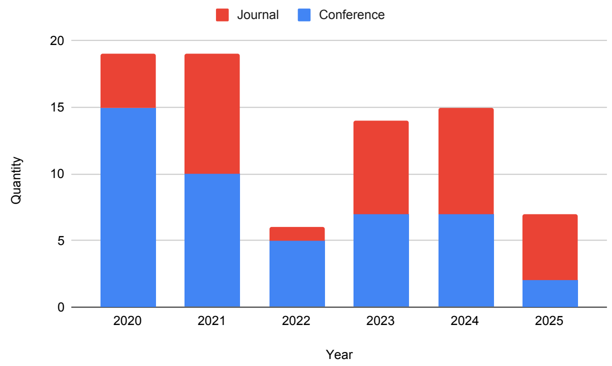

Figure 1. Distribution of publications per year.

journal publications stabilized (7-9 articles annually), while conference publications exhibited greater variability.

Through the data collection cutoff in 2025, 7 publications appeared (2 conference, 5 journal). While the incomplete year precludes definitive comparison, the higher journal proportion may indicate consolidation toward more rigorous publication venues with extended editorial processes.

4.2 Q1: Electoral Contexts Investigated

The analyzed studies span electoral processes across 31 countries with varied geographical distribution (Figure 2). The United States concentrates the largest number of works (27 studies), followed by India (15 studies) and Indonesia (7 studies). This pattern reflects extensive data availability in English-speaking countries and expanding research interest in large-scale Asian democracies. In Latin America, Brazil leads with 5 studies, followed by Mexico (4), Argentina, Chile, and Peru (3 each). European production shows dispersed distribution across 11 countries, with Germany and the United Kingdom presenting 3 studies each. Most African nations remain unrepresented, with South Africa as the sole exception.

This geographical concentration presents methodological implications. When most studies focus on few countries, evaluating whether computational techniques produce consistent results across different electoral realities becomes challenging. Factors such as voting system variations, party diversity, social media usage levels, and cultural differences in political expression can influence model performance. Broader geographical coverage could expand understanding of method stability and contextual interference, favoring development of more robust approaches.

Electoral prediction can be performed at different levels of administrative granularity, each with specific characteristics and methodological challenges. Figure 3 presents study distribution according to investigated electoral level.

The **national** level encompasses elections for offices representing entire country territories, such as presidential or national parliamentary elections. This represents the most frequently investigated level, with 65 studies (81%), likely due to greater data availability and political relevance.

The **subnational state, provincial, or regional** level includes elections in intermediate administrative subdivisions, such as states in federative systems or autonomous regions. Seven studies (8.75%) were identified at this level, which

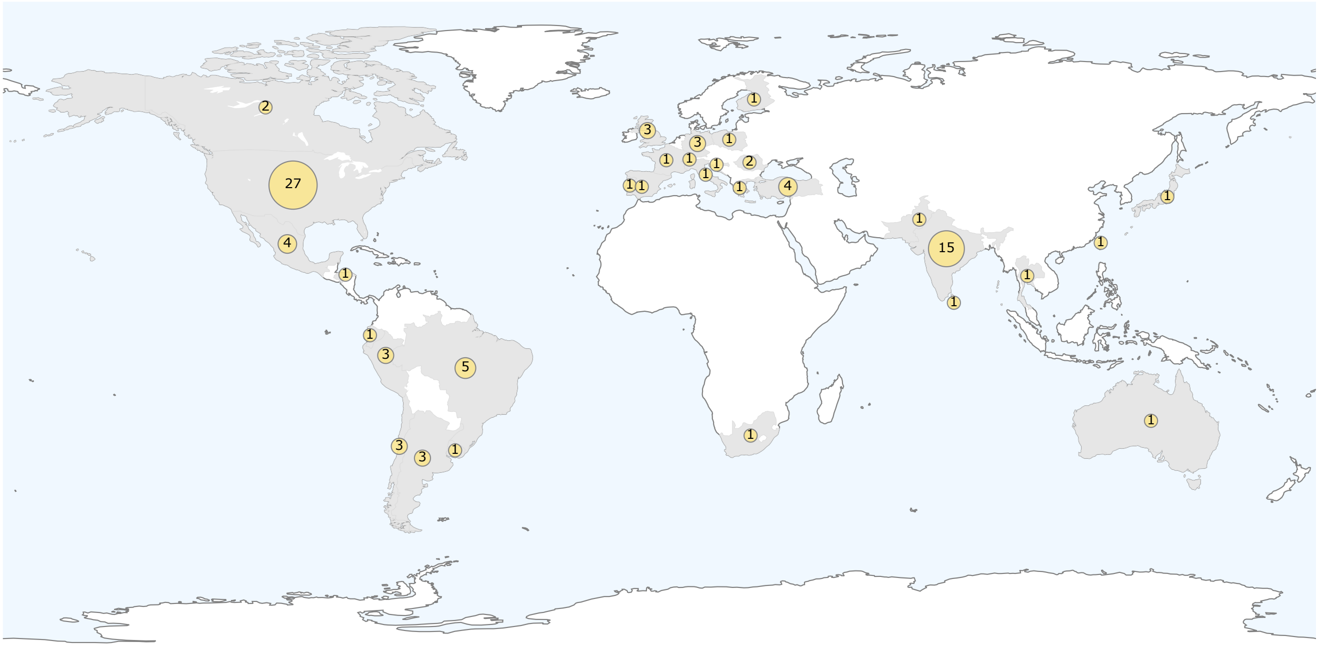

Figure 2. Geographic distribution of studies by country.

presents additional complexities related to capturing specific regional political dynamics.

The **subnational municipal or local** level refers to elections in smaller-scale administrative units. Only 4 studies (5%) were classified at this level, possibly reflecting methodological difficulties in local-scale data collection and reduced availability of historical resources.

The **multiple levels** category groups studies investigating elections at different administrative levels simultaneously or developing methodologies applicable to multiple scales. Three studies (3.75%) were identified in this category.

The **supranational** level refers to elections transcending national borders, such as European Parliament elections. Only 1 study (1.25%) was identified, reflecting both lower election frequency and additional methodological complexities of integrating data from multiple national jurisdictions.

The observed distribution evidences substantial research concentration in national elections, with minimal presence at local and supranational levels. This configuration suggests research expansion opportunities toward less explored electoral levels, which present distinctive characteristics and specific methodological challenges.

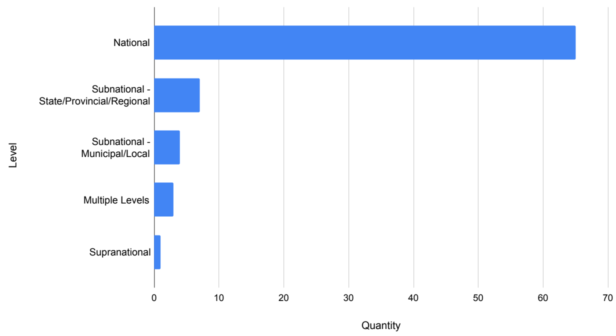

Figure 3. Distribution of studies by investigated electoral level.

4.3 Q2: Data Sources Employed

The analysis of data sources reveals distinct patterns in the types of information utilized for electoral prediction research. As illustrated in Figure 4, data sources originating from social media platforms demonstrate clear predominance throughout the analyzed period. Between 2020 and 2024, these platforms consistently represent between 66.67% and 84.21% of the sources employed in the studies, with particular emphasis on 2021 (84.21%) and 2024 (80.00%).

