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Candidate vote prediction in open-list systems: Forecasting the results of the 2023 Finnish parliamentary election[☆]

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ABSTRACT

The availability of rich online data has opened new opportunities for election forecasting. While typical election forecasting predicts results at the national level, the accumulation of information on candidate and voter behavior enables making predictions on a more granular level. Most studies using online data focus on contests with a small number of candidates, leaving a research gap for elections with larger candidate pools. Elections with numerous candidates differ from races with a limited number of candidates, as voters are more inclined to use heuristics and mental shortcuts when selecting their preferred candidate. Building on this insight, this paper introduces a model to predict each candidate's vote share in the context of Finnish parliamentary elections. An ex ante forecast based on the model was published before the 2023 Finnish parliamentary election, which correctly identified 150 of the 200 candidates elected to parliament from a total pool of 2468 contestants. The results showcase the potential to effectively leverage the rich online data environment, thus complementing existing methodologies. Compared to traditional approaches, the proposed model provides candidate-level estimates, which offer insights into intra-party competition and list rankings.

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1. Introduction

Predicting election outcomes has become an important aspect of democratic processes around the world, influencing both voter behavior and the electoral process itself (Gschwend & Meffert, 2017; Lewis-Beck et al., 2025; Victor, 2021). The most traditional approach in electoral forecasting is based on opinion polls, which can directly gauge voter sentiment (Kang & Oh, 2024; Lewis-Beck & Tien, 2016). In contrast, academic researchers often employ structuralist models that use fundamentals such as economic conditions to predict voting behavior (Lewis-Beck & Dassonneville, 2015; Lewis-Beck & Tien, 2016). Both methods have different trade-offs: structural models tend to perform better with longer lead times, while poll

accuracy improves closer to election day (Lewis-Beck & Dassonneville, 2015; Williams & Reade, 2016). However, each faces significant challenges, as structural models can overlook dynamic political shifts while polling is increasingly hindered by declining public response rates (Bailey, 2024; Groves, 2011).

Recognizing the distinct limitations of relying on either polls or structural factors alone, a prominent trend in contemporary forecasting research is the development of hybrid or synthetic models that combine multiple sources of information (Graefe et al., 2014; Lewis-Beck, 2005). The rationale is that any single method is constrained by the data it uses, and combining forecasts can integrate a wider array of predictive signals, leading to more robust and accurate outcomes (Graefe, 2019). This turn toward synthesis is particularly crucial in electoral environments that pose significant challenges for traditional models. For example, forecasting can be challenging in complex multiparty systems (Montalvo et al., 2019; Nadeau &

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Lewis-Beck, 2020), or a lack of historical data can hinder structural approaches (Kang & Oh, 2024). Similarly, challenges arise when national-level models fail to capture constituency-level dynamics (Gschwend et al., 2022; Munzert, 2017) or when reliable polling data is simply unavailable (Umeda, 2023).

This paper builds on the premise that a candidate-focused, bottom-up approach could offer an alternative way to address these forecasting challenges in open-list elections. The candidate model can provide detailed predictions for local races and does not depend on traditional polling, though it can be combined with other data and forecasts if available. The candidate-based approach is enabled by the large amount of publicly available online data, such as the number of followers on social media and the candidate's past electoral performance. The presented perspective is importantly different from previous work that has used online data to measure public opinion, which has remained controversial and has had limited success (Gayo-Avello, 2013; Huberty, 2015). Unlike previous work that uses social media as a proxy for public opinion, the presented model uses a platform follower count simply to quantify the scale of the online supporter base each candidate has cultivated.

On a theoretical level, the model is grounded in the political psychology of voter heuristics. Cognitive heuristics are mental shortcuts that voters use to navigate complex electoral choices (Lau & Redlawsk, 2006; Popkin, 1991). For instance, a candidate's past electoral performance is a powerful input for the retrospective judgments that voters make about their quality and viability (Fiorina, 1976). Furthermore, a candidate's party affiliation is a well-known heuristic that strongly predicts vote choice (Campbell et al., 1960). Successful candidates also receive more media coverage, and repeated exposure to a candidate's name can foster a sense of cognitive ease and preference in voters (Zajonc, 1968). In the same vein, modern campaign signals can act as cues to voters. A candidate's ability to raise campaign funds serves as a public signal of their viability. At the same time, high social media engagement can provide social proof, a form of endorsement cue that signals widespread support (Lau & Redlawsk, 2001). Recognizing that individuals often use multiple heuristics simultaneously, the model also integrates other vote-earning attributes, such as personal qualities and qualifications (Zittel, 2016).

Some prior literature has incorporated candidate-specific parameters into broader structural forecasting models with some success. For instance, in the context of US presidential elections, evidence suggests that including candidate characteristics, such as political experience, yields a modest but discernible improvement in forecast accuracy (Lewis-Beck & Tien, 2018). It can be hypothesized that in an electoral system with a significantly larger field of candidates, the impact of such individual attributes would be more pronounced.

Building on this candidate-focused perspective, this study proposes and tests a candidate-level forecasting model to evaluate its predictive potential. The model synthesizes publicly available data from various sources, including social media metrics, historical electoral performance indicators, and demographic characteristics of

individual candidates. The methodology employs supervised machine learning algorithms trained on data from previous Finnish elections (2015 and 2019). The research is guided by the following core question: *How accurately can this model predict the number of votes received by individual candidates in the 2023 Finnish parliamentary elections?*

The objectives of this study are multifaceted. First, it tests the predictive capability of the candidate-level model by applying it to the 2023 Finnish parliamentary elections. Second, it explores how various types of public data, including social media metrics, historical electoral performance, and demographic information, can be integrated to enhance the model's overall predictive accuracy. Third, the study aims to provide a clear, transparent view of the model's inner workings by assessing the influence of these measures on the predicted outcome using Shapley Additive Explanations. The detailed analysis and interpretation throughout the paper are based on a slightly refined version of the model, which is discussed in the Methodology section.

2. Research background

2.1. Electoral decision making

Forecasting election results involves predicting which candidates citizens will vote for and understanding the reasons behind their preferences. The study of election forecasting is enriched by theories that explore how and why individuals make their electoral choices (Redlawsk & Pierce, 2016). This research is therefore grounded in the extensive literature showing that voters rely on heuristics and mental shortcuts to make their electoral choices (Bølstad, 2018; Kahneman, 2003; Redlawsk & Pierce, 2016; Simon, 1955).

The candidate perspective in election forecasting centers on analyzing the specific characteristics of candidates that predict their electoral success. In today's digital age, there is a wealth of information available on candidates, including their social media activity, public statements, campaign platforms, and personal attributes (Salganik, 2019). Political candidates actively promote these characteristics through digital platforms to appeal to voters (Carlson & Strandberg, 2024).

Although numerous attributes contribute to a candidate's final number of votes, a few major drivers of electoral choice consistently emerge from political psychology research. Candidate's electoral history and party affiliation serve as foundational heuristics. Past electoral performance is a powerful input into voters' retrospective judgments of a candidate's quality and electability (Fiorina, 1976). A history of winning provides a strong signal of competence and viability. Alongside this record, the party label acts as a comprehensive shortcut for a candidate's ideology, policy positions, and connection to social groups, allowing voters to make a decision that aligns with their own identity with minimal cognitive effort (Campbell et al., 1960).

Other signals related to a candidate's public profile and campaign activities also influence voter choice. Successful candidates, particularly incumbents, command greater

media attention. This repeated exposure can foster a sense of familiarity and cognitive ease in many voters, a phenomenon known as the mere-exposure effect (Zajonc, 1968). The exposure may be amplified by digital campaign signals that serve as direct cues of viability and support. Similarly, high social media engagement can provide powerful social proof, functioning as a modern endorsement cue that can signal grassroots support and momentum (Lau & Redlawsk, 2001).

Beyond broader attributes, voters often rely on a candidate's individual qualities, giving rise to the concept of the personal vote (Zittel, 2016). The specific traits that attract this support, known as personal vote-earning attributes, act as informational cues that signal a candidate's credibility and competence to the electorate (Isotalo et al., 2020; Put et al., 2019). The importance of these attributes, such as political experience or public profile, is especially pronounced in electoral systems like open-list proportional representation, where intra-party competition forces candidates to differentiate themselves (Shugart et al., 2005; Zittel, 2016).

The influence of heuristics extends beyond information limitations, as seemingly arbitrary factors can shape voter decisions (Bølstad, 2018). One well-documented example is the ballot position effect, where international research has often found a J-curved relationship between a candidate's placement on the ballot and their vote share (Faas & Schoen, 2006; Marcinkiewicz & Stegmaier, 2015). Specifically, candidates at the top or bottom of a list tend to gain an advantage over those in the middle (Marcinkiewicz & Stegmaier, 2015; Söderlund et al., 2021). In the Finnish electoral system, the order of candidates on the ballot is determined by a random process, which minimizes the risk that this effect is simply a proxy for pre-existing candidate popularity or experience. While the independent impact of ballot position is modest, its randomized nature makes it a potentially useful data point for modeling.

