Predictive Analytics and the 2024 Presidential Election: A Study of Key Candidate Attributes That Predict Election Results in the 2024 Presidential Election

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ABSTRACT

Marketing is a key component in elections with voters. Political marketing is an important component factor and influence on how voters choose political candidates. The purpose of this study was to examine key candidate attributes and predictive analytics that influenced voter behavior in the 2024 Presidential Election. The Political Marketing Candidate Attribute Scale (PMCAS) was developed specifically for this research on political marketing and voter behavior. This study is the result of a four-year research project on how political candidates win or lose elections based on predictive analytics, which included local and state elections and the 2024 Presidential Election. The results of study reveal the key predictor variables that influenced voter behavior for candidates for local and state elections as well as the presidential election. The researchers had five national samples (N = 1,774) in the U.S. that were used for this research on political marketing and candidate attributes.

For this study, the researchers examined 30 candidate attributes that are key indicators in predicting elections wins. We used three statistical tests to measure a candidate's attributes that influence voter behavior. The results of this four-year study revealed three key factors that influence voter behavior based on candidate attributes. First, we identified the top ten candidate attributes that predict voter behavior and predict candidate wins in an election. Second, we found five key demographic variables that are a significant predictive influence on voter behavior and election wins. Lastly, we found that voters are highly influenced by visual attributes with candidates compared to other attributes. The implication for marketers is that political marketing efforts can be predicted using statistical models and marketing model frameworks.

Keywords: Political marketing, predictive analytics, marketing models, political campaigns, marketing frameworks, political marketing infrastructure.

Introduction

There are numerous key predictive indicators that tie into voter behavior. Past research has shown that voters are not only concerned about standard political concerns (healthcare, school reform, prison reform, taxes, etc.), but age, gender, race, and party affiliation also play a factor. In this current climate, voters are also paying attention to the global economy. Presidential elections throughout the years have evolved as technology and the economy have evolved. Furthermore, with the expansion of technology, politicians are having to find new ways to reach their audience. Obama's campaign is a good example of what happens when the power of social media is used to its full potential. Social media is now considered a leading engagement tool for voters (Choy, Cheong, Laik, Shung, 2012). When we speak of predictive analysis, researchers are paying attention to this new tool and how it is used in politics.

Based on our exhaustive review of the literature, there is a need for more research analysis of candidate attributes in terms of political marketing that influences voter behavior and decisions. Specifically, research is needed to examine the impact of visual candidate attributes and why they are an important element in the American political system. This research is needed to understand how these candidate attributes mitigate voter behavior in terms of political marketing with local, state and federal elections. To date, no studies have specifically analyzed candidate attributes in terms of understanding their influence, risk, and perceptions with voters. Furthermore, because there are no prior instruments or scales that specifically measured candidate attributes in political marketing, the researchers developed a first-generation instrument to measure those attributes.

To fill this gap, the purpose of this study was to see if there were key predictive analytics that predict voter behavior in the 2024 Presidential election. For this study, the researchers used an exploratory factory analysis (EFA) and a confirmatory factor analysis (CFA). We wanted to assess the candidate attributes (dependent variables) by ranking their importance to voters in the 2024 Presidential Election. We also examined the independent variables (e.g., gender, age, ethnicity, political ideology, etc.) to measure their influence on the dependent variables (candidate attributes).

Specifically, the objectives of this study included: (a) developing a preliminary, first-generation scale to measure candidate attributes with quantitative methods (e.g., EFA) and (b) confirming the established psychometric properties of the scale through CFA and structural equation modeling (SEM) with an independent sample. The developed scale provides researchers and practitioners with a tool that can assess the impact of candidate attributes on voter behavior.

In the next section, we will give a comprehensive understanding of the subject background. Following that section, we explain our proposed method. Results are exhibited in the next section and the article ends with conclusions and suggestions for future research.

Background of the Study

There are key predictive indicators that tie into voter behavior that have been studied by researchers. Gregory and Gallagher (2002) looked at elections from 1962-2000 and saw patterns related to candidate voice. These voice qualities tied into the voters' perceptions of a candidate's leadership qualities. Banai, Banai, and Bovan (2016) asserted that voters tend to vote for candidates that they not only relate to but also that have a low-pitched voice. These researchers believe that vocal characteristics can be related to election outcomes.

It is worth noting that fundamentals have and will continue to be indicators for voter behavior. These fundamentals include but are not limited to the economy and which party currently is in the White House. Graefe (2018) found that in most cases election experts rely on the polls for their election predictions, and many do not use data related to the fundamentals directly but indirectly. For example, they can see the indicators related to unemployment, but they still look at polling related to favorability of the candidates while this is going on. Also, as the United States gets closer to elections, third party interests as well as the number of undecided voters decreases.

With the creation of social media, researchers now have new tools and methods for predicting winners and within those methods are also key indicators. Researchers must factor in that social media is a millennial driven tool; most older Americans still rely on television news and the newspapers for candidate information. Oikonomou and Tjortjis (2018) did a study focused on Twitter and analytics from it for the outcome of the November 2016 presidential election. Within the Twitter space they were able to drill down key factors for elections by extracting tweets using sentiment analysis.

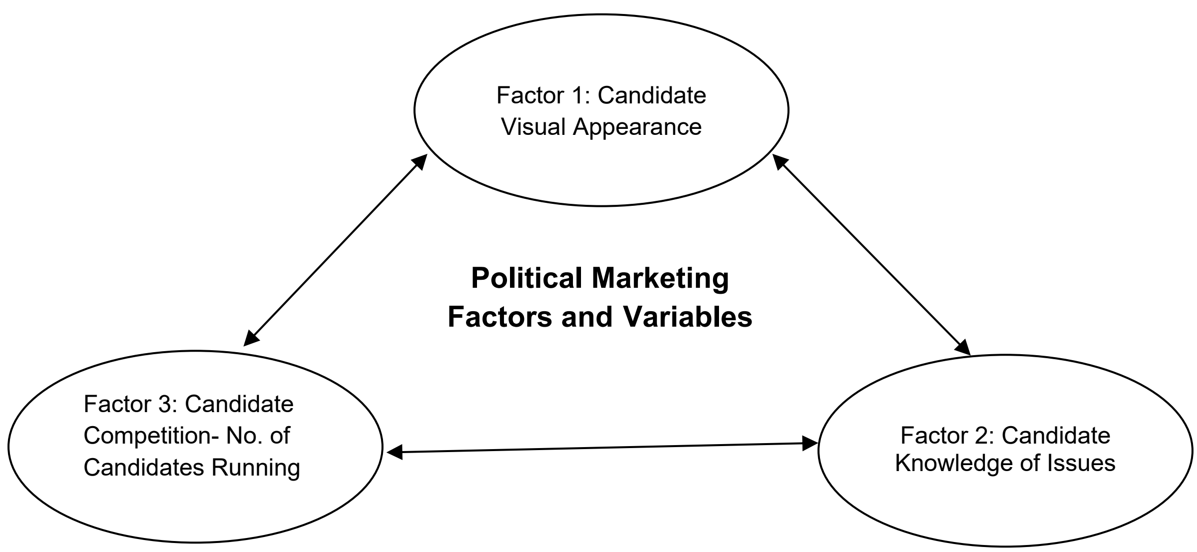
By using this method, the researchers turned tweets into predictive analytics, and their results were close to the actual final outcome. For example, using sentiment analysis researchers Oikonomou and Tjortjis (2018) came up with Trump at 53.26%, Clinton at 38.5%, and 8.69% neutral tweets in the state of North Carolina. Actual results from the 2016 election were Trump 50.5%, Clinton 46.7%, and other 2.8%. The researchers understand that not everyone has a Twitter account so this is not a standard way of gathering data but one must also understand the ever-changing landscape that technology plays in the elections process.

THEORETCIAL FRAMEWORK AND MODELS

Theoretical Model

Our theoretical model is presented with the proposed factors and items for this study. The model is also closely related to literature on politics and political marketing behavior with candidate appeal to voters. One of the important insights of this model is to illustrate the three components that influence voters in political marketing. The constructs of the model proposed for this study are in Figure 1. There are four constructs in the model. Reading from left to right, the model in Figure 1 shows the following four hypothesized constructs. The first factor construct that is important to voters is: (a) *Candidate Visual Appearance*, which underscores voters responding to the visual appearance of the candidates and that visual appeal is important to them. The second factor construct that is important to voters is: (b) *Candidate Knowledge of Issues*, which underscores voters' need to support candidates that are knowledgeable about the voters' issues that are important to them. Lastly, the final construct is (c) *Candidate Competition- No. of Candidates Running*, which underscores voters' need to support selected candidates and the competition in the political races (local, state and federal).

Figure-1: Theoretical Model of Political Marketing Factors and Variables



The research questions that guided this study are as follows: (a) What are the key variables that influence voters to vote for a presidential candidate; (b) How many key factors are there that are a major influence on voters for presidential elections; (c) What are the key high-ranking attributes (variables) that influence voters in presidential elections; and (d) What are the low-ranking key attributes (variables) that do not influence voters in presidential elections? Lastly, the conceptual model of the study is presented (see Figure 1).

Literature Review

Predictive analytics provides politicians and other stakeholders interested in electoral behavior with sound tools to evaluate people's attitude and possible outcomes of the elections. The primary tools employed are predictive modeling, data mining, and machine learning (Buresh & Pavone, 2018). Considerable attention is paid to the effectiveness of such traditional methods used in the prediction of electoral behavior as polls (Buresh & Pavone, 2018; Kenett et al., 2018). Researchers have developed numerous techniques to improve the effectiveness of diverse methods, but new tools appear and contribute to the development of the field (Buresh & Pavone, 2018; Kennedy et al., 2017). For instance, Swani and Tyagi (2017) offered a method incorporating traits of Big Data as the basis for Data Mining through the use of Apache Hadoop. There is still no definite conclusion regarding the potential of election surveys as researchers provide evidence displaying the benefits and downsides of this method. However, the research on predictive analytics in voter behavior analysis is not confined to exact instruments that can be employed.

The type of data to be analyzed is an important area of inquiry, and the focus on social media is apparent. Grover et al. (2019) explored the effects of social media discussions and concluded that networking and social media influence voter behavior. Another conclusion is the relevance of the data extracted from social media to predict voting trends. However, the predictive power of the analysis of social media discussions is limited, which is evident from certain studies. For instance, Vepsäläinen et al. (2017) found that the data extracted from Facebook was not instrumental in predicting voting behaviors in Finland. Smith and Gustafson (2017) noted that the analysis of searches related to the use of social media (such as Wikipedia) could be more illustrative compared to discussions and other types of information.