In contrast, alternative sources, including non-social digital data, structured historical data, computational models, and candidate characteristics, maintain more restricted participation, varying between 15.79% and 33.33% during the same interval. The predominance of social networks appears to be associated with ease of data access through public application programming interfaces and the fact that these platforms record spontaneous expressions of political opinion at high temporal frequency.

However, a pattern shift is observable in 2025, when social networks correspond to 42.86% of sources, while other sources reach 57.14%. This behavior may be related to the partial nature of the year or the inclusion of studies that prioritized structured data or computational models. It is important to note that individual studies may employ multiple data source types, both from social networks and other categories. Therefore, the presented counts are not mutually exclusive, and a study may contribute simultaneously to both classifications.

Regarding specific platforms, Figure 5 presents the temporal distribution of social media platforms utilized as data sources in electoral prediction studies. Twitter emerges as the most frequently employed platform throughout the entire analyzed period, totaling 53 of 66 occurrences (80.3%). Its presence remains consistent across all years, varying between 82% in 2020 and 100% in 2022. Facebook appears

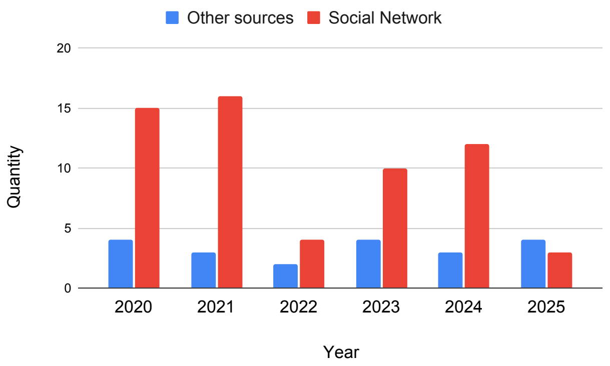

Figure 4. Evolution of social network usage (2020-2025).

as the second most utilized platform, with 8 occurrences (12.1%), being regularly employed between 2020 and 2024. Instagram, YouTube, and Reddit present more restricted usage, with 2, 2, and 1 occurrence, respectively.

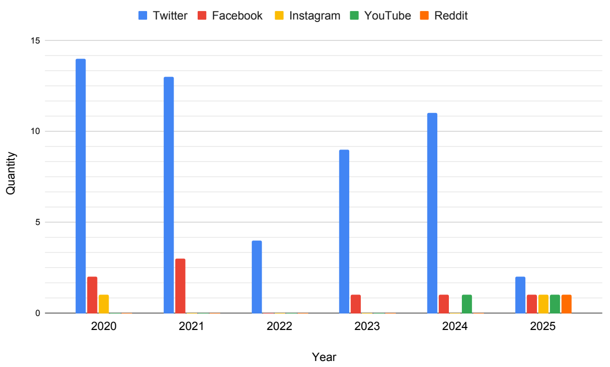

Figure 5. Percentage distribution of social media platforms by year.

It should be noted that 2025 data are partial, which may influence interpretation of recent trends. The observed concentration on Twitter appears to be related to data availability through public APIs and the textual and dynamic format of publications, which favors computational collection and processing for predictive purposes.

4.4 Q3: Computational Approaches

Analysis of the 80 studies revealed methodological diversity in the computational approaches employed. To systematize this variety, a bidimensional taxonomy was developed that classifies studies according to: (i) data integration (unimodal vs. multimodal) and (ii) predictive complexity (single method vs. multiple methods).

The predictive approaches identified in the 80 analyzed studies are organized into five main methodological axes, each representing distinct strategies for capturing different dimensions of electoral behavior. The first axis, termed **Social Network Data**, subdivides into three approaches: volumetric analysis (A1), which quantifies mentions, hashtags, and engagement metrics; sentiment analysis (A2), which identifies emotional polarity and expressed political orientations; and network structure analysis (A3), which examines centrality metrics, community formation, and information diffusion patterns. The second axis, **Digital Behavioral Data** (B), utilizes search and navigation signals such as Google Trends, Wikipedia views, and other patterns of online content access. The third axis, **Historical Structured Data** (C), incorporates traditional information such as opinion polls, economic indicators, demographic data, and previous election results. The fourth axis, **Computational Modeling** (D), employs opinion dynamics simulations and agent-based models to capture social influence processes. The fifth axis, **Candidate Characteristics** (E), considers attributes such as incumbency advantage, prior political experience, and available campaign resources.

The temporal distribution of studies according to the data integration dimension shows a predominance of unimodal approaches throughout the analyzed period. As illustrated in Figure 6, of the 80 primary studies included in the review, 59 (73.75%) employ unimodal data sources, while 21 (26.25%) utilize multimodal integration strategies.

Annual analysis indicates that the proportion between unimodal and multimodal approaches varies across observed years. In 2020, 14 unimodal and 5 multimodal studies were identified, representing 73.68% and 26.32% of publications. The year 2021 presents a similar proportion, with 12 unimodal studies (63.16%) and 7 multimodal (36.84%), being the period with the highest percentage of multimodal approaches in the analyzed corpus.

In 2022, a specific characteristic is verified, with exclusive registration of 6 unimodal studies and absence of multimodal approaches. In subsequent years, a resumption of multimodal studies is observed, although in proportions lower than those of 2021. In 2023, 10 unimodal studies (71.43%) and 4 multimodal (28.57%) were identified. The year 2024 presents 12 unimodal studies (80%) and 3 multimodal (20%), while 2025, considering publications through January, registers 5 unimodal studies (71.43%) and 2 multimodal (28.57%).

The predominance of unimodal approaches indicates that a large portion of studies concentrates the predictive process on homogeneous data sources, dedicating greater attention to methodological refinement within a specific domain. Throughout the analyzed period, no clear trend of increasing adoption of multimodal approaches is observed, with annual variation influenced by the profile of studies published each year.

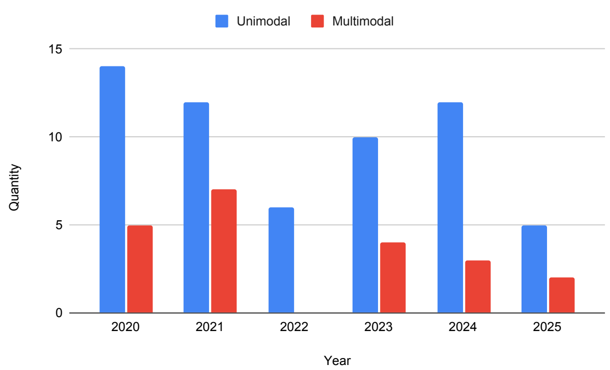

Figure 6. Percentage distribution of data integration.

The temporal distribution of studies according to the methodological complexity dimension, which classifies works into single method (employment of one central predictive approach) and multiple methods (combination of two or more central approaches), allows observation of patterns in the development of the area throughout the analyzed period. Figure 7 presents this distribution, while quantitative data are detailed below.

Of the total of 80 primary studies identified, 57 (71.25%) employ a single method and 23 (28.75%) utilize multiple methods. That is, a predominance of the single method is observed in all examined years. In greater detail, in 2020, this category represents 78.9% of studies (15 of 19), while multiple methods correspond to 21.1% (4 studies). In 2021, the proportion of multiple methods reaches 36.8% (7 of 19), the second highest of the period. In 2022, a year with the lowest absolute volume of publications, the single method represents 83.3% of studies (5 of 6). The years 2023 and 2024 present similar proportions, with multiple methods corresponding to 35.7% (5 of 14) and 40.0% (6 of 15), respectively. In 2025, considering its partial nature, all identified studies utilize a single method (7 works).