Acknowledging the complexity of voter behavior and its theoretical underpinnings has several implications for election forecasting. Firstly, given the intricacies of voter decision-making, no model can entirely capture this complexity. However, focusing on relevant variables informed by voter heuristics can enhance the accuracy of forecasting models. Much like structuralist forecasting models that rely on economic factors, using multiple indicators, such as candidate characteristics, social media presence, and public perception, can improve predictions of voter behavior. By integrating these diverse data sources, it may be possible to create models that reflect the multifaceted nature of electoral decisions.

These comprehensive data can be combined with records of past elections, government performance, and economic conditions to develop robust forecasting models. By understanding how candidates' characteristics align with voters' heuristics, it is possible to predict each candidate's vote count.

2.2. Finnish electoral system

Finland operates under a stable parliamentary democracy characterized by a multiparty system and a framework that emphasizes both representative governance

and the rule of law (Jääskeläinen, 2023). Central to this system are the parliamentary elections, which are governed by the Finnish Constitution (Jääskeläinen, 2023). Sovereign power in Finland belongs to the people and is exercised through the unicameral Finnish parliament (*Eduskunta*), which comprises 200 representatives. These members are elected every four years on the third Sunday in April. All Finnish citizens 18 years or older are entitled to vote.

The Finnish parliament is elected from 14 multi-member constituencies and one single-member district, with a median district magnitude of approximately 13 seats (Jääskeläinen, 2023). Finnish parliamentary elections utilize an Open List Proportional Representation (OLPR) system. Parties and alliances nominate candidates for lists, and the ballot numbers are randomly assigned. Voters cast their votes by writing the number of their chosen candidate on the ballot, without the option to vote solely for a party.

In Finnish parliamentary elections, the allocation of seats is determined using the d'Hondt divisor method (Jääskeläinen, 2023). Initially, the votes received by each candidate are summed to determine the total vote count for each party list at the district level. Seats are first allocated by giving the total list votes to the most popular candidate on the list. For subsequent candidates, the list's total votes are progressively divided by integers: by 2 for the second-most popular, by 3 for the third-most popular, and so on. The candidate associated with the highest total wins the first seat in the electoral district. This process continues, with the vote totals being recalculated and seats being awarded in descending order of votes until all seats in the district are allocated.

In addition to the elected members of parliament, each party establishes a list of substitutes based on the same election results. A substitute is a candidate who was not elected but received the highest number of votes within their electoral district. For example, 73 such substitutes were designated after the 2023 parliamentary election, and 77 after the 2019 election.

Finnish parliamentarism shares characteristics common to parliamentary systems with proportional list systems (Karvonen, 2014). Cabinets rely on the support of the parliamentary majority, making party discipline crucial. Although the d'Hondt method marginally favors larger parties, the Finnish system remains highly proportional. The lack of a minimum vote threshold encourages the representation of smaller parties. Because constituents must always select their preferred candidate, candidates must actively campaign for personal votes, adding a preferential element unique to Finland compared to many other parliamentary countries. Typically, the largest party garners just over a fifth of the seats.

A large number of candidates participate in the elections, and voting advice applications are widely used (Isotalo et al., 2023; Von Schoultz & Papageorgiou, 2021). Digital technologies and social media significantly influence Finnish elections, highlighting the electorate's digital adeptness and connectivity (Kestilä-Kekkonen & von Schoultz, 2020; Strandberg, 2013; Strandberg et al., 2024).

The Finnish Parliamentary elections held on April 2, 2023, are the main subject of this study. In the 2023

elections, the main governing party, the Social Democrats, along with the leading opposition parties, the National Coalition and the Finns Party, showed significant gains compared to the previous elections held four years earlier (Arter, 2024). In contrast, the junior coalition parties, the Centre, the Greens, and the Left Alliance, faced substantial setbacks and emerged as the election's major losers. The Swedish People's Party maintained its previous standing. Within the opposition, the Christian Democrats performed relatively well. The Movement Now party succeeded only in securing its leader's re-election, despite running 177 candidates. The Finns Party achieved its most successful result to date with 20.1% of the vote. The election witnessed a routine change in parliamentary representation, with 60 complete newcomers elected and 22 candidates who had previously run gaining seats. Meanwhile, 31 candidates failed in their re-election campaigns, and 32 Members of Parliament chose not to run again.

The campaign was relatively subdued, with economic issues predominating discussion amid voter fatigue from recent municipal and regional government elections in 2021 and 2022 (Arter, 2024). Economic debates centered on Finland's modest GDP growth and the highest inflation in 40 years, which influenced a voter turnout of 72.6%, marginally lower than the previous election.

3. Method

3.1. Problem definition and methodology overview

Predicting which candidates will be elected can be analyzed through several lenses: classification, regression, and ranking. At its core, the election outcome is a classification problem: a candidate is predicted to be elected or not.

Classifying candidates as elected or not elected depends on the number of votes each candidate receives, introducing a regression component that predicts either the exact number or the percentage of votes a candidate may obtain. Sometimes, knowing the percentage is sufficient, as it indicates relative performance compared to others. This relative performance is tied to the ranking, as election outcomes often depend on how candidates compare to their peers in voter support.

Ranking candidates by total votes isn't always sufficient because electoral systems differ. In the Finnish electoral system, candidates pursue dual goals: gathering votes for their party to maximize the number of seats and competing within the party list to secure their position. This is driven by the d'Hondt method, which ranks candidates and impacts their election outcomes. Despite a trend toward personalization in electoral choices, a majority of voters still prioritize party over individual candidates, indicating that they would not vote for the same candidate if that candidate ran for a different party (Söderlund, 2024). Consequently, candidates must strategically position themselves as the preferred choice within their party to align personal appeal with party loyalty, necessitating greater attention to candidate ranking.

The methodological choices presented reflect this complexity. Fig. 1 illustrates the forecasting process using

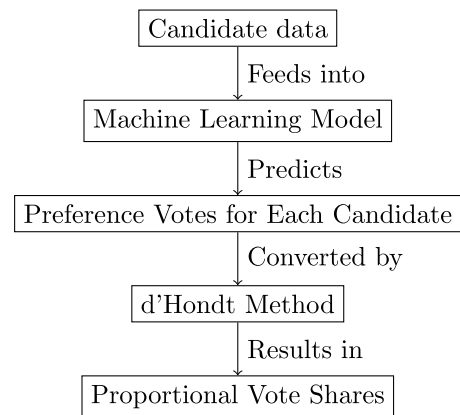


Fig. 1. Forecast structure.

candidate data as input. The forecast is created by first predicting each candidate's preference votes using a machine learning regression model. The algorithm uses the collected dataset to predict each candidate's preference votes. This data is then converted to proportional votes and expected candidate ranking according to the d'Hondt method. The predicted proportional vote shares are used to forecast election outcomes, showing which candidates are likely to win seats in their respective districts.

Fig. 2 presents a simplified view of the input variables used in the machine learning model. It lists the features used in the model, with some variables on the y-axis displayed on a logarithmic scale to enhance clarity and interpretability. This transformation is solely for this figure's visualization. On the right side, the box plot depicts the distribution of the target variable, namely the number of preference votes each candidate received.

3.2. Refined model

The model presented and analyzed throughout this paper is a slightly refined version of the model used to create the ex ante forecast. The refined model was developed to serve as the basis for the scientific evaluation in this paper. The early implementation of the model used for the ex ante forecast had several minor flaws, such as partially incorrectly labeled and imputed campaign budgets. The refined version corrects those errors and also adds the ballot number to the list of variables. While adding new variables ex post is not ideal, the ballot number serves as an interesting benchmark for other variables and is unlikely to increase the risk of overfitting. The predictive power of these two versions is almost identical. The refined model predicted the election of a single candidate more than the initial ex ante variant.

The method discussion, feature analysis, and all detailed results and validation in this paper are based on this refined model. The initial version and the refined model are identical from a technical perspective. The raw performance of the original ex ante forecast is discussed briefly in the Results section for context. All the code and data for both variants are made publicly available to ensure transparency.