In addition to social media use in predicting voter behavior, researchers analyze the relevance of diverse sources of information and trends. Dalege et al. (2017) explained that network structure could shed light on the influence of people's attitudes on voting decisions. As an illustration of this relationship, it was found that people's sentiment concerning the Ebola outbreak had a significant impact on voter behavior as people had enhanced inclinations to conform to the current popular opinion (Beall et al., 2016). People's political views, and as a result, their voting behavior was also affected by their personal ideologies and beliefs that were not related to political aspects. For instance, sexism proved to have a substantial effect on presidential elections in the USA in 2016 (Ratliff et al., 2017). The analysis of different views and public opinion has proved to be a relevant area that can help in predicting voter behavior. The Data Science Foundation (2019) indicates the best way to predict the future is to study past behavior. Data analytics helps the election campaign to understand the voters better and hence adapt to their sentiments.

Newman (2002) gathered data using a predictive model of voter behavior to identify voter motivations for the George W. Bush and AI Gore in the 2000 presidential campaign. The motivations were based on the “value” they sought in a president. The value was the “political marketplace” niche that separated Gore from his competition. The results reveal the complementary roles that the political party and each candidate's campaign organization played in their respective marketing strategies.

Sweetser and Wanta (2008) examined whether the candidate-controlled public relations tools of political ads and candidate blogs were successful in influencing the issue and news agenda during the 2004 George W. Bush and John Kerry presidential election. Cross-lag analyses indicated a strong data correlation between blogs and the media agenda, while advertisements did not correlate with the media agenda.

Finn and Glaser (2010) highlighted the American National Election Studies' (ANES) 2008 national survey data. It was used to predict the effects of pre-election emotional responses to candidates on presidential vote. Self-reported emotional responses to Barack Obama and John McCain, specifically hope, pride, and fear, predicted reported vote choice above and beyond party identification, ideology, and other predictors. In addition, respondents reported that Obama made them feel hopeful, which served as a strong and reliable predictor of voting for Obama.

Towner (2013) examined the influence of traditional and online media, offline political participation, and voter turnout during the Barack Obama and Mitt Romney 2012 presidential campaign. Results included that participation was heightened to online sources, particularly presidential candidate websites, Facebook, Twitter, and blogs. Groshek and Al-Rawi (2013) examined public sentiment as it was expressed in social media, Facebook and Twitter, by just over 1.42 million followers in the Obama and Romney 2012 presidential election campaign. Findings included that neither presidential candidate was framed in an overly critical manner in his opponent’s Facebook space nor on Twitter’s dedicated nonpartisan election page.

Grover et al. (2019) examined how the drivers of voter behavior in the 2016 presidential election of Donald Trump and Hilary Clinton were reflected in Twitter (social media). Social media analytics investigated whether an impact on voting behavior during an election, through acculturation of ideologies and polarization of voter preferences, was identified. Findings indicated that discussions on Twitter could have polarized users significantly, geographical analysis of tweets, users, and campaigns suggests acculturation of ideologies, and network analysis indicated that polarization may have occurred due to differences between the respective online campaigns.

In conclusion, this brief literature review displays the most apparent trends in the current research on predictive analytics in political sciences. Researchers pay attention to such fields as exact statistical tools, diverse analytical instruments, appropriate sources of data, as well as numerous aspects of people’s lives that can have an impact on their decisions during elections. One of the most discussed topics in academia at present is the utilization of social media in predictive analytics. Researchers explore diverse methods of the integration of these sources into their research and the application of different statistical tools in social media content analysis.

Data and Methodology

The data used for this study were acquired via Survey Monkey. The survey was distributed nationwide and conducted online by partnerships with political organizations. The respondents were chosen using a stratified sampling technique that ultimately resulted in success with responses. The researchers attained a final sample population of 1,774 adult voter respondents aged 18 and over. The demographic sample was representative of the demographics of the population nationwide. This is the result of a 5-year study of researching local, state and Presidential Elections.

Instruments

The Political Marketing Candidate Attribute Scale (PMCAS) is a researcher-developed first-generation instrument that was validated for reliability for the study. The PMCAS consists of 40 items in a 7-point Likert format. The scale measures political marketing and candidate appeal. The items in the scale are short phrases and scenario-based phrases. Respondents (voters) were instructed to indicate the candidate attributes that appealed to them as a voter in the 2024 Presidential Election. The instrument is an original first-generation-researcher developed scale was measured for reliability indices. The reliability coefficients ranged from .65 to .90. The researchers were pleased with the reliability coefficients; they prove the instrument shows above average reliability.

Data Analysis

In the current study, the researchers used confirmatory factor analysis to test the hypothesized structure of the political marketing behaviors, the potential effects of method bias on its psychometric properties, and whether a revised version of the scale (in which negatively worded items were rephrased to be positively worded) resulted in improved model fit. The researchers used two different statistical designs: (a) descriptive and (b) inferential statistics. Demographic data were used and analyzed using descriptive statistics, which measured central tendency in the data. The rationale for this was to examine group characteristics between group differences. The objective for the descriptive statistics is to transform large groups of data into a more manageable form (Huck, Cormier & Bounds, 1974).

For the inferential statistics, multivariate statistical tests were used. For our study, we used three types of structural equation models (SEM): (a) Confirmatory Factor Analysis; (b) Path Analysis; and (c) Latent Variable Structural Model. We used these SEM models to help understand and measure voter behavior in the 2024 Presidential Election. An exploratory factor analysis (EFA) and confirmatory factory analysis (CFA) were used for the study. The purposes of the study were to: (a) establish the factor structure of the via EFA; (b) test the measurement model derived from EFA via CFA; and (c) to assess the internal consistency of the instrument. This approach involves including method-specific factors (e.g., one factor comprising only positively worded items and another factor comprising only negatively worded items) within the model being tested. We present our analyses on a sample of 1,774 voters.

Variables

The independent variables are the demographic variables in the instrument. The scale used in the study is a first-generation, researcher-developed instrument. The instrument is a 40-item instrument with statements scored on a seven-point Likert Scale ranging from *Strongly Agree* (7) to *Strongly Disagree* (1). The seven-item statements were used to measure the underlying attitudinal cluster of voter candidate interest. The dependent variables in this study are seven-point Likert questions. They are measuring voter behavior and political marketing of candidates. The voters answered questions on the candidate attributes (physical characteristics, knowledge, and others) that are appealing to them as a voter. Political candidate trust was measured using a series of three questions, where high scores indicated low levels of political marketing and candidate attributes that appeal to the voter. Again, the questions were developed to analyze political marketing and candidate influences on voters.

Sample

Participants in the sample (N = 1,774) were sent a survey in 2023 as part of an initial nationwide study of political marketing and predictive analytics with factors that determine election wins. The study took place in the United States. The sample consisted of 1,774 American citizens across the United States during the local, state and federal elections. Each subject was given a questionnaire booklet that contained, among other things, a measure of sociopolitical attitudes and questions concerning the subjects' political party preferences.

The sampling frame for the pilot sample was developed using a stratified sampling method selected for the study. The data collection for the study was taken completely online via Survey Monkey. Of these individuals, a total of 1,774 completed the instrument. The instrument is a 40-item survey used for this analysis. In terms of gender, the participants in the study were: 43.5%, male; 55.5%, female. The age range of the sample was: 41.1 % were age 19 to 29; 36.3% were 30 to 39; 12.3% were 40 to 49; 7.8% were 50 to 59; and 3.4% were 60 and over.

Data Predictive Analytic Strategy

For this extensive research on voter behavior and political marketing, the researchers used a series of multivariate statistical tests. The researchers used both EFA and CFAs to perform the analyses with the four datasets. For the sample (N = 1,774), again, the researchers used both EFA and CFAs to perform the analyses (SEM). The researchers wanted to be consistent with the research testing with the samples by testing the effects of method bias in the proposed model compared to the revised model and scale factor structure. The researchers wanted to estimate indicator uniqueness and factor intercorrelations in the models. The CFA was used with all of the samples for the study. Sample 1 used PLS-SEM (Hair et al, 2016)., while AMOS 27.1 was used with the samples (Arbuckle & Wothke, 2014). The indices that we interpreted are considered to be acceptable measures of fit (Hoyle, 1995; Kline, 2010).

RESULTS

Descriptive Statistics

The sample is a representative, stratified national household sample of individuals that were voters. To qualify for inclusion, the individual had to be at least 18 years of age or legal voting age. The study took place in the United States. The sample consisted of 1,774 American citizens across the United States during the local, state and federal elections. Each subject was given a questionnaire booklet that contained, among other things, a measure of sociopolitical attitudes and questions concerning the subjects' political party preferences. We collected data based on six demographic questions in the Political Marketing Candidate Attribute Scale (PMCAS). Participants in the sample (N = 1,774) were sent a survey in 2023 as part of an initial nationwide study of political marketing and predictive analytics with factors that determine election wins. The instrument is a 40-item survey used for this analysis (see Tables 1 and 2).

Table 1: Descriptive Statistics of the Study of Voters (N = 1,774)

Gender	Frequency	Percentage
Males	998	56.3
Females	776	43.7
Total	1,774	100%
Age	Frequency	Percentage
18 – 29	561	31.6
30 – 39	737	41.5
40 – 49	230	13.0
50 – 59	161	9.1
60 and over	85	4.8
Total	1,774	100%
Ethnicity	Frequency	Percentage
African American (Black)	117	6.6
Asian (Pacific Islander)	234	13.2
Caucasian (White)	1004	56.6
European (White)	202	11.4
Hispanic (Latino)	158	8.9
Other	59	3.3
Total	1,774	100%

Table 2: Descriptive Statistics of the Study of Voters (continued) ($N = 1,774$)

Marital Status	Frequency	Percentage
Single	571	32.2
Married	1,067	60.1
Divorced	85	4.8
Separated	13	.8
Widowed	20	1.1
Other	18	1.0
Total	1,774	100%
Education	Frequency	Percentage
Did not finish H.S.	5	.3
High School Diploma	114	6.4
Some College	239	13.5
Associates	123	6.9
Bachelors	970	54.7
Master's Degree or Higher	323	18.2
Total	1,774	100%
Political Ideology	Frequency	Percentage
Conservative	532	30.0
Moderate	408	23.0
Liberal	722	40.7
Radical	56	3.2
Alternative	18	1.0
Other	38	2.1

Study: Factor Analysis and Factor Solution

Table 1 presents fit indices for the three models tested in this study. The sample for the study was (N = 1,774). Table 1 presents factor loadings for the hypothesized model tested in this study. EFA was employed for the sample. A principal component analysis factor analysis was employed using a varimax rotation of the data. The researchers used eigenvalues greater than 1.0 to extract the number of factors, which resulted in the three-factor solution (Hair, Anderson, Tatham, & Black, 1998). The varimax oblique rotation of the four-factor solution, for the factors and cognition loaded robustly on their respective factor rankings. Table 1 displays the factor loadings, varimax pattern coefficients, and percentage of variance recovered by each factor after the oblique rotation.

The Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO) was at .971 and the Bartlett's Test of Sphericity was at 37076.638. Following the varimax rotation, the eigenvalue variance accounted for the distribution among the three factors, with 41.67% accounted for by Factor 1, 13.57% for Factor 2, 4.48% and for Factor 3. The three-factor solution accounted for 59.71% of the total variance.

Model: Confirmatory Factor Analysis-Structural Equation Modeling (SEM)

We conducted a confirmatory factor analysis (CFA) to assess the construct validity of the model. We used AMOS 30.0 to measure convergent validity can be assessed and tested using the measurement model by determining the significant value of each factor and factor item's estimated pattern coefficient on its posited underlying construct factor. To assess convergent validity, we measured the loading estimates and construct reliability. Confirmatory factor analysis (CFA) was also performed using AMOS 30.0 to measure unidimensionality, convergent and discriminant validity.

The results, obtained from CFAs conducted separately on the four age groups, partially support this solution (see Table 2). The results were obtained from the CFA that was conducted on the three factors (see Figure 3). The CFA was performed through AMOS 30.0 software on data collected from the voters in the 2024 Presidential Election. Structural Equation Modeling (SEM) was used for the sample. The hypothesized model is presented in Figure 3 where circles represent latent variables and rectangles represent measured variables. A three-factor model is hypothesized. The information in the factors and digit span subtests serve as indicators of candidate appeal to voters with political marketing. The three factors are hypothesized to covary with one another. As for the other factor relationships, we found some moderate path coefficients between the factors (see Figure 3 & 4).

In Figure 3, we used AMOS 30.0 for SEM to examine the path coefficients among the three factors in the EFA. We found some significant relationships with some of the factors. We found two variables that indicated strong relationships. We found Factor 1 had a strong relationship with Factor 3 with a path coefficient of 0.76; Factor 1 had a weak and inverse relationship with Factor 2 with a path coefficient of -0.09; lastly, Factor 2 had a moderately strong relationship with Factor 3 with a path coefficient of 0.33. These relationships are the strongest in their path coefficients in the data. As for the other factor relationships, we found some moderate path coefficients between the factors (see Figure 3 & 4).

Table 3. Principal Component Analysis -Political Marketing-Exploratory Factor Analysis

Factors and Variable Items	F1	F2	F3
V27-Candidate Visual Appearance-Glasses	**.853**		
V39-Candidate Fraternity Organization Affiliation	.853		
V36-Candidate Family (wife & children)	.849		
V26-Candidate Visual Appearance-Facial Hair	.839		
V28-Candidate Visual Appeal/Attractiveness	.835		
V33-Candidate Ethnicity	.831		
V22-Candidate Gender	.828		
V35-Candidate Sexual Orientation	.820		
V25-Candidate Visual Appearance-Weight	.819		
V24-Candidate Visual Appearance-Height	.792		
V37-Candiate Military Background	.688		
V34-Candidate Age	.603		
V31 Candidate Image and Presence	.555		
V13-Verbal Attacks	.552		
V21-Candidate Knowledge of Issues		**.653**	
V30-Candidate Intelligence and Knowledge		.633	
V19-Candidate Credibility		.601	
V20-Candidate Moral Character		.598	
V18-Candidate Connection with Voters		.537	
V29-Candidate Physical Health		.483	
V23-Candidate Education		.475	
V16-Candidate Defense against Opponents		.405	
V12-Candidate Competition- No. of Candidates Running			**.542**
V11-Candidate Ranking			.541
V15-Candidate Marketing			.519
V14-Candidate Likeability			.486
V17-Candidate Differentiation			.446
V10-Candidate Value Proposition			.364

Note: Results of 3-factor solution (and 30 items) with Principal Component Analysis extraction method with a Varimax rotation and a Kaiser Normalization. Benchmark for this study, a minimum coefficient of .3 and higher will be used as the standard.

Figure 3: Model 1 – Confirmatory Factory Analysis-Structural Equation Model (SEM)

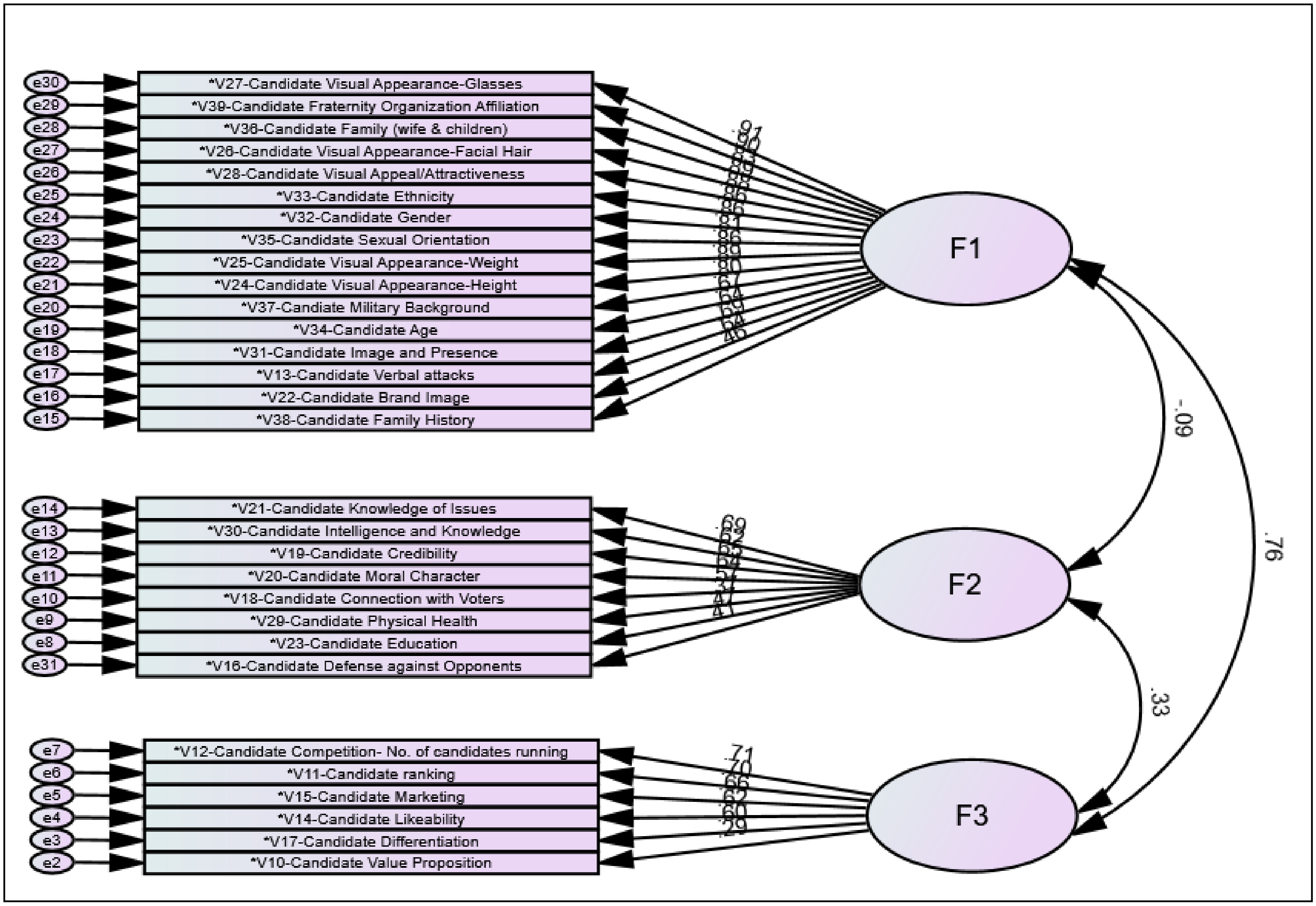


Figure 4*:* Model 2 – Renamed Structural Equation Model (SEM): Political Marketing