Temporal analysis does not indicate a linear trend of growth or reduction in any of the methodological categories. The participation of multiple methods oscillates between 0% (2025, partial data) and 40.0% (2024), without a consolidated pattern of evolution. This variation may be associated with factors such as characteristics of electoral contexts investigated in each period, data availability, choice of techniques by the scientific community, or specific research conditions observed in certain years.

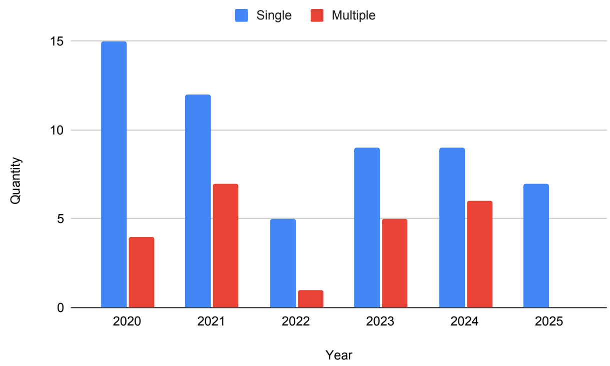

Figure 7. Percentage distribution of methodological complexity by year.

4.5 Q4: Performance Metrics and Electoral Result Types

Electoral prediction studies present different types of predictive objectives. Figure 8 presents the distribution of the five objectives identified in the analyzed corpus.

4.5.1 *Methodological Characteristics of Electoral Prediction*

The fourth research question investigates two methodological dimensions that characterize the predictive validation process in the analyzed studies. The first examines the nature of electoral prediction, identifying which results the models seek to estimate. The second analyzes the metrics used to evaluate predictive performance. These dimensions are interdependent, as the choice of appropriate metrics depends directly on the type of result predicted. Joint analysis enables understanding both the scope of predictive objectives

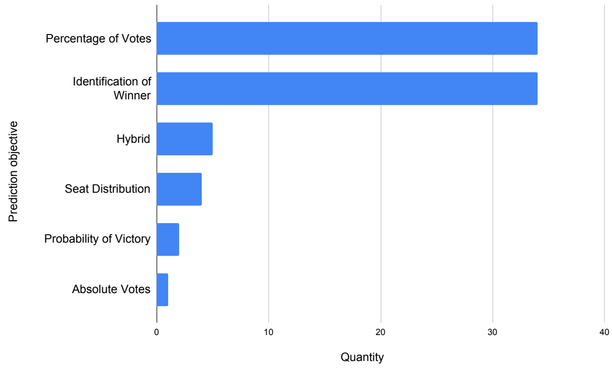

Figure 8. Distribution of prediction objectives.

and the strategies adopted to measure prediction quality, offering a more complete view of the field's methodological maturity.

The nature of electoral prediction refers to the type of result the model seeks to estimate. Different natures present distinct levels of complexity and require specific approaches. Figure 8 shows six main categories identified in the corpus.

Vote percentage prediction appears in 34 studies, where the objective is to estimate the proportion of votes allocated to each candidate or party, usually expressed in percentage points. This prediction nature provides detailed estimates of electoral preference distribution, which is useful in multiparty scenarios where support composition influences subsequent negotiations and strategies.

Winner identification, also present in 34 studies, constitutes a less detailed approach. In this modality, the objective is to determine which candidate or party will obtain the highest number of votes, without estimating exact numerical values. This is a binary or multiclass classification problem, depending on the number of competitors. This nature is appropriate for majoritarian systems, where correct winner identification has direct impact on electoral results.

Hybrid predictions appear in 5 studies and combine different predictive natures in the same work. A study may, for example, simultaneously predict vote percentages and winners, or combine vote estimates with legislative seat distribution.

Seat distribution prediction, present in 4 studies, appears in works on proportional or mixed systems. The objective is to estimate the number of legislative seats won by each party. This type of prediction requires consideration of vote-to-seat conversion rules, which vary between electoral systems and may include legal thresholds or specific coefficients.

Present in 2 studies, victory probability prediction quantifies uncertainty associated with the outcome. Instead of indicating only one winner, the model estimates each candidate's victory probability. Probabilistic approaches are useful in balanced elections, as they provide information about predictive confidence.

Absolute vote prediction is observed in 1 study and seeks to estimate the total number of votes received by each candidate, rather than percentages. Although less common, this approach may be relevant in scenarios analyzing variations in electorate size or participation patterns.

The observed distribution indicates that scientific production concentrates mainly on vote percentage prediction and winner identification, which together represent 85% of the corpus. The remaining natures, although methodologically important, present reduced presence in the analyzed set.

Predictive performance evaluation is an essential component of the methodological process. Identified metrics can play distinct roles in studies: directly evaluating electoral prediction, evaluating intermediate model stages, or providing complementary statistical measures. In studies based on sentiment analysis, this distinction is evident. A sentiment classifier may, for example, present 92.9% accuracy in identifying textual sentiments, but this metric does not represent performance in electoral prediction. That is, the same study may report that the model correctly predicted the winner in 28 of 29 analyzed states, also termed accuracy (this one does evaluate electoral prediction). Correct metric interpretation requires clarity about which model component is being evaluated.

Metric choice in studies depends on electoral prediction nature and study objectives. Numerical predictions, such as vote percentages, are evaluated with regression metrics. Categorical predictions, such as winners, use classification metrics. Identified metrics were grouped into four categories, presented below:

Regression. This group gathers metrics that quantify numerical deviations between predicted values and official results, being used mainly in vote percentage predictions.

Mean Absolute Error (MAE) is the most frequent metric, present in 27 studies. It calculates the average of absolute differences between real and predicted values, expressing the result in percentage points. MAE treats errors symmetrically and is less sensitive to extreme values than quadratic metrics.

Root Mean Squared Error (RMSE), present in 10 studies, penalizes larger errors more intensely and provides indication of extreme variation in deviations. When RMSE and MAE present similar values, errors tend to be uniformly distributed; when they differ greatly, there are elevated punctual errors.

Other metrics observed less frequently are: Mean Squared Error (MSE), present in 5 studies, corresponds to RMSE without root extraction; Mean Absolute Percentage Error (MAPE), present in 3 studies, expresses differences relatively; Total Absolute Error, present in 3 studies, sums absolute differences without calculating average; while Total Percentage Error, present in 2 studies, aggregates absolute percentage deviations.

Categorical Classification. This group is applied when prediction is structured as a classification problem. Accuracy is the most recurrent metric, present in 24 studies. In electoral prediction, it indicates the proportion of electoral units or candidates correctly classified. For example, a model that correctly predicts the winner in 45 of 50 states presents 90% accuracy.

Qualitative Comparative Evaluation. Qualitative comparative evaluation, present in 21 studies, consists of comparing predictions with real results without using numerical metrics. Analysis may occur through texts, graphics, or interpretive descriptions. Although useful for exploratory observations, this evaluation form limits comparisons between studies, as it does not quantify performance.

Other Evaluation Metrics. This category gathers less usual metrics, but which evaluate specific dimensions of predictive performance.

Correlation metrics evaluate association between predicted and real values. The Coefficient of Determination (R^2), present in 6 studies, quantifies the proportion of variance explained by the model. The Correlation Coefficient, present in 3 studies, evaluates direction and strength of linear association. These metrics do not replace error metrics, as a model may present high correlation and still possess systematic bias.