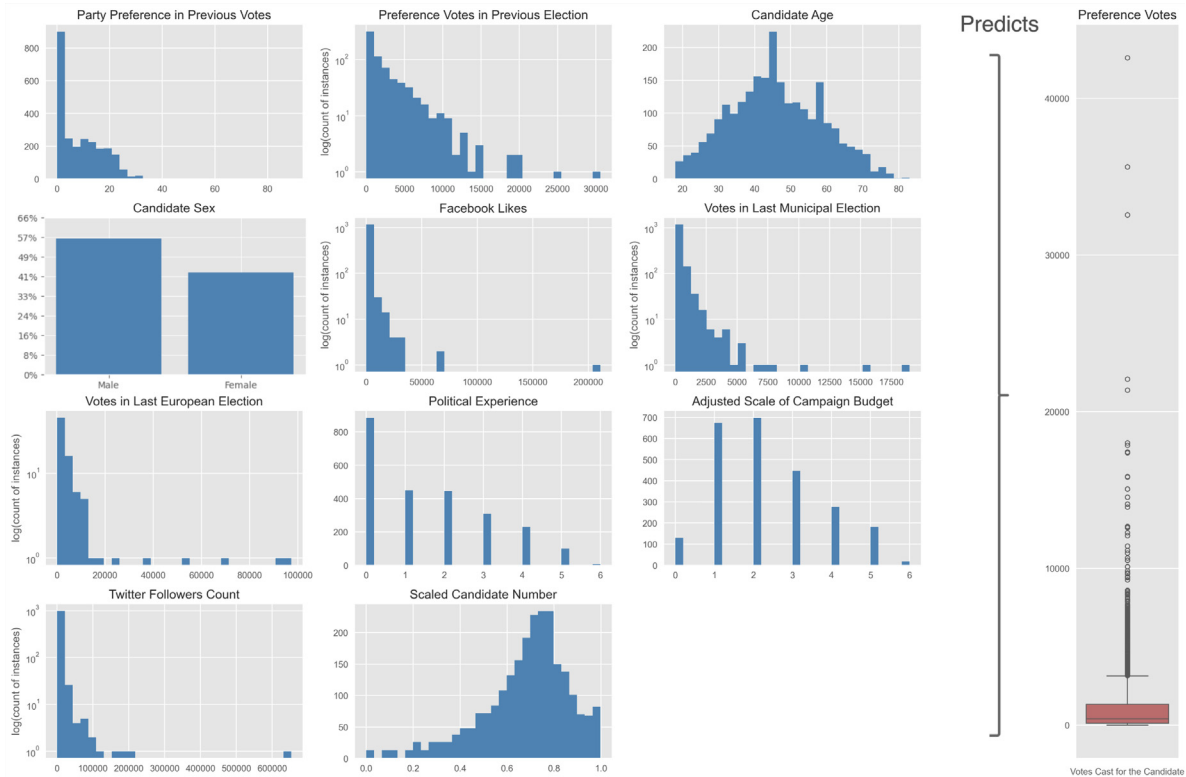


Fig. 2. Model inputs.

3.3. Data collection and description

The data set comprises openly available data from three consecutive parliamentary elections in Finland. The datasets include diverse features, such as social media profiles and votes received in previous elections. Over these three election cycles of 2015, 2019, and 2023, a total of 7038 candidates aimed for a seat, but as many candidates participated in several elections, the number of unique candidates is lower. In the 2015 election, there were 2146 candidates; in 2019, 2468; and in the 2023 election, 2424. Eleven key features of each candidate were selected for further examination.

The dataset was compiled from various sources across different election cycles. For the 2015 elections, Facebook likes were accessed using the Facebook API, and Twitter data was collected manually. In 2018, Facebook restricted access to its API for data collection, necessitating web scraping (Bruns, 2019). Twitter’s API was still available during the 2019 elections and was used for data retrieval. However, following its acquisition, Twitter restricted access to its API in early 2023. Consequently, both Facebook and Twitter data for the 2023 elections were collected using the Bing Search API.

The data set includes information from Yle Vaalikone, a voting compass service provided by the Finnish public broadcaster Yleisradio, as one of its data sources. One notable piece of information was the self-reported campaign budgets. It should be noted that reporting campaign

budget information to the voting advice application is voluntary. Officially, candidates must disclose their funding after the elections if they are elected, but only voluntary values can be used to predict election outcomes. Therefore, candidates can provide any values they wish, which means there is a potential to enter incorrect values by accident. Other data were collected from the Finnish Ministry of Justice, the Finnish Central Electoral Commission, and the Finnish National Bureau of Statistics.

The dataset provides comprehensive coverage of all candidates in the 2015, 2019, and 2023 parliamentary elections. The availability of variables varies over time due to factors such as data accessibility. There are a few details that should be disclosed for transparency: (1) Twitter followers for candidates running for election in 2015 were only collected for 49 high-profile candidates. (2) Social media data was collected for all candidates in 2019. However, in 2023, due to data accessibility issues, data for low-profile candidates was unavailable. Demographic data, such as age, is available for all candidates.

The number of candidates who provided their estimated campaign budget before the elections fluctuated over the years. In 2015, 92.45% provided a value; in 2019, 91.77% disclosed in advance how much they intended to spend; but in 2023, only 61.39% of candidates disclosed the value. The cause of the disparity between election cycles is unknown. In each of the three election years, Facebook data covered more than half of the candidates, with observations at 52.47% in 2015, 60.90% in 2019, and 50.21% in 2023. The higher number in 2019 is explained

Table 1

Data Overview. The numbers in the columns show the count of non-missing observations for each feature, followed by the percentage of total observations for that year (in parentheses).

Features	2015	2019	2023
Age (A)	2146 (100.00%)	2468 (100.00%)	2424 (100.00%)
Campaign budget (CB)	1984 (92.45%)	2265 (91.77%)	1488 (61.39%)
Facebook likes (FL)	1126 (52.47%)	1503 (60.90%)	1217 (50.21%)
Votes in the last European Parliament elections (EVL)	114 (5.31%)	73 (2.96%)	80 (3.30%)
Votes received by the candidate in the last municipal elections (MVL)	1399 (65.19%)	1454 (58.91%)	1392 (57.43%)
Votes in the last parliamentary elections (PVL)	762 (35.51%)	757 (30.67%)	705 (29.08%)
Twitter followers (TF)	49 (2.28%)	1466 (59.40%)	1031 (42.53%)
Ballot Position (BP)	2146 (100.00%)	2468 (100.00%)	2424 (100.00%)

by the fact that scraping enabled more efficient data retrieval, including for low-profile candidates. Information on votes from the last European Parliament elections appears to be minimal throughout the data set, with 5.31% in 2015, 2.96% in 2019, and 3.30% in 2023. The dataset has recorded votes from the last municipal elections for 65.19% of candidates in 2015, 58.91% in 2019, and 57.43% in 2023. Coverage of votes from the previous parliamentary elections was noted for 35.51% of candidates in 2015, dropping to 30.67% in 2019 and 29.08% in 2023. Twitter followers are noted for 2.28% of candidates in 2015, which increased substantially to 59.40% in 2019 and then to 42.53% in 2023. The scaled candidate's number, used to analyze potential position bias, was logically available for all candidates. The data overview is available in [Table 1](#).

The focus of this study is on the 2023 elections. The dependent variable, which is the outcome this model seeks to predict, is the number of preference votes (PV) each candidate received. The model uses a range of candidate attributes as its independent variables. These predictors include votes received by each party in previous parliamentary elections (PPVL), individual preference votes from preceding elections (PVL), age (A), sex (S), Facebook likes (FL), votes from the last municipal elections (MVL), votes from the previous European Parliament elections (EVL), political experience (PE), campaign budget (CB), Twitter followers (TF), and ballot position (BP). An overview of these features is presented in [Table 2](#).

National party-level opinion polls were not included in the feature set for two primary reasons. First, as polling data are well-established predictors of election outcomes, incorporating them would make a comparison between the model's performance and poll-based forecasts circular, complicating a key evaluation benchmark. Second, integrating party-level data would necessitate a multi-stage modeling approach to disaggregate poll results. This additional complexity was intentionally avoided to maintain a clear and direct focus on assessing the predictive power of the candidate-specific features central to this study.

3.4. Data preprocessing

A noteworthy challenge encountered during data analysis was that a large proportion of candidates had missing

values in almost all rows. Many of the candidates had not participated in past elections, did not disclose their campaign budgets, or had a public social media profile. Removing these rows from the data set was not an option, as this would have misrepresented the actual probability that a candidate was elected.

Several data preprocessing steps were required to make the data compatible with statistical models. Particular focus was placed on handling missing values and encoding categorical variables. Missing values required careful treatment to ensure that the analysis remained representative and unbiased, utilizing strategies such as imputation where appropriate. Categorical variables, such as candidate attributes, were converted to numerical formats, which are essential for statistical models to process the data accurately.

Past election vote counts were notably incomplete for many candidates, as illustrated in [Table 1](#). To address gaps in past election vote counts, missing values were set to zero. This approach helped maintain consistency across the data set and was complemented by the introduction of a binary indicator column. This column specified whether each candidate had participated in those elections, allowing us to capture potentially relevant participation information for a more accurate analysis.