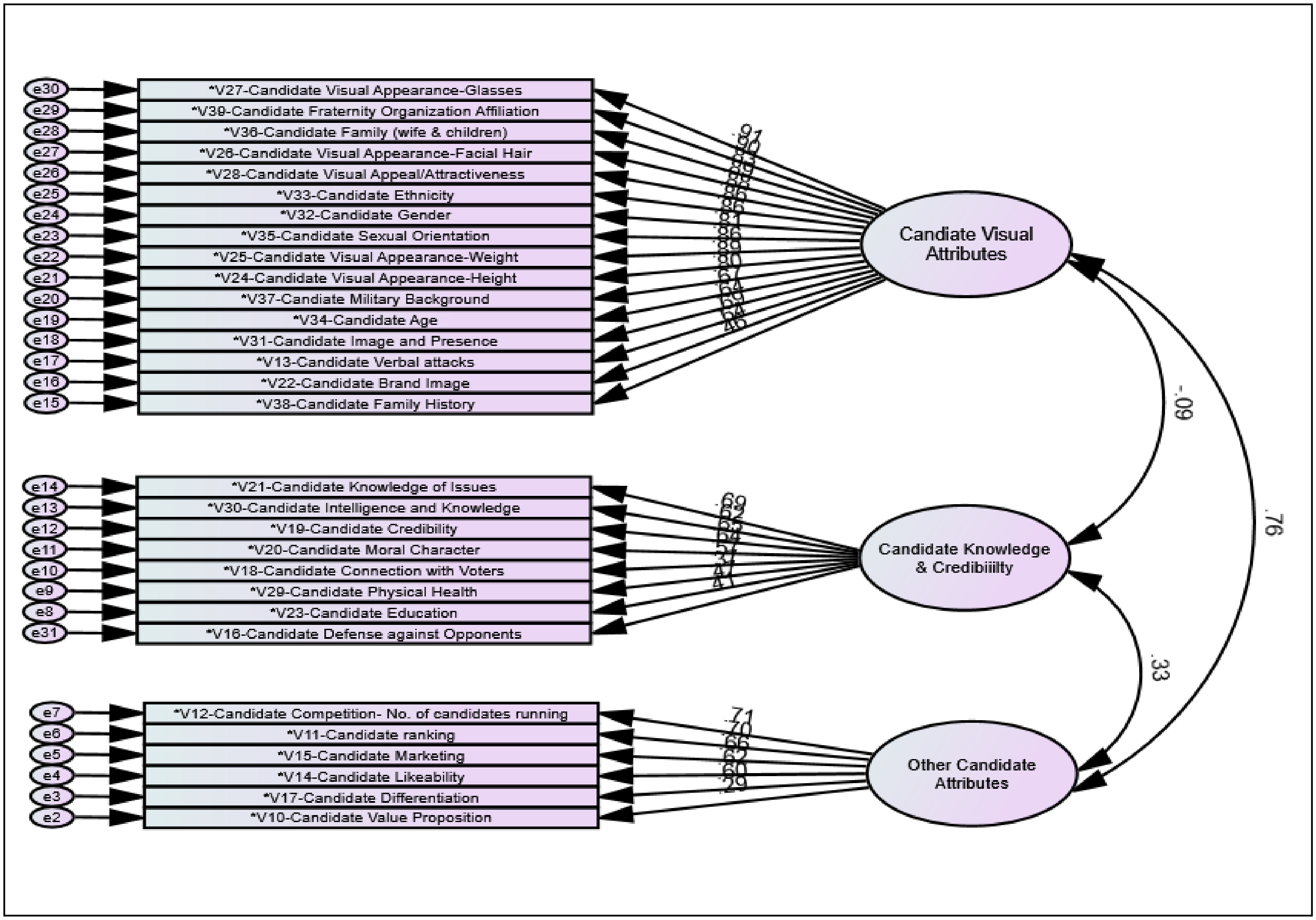
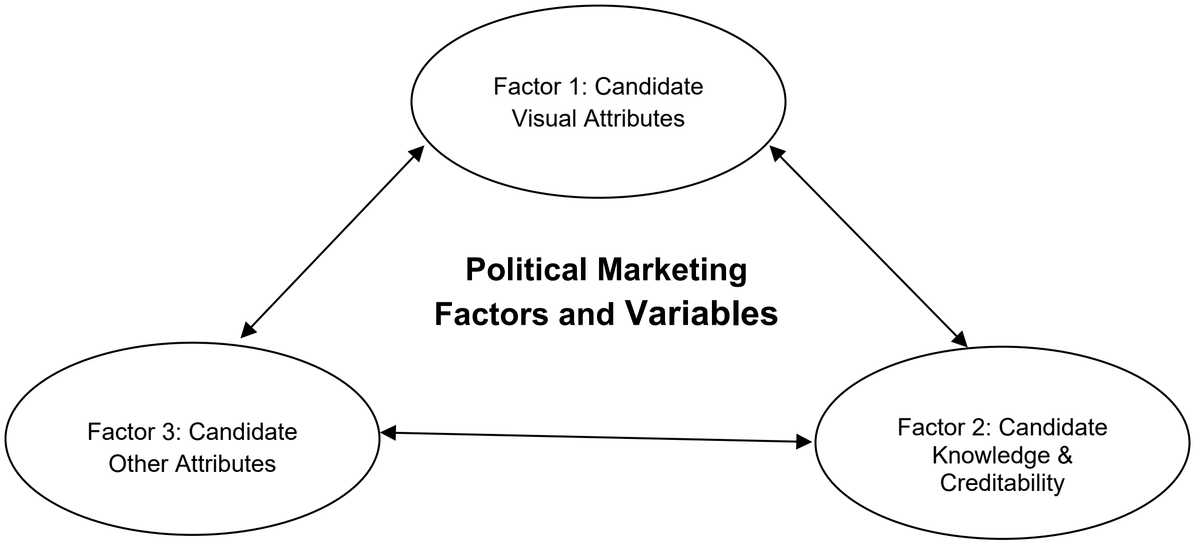


Figure-5: Revised Theoretical Model of Political Marketing and Candidate Appeal



Factorial Linear Regression and Predictor Variables

A standard multiple regression was performed to examine the predictor variables influence on voters' behavior in elections with candidate attributes. We used predictor variables (gender, age, ethnicity, education, political ideology, and so on). The regression analyses were performed using SPSS 27.0 for evaluation of assumptions. The multiple linear regression was used to test if the independent variables (gender, ethnicity and so on) significantly predicted voter preference with the candidate attributes (see equation below):

General Linear Equation 1.1

$$Y^1 = A + B_1X_1 + B_2X_2 + \dots + B_kX_k \qquad (1.1)$$

where Y_1 is the predicted value of Y, A is the value of Y^1 when all Xs are zero, B_1 to B_k represent regression coefficients, and X_1 to X_k represent the IVs. We found some predictors variables that showed some significance. It was found that gender, education political ideology and the Presidential election were strong predictors of the candidate attributes were favorable to voters (see below).

Path Analysis and Structural Equation Modeling

For our study, we used three types of structural equation models (SEM): (a) Confirmatory Factor Analysis; (b) Path Analysis; and (c) Latent Variable Structural Model. We used these SEM models to help understand and measure voter behavior in the 2024 Presidential Election.

Data Analysis

A variety of fit indices were adopted to assess the appropriateness of the SEM, including the classic goodness-of-fit index chi-square; the standardized root mean square residual (SRMR) We used the following fit indices to measure the fit of the models used in the calculation of many other fit measures: (1) the Root Mean Square Error of Approximation (RMSEA; Steiger, 1990; Steiger & Lind, 1980), is an index of approximate fit: less than .05 indicates good fit, equal to .0 indicates exact fit, from .08 to .10 indicates mediocre fit, greater than .10 indicates poor fit; (2) the Adjusted Goodness of Fit Index (AGFI); Joreskog & Sorbom, 1984; Kline, 2005; Tabachnick & Fidell, 2010),is an index of the average discrepancy among the observed and fitted covariance matrices: a good model should have a SRMR smaller than .05; (3) the Comparative Fit Index (CFI; Bentler, 1989, 1990), is an index that compares the fit of a target model with the fit of a null model where no structure is defined on the date: values close to; (4) Normed Fit Index (NFI); and (5) Incremental Fit Index (IFI). These were the indices that were used in the study. AMOS 30.0 was used to construct and test the SEM models and procedures. SPSS 30.0 software was used for the remaining statistical analyses.

Results of the SEM Analyses

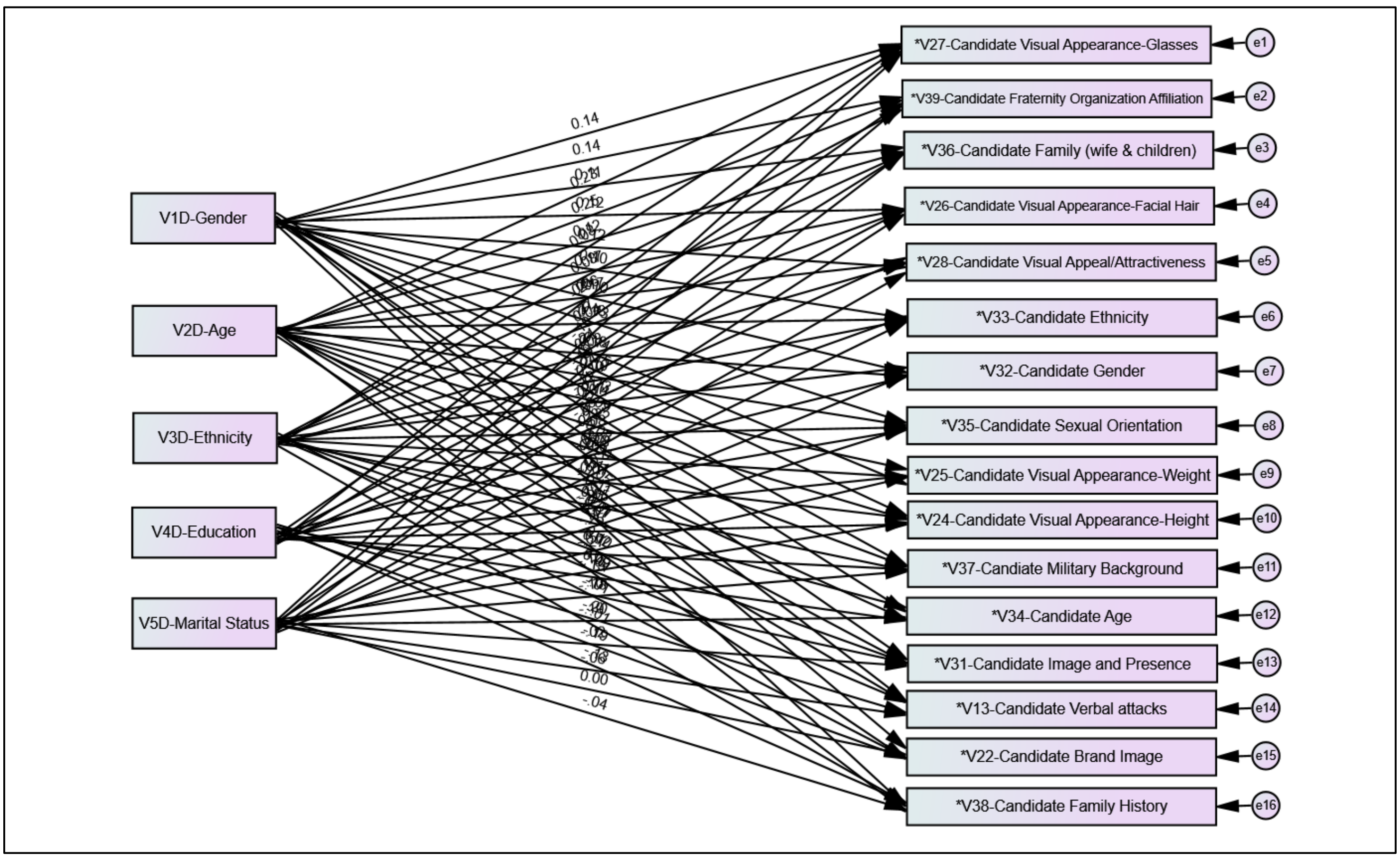
The results of the SEM analyses (AMOS) are presented in Figures 6 to Figure 9. All items loaded significantly on the subscales were specified. An examination of the modification indices indicated that only two additions to the resulting model were theoretically meaningful: the correlation between error terms for two items on the Political Marketing Candidate Attribute Scale (PMCAS) (Figure 6).