Ranking metrics evaluate whether the model correctly predicts the relative position of candidates or parties. Ranking Accuracy, present in 1 study, verifies whether the complete ranking was correctly estimated. Spearman Footrule Distance, also present in 1 study, measures dissimilarity between real and predicted ranking. These metrics are useful in multiparty scenarios but appear in limited form in the analyzed corpus.

4.6 Q5: Challenges and Limitations Reported in the Literature

Identifying methodological challenges is fundamental for advancing computational electoral prediction. Analysis of the 80 selected studies revealed diverse technical, conceptual, and practical limitations that vary according to data sources and methodological approaches employed.

Identified challenges were organized into six thematic categories: (1) data quality and representativeness, (2) natural language processing and sentiment analysis, (3) methodological validation and performance evaluation, (4) computational resources and scalability, (5) generalization and contextual dependency, and (6) ethical and privacy issues. For each category, challenges are presented distinguishing three data groups according to the nature and origin of the primary source.

The first group comprises studies employing social media platform data, specifically Twitter, Facebook, and Instagram. These studies analyze spontaneous user-generated content, characterized through large message volumes, informal language, non-standardized data structure, and content generated without institutional oversight.

The second group encompasses studies utilizing traditional electoral polls. These surveys collect vote intentions through structured interviews applied to planned population samples, following statistical sampling methodologies. Data are obtained through different contact modalities including telephone, face-to-face interviews, and online questionnaires, undergoing weighting processes to adjust samples to known demographic characteristics of the electorate.

The third group comprises studies working with structured historical data. This category encompasses official economic indicators produced from governmental institutions, demographic variables obtained from population censuses and administrative records, official results from previous elections compiled through electoral bodies, and aggregated digital behavior data such as online search records. These data are organized in structured databases, institutionally validated, and available in standardized formats.

4.6.1 Data Quality and Representativeness

Data quality and representativeness constitute fundamental challenges for electoral prediction reliability. Analysis revealed concerns related to sample adequacy and presence of noisy or distorted information, with marked differences between data modalities.

Social media-based studies. Studies utilizing social media data faced three main limitation types. First, demographic representativeness: platform users do not faithfully represent the electorate. Social networks present greater concentration of young, urban, and higher-educated users, creating systematic bias [Grimaldi *et al.*, 2020; Chandra and Saini, 2021; Chaudhry *et al.*, 2021; Huang *et al.*, 2022; Zhou *et al.*, 2021; Perera and Karunanayaka, 2022; Rita *et al.*, 2023; Rizk *et al.*, 2023; Tripathi and Neelakantappa, 2024].

Second, informational noise was identified [Grimaldi *et al.*, 2020; Jhawar *et al.*, 2020; Huang *et al.*, 2022], including spam, promotional content, automated messages, and non-election-related discussions appearing mixed with collected data, hindering identification of genuine opinions about candidates.

Third, authenticity issues emerged as central concern in approximately 20 studies. Presence of automated accounts (bots) and fake profiles was mentioned [López-López *et al.*, 2020; Chaudhry *et al.*, 2021; Bayrak and Kutlu, 2023; Qorib and Kim, 2024; Sarapugdi and Namkhun, 2023; Tripathi and Neelakantappa, 2024; Wang *et al.*, 2024]. Kišić and Kliček [2021] highlighted that ease of creating fake Facebook accounts represents significant methodological limitation, as these accounts can generate artificial volumes of candidate support or rejection manifestations.

Electoral poll-based studies. Studies in this group faced distinct challenges. Social desirability bias was mentioned [Costa *et al.*, 2021] as primary limitation. This bias occurs when respondents provide socially acceptable responses instead of expressing true vote intentions, especially in high political polarization contexts. Supporters of controversial candidates may avoid publicly manifesting real preferences due to fear of social disapproval, compromising prediction accuracy. Another identified challenge refers to temporal lag between poll collection and election day, period during which public opinion can undergo significant changes [Topîrceanu and Precup, 2020; Topîrceanu, 2025].

Structured historical data-based studies. Studies in this group faced problems related to record availability and quality. Data access difficulties were mentioned [Parida *et al.*, 2023], especially in contexts with lower institutional coverage. Inconsistencies in official databases and informational gaps were identified [Richardson and Hougen, 2020; Fachrie and Ardiani, 2021; Topîrceanu, 2025; Woodward *et al.*, 2025], particularly in elections with multiple geographic levels where not all districts possess complete records. The cold-start problem was reported [Immer *et al.*, 2020], where models cannot make predictions for localities without previous election history, particularly relevant in new electoral districts.

4.6.2 Natural Language Processing and Sentiment Analysis

Automated text processing complexity constitutes methodological challenge, especially for studies utilizing sentiment analysis to identify whether manifestations about candidates are positive, negative, or neutral. Reported difficulties vary according to textual data type and linguistic context.

Social media-based studies. Studies analyzing social network texts faced technical challenges related to sarcasm and irony identification. Sentiment analysis algorithms frequently interpret sarcastic messages literally, incorrectly classifying ironic criticisms as praise or vice versa [Moudhich and Fennan, 2021; Chaudhry *et al.*, 2021; Gunhal *et al.*, 2022; Chauhan *et al.*, 2023; Rita *et al.*, 2023].

Language informality used in social networks represented another important difficulty. Slang, abbreviations, emojis, and deliberate spelling errors hinder automated analysis [Singhal *et al.*, 2023; Tundjungsari *et al.*, 2024; Mishra *et al.*, 2024]. Words written unconventionally may not be recognized through processing systems.

Linguistic diversity emerged as additional challenge in electoral contexts where English is not the predominant language. Sentiment analysis systems are developed predominantly for English, limiting direct application to other languages. Specific difficulties in automatic processing were reported for Turkish [Baker Al Barghuthi and E. Said, 2020], Hindi [Jhawar *et al.*, 2020], and Thai [Sarapugdi and Namkhun, 2023]. In the Brazilian context, Martins *et al.* [2020] identified absence of emotional dictionaries specialized in Portuguese political vocabulary as methodological limitation.

Neutral message predominance was reported [Arya *et al.*, 2025; Tundjungsari *et al.*, 2024]. In some studies, up to 70% of messages were classified as neutral, hindering extraction of clear electoral preference signals. Implicit message interpretation difficulties were mentioned [Flores-Geronimo *et al.*, 2024]. Dependence on sentiment dictionaries specific to each language and political context was highlighted [Grimaldi *et al.*, 2020; López-López *et al.*, 2020].

4.6.3 Methodological Validation and Performance Evaluation

Challenges related to methodological validation and predictive performance evaluation were consistently reported, reflecting electoral prediction measurement complexity.

Social media-based studies. Studies in this group faced the problem of appropriate reference data absence during collection period. There is no certainty before election what would be the correct response to validate if models are functioning adequately [Brito *et al.*, 2021]. This problem, technically known as ground truth absence, means researchers can only definitively evaluate models after election occurrence.

Difficulty establishing adequate comparison points was reported [Gayo-Avello, 2013; Brito *et al.*, 2021]. Without clear reference models, determining whether a new method represents genuine advance becomes difficult. Adequate model calibration emerged as technical challenge [Grimaldi *et al.*, 2020]. Another methodological challenge refers to data volumetric bias. Users may publish multiple messages about same theme, which can distort sample representativeness [Das *et al.*, 2020]. When each message receives equal weight in analysis, particularly active user influence may be overestimated.