The campaign budget data required a structured approach to address its variety and to fill in missing values effectively. Initially, the budget figures were transformed into an ordinal scale, grouped into categories ranging from 1 to 5. A score of 1 represented budgets of 0–5000 euros, 2 of 5000–10,000 euros, 3 of 10,000–20,000 euros, 4 of 20,000–50,000 euros, and 5 of budgets exceeding 50,000 euros. This categorization simplified subsequent analysis by providing a standardized measurement.

After this ordinal transformation, missing values were imputed by estimating based on the average campaign budgets of other candidates from the same party within the same district. This approach aimed to fill in data gaps as plausibly as possible, allowing the analysis to proceed with a more comprehensive data set. The missing values were imputed for 1067 candidates, of which 936 did not answer the questionnaire at all, while 131 skipped the question. More details on campaign budgets are presented in [Table 3](#).

Political experience, in this context, is evaluated using a composite score derived from eight distinct binary

Table 2
Features and measurements*.

Features	Measurement
Preference votes (PV)	The number of preference votes for a candidate in an election.
Twitter followers (TF)	The number of Twitter followers of a candidate.
Facebook likes (FL)	The number of Facebook likes for a candidate.
Political experience (PE)	A sum of incumbency, status as a member of the European Parliament, whether the candidate has a seat in a regional office, whether they ran for the last parliament elections, and if they hold a municipal office. Each included variable is represented as 0-1 (0: no experience, 1: has experience) in the initial data. The final value for political experience is the sum of those values (0-8, ordinal variable; higher values indicate more experience).
Age (A)	The age of a candidate.
Party (P)	Which party a candidate sits in. Ten parties: PS, KOK, KESK, KD, VIHR, LN, VAS, SDP, RKP, FÅ.
District (D)	District of candidacy. Thirteen districts: HEL, UUS, VAR, SAT, AHV, HÅM, PIR, KAA, SKA, VAA, KES, OUL, LAP.
Campaign budget (CB)	Campaign budget category self-reported by candidate (1-5 code). (1: <5000 EUR; 2: 5000 – 10,000 EUR; 3: 10,000 – 20,000 EUR; 4: 20,000 – 50,000 EUR; and 5: >50,000 EUR).
Sex (S)	Female or male (0: male; 1: female).
Preference votes in the last parliamentary elections (PVL)	Votes in the last elections.
Votes in the last Municipal elections (MVL)	Votes in the last municipal elections.
Votes in last EU elections (EVL)	Votes in last EU elections.
Vote share of the party in the last parliamentary elections (PPVL)	The share of votes by the party in the last elections in the same region where the candidate is running for a seat.
Ballot Position (BP)	The Min-Max scaled candidate number

Party abbreviations: PS: True Finns, KOK: National Coalition, KESK: Centre party, KD: Christian Democrats, VIHR: The Green party, SIN: Blue Reform, LN: Movement Now, VAS: Left Alliance, SDP: Social Democratic Party, RKP: Swedish People's party, FÅ: The Åland representative.

District abbreviations: HEL: Helsinki, UUS: Uusimaa, VAR: Finland Proper, SAT: Satakunta, AHV: Åland, HÅM: Tavastia, PIR: Pirkanmaa, KAA: South-East Finland, SKA: Savonia-Karelia, VAA: Vaasa, KES: Central Finland, OUL: Oulu, LAP: Lapland).

Table 3
Campaign budgets reported in the voting advice service a month before the 2023 elections.

Budget category	Number of candidates
0-1000 euros	341
1000-5000 euros	438
5000-10,000 euros	252
10,000-20,000 euros	163
20,000-50,000 euros	180
Over 50,000 euros	18
Details	
Highest Recorded Budget	130,000 euros
Average Budget for All Candidates	1971 euros
Budget Not Provided	1067

facets of political engagement, following a similar approach to that of [Isotalo and von Schoultz \(2024\)](#). The ordinal political experience score is calculated by summing these attributes, reflecting the cumulative depth and diversity of the individual's political experience.

The facets considered for this score include election as a Member of the European Parliament (MEP), membership in the Finnish national parliament, candidacy in the most recent Finnish parliamentary elections, service within a municipal council, involvement in a county council, candidacy for the European Parliament, candidacy in Finnish presidential elections, and candidacy in municipal

elections. Each of these roles or activities represents a significant form of political involvement that contributes equivalently to the overall score.

Consequently, the maximum achievable score is 8, indicating a comprehensive political career encompassing all of these roles and experiences. This holistic approach to measuring political experience allows comparisons among individuals, with higher scores indicating greater and more varied engagement in the political sphere. In this way, the score captures not only the frequency of participation in political processes but also the range of activities and levels of responsibility undertaken by the individual. More details are presented in [Table 4](#).

The effect of ballot position (BP) was also considered a feature. Given that different districts have varying numbers of candidates, direct comparison of raw positions would be inappropriate. Therefore, the ballot positions were transformed using a min-max normalization technique to ensure comparability across all districts.

Normalization was implemented using 'MinMaxScaler' from sklearn. This transformation scales each ballot position to the range [0, 1], where 0 corresponds to the first candidate on the list and 1 to the last. In doing so, the model consistently accounts for the positional effect, accommodating district-size differences.

The relationship between ballot position and its effect is unlikely to be linear, possibly exhibiting a more complex shape in which specific positions, notably those at

Table 4
Political Experience totals for candidates in the 2023 elections.

Feature	Frequency
Member of the Finnish Parliament	170
Candidate in Previous Parliamentary Elections (2019)	705
Municipal Council Membership	904
Municipal Elections Candidate (2021)	1392
Member of European Parliament	3
Candidate in European Parliament Elections (2019)	80
Regional Council Membership	470
Candidate in Presidential Elections (2019)	4
Distribution of Political Experience Scores	
0	36.43%
1	18.56%
2	18.36%
3	12.75%
4	9.53%
5	4.08%
6	0.29%

the extremes, may be more favorable (Söderlund et al., 2021). This expectation highlights the need to employ a model capable of capturing non-linear relationships, which will be further addressed in the upcoming model selection section.

To account for the influence of party and district without directly including them as variables, a party-preference score, the Party Preference Vote Level (PPVL), was calculated for each candidate. This score reflects the percentage of votes (%) their party received in the candidate's district during the previous election. For example, if a party secured 25% of the total votes in a specific district in the last election, every candidate from that party in that district would receive a PPVL of 25%. This approach effectively captures essential historical voting patterns related to party influence, while maintaining the model's simplicity and interpretability.

The reason for employing this approach is to provide the model with contextual information about past voting patterns, a key indicator of party support within different districts. Incorporating this information indirectly allows us to acknowledge the significant impact of party and district dynamics without complicating the model. This strategy preserves the model's interpretability and helps avoid the pitfalls of overfitting that can occur when numerous direct variables are added.

Except for MinMax scaling of the ballot position, no other feature-scaling transformations were applied. Pre-processing choices are often context-dependent. For instance, in electoral systems experiencing significant population growth, scaling predictors, such as absolute vote counts, may be necessary to ensure comparability across elections. However, given the binning strategy already applied to the campaign data and the specific analytical context of this study, no additional transformations were considered necessary.

3.5. Feature analysis

Table 5 presents the Kendall's Tau rank correlation of the variables included in this study. The variable votes in the last parliamentary elections (PVL) shows the highest

correlation with preference votes (PV) at 0.71, followed by strong correlations from both campaign budget (CB) and Facebook likes (FL) at 0.50. Political experience (PE) and the number of Twitter followers (TF) also show substantial correlations with PV at 0.44 and 0.43, respectively. The percentage of votes received by the party in the last parliamentary elections (PPVL) shows a moderate correlation of 0.37 with PV. In contrast, other variables show much weaker relationships: sex (S) shows a weak but significant positive correlation of 0.06, while the candidates' age (A) shows no statistically significant correlation. As expected, ballot position (BP) shows no significant correlation, consistent with the hypothesis that its effect is non-monotonic. The analysis suggests that a candidate's previous electoral success, campaign budget, and number of social media followers are more closely related to the number of preference votes received. In contrast, demographic factors such as age, sex, and ballot position are less closely related. The percentage of votes the party received in the last parliamentary elections is relevant, but it is split among candidates from the same party in the same district.

3.6. Model selection

The primary goal of this study is to predict the number of preference votes for each candidate. While traditional linear regression models are a standard starting point, they rely on linear relationships between predictors and the outcome. However, in electoral politics, these relationships are often more complex. For example, the effect of age on votes is likely non-linear, as neither very young nor very old candidates are favored. Similarly, the earlier presented ballot position bias is also non-linear (Söderlund et al., 2021). There can also be relevant interaction effects between variables, such as how social media follower count interacts with incumbency (Vepsäläinen et al., 2024a). To capture these complex relationships without specifying them in advance, a supervised machine learning approach was adopted.