The first path model, Model 1a, shows the link between exogenous variables and endogenous variables with voter behavior with the 2024 Presidential Election can be seen in Fig. 6. The pathways (arrows) from in the model represent the hypothesized effects. The variables on the left side of the model are endogenous variables (independent). The variables on the right eft of the model are exogenous variables (dependent). The exogenous variables (voter behavior) on the right of the model are influenced by the endogenous variables. Factor 1(1a) path coefficients represent the predictive relationships in the model between sociodemographic variables and vote behavior. The model's initial fitness was assessed using various indices.

Based on the results of the model, we could not find a strong relationship between the influence of sociodemographic variables and vote behavior. The model's initial fitness was assessed using various indices. The CMIN/Df value was 187.577, which is higher than the adequate fit of less than 5. The Goodness of Fit Index (GFI) was .193, exceeding the below threshold of 0.90, while the Adjusted Goodness of Fit Index (AGFI) was -.434, falling below the 0.90 requirement.

The Root Mean Square Error of Approximation (RMSEA) was 0.324, higher than the desired less than 0.10. Thus, the initial model was not absolutely fit as three out of four absolute fit indices did not meet the requirements. However, incremental fit measures including the Normed Fit Index (NFI) at 0.118, Comparative Fit Index (CFI) at 0.116, and Incremental Fit Index (IFI) at 0.119 all was below 0.90, indicating the incremental lacks fitness. Parsimonious fit measures such as PGFI (0.109), PCFI (0.072), and PNFI (0.073) also indicated an inadequate fit as they were all above 0.50. The hypothesis that sociodemographics has a significant influence on voter behavior (HA1) was tested. The path analysis results indicated a statistically insignificant positive influence of sociodemographic on voter behavior, with an estimate of 0.59, a standard error (S.E.) of 29.774 and a critical ratio (C.R.) of 6.510. Overall, the individual path model of the endogenous variables was not a strong influence on the exogenous variables (dependent) (see Figure 6).

Figure-6: Regression Factorial Path Model 1a Political Marketing and Candidate Appeal for Factor 2: Candidate Knowledge & Creditability - Sociodemographics

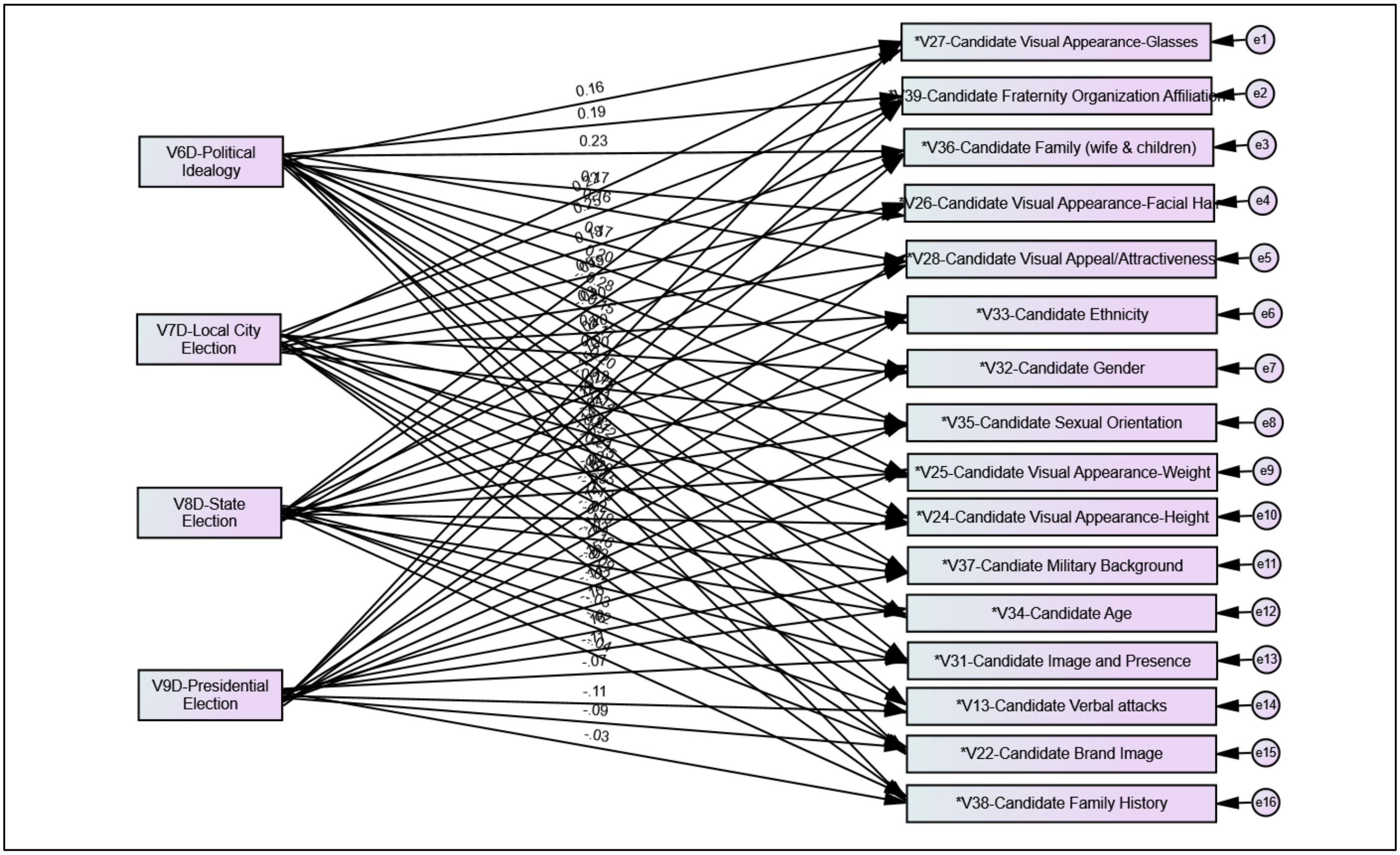


The second path model, Model 1b shows the link between exogenous variables and endogenous variables with voter behavior with the 2024 Presidential Election can be seen in Fig. 7. The pathways from in the model represent the hypothesized effects. The second path model, Model 1b shows the link between exogenous variables and endogenous variables with voter behavior with the 2024 Presidential Election can be seen in Fig. 7. The pathways from in the model represent the hypothesized effects. Again, the variables on the left of the model are endogenous variables (independent). The variables on the right eft of the model are exogenous variables (dependent). The exogenous variables (voter behavior) on the right of the model are influenced by the endogenous variables. Factor 1(1b) path coefficients represent the predictive relationships in the model between sociodemographic variables and vote behavior. The model's initial fitness was assessed using various indices.

Based on the results of the path model, we could not find a strong relationship between the influence of political affiliation variables and vote behavior. The model's initial fitness was assessed using various indices. The CMIN/Df value was 209.216, which is less than the adequate fit of less than 5. The Goodness of Fit Index (GFI) was 0.179, exceedingly the below threshold of 0.90, while the Adjusted Goodness of Fit Index (AGFI) was -0.358, falling below the 0.90 requirement. The Root Mean Square Error of Approximation (RMSEA) was .343, higher than the desired less than 0.10. Thus, the initial model was not absolutely fit as three out of four absolute fit indices did not meet the requirements. However, incremental fit measures including the Normed Fit Index (NFI) at 0.071,

Comparative Fit Index (CFI) at 0.070, and Incremental Fit Index (IFI) at 0.072 all were below 0.90, indicating the incremental lacks fitness. Parsimonious fit measures such as PGFI (0.108), PCFI (0.047), and PNFI (0.048) also indicated an inadequate fit as they were all above 0.50. The hypothesis that political affiliations have a significant influence on voter behavior (HA1) was tested. The path analysis results indicated a statistically insignificant positive influence of sociodemographic on voter behavior, with an estimate of 0.59, a standard error (S.E.) of 29.774 and a critical ratio (C.R.) of 6.510. Overall, the individual path model of the endogenous variables (political affiliation) was not a strong influence on the exogenous variables (dependent) (see Figure 7).

Figure-7: Regression Factorial Path Model 1b Political Marketing and Candidate Appeal for Factor 2: Candidate Knowledge & Creditability – Political Affiliation