Structured historical data-based studies. Studies in this category faced specific methodological challenges. The cold-start problem was identified [Immer *et al.*, 2020]. Costa *et al.* [2021] reported temporal independence assumption violation, where electoral behavior at specific moment presents greater statistical dependence on previous periods than the model initially assumed. Vote count order during counting process also presented methodological implications [Deb *et al.*, 2024]. Evaluation metric adequacy to different electoral systems emerged as methodological challenge [Gayo-Avello, 2013]. Additionally, different data source integration requires careful temporal parameter calibration [Behnert *et al.*, 2024].

4.6.4 Computational Resources and Scalability

Technical limitations related to large data volume processing were reported, reflecting operational costs of large-scale digital data analysis.

Social media-based studies. Studies collecting and processing large social network message volumes faced important computational challenges. Time necessary to process millions of messages was reported [Moudhich and Fennan, 2021; Sarapugdi and Namkhun, 2023] as methodological limitation, making real-time analysis impractical. Processing millions of user geographic locations required considerable computational resources [Chan *et al.*, 2020].

Platform data access limitations represented important methodological challenges. Programming interface restrictions limiting complete data collection were identified [Grimaldi *et al.*, 2020; Rita *et al.*, 2023; Feng *et al.*, 2023]. Liu *et al.* [2021] highlighted that only 1% of tweets were available through free interface, compromising collected sample representativeness. Access conditions varied over the analyzed period, particularly after changes implemented through X (formerly Twitter) from 2023.

Structured historical data-based studies. Studies employing simulations, complex mathematical models, or large historical data volumes faced distinct computational challenges [Vendeville *et al.*, 2021; Immer *et al.*, 2020; Woodward *et al.*, 2025].

4.6.5 Generalization and Contextual Dependency

Difficulty in applying models developed for a specific electoral context to other contexts has emerged as an important methodological limitation.

Social media-based studies. Works using social networks reported limitations related to model transfer between distinct contexts. Model testing in only one specific election was mentioned [Gustisa Wisnu *et al.*, 2020] as methodological limitation. The need for temporal validation of models was highlighted [Bayrak and Kutlu, 2023; Vepsäläinen *et al.*, 2024]. Specific keyword dependence was reported [Huang *et al.*, 2022; Wang *et al.*, 2024].

Structured historical data-based studies. Studies employing economic indicators, demographic variables, previous electoral results, or aggregated online search data faced challenges related to identified pattern temporal stability. Models assuming regional voting pattern stability over time were recognized [Immer *et al.*, 2020]. Difficulty incorporating unique events without historical precedents, such as COVID-19 pandemic [Thomas *et al.*, 2021]. Candidate unconventional behavior unpredictability was highlighted [Walker, 2023]. Electoral system specific limitations were identified [Behnert *et al.*, 2024; Vergara-Perucich, 2022]. Prediction reliability depending on past observed political stability was mentioned [Kikawa *et al.*, 2020].

4.6.6 Ethical and Privacy Issues

Ethical and privacy concerns were reported less frequently than technical and methodological challenges. However, these issues represent important dimension for responsible field development.

Analysis identified three main ethical and privacy concern categories. The first category refers to publicly available personal data use on social networks [Baker Al Barghuthi and E. Said, 2020; Grimaldi *et al.*, 2020]. The second category involves electoral prediction potential effects on voter behavior and democratic process integrity. Baker Al Barghuthi and E. Said [2020] highlighted risk that publicly disclosed predictions may produce self-fulfilling prophecy effects. The third category concerns secondary use of data originally collected for other purposes.

Additionally, methodological transparency and predictive model auditability issues were mentioned [Gaur and Yadav, 2025]. A central concern lies in unequal access to sophisticated predictive models.

It is important to recognize that these ethical concerns appear only to a limited extent. Most studies concentrate attention on technical and methodological aspects, without explicit discussion about personal data use ethical implications or prediction disclosure associated responsibilities.

5 Discussion

The systematic review of 80 studies published between 2020 and 2025 enables assessment of the current state of computational electoral prediction and comparison of its advances relative to knowledge consolidated in previous reviews. This discussion organizes findings into four main dimensions: temporal and geographic evolution of scientific production, predominant methodological choices, validation and predictive performance, and persistent challenges in the field.

Temporal distribution identified an irregular pattern, with greater concentration in 2020 and 2021, totaling 19 publications each year, retraction in 2022 to 6 studies, and gradual recovery in 2023 and 2024. This temporal pattern may be associated with high-visibility electoral contexts, particularly the 2020 United States presidential election, which historically mobilizes academic interest due to wide availability of digital data. However, this dependence on specific events compromises systematic field development, as methodologies developed for particular elections are often not validated in subsequent contexts, hindering construction of cumulative knowledge.

Geographic concentration remains a structural characteristic of the area. The United States leads with 27 studies, followed by India with 15 and Indonesia with 7, replicating the pattern identified through Khan *et al*. [2021] in a previous systematic mapping. The present review identified studies in 31 countries, modestly expanding coverage relative to the 28 countries reported through Khan *et al*. [2021]. However, this expansion does not alter the fundamental problem: predominance of English-speaking contexts and large-scale Asian democracies limits the ability to evaluate whether predictive techniques function consistently across distinct electoral systems, political cultures, and levels of digital penetration. The almost total absence of studies on African contexts, with the exception of South Africa, and partial representation of Latin America and Europe evidence an important methodological gap.

Regarding investigated elections, predominance of national presidential and legislative disputes was observed, concentrated at the national administrative level. This configuration reflects both data availability and academic interest in larger-scale elections. Municipal and state elections, which present lower volumes of digital data and more localized political contexts, remain substantially underexplored. This gap represents a methodological opportunity, as local elections constitute a more rigorous test for approach robustness, given lower informational availability and greater contextual specificity.

Twitter's persistence as the dominant source, present in 80.3% of social media usage occurrences, confirms the structural dependence identified in all previous reviews [Gayo-Avello, 2013; Chauhan *et al*., 2021; Brito *et al*., 2021; Khan *et al*., 2021; Alvi *et al*., 2023]. Facebook appears second with only 8 occurrences, while Instagram, YouTube and Reddit present marginal use. This concentration on a single platform exposes the field to biases inherent to Twitter user demographics, which tends to overrepresent young, urban, and higher education individuals, as documented in challenges reported through analyzed studies. The change observed in 2025, when other sources reached 57.14%, should be interpreted cautiously given the partial nature of the year and the absence of evidence of a consolidated trend.

The implications of this platform dependence extend beyond demographic bias. Results obtained exclusively from Twitter may not transfer to other digital environments with distinct user profiles and interaction patterns, which limits the generalization capacity of developed models to broader population contexts. An additional concern relates to data access conditions. As documented among the reported challenges, programming interface restrictions limit the volume of data available for collection. These restrictions, intensified following the policy changes implemented on the platform from 2023 onward, directly affect the feasibility of replicating methodologies from previous studies and conducting new investigations under equivalent conditions. When access to historical data is reduced or interrupted, the continuity of longitudinal research lines and the possibility of systematic comparisons between electoral cycles are compromised. This situation reinforces the importance of diversifying data sources as a strategy to reduce the field's vulnerability to changes in platform policies.

The developed taxonomy revealed that 73.75% of studies employ unimodal approaches and 71.25% utilize a single method. This predominance of methodologically simpler strategies, concentrated in the unimodal with single method category, contrasts with the hypothesis that more sophisticated approaches, integrating multiple heterogeneous sources and complementary methods, would present superior performance. Lower adoption of multimodal strategies with multiple methods may reflect elevated computational costs, difficulties accessing heterogeneous data, or absence of consistent evidence of predictive gains that justify additional complexity.