Initially, the Extreme Gradient Boosting Regressor (XGBoost) model was selected for the ex-ante forecast. This choice was motivated by the well-documented success of tree-based ensemble models in capturing the types of non-linear and interactive effects expected in this data (Argandoña-Mamani et al., 2024; Chen & Guestrin, 2016; Lundberg et al., 2020).

To formally validate this choice and ensure methodological rigor, a detailed ex post analysis was conducted after the 2023 election results were available. This analysis systematically compared XGBoost against a range of other algorithms, including Random Forest, several linear regression models, and others. The results confirmed that while several non-linear models delivered strong, broadly similar out-of-the-box performance, the XGBoost model was slightly superior, particularly in correctly ranking candidates, as measured by Kendall's rank correlation. Because of the conceptual nature of the work and the similar performance of the models, it was concluded that extensive hyperparameter tuning was outside the scope of this paper. A detailed breakdown of this comparative

Table 5
Correlation matrix.

	PV	TF	FL	PPVL	PVL	A	PE	CB	S	BP
PV	1.0	0.43***	0.5***	0.37***	0.71***	0.01	0.44***	0.5***	0.06*	−0.04
TF	0.43***	1.0	0.59***	0.18***	0.45***	−0.11***	0.42***	0.32***	0.05	0.07**
FL	0.5***	0.59***	1.0	0.22***	0.47***	−0.14***	0.42***	0.37***	0.03	0.04
PPVL	0.37***	0.18***	0.22***	1.0	0.35***	0.03	0.21***	0.35***	0.03	−0.08**
PVL	0.71***	0.45***	0.47***	0.35***	1.0	0.1***	0.49***	0.45***	0.03	−0.03
A	0.01	−0.11***	−0.14***	0.03	0.1***	1.0	0.06*	0.0	−0.08**	−0.01
PE	0.44***	0.42***	0.42***	0.21***	0.49***	0.06*	1.0	0.31***	0.05	−0.0
CB	0.5***	0.32***	0.37***	0.35***	0.45***	0.0	0.31***	1.0	−0.02	−0.02
S	0.06*	0.05	0.03	0.03	0.03	−0.08**	0.05	−0.02	1.0	0.03
BP	−0.04	0.07**	0.04	−0.08**	−0.03	−0.01	−0.0	−0.02	0.03	1.0

Note: The first column and row headers are abbreviations. PV: Preference Votes; TF: Twitter Followers; FL: Facebook Likes; PPVL: Percentage of party votes in last election; PVL: Votes in last parliamentary election; A: Age; PE: Political Experience; CB: Campaign Budget; S: Sex; BP: Ballot Position.

* Significance level $p < 0.05$.

** Significance level $p < 0.01$.

*** Significance level $p < 0.001$.

analysis, including all models and evaluation metrics, is provided in the appendix and the project's public repository. Each algorithm, except XGBoost, was implemented using the Scikit-learn machine learning library (Pedregosa et al., 2011).

A crucial difference from a traditional regression model is the method of interpretation. A linear model provides a single, global coefficient for each predictor, representing its average effect across all observations (Geron, 2019). In contrast, tree-based ensembles like XGBoost do not have a simple coefficient table. This is because the impact of any single variable is conditional on the values of other variables within the model's many decision trees (Chen & Guestrin, 2016). Therefore, to understand the model's logic and the influence of each predictor, alternative interpretation techniques are required, as presented in the next section.

3.7. Model evaluation and validation

The election forecast model is evaluated using a comprehensive set of analytical techniques, including classification and regression metrics and ranked correlations. Additionally, Shapley values provide a deeper understanding of the model's inner workings. This multifaceted approach allows for a nuanced understanding of the model's strengths and weaknesses. Furthermore, the model performance is analyzed across different political parties to identify potential biases.

The classification part of the model is evaluated using standard classification metrics. In this context, classification determines whether a candidate is elected based on the model's final output. A distinctive aspect of this classification problem is the fixed number of predictions, as exactly 200 candidates are invariably elected. To better understand the classification results, a confusion matrix is included to clarify the model's performance. While accuracy is often used, it is not usually the best performance measure for classifiers handling unbalanced datasets (Geron, 2019).

A confusion matrix shows how often examples from one class are misclassified as another, covering all possible class combinations (Geron, 2019). Although the confusion matrix provides extensive information, a more concise metric, such as the classifier's precision, can be helpful (Geron, 2019). This is particularly relevant in this

scenario, since predictions are consistently made for 200 candidates. Consequently, metrics such as recall and F1 score are not applicable, as they yield the same result. Similarly, there is no need to calculate additional metrics such as ROC, since the prediction threshold remains constant.

Election forecasting models are typically framed as regression problems, and this model is no exception. A typical approach to election forecasting involves analyzing multiple election cycles and using metrics such as mean absolute error (MAE) to evaluate overall performance across these elections (Lewis-Beck, 2005). However, this approach is not optimal when only one forecast is available. In such cases, the root mean square error (RMSE) is generally the preferred performance measure for regression tasks (Geron, 2019). MAE can also be used to calculate the average absolute differences between the predicted and actual values, providing information on the accuracy of the predictions (Geron, 2019).

Earlier research has shown a tendency to systematically overestimate or underestimate certain groups in studies using social media metrics (Vepsäläinen et al., 2017). Therefore, in addition to standard metrics, a straightforward measure of systematic error, referred to here as bias, was calculated. This bias is determined as the average prediction error and is represented by the formula:

$$\text{Bias} = \frac{1}{n} \sum_{i=1}^n (\hat{y}_i - y_i)$$

This calculation helps in understanding the extent to which predictions are consistently off-target for specific subgroups.

The metrics provided are designed to allow comparisons between this model and other approaches. However, there are numerous state-of-the-art models useful across different races and contexts, making comparisons difficult. Structuralist models in the multiparty context typically aim to predict which party or coalition will form the new government (Nadeau & Lewis-Beck, 2020; Walther, 2015). Many models leverage poll data for their predictions, which basically measures the popularity of different contestants (Kang & Oh, 2024). Some models rely on social media data to forecast election outcomes (Vepsäläinen

et al., 2024b), and approaches that focus on combining multiple forecasts for improved accuracy (Graefe, 2018). Comparing this model with any of the aforementioned methods is challenging, as the diverse research methodologies may not be applicable in the same setting, or they may aim to forecast different aspects of an election, complicating direct comparisons.

Given the context, it appears more reasonable to compare the results with opinion polls, a common approach among researchers. One caveat is that opinion polls generally provide national-level estimates rather than predicting outcomes for individual candidates. Therefore, for this comparison, the model performance must be translated to a national scale. This was achieved by summing the predicted votes for all candidates within each party to obtain a total national vote-share forecast. After converting the results to the national level, they can be evaluated against polling averages using the mean absolute error (MAE) for each party's predictions. However, much valuable information is lost when results are translated on a national scale.

An additional consideration is to verify whether the results could be obtained using a more straightforward method, as there is a risk of overlooking simpler ways to achieve the same findings. In this analysis, the forecast is compared to two straightforward baselines: assuming that the same candidates will be re-elected and assuming that the party will secure the same percentage of votes as before. These differences are qualitatively analyzed in the results section to provide further insight.

In the context of one-off supervised machine learning models, such as the XGBoost model presented here, understanding which features influence predictions helps interpret the results. The SHAP analysis was applied to improve transparency and interpretability of the model; it offers a way to analyze how each feature contributes to each prediction (Lundberg & Lee, 2017).

SHAP analysis can reveal potential biases in the model and provide insight into both global and local decision-making processes. Global interpretation aggregates SHAP values across multiple instances, whereas local interpretation focuses on a single instance. On a global level, mean SHAP values can be used to rank features by importance. There are various versions of SHAP algorithms (Mosca et al., 2022). This study uses TreeSHAP and the Python SHAP library. TreeSHAP improves the explanation of tree-based models by including an algorithm to calculate optimal explanations and to understand local feature interactions, which together help outline the model's overall structure (Lundberg et al., 2020).

Election forecasting can be somewhat controversial (Victor, 2021). Similarly to polls, election forecasts might influence voter behavior (Blais et al., 2006). Various factors can affect the accuracy and validity of these forecasts, occasionally leading to unexpected election results (Victor, 2021). Defining the parameters to be estimated and prioritizing vote-share predictions over win probabilities can aid in understanding forecast outcomes.

Table 6

Confusion matrix and performance metrics.