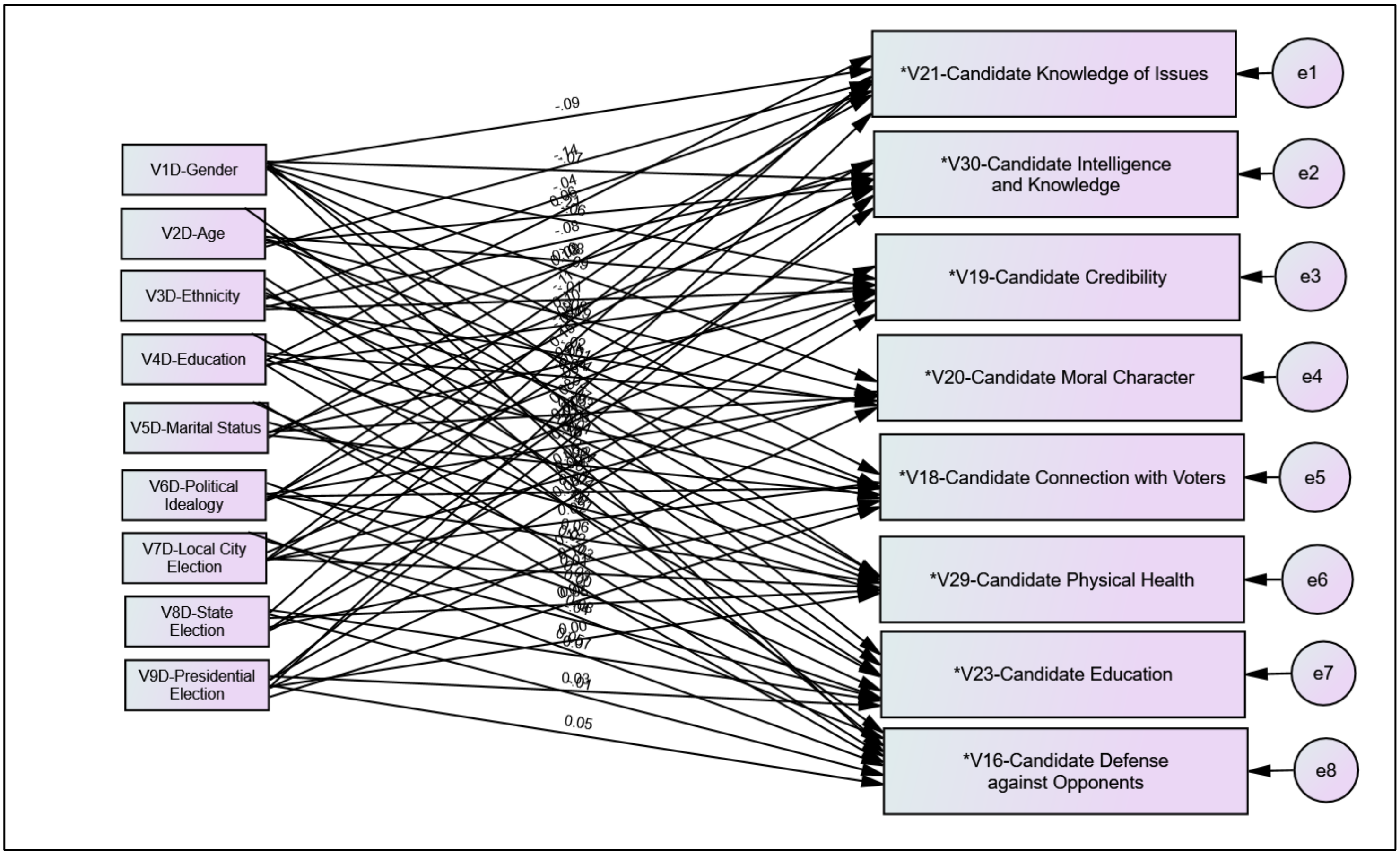


For Factor 2, in our study, the second path model, Model 2 shows the link between exogenous variables and endogenous variables with voter behavior with the 2024 Presidential Election can be seen in Figure 8. The pathways from in the model represent the hypothesized effects. Again, the variables on the left of the model are endogenous variables (independent). The variables on the right eft of the model are exogenous variables (dependent). The exogenous variables (voter behavior) on the right of the model are influenced by the endogenous variables. Factor 3 path coefficients represent the predictive relationships in the model between sociodemographic variables and vote behavior. The model's initial fitness was assessed using various indices.

Based on the results of the path model, we could not find a strong relationship between the influence of sociodemographic variables and vote behavior. The model's initial fitness was assessed using various indices. The CMIN/Df value was 73.157, which is less than the adequate fit of less than 5. The Goodness of Fit Index (GFI) was 0.688, exceedingly the below threshold of 0.90, while the Adjusted Goodness of Fit Index (AGFI) was 0.266, falling below the 0.90 requirement. The Root Mean Square Error of Approximation (RMSEA) was 0.202 higher than the desired less than 0.10. Thus, the initial model was not absolutely fit as three out of four absolute fit indices did not meet the requirements. However, incremental fit measures including the Normed Fit Index (NFI) at -0.847.

Comparative Fit Index (CFI) at 0.107 and Incremental Fit Index (IFI) at 0.119 all were below 0.90, indicating the incremental lacks fitness. Parsimonious fit measures such as PGFI (0.292), PCFI (0.051), and PNFI (0.056) also indicated an inadequate fit as they were all above 0.50. The hypothesis that sociodemographics have a significant influence on voter behavior (HA1) was tested. The path analysis results indicated a statistically insignificant positive influence of sociodemographic on voter behavior, with an estimate of 0.59, a standard error (S.E.) of 29.774 and a critical ratio (C.R.) of 6.510. Overall, the individual path model of the endogenous variables (sociodemographics) was not a strong influence on the exogenous variables (dependent) (see Figure 8).

Figure-8: Regression Factorial Path Model 2 Political Marketing and Candidate Appeal for Factor 2: Candidate Knowledge & Creditability

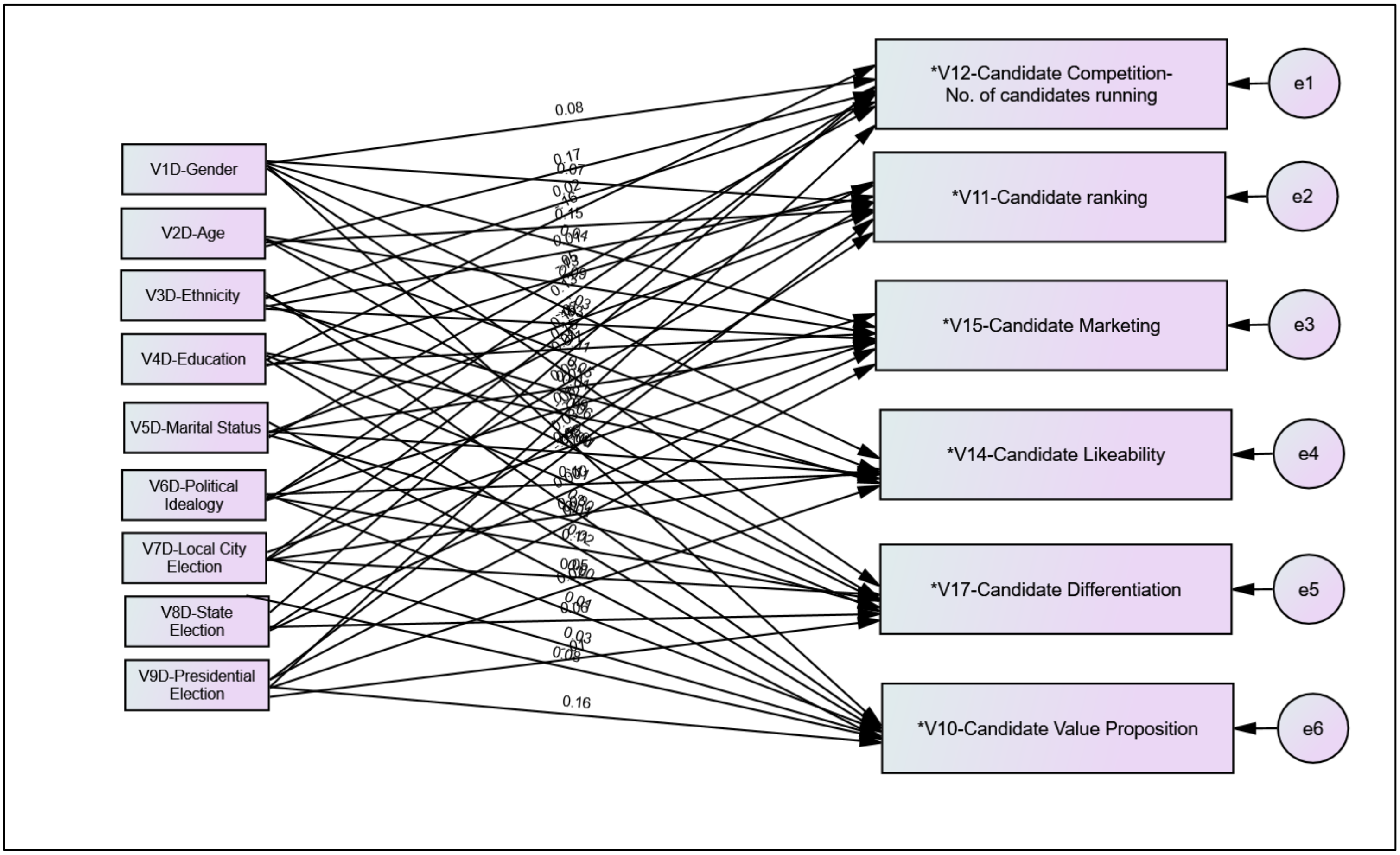


For Factor 3, in our study, the third path model, Model 3 shows the link between exogenous variables and endogenous variables with voter behavior with the 2024 Presidential Election can be seen in Figure 9. The pathways from in the model represent the hypothesized effects. Again, the variables on the left of the model are endogenous variables (independent). The variables on the right eft of the model are exogenous variables (dependent). The exogenous variables (voter behavior) on the right of the model are influenced by the endogenous variables. Factor 3 path coefficients represent the predictive relationships in the model between sociodemographic variables and vote behavior. The model's initial fitness was assessed using various indices.

Based on the results of the path model, we could not find a strong relationship between the influence of sociodemographic variables and vote behavior. The model's initial fitness was assessed using various indices. The CMIN/Df value was 78.276, which is less than the adequate fit of less than 5. The Goodness of Fit Index (GFI) was 0.717, exceedingly the below threshold of 0.90, while the Adjusted Goodness of Fit Index (AGFI) was 0.359, falling below the 0.90 requirement. The Root Mean Square Error of Approximation (RMSEA) was 0.209, higher than the desired less than 0.10. Thus, the initial model was not absolutely fit as three out of four absolute fit indices did not meet the requirements. However, incremental fit measures including the Normed Fit Index (NFI) at 0.209

Comparative Fit Index (CFI) at 0.141 and Incremental Fit Index (IFI) at 0.072 all were below 0.90, indicating the incremental index lacks fitness. Parsimonious fit measures such as PGFI (0.317), PCFI (0.071), and PNFI (0.075) also indicated an inadequate fit as they were all above 0.50. The hypothesis that political affiliations have a significant influence on voter behavior (HA1) was tested. The path analysis results indicated a statistically insignificant positive influence of sociodemographic on voter behavior, with an estimate of 0.59, a standard error (S.E.) of 29.774 and a critical ratio (C.R.) of 6.510. Overall, the individual model of the endogenous variables (sociodemographics) was not a strong influence on the exogenous variables (dependent) (see Figure 9).