The two dimensions of the taxonomy, data integration and methodological complexity, can be used in a complementary manner by researchers at different stages of study design. The data integration dimension allows researchers to identify whether the available sources support a unimodal or multimodal configuration. Unimodal studies concentrate the predictive process on a single data source, such as Twitter posts or historical electoral results, which simplifies collection and processing procedures. Multimodal studies, in contrast, combine data from different origins, such as social media posts, opinion polls, and economic indicators simultaneously. This combination requires that the data sources share compatible formats, cover the same collection period, and can be processed together, which involves greater technical and computational effort. The methodological complexity dimension, in turn, allows researchers to evaluate whether the combination of multiple predictive approaches is justified by the characteristics of the electoral context under investigation or by the prediction objective defined. Additionally, the taxonomy allows identification of underexplored configurations in the literature. As documented in the results, multimodal approaches with multiple methods represent a minority in the analyzed corpus, which indicates research opportunities in configurations that have received limited empirical attention. Researchers can use this information to position new studies in areas where the accumulated evidence is still insufficient, contributing to a more balanced development of the field.

The methodological and contextual heterogeneity observed across the analyzed corpus warrants a direct note on the analytical scope of the present review. The 80 primary studies were conducted in 31 countries with distinct electoral systems, covered different administrative prediction levels, employed varied data sources, and adopted heterogeneous evaluation metrics. Vote percentage prediction evaluated by Mean Absolute Error in a two-candidate majoritarian election, for instance, is not directly comparable to winner identification measured by accuracy in a multiparty proportional system. Sentiment-based approaches were applied predominantly to social media data in specific linguistic contexts, while structured historical data approaches operated with different dependent variables and temporal windows. Under these conditions, direct numerical comparisons of performance between methodological categories would risk producing misleading conclusions, as observed variations would more likely reflect differences in electoral context, data quality, or platform characteristics than differences attributable to the methodological choices themselves. The absence of uniform validation protocols constitutes a persistent methodological challenge in the field, limiting systematic aggregation of results and the establishment of reliable benchmarks across studies.

Analysis of predictive approaches identified sentiment analysis as the predominant technique, with 44.25% of occurrences, followed through use of structured historical data with 27.43% and volumetric approach with 16.81%. This distribution is consistent with Khan *et al.* [2021], who reported 89% of studies using sentiment analysis. Concentration in this technique reflects both growing availability of natural language processing tools and the intuition that emotional polarity captures electoral preferences. However, reported technical challenges related to sarcasm, irony, and linguistic informality indicate this approach faces persistent limitations. Approaches based on structural analysis of social networks, opinion dynamics modeling, and candidate characteristics remain substantially underexplored, with only 6.19%, 1.77%, and 1.77% of occurrences respectively.

Electoral prediction types revealed concentration in vote percentages and winner identification, each present in 34 studies, totaling 85% of the corpus. This distribution indicates two distinct methodological objectives: detailed numerical estimates, appropriate for evaluation through regression metrics like Mean Absolute Error, and categorical classifications of results, evaluated through accuracy metrics. Other prediction natures, including distribution of legislative seats, victory probabilities, and absolute votes, remain less frequent, possibly due to complexity of modeling vote conversion rules in proportional systems or scarcity of calibrated data for probabilistic estimates.

Identified evaluation metrics directly reflect employed prediction types. Mean Absolute Error, present in 27 studies, predominates in numerical predictions due to its direct interpretability in percentage points. Accuracy, used in 24 studies, concentrates on categorical predictions. Notably, 21 studies employed qualitative evaluation without formal numerical metrics, through graphical or textual comparisons between predictions and actual results. This practice severely compromises comparability between works, as it makes quantitative synthesis of performance impossible and hinders establishment of reliable benchmarks. Alvi *et al.* [2023] identified this absence of uniform criteria as a persistent field limitation, a situation that findings of this review confirm remains unresolved.

Systematic analysis of reported challenges organized limitations into six thematic categories. Data quality and representativeness emerged as central concerns, manifesting in distinct forms according to employed source. Studies based on social networks faced demographic bias, presence of automated accounts, and informational noise. Studies based on electoral surveys dealt with social desirability bias and temporal lag. Studies based on structured historical data encountered record completeness problems and difficulty incorporating unprecedented events. These limitations, identified through Gayo-Avello [2013] as structural problems of sampling bias over a decade ago, remain without consensual methodological solution.

Natural language processing presented recurrent technical challenges, including identification of sarcasm and irony, linguistic informality, idiomatic diversity, and predominance of neutral messages, which in some studies reached 70% of the analyzed corpus. These problems, also documented through Chauhan *et al.* [2021], indicate that advances in language models have not yet completely resolved contextual interpretation difficulties in informal digital environments. Methodological validation revealed absence of ground truth during collection periods, difficulty establishing appropriate baselines, and need for careful parameter calibration.

Computational resources limited real-time analysis of large data volumes, while programming interface restrictions compromised sampling representativeness. Liu *et al.* [2021] highlighted that only 1% of tweets was available through free interface, compromising coverage of collected data. Generalization and contextual dependence evidenced difficulty transferring models between distinct contexts and pattern instability in situations of profound political changes, a limitation identified through Thomas *et al.* [2021] when working with COVID-19 pandemic impacts. Ethical questions related to privacy and misinformation impact remain underexplored, although Qorib and Kim [2024] demonstrated that removal of false messages improved predictive accuracy from 74.51% to 86.27%.

Comparing findings with previous reviews, continuity in fundamental limitations is observed. The meta-analysis conducted through Skoric *et al.* [2020] concluded that performance of predictions with social media fell short of traditional electoral surveys, with mean absolute error of 2.3 percentage points. The present review did not identify evidence of reversal of this pattern in the period from 2020 to 2025. Standardization challenges pointed out through Brito *et al.* [2021] remain present, with heterogeneity in validation criteria and evaluation protocols. The geographic limitation highlighted through Khan *et al.* [2021] persists, with predominance of English-speaking contexts.

Findings suggest the field remains in a stage of methodological maturation. Production has expanded numerically and diversified geographically in a modest way, but has not resolved fundamental challenges related to sampling representativeness, generalization between contexts, and protocol standardization. Twitter dependence represents both strength, allowing longitudinal comparisons, and fragility, exposing the field to changes in platform access policies. The proposed taxonomy offers a framework to organize methodological diversity and identify specific gaps, particularly in underexplored categories such as multimodal studies with multiple methods integrating opinion dynamics modeling and candidate characteristics.

6 Conclusion

This systematic review analyzed 80 primary studies published between 2020 and 2025 on prediction of electoral results using digital data. The work offers two main contributions to the field.

First, it updates the temporal scope to the most recent period, incorporating developments subsequent to reviews conducted through Brito *et al.* [2021], Khan *et al.* [2021], and Alvi *et al.* [2023]. This update allows identification of continuities and changes in scientific production of the area in the last five years.

Second, it proposes a taxonomy that organizes and classifies studies according to data integration and predictive complexity. This system facilitates understanding of different methodological approaches, allows systematic comparisons between studies, offers common language for scientific communication, and assists in identification of research gaps.

The work presents limitations that should be considered. Restriction to three databases may have excluded relevant works published in other venues. Additionally, the expanded taxonomy of predictive approaches proposed in this review requires evaluation from other researchers to validate its adequacy and applicability in different analysis contexts.

Future research directions include geographic expansion of studies, prioritizing less represented electoral contexts. Development of language processing resources for languages beyond English can expand technique applicability, and data source diversification, reducing dependence on a single platform, can mitigate inherent biases. Moreover, as Gaur and Yadav [2025] highlighted, there is need for rigorous validation of collection techniques and mitigation of biases introduced through artificially generated content.