Confusion matrix		
Actual	Predicted	
	Positive	Negative
Positive	True Positives: 151	False Negatives: 49
Negative	False Positives: 49	True Negatives: 2175
Metrics		
Accuracy	0.96	
Precision	0.76	

4. Results

4.1. Forecast

A forecast was published ahead of the Finnish Parliament election results, with the initial release on March 17 via the researcher's home university website and local newspapers. The elections took place on April 2, leaving a 16-day lead time between the forecast release and election day. The forecast model depends on the information on which candidates have been nominated. The candidate nomination is finalized roughly one month before election day; therefore, the maximum lead time for the model using the selected method is one month.

In terms of results, the ex ante forecast accurately predicted the election of 150 candidates and correctly identified 23 who would be elected as substitutes. However, 27 candidates who were predicted to win were not elected to a seat or as a substitute. A simple benchmark for the accuracy is to compare the forecasted results with the assumption that all incumbents would be re-elected. Of the 170 incumbents seeking re-election, 139 successfully retained their seats, 13 became substitutes, and 18 were not re-elected.

Compared to this simplistic baseline, the forecast model shows some improvement. The model predicted the election of 150 candidates, besting the 139 re-elected incumbents. Almost half of the incorrectly predicted candidates were elected as substitutes, suggesting that the model grasped intricate electoral dynamics. Although the advantage of the model over a basic heuristic is modest, it still provides valuable insights beyond simple assumptions, underscoring its potential for understanding electoral trends.

4.2. Model evaluation

The refined model had slightly higher accuracy. In Table 6, the confusion matrix illustrates the classification capabilities of the model, detailing how it distinguishes between candidates who are elected and those who are not. The matrix shows that the model accurately identifies 151 candidates as elected, but it also misses 49 elected candidates, incorrectly classifying them as not elected, resulting in false negatives. Additionally, the model erroneously classifies 49 non-elected candidates as elected, resulting in false positives. Nevertheless, the model excels in correctly identifying a substantial number of candidates

Table 7
Regression metrics.

Subgroup	MAE	RMSE	Bias	Mean prevote	Mean predicted
All candidates	635.14	1470.92	160.02	1276.98	1437.00
KOK	1190.96	2072.08	130.76	3040.35	3171.12
PS	1404.98	3042.53	−214.19	2861.66	2647.47
SDP	1165.97	2203.67	−126.64	2845.86	2719.22
KESK	765.44	1211.19	354.25	1704.54	2058.78
VIHR	771.75	1336.90	647.29	1003.66	1650.95
VAS	554.25	1040.34	344.48	1006.59	1351.07
RKP	595.48	884.08	380.69	1202.86	1583.56
KD	252.89	482.00	−17.59	695.18	677.59
LN	334.13	723.41	112.97	423.70	536.67
FÄ	785.48	1152.40	785.48	3817.33	4602.81
Other	165.78	428.75	128.78	115.14	243.92

as not elected, underscoring its ability to manage the majority class effectively.

Although the model achieves a high overall accuracy of 0.96, which suggests strong classification performance, accuracy alone might not provide a complete picture due to the class imbalance inherent in this data set. In this context, precision, which is reported at 0.76, becomes a more interesting metric. Precision measures the accuracy of positive predictions—indicating that when the model predicts a candidate as elected, it is correct 76% of the time. This is decent given the unchanging number of elected candidates and the possibility of false-positive predictions, underscoring the model's ability to identify truly elected candidates among those it predicts as such. This precision-focused evaluation helps provide a clearer understanding of the model's predictive ability.

Table 7 presents regression metrics that provide detailed insights into the vote-prediction model's performance across all candidates and specific political parties. The MAE and RMSE serve as key indicators of the model's predictive accuracy, with general trends indicating substantial variability in performance across subgroups. In particular, the Christian Democrats (KD) demonstrate relatively low prediction errors (MAE: 252.89, RMSE: 482.00), suggesting excellent model performance and a strong fit to the data.

Conversely, Greens (VIHR) exhibit a significantly higher RMSE of 1336.90, indicating greater prediction discrepancies. Additionally, bias values reveal systematic over- or under-predictions; for instance, Finns Party (PS) shows a negative bias of −214.19, suggesting under-prediction of votes. This analysis underscores the benefits of subgroup-specific performance analysis, as the model's accuracy and reliability vary.

The factors contributing to the overestimation of Greens were multifaceted. Strategic voting emerged as an important influencer, as voters realigned their support to the major parties in a closely contested race (Grönlund & Strandberg, 2023; Kestilä-Kekkonen et al., 2024). Economic issues were a central focus in public discourse during the campaign period, making it harder for the party to differentiate itself from other left-leaning parties (Arter, 2024). These dynamics, compounded by the model's reliance on historical data that lack similar precedents, contributed to the significant underperformance of the Greens, revealing the challenges predictive models face amid rapidly shifting political landscapes.

Table 8
National results.

Party	Actual	Baseline	Prediction	Poll average
KOK	20.82	17.00	19.74	19.80
PS	20.06	17.48	16.48	19.35
SDP	19.95	17.73	17.16	18.95
KESK	11.29	13.76	11.78	11.05
VAS	7.06	8.17	8.48	8.50
VIHR	7.04	11.49	10.60	8.70
RKP	4.31	4.53	5.28	4.30
KD	4.22	3.90	3.56	4.20
LN	2.42	2.25	2.81	1.85
Other	2.82	3.68	4.12	3.30
Mean Error %		1.82	1.62	0.72

Table 8 presents a comparison of actual results with baseline, prediction, and poll averages. The polls performed well in the elections, with the poll average falling within the typical 2-percentage-point error margin, reflecting their effectiveness in capturing voter sentiment. These data show varying degrees of accuracy among different parties in estimating actual election outcomes.

For the National Coalition Party (KOK), the prediction model forecasted 19.74%, which is close to the poll average of 19.80%, but both underestimated the actual result of 20.82%. In contrast, the model significantly overestimated the Greens' (VIHR) vote share to 10.60%, compared to the actual result of 7.04%. The poll average provided a slightly better estimate at 8.70%, though it was still off target. The prediction model outperformed the polls only for Movement Now (LN), with a forecast of 2.81% that was closer to the actual result of 2.42% compared to the poll average of 1.85%.

Regarding the order of the parties, while the winner was correctly predicted, given the importance of government formation, the order was not entirely accurate for some parties. Specifically, the prediction model reversed the actual order of the Finns Party (PS) and the Social Democratic Party (SDP). Similarly, both the prediction model and poll averages incorrectly ordered the Greens (VIHR) and Left Alliance (VAS).

A unique feature of the presented model is its granularity, which provides predictions for every individual

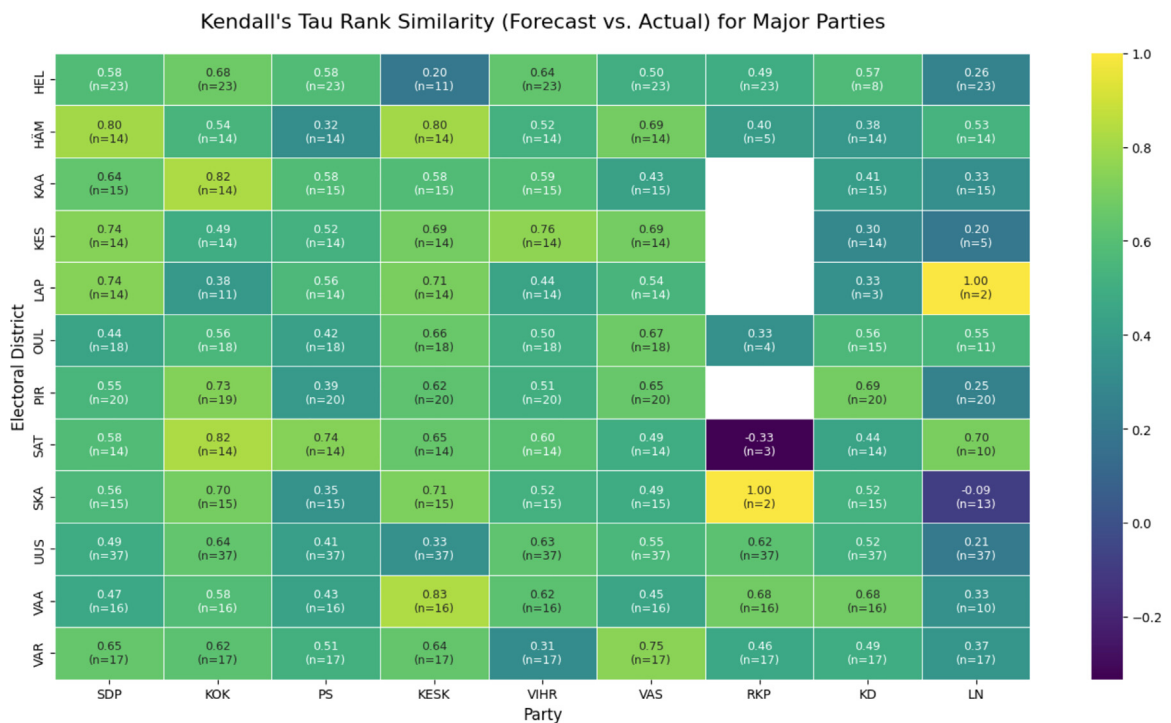


Fig. 3. Kendall's Tau Rank Similarity Score Comparing Forecast and Actual Rankings per District and Party. The value in each cell represents the Kendall's Tau score, while (n) indicates the number of candidates on that list.

candidate. This capability enables an analysis not possible with conventional party-level forecasts by evaluating the model's ability to capture the dynamics of intra-party competition. In open-list proportional representation (OLPR) systems, where voters select specific candidates within a party, understanding this internal hierarchy is a central topic of political science research. Evaluating the model on this dimension thus serves as a crucial test of whether its underlying logic and feature attributions are politically coherent and reflect real-world electoral dynamics.