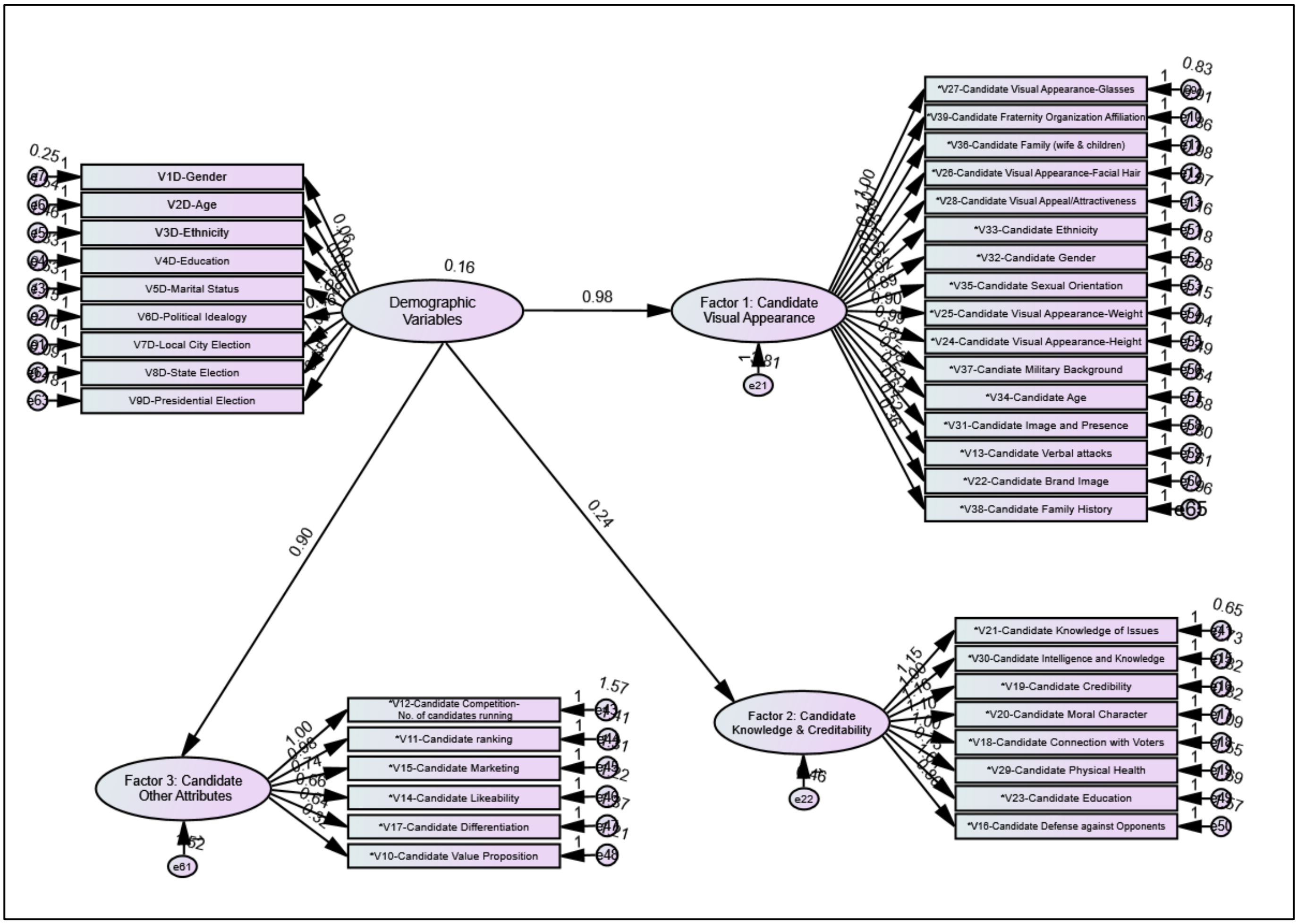
Figure-9: Regression Factorial Path Model 3 Political Marketing and Candidate Appeal for Factor 3: Candidate Other Attributes



For the last path model, we examined the overall influence of sociodemographics on the three political factors in study. We used a path regression model using AMOS estimates the path coefficients on a set of linear structural equations. The structural equations comprise of the exogenous variables (independent influence on the endogenous variables (dependent). In this model, we found the outputs from these path regression lines, and bivariate regression analysis represent the structural equations and the estimated relationships between independent variables and dependent variables. The regression path model output shows four different inputs from structural equations and reduced form equations.

The results of the path model showed some significant relationships. First, we found the results in the model showed that sociodemographics construct had a significant predictive analytic influence on the factor, F1- *Candidate Visual Appearance.* The path coefficient of (p = 0.98) indicated at strong predictive relationship with the factor. We also found sociodemographics had a strong predictive relationship with the factor, F3-*Candidate Visual Appearance* with a path coefficient of (p = 0.90). Lastly, however sociodemographics did not have a significance influence on the factor, F2- *Candidate Knowledge and Credibility with a coefficient of* (p = 0.24). We found sociodemogrpahics collectively, had a significant predictive relationship on two of the factors (see Figure 10).

Figure 10: Regression Model of Predictive Analytics that Influence Voters in the 2024 Presidential Election



DISCUSSION

In this study, we examined the impact of candidate attributes on voters in presidential voting. We tested the hypothesized factor structure of the Political Marketing Candidate Attribute Scale (PMCAS), a first-generation researcher-developed instrument used for this four-year research study. Our CFA results were replicated across four samples with very different results that focused on candidate attributes that were important to voters in the spectrum of political marketing. The researchers developed and analyzed a hypothesized model of political marketing with candidate attributes with voters. The results help to improve our understanding of what happens with candidate attributes in the voting process. We found five key findings in the research on political marketing in the 2024 Presidential Election.

The first key finding observed in the results with the voters was that the majority of the voters were liberal or considered themselves to be liberal. We found this result to be surprising. We found that political ideology is a key indicator in what candidate attributes attract voters in the presidential election. We observed that political ideology was consistent in all four samples for the study. This was surprising to us because some of the attributes that are important based on political ideology were a contrast. For example, because of the beliefs associated with liberal ideology, the two variables *Candidate Sexual Orientation* and *Candidate Family Values* were important. That was also surprising to the researchers.

The second key finding observed in the results was that gender is a factor in terms of candidate attributes and candidate attraction with the voters. There were also significant differences in what candidate attributes influenced voters based on gender. We found that gender was a key indicator in what candidate attributes attract voters in the presidential election. This finding was consistent in all our samples for the study. Gender is a key indicator of political ideology. The comparison of the genders resulted in significant coefficient differences between male and females when voting for the President. There were significant gender differences with the candidate attributes and marketing variables. The research showed that males and females had striking differences between them.

The third key finding observed in the results with research is with the candidate visual attributes. The most important candidate visual attributes to the voters in the Presidential Election were ranked in terms of importance. One critical observation is we found in our samples, there was a consistent pattern in terms of the ranking of the most important candidate attributes with voters. The majority of the voters ranked visual attributes as most important compared to other attributes. For example, the ten candidate attributes involved visual attributes with the voters: (1) *Candidate Fraternity Organization*; (2) *Candidate Ethnicity*; (3) *Candidate Visual Attractiveness*; (4) *Candidate Visual Appearance-Glasses*; (5) *Candidate Visual Appearance-Hair*; (6) *Candidate Visual Appearance-Height*; (7) *Candidate Visual Appearance- Weight*; (8) *Candidate Gender*; (9) *Candidate Sexual Orientation*; and (10) *Candidate Family Values*. This was a rather surprising finding. What this tells us in political marketing with the Presidential Election and other elections, candidate visual attributes are more important compared to more substantive qualities that we should be looking for in candidates.

The fourth key finding observed in the results with research is again with the candidate attributes. The least important candidate attributes to the voters in the Presidential Election were ranked in terms of importance. We found these were more substantive candidate attributes that voters should consider when voting for candidates. For example, the least important candidate attributes were: (1) *Candidate Value Proposition*; (2) *Candidate-Connection with Voters*; (3) *Candidate-Credibility*; (4) *Candidate-Defense Against Opponents*; (5) *Candidate-Education*; (6) *Candidate-Differentiation*; (7) *Candidate Moral Character*; (8) *Candidate-Likeability*; (9) *Candidate-Family History*; and (10) *Candidate Marketing*. Again, this was a surprising finding. What this tells us in political marketing with the Presidential Election and other elections, substantive candidate visual attributes least important to voters. We should be concerned based on this observation with this research. We have voters that elect candidates based primarily on visual attributes which is shallow compared to substantive attributes that qualifies them. This is a disturbing finding with regards to our American political system.

Lastly, the key finding observed in the results with the research is factor structure. Our confirmatory factor analysis results, which were replicated across four samples with very different factor structures. We had factor structures that ranged from a five-factor solution to three-factor solution primarily. All of the factor structures follow a similar pattern with candidate visual attributes ranking the highest among the voters in elections. Again, this is a disturbing finding with regards to our American political system.

CONCLUSIONS

There are key conclusions in this study. First, we must focus on the issue of gender differences with voters and explain why they strong ingredient with local, state and presidential elections. By asking what is necessary for genders to influence candidate and presidential elections, we have found that key variables such as gender that cannot be ignored or dismissed in their salience to the public and in their impact on presidential elections. Equally important, the salience of gender to the voters directly affects their impact on the voters' evaluation of the president.

Second, we conclude there must be an awareness concerning the issue of candidate visual attributes as a standard with voters. The preference of visual attributes over more substantive attributes has an impact on voters that cannot be understated. This type of optic centered view of candidates is problematic and can get us in trouble with voters, electing candidates in this manner. Clearly, our results imply that we are humans are, at heart, visual creatures. Political marketing and candidate attributes are not simply an afterthought and while largely measured in voter behavior, these visual elements exist as part of our core disposition and appear to be an important component to shaping how people function in voter behavior.

Lastly, we conclude the evidence our research suggests that we must improve the manner in which people vote. That means we need voters to vote on more substantive criterion, such can candidate credibility, moral character, and education. Politics cannot be a popularity contest based on voting for candidates with the best visual attractiveness to voters. This pattern is in part a predictable response of visual appeal to voters, and at the same time minimizes the focus on unqualified candidates' shortcomings. We have to do better at electing the best candidates with a minimal focus on visual attributes. That raises a dark concern over with our presidential elections. In this study we argue that to increase our voters' understanding of the public's evaluation of the local, state and presidential elections. This requires us to make progress in both theory, methodology and practice with the election system voter behavior. Therefore, our results provide informative evidence for deterring voting on visual attractiveness as a primary method of evaluation criteria for electing presidential candidates.

LIMITATIONS AND FUTURE RESEARCH

Limitations

There were some limitations to our research. First, Self-reported data and the length of the survey are limitations. The length of the survey may have contributed to some participants not completing the survey. The sample of convenience method of surveying was used, and limitations are constraints to the study based on the research design and methodology. Second, another limitation is the insufficient sample size for statistical measurement, and lack of previous research studies on the topic. Future research could be expanded and might be considered, using other measuring instruments. Last, another limitation is the reliance on a single channel of data collection. The researchers exclusively used the internet (via Survey Monkey.com) to collect the data. With this research, this could be a limitation because of unexploited avenues to collect data (e.g., telephone, in-person interviews, paper surveys and etc.). It would be an advantage to collect data using multiple channels of data collection could possibly enable a more diverse pool of voters for the study.

