The Decision Science of Voting: Behavioral Evidence of Factors in Candidate Valuation

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Abstract

Despite decision science have increased our understanding of human decision-making in different contexts, voters' decision has been studied less from this point of view. Therefore, we investigated, how electorate- and candidate-related factors affect electorate's (N=1334) valuation to the Prime Minister candidates (N=11) on the multiparty democracy. Electorates valuated candidates individually and through pairwise candidate comparison. We collected the data by using anonymous questionnaire and sent it via mass emailing and social media. We applied linear mixed-effects and Bayesian network models to analyze the data. Electorate-related variable Valence and candidate-related variables Trustworthiness and Righteousness was found as the strongest main effects. The pairwise analysis comparison highlighted voters' personal characteristic. In particular, the interactions associated to valence, arousal and gender had high effect only in pairwise comparisons. Our results suggest that the pairwise comparisons - which is typical for elections, e.g., in USA - highlights the importance of emotional and gender-related factors.

Keywords: decision making; politics: valuation; voting; linear mixed-effects model; Bayesian networks

Introduction

Mainstream scholarly research assumes that voting decision is driven by rational preferences over policy proposals offered by political parties (Bischoff, Neuhaus, Trautner, & Weber, 2013; Hibbing, Smith, & Alford, 2014; Knutson, Wood, Spampinato, & Grafman, 2006). However, recent decision science studies have suggested that decision involves, besides explicit processes, psychological, social and cultural processes (Blouw, Solodkin, Thagard, & Eliasmith, 2016; Tymula & Glimcher, 2016). Whereas these studies have increased our understanding about human decisions in the marketing-, social- and risks contexts (Tymula & Glimcher, 2016), voters' decision have been less studied from decision science point of view. In addition, the multiparty democracies have been less studied compared to two-party democracies, especially USA (Walther, 2015). Therefore, we investigated, how electorate-related and Prime Minister candidate-related factors affect electorate's valuation. We chose eleven Prime Minister candidates (three females) on the multiparty democracy which were valuated using judgements of each candidates' directly and in pairwise comparison between candidates. We used linear mixed-effect models (Gelman & Hill, 2007) and Bayesian networks (Borgelt, Steinbrecher, & Kruse, 2009) to test statistical dependencies between candidate valuation and battery of ratings for features of both candidates and the rater himself/herself. Below we describe these dimensions more specifically.

Electorate-related Factors and Voting Decision

Political orientation has been studied with The Big-Five framework (Gosling, Rentfrow, & Swann, 2003; Hibbing, Smith, & Alford, 2014). Current study (Sibley, Osborne, & Duckitt, 2012) found, that political conservatism had negative correlation to Openness to Experience and positive correlation of Conscientiousness variables. In the same vein, Carney et al. (2008) showed that both low Openness to Experience and high Conscientiousness were associated with participants' self-reported conservatism. Thus, conservatives are more orderly, conventional, and better organized, whereas liberals are more open-minded, creative, curious, and novelty seeking (Carney, Jost, Gosling & Potter, 2008).

People with different political orientations have been found to resolve risk-decisions different ways (Hibbing, Smith, & Alford, 2014). Relative to liberals, politically conservative individuals are remembered which stimuli have bad value and pursued a more risk-avoidant strategy to the game. On the contrary, Liberals have greater tendency to explore, take more risk by choosing more unknown possibilities than Conservatives have (Shook & Fazio, 2009).These studies indicate that Conservatives show greater sensitivity to threatening stimuli in the environment than Liberals and have to tendencies to behave without risk-taking.

Prime Minister Candidate-related Factors and Voting Decision

In most of democracies the party leaders are also prime minister candidates and influential electoral force in election campaigns (Bean & Mughan, 1989). This candidate-centered politics (Garzia, 2011; Wattenberg, 1991) is accompanied by a great importance of leaders' personal characteristics in the eyes of voters. Thus, this study concentrates electorate's opinions about politicians' leadership skills and their opinions about the suitability of these candidates to the prime minister in the multi-party democracy country.

Previous studies have found that trustworthiness is one of the most important attribute for a political leader (Barisione, 2009; McAllister, 2000; Rule et al., 2010) as well as communication and collaboration skills (Barisione, 2009). In addition, voters want that political leader is one of them and works for their benefits (Garzia, 2011). Moreover, the voters give values for the fair leaders as well as "traditional" hard leadership skills like the capacity to make decisions (Bean & Mughan, 1989; Rule et al., 2010).