Validation protocol standardization represents a methodological barrier, as absence of uniform criteria hinders comparisons between studies. Establishment of metrics for different prediction types, definition of consistent reference models, and development of public datasets for comparative evaluation can favor field advancement. Similarly to this study, this need is also presented in meta-analysis performed through Skoric *et al*. [2020].

Predominance of sentiment analysis, identified in approximately 44% of predictive approaches in the analyzed corpus, evidences methodological concentration that may limit diversity of perspectives on the electoral phenomenon. This concentration represents both a gap and an opportunity for methodological innovation, suggesting space for exploration of complementary techniques that can capture distinct dimensions of electoral behavior. Chauhan *et al*. [2021] observed a similar pattern in their review, highlighting the need to expand the methodological repertoire of the area.

Longitudinal studies that validate models in multiple contexts over time are necessary to evaluate generalization. Positive results in specific elections do not guarantee consistent performance in other scenarios [Brito *et al*., 2021]. Validation in diverse electoral contexts allows identification of factors that affect methodology transfer between different electoral systems and political cultures.

Ethical questions related to privacy, potential opinion manipulation, and misinformation impact demand growing attention. Gayo-Avello [2013] warned that electoral predictions publicly disseminated can influence voter behavior. Future research should consider not only technical accuracy of models, but also their social implications and associated risks.

Prediction of electoral results with digital data remains a methodologically diverse and conceptually challenging field. The present review offers state-of-the-art mapping and analytical structure to guide future research toward greater methodological rigor, contextual diversity, and development of scientific knowledge about the electoral phenomenon in digital environments.

Table 1: Characterization of studies selected in the systematic review

Authors	**Country and Year**	**Election Type**	**Integration**	**Data Volume**	**Data Type**	**Combination**	**Approaches**	**Prediction Type**	**Metrics**
Das *et al.* [2020]	Australia 2019	National Legislative - Lower House	Unimodal	Large scale	Twitter - posts/tweets	Single method	Volumetric	Vote Percentage	MAE, RMSE
Agarwal *et al.* [2020]	India 2019	National Legislative - Lower House	Unimodal	Massive scale	Twitter - posts/tweets	Single method	Sentiment	Winner Identification	Total Absolute Error
Baker Al Barghuthi and E. Said [2020]	Turkey 2018	President	Unimodal	Medium scale	Twitter - posts/tweets	Single method	Sentiment	Vote Percentage	Accuracy
Brito and Adeodato [2020]	Brazil 2018, United States of America 2016	President	Multimodal	Medium scale	Facebook - posts and interactions, Twitter - posts and interactions, Instagram - posts and interactions, Opinion polls	Multiple methods	Volumetric, Structured Historical	Vote Percentage	MAE, MAPE
Chan *et al.* [2020]	United States of America 2016	President	Unimodal	Large scale	Twitter - follower profiles, Geographic data	Single method	Volumetric	Winner Identification	Accuracy
Davidson and White [2020]	United States of America 2018	Comparative Contexts / Multiple Elections	Unimodal	Medium scale	Facebook - profile images	Single method	Candidate Characteristics	Percentage, Binary Identification	Accuracy, R^2, Correlation Coefficient
Davidson and White [2020]	Canada 2019	National Legislative - Lower House	Multimodal	Large scale	Twitter - user data, Aggregated opinion polls, Historical electoral data	Single method	Volumetric	Seat Distribution	Total Absolute Error, Confidence Intervals
Firmansyah *et al.* [2020]	Indonesia 2019	President	Unimodal	Small scale	Twitter - posts/tweets	Single method	Sentiment	Winner Identification	Accuracy, Precision, Recall, F1-Score
Grimaldi *et al.* [2020]	Spain 2019	President	Multimodal	Large scale	Twitter - posts/tweets	Multiple methods	Volumetric, Sentiment, Structured Historical	Vote Percentage	MAE, RMSE, Accuracy, Precision, Recall, F1-Score
Gustisa Wisnu *et al.* [2020]	Indonesia 2018	Governor / State Chief Executive	Unimodal	Small scale	Twitter - labeled posts/tweets	Single method	Sentiment	Winner Identification	Accuracy, Precision, Recall, F1-Score, Qualitative Comparative Assessment
Immer *et al.* [2020]	Switzerland 2019-2020, United States of America 2016, Germany 2009, Germany 2005	Comparative Contexts / Multiple Elections	Multimodal	Not applicable	Official electoral data	Single method	Structured Historical	Vote Percentage	MAE, Accuracy, Spearman Footrule Distance

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Table 1: Characterization of studies selected in the systematic review (Continued)

Authors	Country and Year	Election Type	Integration	Data Volume	Data Type	Combination	Approaches	Prediction Type	Metrics
Chin and Wang [2021]	Taiwan 2018	Comparative Contexts / Multiple Elections	Multimodal	Medium scale	Facebook - unspecified data, Opinion polls, Prediction markets	Multiple methods	Volumetric, Structured Historical	Percentage, Binary Identification	MSE, AUC-ROC
Costa *et al.* [2021]	Portugal 2019	National Legislative – Lower House	Unimodal	Not applicable	Survey/longitudinal questionnaires	Single method	Structured historical data	Vote percentage	Accuracy, Precision, Recall, AUC–ROC, Specificity, χ^2
Dutta *et al.* [2021]	India 2021	Subnational Legislative	Unimodal	Small scale	Twitter - posts/tweets with hashtags	Multiple methods	Sentiment Analysis, Network Structure	Win Probability	Qualitative Comparative Assessment
Fachrie and Ardiani [2021]	Indonesia 2007-2020	Comparative Contexts / Multiple Elections	Unimodal	Not applicable	Official electoral data, Wikipedia, News portals	Single method	Structured Historical	Winner Identification	RMSE, Accuracy, Precision, Recall, F1-Score
John Joseph and Nonsiri [2021]	India 2020	Subnational Legislative	Unimodal	Medium scale	Twitter - posts/tweets	Single method	Sentiment Analysis	Seat Distribution	Total Absolute Error
Kišić and Kliček [2021]	Croatia 2017	Mayor / Municipal Chief Executive	Unimodal	Small scale	Facebook - candidate pages, Candidate data, Official electoral data	Single method	Volumetric	Vote Percentage	RMSE, R^2
Kumar *et al.* [2021]	India 2019	National Legislative - Lower House	Unimodal	Medium scale	Twitter - posts/tweets with sentiment analysis	Single method	Sentiment Analysis	Winner Identification	Accuracy, Qualitative Comparative Assessment
Liu *et al.* [2021]	United States of America 2016	President	Multimodal	Medium scale	Twitter - posts/tweets aggregated by county, Economic data	Multiple methods	Sentiment Analysis, Structured Historical	Percentage, Binary Identification	RMSE, Accuracy, Precision, Recall, F1-Score
Moudhich and Fennan [2021]	United States of America 2020	President	Unimodal	Large scale	Twitter - posts/tweets	Single method	Sentiment Analysis	Vote Percentage	Accuracy, Qualitative Comparative Assessment
Nugroho [2021]	United States of America 2020	President	Unimodal	Not applicable	Twitter - posts/tweets	Single method	Sentiment Analysis	Percentage, State Ranking	Qualitative Comparative Assessment
Okimoto *et al.* [2021]	Japan 2019	National Legislative - Upper House	Unimodal	Large scale	Twitter - responses/replies	Multiple methods	Sentiment Analysis, Volumetric, Network Structure	Winner Identification	Accuracy, Precision, Recall, F1-Score
Padwal and Koshy [2021]	United States of America 2020	President	Multimodal	Not applicable	Twitter - posts/tweets with sentiment and personality analysis, Candidate speeches	Multiple methods	Sentiment Analysis, Candidate Characteristics	Win Probability	Accuracy, Qualitative Comparative Assessment