To conduct this evaluation, Kendall's Tau rank correlation was calculated for each party list within every electoral division, focusing on the nine largest parties for clarity. This metric compares the model's predicted candidate hierarchy against the actual electoral outcome in each electoral district. The analysis serves as powerful internal validation, enabling us to assess whether the model's predictions are directionally correct and internally consistent across different political contexts, providing valuable support for the model's overall validity.

The results, visualized in the heatmap in Fig. 3, show a generally positive correlation. Most scores fall in the 0.40 to 0.80 range, indicating that the model successfully captured the relative ordering of candidates in many cases. The model achieved notably high scores for some party lists, including Keskusta (KESK) in the Vaasa (VAA) district (0.83) and the National Coalition Party (KOK) in Kaakkois-Suomi (KAA) and Satakunta (SAT) (both 0.82). Conversely, the model's predictive power was weaker for some other party lists, including the Finns Party (PS) in Häme (HÄM)

(0.32) and the Greens (VIHR) in Varsinais-Suomi (VAR) (0.31).

A closer look at specific low scores reveals different model limitations. The low score for Keskusta in Helsinki (0.20) reflects the party's predictable volatility as an agrarian party in the capital. Conversely, the poor performance for the Greens in Varsinais-Suomi (0.31) likely indicates a true model failure to capture unpredictable local dynamics or candidate-specific surges.

The heatmap also highlights anomalies that are largely attributable to the small number of candidates on certain party lists. For instance, the perfect scores of 1.00 for Liike Nyt (LN) in Lapland and the Swedish People's Party (RKP) in Savo-Karjala, as well as the negative correlation of -0.33 for RKP in the Satakunta (SAT) district, all occurred on lists with very few candidates. With a small sample size, the rank correlation metric becomes highly sensitive; a perfect alignment is easier to achieve, while a single misordering can result in a strongly negative score. Therefore, these extreme values are more indicative of the statistical properties than of the model's profound success or failure.

Shifting the focus to exploring the model's behavior, SHAP is employed to gain deeper insights into the relative importance and contributions of features within the XGBoost model. This analysis is key to unveiling how individual features drive predictions and interact within the model's framework. With SHAP visualizations such as the bar plot and beeswarm plot, both the global importance of each feature and its nuanced local interactions are elucidated. These visual tools improve the understanding of model dynamics by highlighting important predictors and

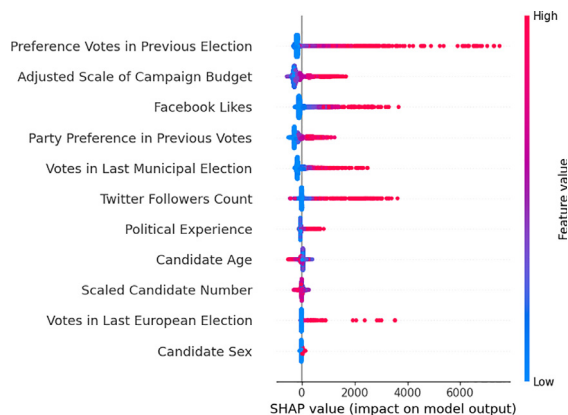


Fig. 4. SHAP Beeswarm summary plot.

potential variances in feature impacts, setting the stage for a more straightforward interpretation of the model.

The SHAP value bar plot (Fig. 4) provides a visualization of the relative importance of the features that influence the model’s predictions. The most significant contributor is Preference Votes in the Previous Election, with a mean SHAP value of +382.31, indicating a strong impact on the model’s output. The adjusted scale of the campaign budget follows, demonstrating substantial influence with a value of +292.86. Facebook Likes and Party Preference in Previous Votes are also prominent, showing SHAP values of +251.32 and +244.89, respectively, highlighting their importance in the prediction process.

Other notable factors include votes in the last municipal election and the Twitter follower count, with values of +207.37 and +132.64, respectively. While Political Experience, Candidate Age, and Scaled Candidate Number have moderate impacts, factors such as Votes in the Last European Election and Candidate Sex appear less influential, with lower SHAP values. This plot effectively elucidates which features are most critical in driving the model’s decisions.

The SHAP value beeswarm plot (Fig. 5) illustrates the impact of features on the model’s output, with colors representing feature values. Preference Votes in Previous Election stand out as significantly influential, showing wide dispersion in SHAP values and a notable impact across different feature values. Similarly, the Adjusted Scale of Campaign Budget, Facebook Likes, and Party Preference in Previous Votes all demonstrate considerable influence, as indicated by their spread along the SHAP value axis.

Votes in Last Municipal Election and Twitter Followers Count also show varied impacts, contributing to the model’s prediction diversity. Features such as Political Experience and Candidate Age illustrate a moderate impact, while Votes in Last European Election and Candidate Sex show less pronounced effects. This visualization captures the variability and importance of each feature, emphasizing their roles in shaping model predictions.

In the analysis of feature interactions, SHAP dependence plots were used to explore potential interactions

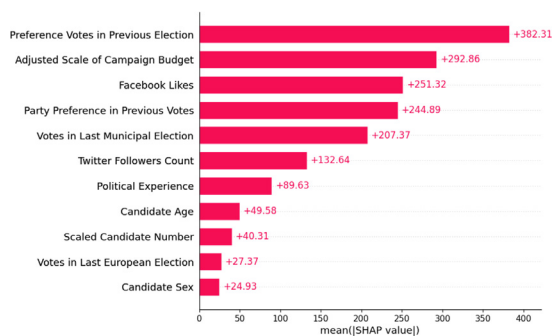


Fig. 5. Global SHAP value mean.

and their effects on the model’s predictions. However, these plots did not reveal any notable interaction effects. Instead, they confirmed the direct influence of individual features, as seen in previous analyses, without uncovering significant interactions warranting further investigation. This suggests that the features largely operate independently in contributing to the model’s predictions.

5. Discussion

The candidate-based approach in this study outperforms the simple baseline model used for comparison, providing evidence for the model’s effectiveness. However, the results were not as accurate as those of national pollsters, suggesting some limitations. A comparison with other state-of-the-art models was beyond the scope of the study, as these models have not been applied in the same context.

Deciding which features to include and how to incorporate them is crucial to this type of model. The availability of useful metrics also constrains feature selection, as publicly available data are limited. During the model training and testing period before the elections, data from 2015 and 2019 were used with various train-test splits. This phase involved experimenting with the inclusion of numerous features. The final set of characteristics was selected based on these tests. If this process were to be repeated using 2015, 2019, and 2023 data, the chosen feature set might differ. Therefore, the feature selection is not exhaustive.

The SHAP analysis presented in the results section provides insight into each feature’s contribution to the model’s outcomes. For the most part, the findings of this SHAP analysis align with theoretical expectations, though the influence of political experience appears less significant than anticipated.

Interestingly, Facebook likes emerge as a notable feature, closely following adjusted campaign budgets and previous election preference votes. The importance of the scaled candidate number suggests potential ballot-position bias, supporting earlier findings that these factors influence electoral outcomes.

Although the influence of votes in the last EU parliamentary elections generally showed a low mean impact, the beeswarm plot revealed a substantial effect for certain

candidates. Given that only a few candidates participated in the European Parliament elections, this influence was unevenly distributed. In contrast, party-preference votes from the last elections exhibited a much tighter distribution than candidate-specific preference votes from previous elections, suggesting that the effects of party and district were more stable than those of the candidate's earlier votes.