Second important dimension is electorate's emotional reactions to politicians' faces. Valence and arousal are two independent dimensions of emotion. When subjects anticipate pleasurable events, positive arousal increases, and when they anticipate unpleasant event, negative arousal increases. Studies have found that positive arousal has important effect on people's behavior towards the issues, which trigger these positive arousal (Knutson & Greer, 2008). Thus, we measured participants' valence and arousal as they imagined each candidate as a prime minister. We used above described individual and Prime Minister candidate–related factors as the framework for questionnaire. The faces of politicians have many learned symbolic and cultural meanings (Knutson et al., 2006). Therefore, we used politicians' faces as basic stimuli in order to clarify how much each politician's face can produce emotional reactions. Judgements of each candidates' direct valuation and pairwise candidate comparison were used as dependent variables.

Methods

Participants

Participants were recruited via mass emailing and social media to participate in the research. Total 1653 full responses were received over 4 months from which we removed 50 responses with missing/corrupted data, 9 duplicates (same subject), 176 responses with unrealistically fast response times (median time <7s per page) and 84 responses with zero of very low response variance. This resulted in 1334 responses (503 males) in final analysis. Filling the full questionnaire allowed participants to join lottery of 20 gift cards (each worth 25 euros).

Questionnaire Procedure

In the questionnaire, electorate-related variables included gender, age-group (between 18 and 60+) and eight self-spaced personal qualities. Variables dependable/self-disciplined and disorganized/careless measure characteristic conscientiousness, whereas variables open to new experiences and conventional/uncreative measure characteristic openness to experiences from Big Five personality scale. In addition, participants' opinions about his/her level of conservatism and level of liberalism were measured separately. Finally, participants' risk-sensitivity was measured by using social and investment risk variables from Weber et al. (2002) risk-attitude scale.

Prime Minister candidate-related variables included candidate's gender, candidate's familiarity and candidate's leadership skills. Leadership skills included variables trustworthiness, communication skills, fairness, tendency to work for nation, and decision skills. All candidates were established figures for their parties, i.e., the name and face were familiar to majority of people on national level. In addition, the emotional components valence and arousal were measured by showing candidates face with his name and party. Below of the face was two statements "She/He has just been elected Prime Minister of Nation X. What is the emotion (valence) of the choice in you? How intensive this emotion is (arousal)?"

In summary, the questionnaire contained four mandatory sections with following questions (variable labels in parenthesis):

1. Responder's background (x^{b}_{1-10}): Gender [binary], age [Likert scale; 1-7] and 8 personal qualities [1-7].
2. *Individual* candidate valuation (x^{r}_{1-8}): candidate gender [binary], 5 ratings, familiarity and suitability scores [1-7].
3. Emotion ($x^{e}_{1,2}$): Valence and arousal assuming the candidate was chosen as a Prime minister [1-7].
4. *Pairwise* candidate valuation (x^{c}): Preference between two randomly chosen candidates [-4-4].

Suitability score (x^{r}_{8}) and pairwise comparison score (x^{c}) were considered as the *responses* (valuations). Variables x^{r}_{1-7} encoded the *feature vector* of a candidate (1334 vectors in total, one from each subject). Candidate's order was randomized in all parts of the survey. In part 4, out of the pool of 55 possible candidate pairs, we presented randomly chosen 20 (randomized for each subject). In the analysis, genders (responders and candidates) were one-hot encoded using "female" label as the (arbitrary) reference level.

Data Analysis

Linear Mixed-effect Models First we fitted linear mixed-effects models (Gelman & Hill, 2007; Wu, 2009) to the data using Matlab (R2018a). Subject *id* and response date (*month*) were set as random effects of no interest. We fitted total of 4 models; two for the direct valuation and two for the pairwise valuation. Two of these models contained all variables (*full models*) and the remaining two (*reduced models*) did not include valence (x^{e}_{1}). Valence was highly correlated with valuations, hence it was deemed useful to repeat fitting without it. As there was no variation in background variables

(x_i^b) within a subject, those were entered into models through interactions.

For the individual valuation, using Wilkinson's notation (Wilkinson & Rogers, 1973), the formula of the full model was:

$$x_8^r \sim 1 + (x_1^r + \cdots + x_7^r + x_1^e + x_2^e):(1 + x_1^b + \cdots + x_{10}^b) + (1|id + month),$$

where the total number of non-constant fixed terms (aka *predictors*) was 99 with 1338 random-effects intercepts. We used maximum likelihood criterion to fit parameters (Wu, 2009). The equation for the reduced model was similar, but without the valence term (88 fixed-effects terms).

For the pairwise valuations, the formulas were identical, but as the valuation was indirect, the features were transformed into differences, i.e., $x_i^r \coloneqq x_{i,A}^r - x_{i,B}^r \;\; \forall\, i = 1, \dots, 7$ (same for $x_{1,2}^e$ and x^c), where A and B correspond to two candidates in comparison. In this case the random-effects term id also covers the randomness related sampling of candidate pairs. Note that a linear model is invariant for the order of candidates in the differencing, i.e., flipping the order also flips the predictors and response. As a result, interpretation of the coefficients remains similar to direct valuation.