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Table 1: Characterization of studies selected in the systematic review (Continued)

Authors	Country and Year	Election Type	Integration	Data Volume	Data Type	Combination	Approaches	Prediction Type	Metrics
Feng *et al*. [2023]	United States of America 2012, United States of America 2016, United States of America 2020	President	Multimodal	Large scale	Twitter - posts/tweets, Demographic data, Economic data, Opinion polls	Multiple methods	Sentiment Analysis, Structured Historical	Winner Identification	Accuracy, Precision, Recall, F1-Score
Irmalasari and Dwiyanti [2023]	Indonesia 2019	Subnational Legislative	Unimodal	Not applicable	Candidate data	Single method	Structured Historical	Winner Identification	Precision, Recall, F1-Score
Khan *et al*. [2023]	United States of America 2020	President	Unimodal	Large scale	Twitter - posts/tweets	Single method	Sentiment Analysis	Vote Percentage	MAE, RMSE, Accuracy
Oueslati *et al*. [2023]	United States of America 2016	President	Unimodal	Medium scale	Facebook - posts/messages	Single method	Sentiment Analysis	Vote Percentage	MAE, F1-Score, AUC-ROC
Rita *et al*. [2023]	United Kingdom 2019	Prime Minister / Head of Government	Unimodal	Medium scale	Twitter - posts/tweets	Single method	Sentiment Analysis	Winner Identification	Accuracy, Precision, Recall, Qualitative Comparative Assessment
Rizk *et al*. [2023]	United States of America 2020	President	Unimodal	Large scale	Twitter - posts/tweets	Single method	Sentiment Analysis	Winner Identification	Accuracy
Sarapugdi and Namkhun [2023]	Thailand 2023	Prime Minister / Head of Government	Unimodal	Medium scale	Twitter - posts/tweets	Multiple methods	Sentiment Analysis, Network Structure	Winner Identification	Qualitative Comparative Assessment
Singhal *et al*. [2023]	United States of America 2022	National Legislative - Lower House	Unimodal	Medium scale	Twitter - posts/tweets	Single method	Sentiment Analysis	Winner Identification	Qualitative Comparative Assessment
Vigna-Gómez *et al*. [2023]	Mexico 2021	National Legislative - Lower House	Unimodal	Massive scale	Twitter - posts/tweets	Multiple methods	Volumetric, Sentiment Analysis, Structured Historical	Vote Percentage	Accuracy, F1-Score, AUC-ROC, Confidence Intervals
Walker [2023]	United States of America 2020, United States of America 2024	President	Multimodal	Not applicable	Economic data, Official electoral data, Demographic data	Single method	Structured Historical	Vote Percentage	MAE, R^2
Ayma Quirita *et al*. [2024]	Peru 2021	President	Unimodal	Large scale	Twitter - posts/tweets	Multiple methods	Volumetric, Sentiment Analysis	Winner Identification	Accuracy, F1
Behnert *et al*. [2024]	Germany 2009, Germany 2013, Germany 2017, Germany 2021	National Legislative - Lower House	Unimodal	Not applicable	Google Trends - search data, Opinion polls, Official electoral data	Multiple methods	Behavioral, Structured Historical	Vote Percentage	MAE, RMSE, Ranking Accuracy
Deb *et al*. [2024]	India 2020	Comparative Contexts / Multiple Elections	Multimodal	Not applicable	Official electoral data - real-time vote counting	Single method	Structured Historical	Winner Identification	RMSE, Accuracy
Flores-Geronimo *et al*. [2024]	Mexico 2018	President	Unimodal	Medium scale	Twitter - classified posts/tweets	Single method	Sentiment Analysis	Vote Percentage	Qualitative Comparative Assessment

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Table 1: Characterization of studies selected in the systematic review (Continued)

Authors	Country and Year	Election Type	Integration	Data Volume	Data Type	Combination	Approaches	Prediction Type	Metrics
Gutiérrez *et al.* [2025]	Mexico 2024	President	Unimodal	Not applicable	Twitter - engagement metrics, Facebook - engagement metrics, Instagram - engagement metrics, YouTube - engagement metrics, Offline polls	Single method	Volumetric	Vote Percentage	Qualitative Comparative Assessment
Mancilla *et al.* [2025]	Mexico 2021	Governor / State Chief Executive	Multimodal	Not applicable	Survey/sociodemographic questionnaires	Single method	Structured Historical	Winner Identification	Accuracy, AUC-ROC
Topîrceanu [2025]	Argentina 2023, Brazil 2022, Canada 2021, France 2022, Indonesia 2024, Poland 2020, Romania 2024, Turkey 2023, United States of America 2020, United States of America 2024	Comparative Contexts / Multiple Elections	Unimodal	Not applicable	Opinion polls	Single method	Structured Historical	Vote Percentage	RMSE, MAPE, Total Percentage Error, Accuracy
Woodward *et al.* [2025]	India 2024	National Legislative - Lower House	Unimodal	Not applicable	Official electoral data	Single method	Structured Historical	Winner Identification	MAE, RMSE, MAPE, MSE, Accuracy, Precision, Recall, F1-Score, Specificity
Gohil *et al.* [2023]	India 2023	Subnational Legislative	Multimodal	Small scale	Twitter - posts/tweets, Historical electoral data	Multiple methods	Sentiment Analysis, Structured Historical	Winner Identification	Accuracy, Precision, F1-Score
Parida *et al.* [2023]	India 2014, India 2019, India 2024	National Legislative - Lower House	Multimodal	Massive scale	Twitter - posts/tweets, Social media - various posts, Journalistic publications, Historical electoral data	Single method	Structured Historical	Seat Distribution	MAE
Qorib and Kim [2024]	United States of America 2020	President	Unimodal	Large scale	Twitter - posts/tweets with filtered hashtags	Single method	Sentiment Analysis	Winner Identification	Accuracy, Precision, Recall, F1-Score
Tundjungsari *et al.* [2024]	Indonesia 2024	President	Unimodal	Medium scale	Twitter - posts/tweets	Single method	Sentiment Analysis	Winner Identification	Qualitative Comparative Assessment
Vepsäläinen *et al.* [2024]	Finland 2019	National Legislative - Lower House	Unimodal	Medium scale	Facebook - candidate data, Twitter - candidate data, Demographic data, Political data - campaign budget and education	Multiple methods	Volumetric, Structured Historical	Absolute Votes	MAE, R^2

Source: Prepared by the author (2025).
Note: Data volume categorization – Small scale: < 10,000; Medium scale: 10,000–99,999; Large scale: 100,000–999,999; Very large scale: 1,000,000–9,999,999; Massive scale: $\geq$ 10,000,000; Not applicable: no social media data or not specified.

Declarations

Authors' Contributions

All authors contributed equally to the conception, methodology, investigation, analysis, and writing of this manuscript. All authors read and approved the final manuscript.

Competing interests

The authors declare that they have no competing interests.

Availability of research artifacts

The data and other materials created and/or used in this literature review will be made available upon request.

Use of Artificial Intelligence

The authors used the generative artificial intelligence tool ChatGPT (OpenAI, GPT-4) to assist with the writing and textual revision of the manuscript.

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