Regarding candidate data, sex had a negligible effect, though the model showed a slight bias toward female candidates. The impact of candidate age on predictions showed a non-linear distribution, as evidenced by the beeswarm plot, which shows red and blue values at both extremes. Despite this, there was a noticeable tendency to favor older politicians. In general, the total impact of age was relatively small.

Based on the findings, the candidate-based model faces several challenges that warrant attention. A key issue is its reliance on historical election data, which constrains its ability to adapt to changing public opinions and unforeseen electoral events. To mitigate this, the model integrates social media data, but this approach presents its own challenges. Together, these issues create a complex dynamic that requires further analysis. This complexity becomes particularly visible when assessing the model's performance across various subgroups.

A closer look at the results of the subgroups highlights the predictive challenges faced by the candidate-based model, particularly with parties such as the Greens, the Finns Party, and the Social Democrats. The Greens' vote share was overestimated, primarily due to strong social media metrics, historical voting patterns, and a shift in voter sentiment away from environmental issues. To address these shortcomings, the model should incorporate additional indicators that provide insights into current political sentiment and highlight the main topics influencing the elections.

Conversely, the Finns Party (PS) was underestimated, likely because of its smaller social media following and the candidates' relatively limited political experience. The lack of political experience stemmed from the party's split during the 2015–2019 election season, which led to coalition-aligned politicians leaving and the emergence of many new political figures. Since many voters prioritize party affiliation over individual candidates, the candidate profile was insufficient for predicting future voting and did not capture the growing partisan support. Consequently, these factors led the model to miss the party's growth trajectory.

The underestimation of the Social Democrats is more complex to explain, but may be related to strategic voting. The model failed to capture the political sentiment that led previous supporters of the Greens and the Left coalition to vote for the Social Democrats to prevent a right-leaning government (Grönlund, 2023). This analysis of subgroups underscores the need to address specific biases to improve the model's predictive accuracy and better capture the complexities of electoral dynamics.

Data collection presents another noteworthy challenge. The process is both fragile and susceptible to bias and can only be conducted at specific times, making it difficult to

obtain the historical data necessary for effective model training. Without a record of past online followings, training the model to predict future elections becomes problematic, underscoring the need for systematic historical data collection.

Many potential future improvements could address the mentioned challenges. One of them would be developing a comprehensive measure of online popularity by monitoring party activities throughout the term and employing network analysis to capture candidates' communication channels. Including platforms such as TikTok, Instagram, and popular blogs could improve predictive accuracy and reduce bias. Furthermore, integrating traditional media metrics at both the candidate and party levels is feasible and has precedents, such as using brand importance metrics to gauge party or opinion popularity. This would not remove all bias, as not all candidates are active online, but it could smooth it out.

Another future improvement would be to expand the feature set with new metrics, such as candidate attractiveness or candidate alignment with party politics. Voting advice application data could be used to calculate the distance between candidate and party positions. They could provide further insight into electoral success, especially when multiple candidates in the same district appear similar. Furthermore, enhancing the measure of political experience by including information on political roles, party influence, and local municipal impact could provide valuable information, as locality is a known predictor of electoral success (Put et al., 2020). In addition, incorporating economic metrics could be informative, particularly if a candidate represents a coalition government facing economic downturns, which may affect their popularity.

Given the trend towards increased online activity, the model holds significant future potential. Although some candidates still succeed without an online presence, the growing popularity of digital platforms in Finland suggests an expanding role for online metrics. Testing this approach in political races outside Finland could offer further insights into its applicability and accuracy in diverse contexts.

Overall, the findings align with the theoretical expectations outlined in the theory section. The importance of features in the models aligns well with established theories, especially those on voters using heuristics and mental shortcuts when choosing candidates. This consistency not only strengthens the theoretical foundation but also highlights the model's relevance in capturing voter behavior.

Although the current practical applicability of the candidate-based model is limited by its lower accuracy compared to polling, it offers a unique perspective in election forecasting by focusing on individual candidates' vote shares rather than party-level results. Consequently, this approach has the potential to complement other methods focused on party outcomes, thus enriching the forecast landscape. As such, it can serve as a foundation for integrating innovative methodologies, conventional polling, and structuralist models, thereby fostering the development of a more comprehensive electoral prediction framework.

Furthermore, as polling faces growing challenges, such as declining response rates, interest in new approaches is increasing. Therefore, researchers and practitioners in election forecasting are likely to adopt complementary methodologies in the future. Approaches, such as the candidate-based model, could become very valuable, as combining multiple methods is suggested to improve the accuracy and reliability of electoral forecasts.

Specifically, the candidate-based approach offers a valuable data stream that can be integrated into broader forecasting frameworks to address several well-documented challenges. Many prominent forecasting models operate at the national or party level, which can obscure crucial constituency-level dynamics and the personal appeal of individual candidates. By generating predictions from the bottom up, this approach provides a granular measure of candidate strength. This measure can act as a corrective, particularly in open-list systems where personal votes are decisive for the final intra-party allocation of seats. Furthermore, this aggregate measure of candidate strength could be incorporated as a dynamic predictor within synthetic or hybrid models, offering a novel input that complements or, in data-scarce environments, even serves as an alternative to fundamentals like early opinion polls. In this way, the model provides a flexible, candidate-centric component that may enhance the robustness and local accuracy of existing forecasting systems.

6. Conclusions

The results of this study suggest that the proposed approach holds promise as a supplementary method for election forecasting. Although it is not yet a standalone solution, it provides unique insights that current methods do not. The findings align well with existing theoretical frameworks, indicating that it should become more accurate over time. Furthermore, if the traditional polling continues to face issues with non-response rates and the like, the value of this approach will improve over time.

The presented research contributes to the literature on election predictions in several ways. Firstly, it addresses the growing demand for innovative forecasting methods by combining publicly available data on candidates' characteristics with information drawn from social media platforms. This approach represents a new frontier in election prediction research. Secondly, unlike many existing methods that operate on a macro level, this study offers a candidate-specific perspective. By focusing on individual candidates, the research enhances the theoretical foundation of electoral studies and supports existing theories with granular data.

Furthermore, while this study focused on the Finnish context, its methodological approach is generalizable to other electoral systems that foster a personal vote. The theoretical underpinnings of this transferability are well established, as the degree of intra-party competition is a direct function of a country's electoral formula (Carey & Shugart, 1995). The model is therefore most relevant in systems with high levels of candidate-centered competition, including open-list systems like those in

Poland and Brazil, as well as flexible-list systems like the Netherlands and Belgium, where the literature has documented similar electoral incentives and the effectiveness of personal vote-seeking behaviors (Däubler et al., 2016; Marcinkiewicz & Stegmaier, 2015; Samuels, 2002). Future comparative research could thus test and adapt this candidate-centric model in these comparable electoral arenas.

Additionally, the analysis advances the ongoing exploration of social media as a predictive tool for elections. The study demonstrates that social media data can be effectively utilized to quantify a candidate's established online reach, rather than as a proxy for dynamic public opinion or sentiment. This finding addresses and effectively bypasses many of the challenges associated with sentiment analysis that have historically hindered this research area. Although platform-related biases remain an issue, the study highlights potential strategies to mitigate their impact, suggesting a robust avenue for future research and development in this area.

From a practical point of view, the study offers dual contributions. For commercial entities seeking new methods, this approach presents an intriguing avenue for innovation in electoral forecasting. A hybrid strategy could potentially improve prediction accuracy by incorporating the model's aggregate measure of candidate strength as a dynamic predictor, helping to correct for local dynamics and personal vote effects not captured by national-level polls.

For candidates themselves, access to candidate-level information can be practical. Although it does not offer solutions to larger electoral hurdles, it can provide valuable insights into self-assessment relative to peer candidates. However, it is crucial to interpret these insights with caution, acknowledging their limitations and leveraging their potential utility.

The candidate-based model has its drawbacks. It may not account for dynamic campaign issues and is unlikely to capture the nuanced developments during the campaign period to the same extent as opinion polling. Furthermore, it does not directly address societal cleavages and other sociopolitical determinants of voting behavior. However, incorporating training on past vote shares from multiple election cycles helps mitigate these limitations, as it indirectly captures historical preferences.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the author used Writeful, gpt-4o, and Gemini 2.5 Pro to improve language. After using this tool/service, the author reviewed and edited the content as needed and takes full responsibility for the publication's content.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at <https://doi.org/10.1016/j.ijforecast.2025.12.008>.

Data and code availability

The code and data supporting the findings of this study are available in the reproducibility package hosted on GitHub at: <https://github.com/vepsala/candidate-model>. This repository includes the Python-based forecasting model, Jupyter notebooks used in the 2023 Finnish Parliamentary Election forecasting and analysis, and the historical training datasets. To ensure privacy, all individual candidate names have been removed from the datasets. Detailed instructions for environment setup and dependency installation are provided in the repository's documentation.

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