Future Research

In summary, our work here suggests some potentially fruitful lines of inquiry for future analysis. There were some implications for future research based on the findings of the study A future line of inquiry could focus on female voters and items that influence their voting patterns with candidates, also, the candidate attributes that influence female voters. That would be a fruitful endeavor worth pursuing. A second line of inquiry for future research emanating from this study relates to the role of candidate competency with voter behavior. This line of inquiry for future research could focus on candidate competency and what influences voters to vote for a candidate. This line of inquired could focus on investigating the key characteristics that could improve voters influence on more substantive candidate attributes (e.g., education, knowledge, credibility and value proposition).

Lastly, a line of inquiry for future research could consider further examining the role of candidate presentation and oratory attributes and how they shape voter opinion and beliefs. Additionally, with our research, future research could explore other lines of inquiry that may acquire substantial knowledge on the phenomenal of candidate attributes and political marketing through an examination of other factors that influence political choice. This line of inquiry would provide an interesting line of inquiry into the influence of candidate attributes with political marketing and election policy.

REFERENCES

Alvarez, R. M., & Nagler, J. (1997). Economics, Entitlements and Social Issues: Voter Choice in the 1996 Presidential Election. *Social Science Working Paper 1021*.

Awad, E. (2020). Persuasive Lobbying with Allied Legislators. *American Journal of Political Science, 00*(0), 1–14.

Beall, A. T., Hofer, M. K., & Schaller, M. (2016). Infections and elections. *Psychological Science, 27*(5), 595-605. https://doi.org/10.1177/0956797616628861

Bechtel, M.M., Hangartner D., & Schmid, L. (2016). Does Compulsory Voting Increase Support for Leftist Policy? *American Journal of Political Science, 60*(3), 752–767.

Buresh, D. L., & Pavone, T. (2018). Why no one knew that Hillary Clinton would lose the 2016 election. *American Journal of Political Science Review,* 1-19.

Choy Murphy, Cheong Michelle, Laik Ma Nang, Shung Koo Pong 2012. US Presidential Election 2012 Prediction using Census Corrected Twitter Model.

Cox, G. W., & Katz, J. N. (1995). Why Did the Incumbency Advantage in U.S. House Elections Grow? *Social Science Working Paper 939*.

Dalege, J., Borsboom, D., van Harreveld, F., Waldorp, L. J., & van der Maas, H. L. J. (2017). Network structure explains the impact of attitudes on voting decisions. *Scientific Reports, 7*(1), 1-11. https://doi.org/10.1038/s41598-017-05048-y

Data Science Foundation (2019, April 1). *Big Data Analytics and Predicting Election Results.* Retrieved from https://datascience.foundation/sciencewhitepaper/big-data-analytics-and-predicting-election-results

Edwards III, G. C., Mitchell, W., & Welch, R. (1995). Explaining Presidential Approval: The Significance of Issue Salience. *American Journal of Political Science, 39*(1), 108–134.

Finkel, S. E. (1985). Reciprocal Effects of Participation and Political Efficacy: A Panel Analysis. *American Journal of Political Science, 29*(4), 891–913.

Finn, C. & Glaser, J. (2010). Voter Affect and the 2008 U.S. Presidential Election: Hope and Race Mattered. *Analysis of Social Issues and Public Policy, 10*(1), 262-275. https://spssi.onlinelibrary.wiley.com/doi/abs/10.1111/j.1530-2415.2010.01206.x

Gomez, B.T., & Wilson, J. M. (2001). Political Sophistication and Economic Voting in the American Electorate: A Theory of Heterogeneous Attribution. *American Journal of Political Science, 45*(4), 899–914.

Gregory, S. W., Jr., & Gallagher, T. J. (2002). Spectral analysis of candidates' nonverbal vocal communication: Predicting U. S. presidential election outcomes. Social Psychology Quarterly, 65(3), 298 –308. http://dx.doi.org/10.2307/3090125.

Groshek, J. & Al-Rawi, A. (2013). Public Sentiment and Critical Framing in Social Media Content During the 2012 U.S. Presidential Campaign. *Social Science Computer Review, 31*(5). https://doi.org/10.1177/0894439313490401

Grover, P., Kar, A., Dwivedi, Y. K., & Janssen, M. (2019). Polarization and acculturation in U.S. Election 2016 outcomes – Can twitter analytics predict changes in voting preferences? *Technological Forecasting and Social Change, 145*, 438-460. https://doi.org/10.1016/j.techfore.2018.09.009

Hagar, A., & Hilbig, H. (2019). Do Inheritance Customs Affect Political and Social Inequality? *American Journal of Political Science, 63*(4), 758–773.

Joreskog, K. G., & Sorbom, D. (1984). LISREL VI: Analysis of linear structural relationship by maximum likelihood, instrumental variables, and least squares methods. Morresville, IN: Scientific Software, Inc.

Kalla, J. L. & Broockman, D. E. (2016). Campaign Contributions Facilitate Access to Congressional Officials: A Randomized Field Experiment. *American Journal of Political Science, 60*(3), 545-558.

Kenett, R. S., Pfeffermann, D., & Steinberg, D. M. (2018). Election polls—A survey, a critique, and proposals. *Annual Review of Statistics and Its Application, 5*(1), 1-24. https://doi.org/10.1146/annurev-statistics-031017-100204

Kennedy, R., Wojcik, S., & Lazer, D. (2017). Improving election prediction internationally. *Science, 355*(6324), 515-520. https://doi.org/10.1126/science.aal2887

Kline, R. B. (2005). *Principles and Practice of Structural Equation Modelling*. New York, NY: Guilford Press.

Kuklinski, J. H., Quirk, P. J., Jerit, J., & Rich, R. F. (2001). The Political Environment and Citizen Competence. *American Journal of Political Science, 45*(2), 410–424.

Mahoney, J., & Terrie, P. L. (2008). Comparative-Historical Analysis in Contemporary Political Science. *The Oxford Handbook of Political Methodology*.

Nadeau, R., Niemi. R. G., & Amato, T. (1995). Emotions, Issue Importance, and Political Learning. *American Journal of Political Science, 39*(3), 558–574.

Newman, B.I. (2002). Testing a Predictive Model of Voter Behavior on the 2000 U.S. Presidential Election. *Journal of Political Marketing, 1*(2-3). https://www.tandfonline.com/doi/abs/10.1300/J199v01n02_11

Niemi, R. G., Craig, S. C., Mattei, F. (1991). Measuring Internal Political Efficacy in the 1988 National Election Study. *The American Political Science Review, 85*(4), 1407–1413.

Oikonomou, Lazaros & Tjortjis, Christos. (2018). A Method for Predicting the Winner of the USA Presidential Elections using Data extracted from Twitter. 1-8. 10.23919/SEEDA-CECNSM.2018.8544919.

Pavela Banai, Irena & Banai, Benjamin & Bovan, Kosta. (2016). Vocal characteristics of presidential candidates can predict the outcome of actual elections. Evolution and Human Behavior. 10.1016/j.evolhumbehav.2016.10.012.

Peterson, N. A., Lowe, J. B., Hughey, J., Reid, R. J., Zimmerman, M. A., & Speer, P. W. (2006). Measuring the Intrapersonal Component of Psychological Empowerment: Confirmatory Factor Analysis of the Sociopolitical Control Scale. *Am J Community Psychol, 38*, 287–297.

Porter, J. R. (2008). Using Structural Equation Modeling to Examine the Relationship Between Political Cynicism and Right-Wing Authoritarianism. *Sociological Spectrum, 28*(1), 36-54.

Ratliff, K. A., Redford, L., Conway, J., & Smith, C. T. (2017). Engendering support: Hostile sexism predicts voting for Donald Trump over Hillary Clinton in the 2016 U.S. presidential election. *Group Processes & Intergroup Relations, 22*(4), 578-593. https://doi.org/10.1177/1368430217741203

Sidanius, J. (1988). Political Sophistication and Political Deviance: A Structural Equation Examination of Context Theory. *Journal of Personality and Social Psychology, 55*(1), 37-51.

Smith, B., & Gustafson, A. (2017). Using Wikipedia to predict election outcomes. *Public Opinion Quarterly, 81*(3), 714-735. https://doi.org/10.1093/poq/nfx007

Steiger, J. H. (1990). Structural model evaluation and modification: An interval estimation approach. *Multivariate Behavioral Research*, 25, 173_180.

Steiger, J. H., & Lind, J. C. (1980). *Statistically-based tests for the number of common factors*. Paper presented at the meeting of the Psychometrika Society, Iowa City, IA.

Swani, L., & Tyagi, P. (2017). Predictive modelling analytics through data mining. *International Research Journal of Engineering and Technology, 4*(9), 5-11.

Sweetser, K.D., Wanta, G., & Wanta, W. (2008). Intermedia Agenda Setting in Television, Advertising, and Blogs During the 2004 Election. *Journal of Mass Communication and Society*, *11*(2), 197-216. https://www.tandfonline.com/doi/abs/10.1080/15205430701590267

Tabachnick, B. G., & Fidell, L. S. (2010). *Using Multivariate Statistics*. New York, NY: Harper Collins College Publishers.

Towner, T.L., (2013). All Political Participation Is Socially Networked?: New Media and the 2012 Election. *Social Science Computer Review*, *31*(5), 2013. https://journals.sagepub.com/doi/full/10.1177/0894439313489656

Trantor, B. (2007). Political Knowledge and its Partisan Consequences. *Australian Journal of Political Science 42*(1), 73-88.

Vepsäläinen, T., Li, H., & Suomi, R. (2017). Facebook likes and public opinion: Predicting the 2015 Finnish parliamentary elections. *Government Information Quarterly, 34*(3), 524-532. https://doi.org/10.1016/j.giq.2017.05.004

Verhulst, B., Eaves, L. J., & Hatemi, P. K. (2012). Correlation not Causation: The Relationship between Personality Traits and Political Ideologies. *Am J Pol Sci. 56*(1), 34–51.

Wiebke, M. J. (2019). When Diversity Works: The Effects of Coalition Composition on the Success of Lobbying Coalitions. *American Journal of Political Science, 63*(3), 660–674.