Statistical significance of linear models and their predictors were estimated using permutation testing scheme where responses were randomly shuffled while preserving subject-level grouping hierarchy. Original, un-shuffled t-values of each predictor were compared against distributions of 10.000 t-values obtained via permutation. False Discovery Rate (FDR; Benjamini & Hochberg, 1995) was applied to adjust for multiple comparisons over fixed-effects predictors. Overall model performance was measured with Mean Squared Error (MSE) compared against constant-only null models (with MSE_{null}) and those obtained via permutations.

Bayesian Network Models Next we dropped the assumption of the linearity and fitted Bayesian network probabilistic graphical model to the data (Borgelt, Steinbrecher, & Kruse, 2009; Nagarajan, Scutari, & Lèbre, 2013). For this, we used *bnlearn*[1] toolbox. Bayesian network models allow estimation of a full probability distribution via Directed Acyclic Graph (DAG) structure that represents relationships between data variables (nodes in the graph). Here we were mainly interested in the structure of DAGs and causal relationships between variables.

We adopted the approach of Scutari et. al (2017) with network bootstrapping and cross-validation to estimate DAGs and the quality of models. The aim was to find networks that fit the data best. We used Tabu and Hill-Climbing (HC) structure search algorithms with Akaike and Bayesian Information Criteria (AIC and BIC) scoring, which allow both fast computations and are robust in modeling real data (Beretta, Castelli, Gonçalves, Henriques, & Ramazzotti, 2018; Olmedilla, Rubio, Fuster-Parra, Pujals, & García-Mas, 2018). By varying scores and search methods, we build 1200 candidate networks using bootstrapped dataset by keeping 80% of all samples in each iteration. We restricted the size of network search space by blacklisting total 137 causally unfeasible directed edges. Variables related to subject's background were allowed to be parents for the candidate-related choices. All variables related to age and gender were only allowed to serve as parents. After model bootstrapping, we varied the edge frequency threshold and estimated the classification accuracy of the resulting DAG for the responses (individual or pairwise) using 10-fold cross validation.[2] For the model inference, we used maximum likelihood criterion and in validation we used posterior classification error loss (Nagarajan, Scutari, & Lèbre, 2013). Above steps were repeated separately for individual and pairwise response data. All variables, including valence, were kept in the data in this analysis.

Results

The relative valuation scores of candidates' for individual and pairwise valuation methods and pooled over all subjects are depicted in Fig. 1. Individual scores were computed by averaging over all ratings (x_8^r) for each candidate. Pairwise scores were computed by averaging over rows of an anti-symmetric pairwise rating matrix where each element was the sum of pairwise ratings (x^c) for all 55 combinations of candidates. As the scale of the scores was arbitrary, score distributions were standardized before plotting. Distributions were highly similar (Pearson correlation 0.958), thus confirming that both methods resulted in similar relative valuation of candidates.

From now on, as we report the modeling results, all variables (predictors) are referred with their alphabetic abbreviations. Variables x^r and x^e , which we consider as *main-effects*, are capitalized. The alphabetic abbreviations for the responses were SUITABILITY for x_8^r and SELECTION for x^c .

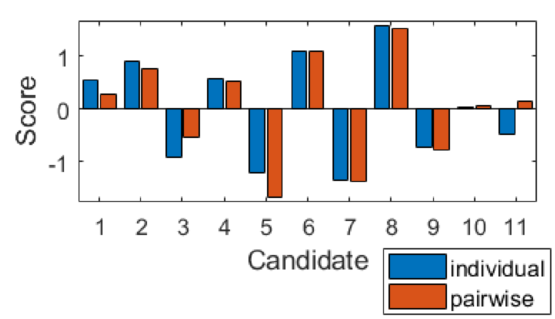

Figure 1: Mean valuation scores of all 11 candidates measured by individual (direct) and pairwise (indirect) method

[1] http://www.bnlearn.com for R (ver. 3.4).

[2] Note that until this point all nodes were equal and no "response" nodes were specified during bootstrapping

Linear Mixed-effect Models Results for the full and reduced linear models for the individual and pairwise responses are listed in Table 1. Positive t-values indicate increase of valuation (and vice versa). Total 6+7 individual and 24+26 pairwise fixed-effects terms surpassed $p<0.05$ (FDR adjusted over 99 and 88 terms) for full and reduced models. All predictors that were significant for at least one of the four models are shown in table (total 44 terms). Total 14 predictors were significant for at least two of the four models. Three of these were the main effects including variables TRUSTWORTHINESS, VALENCE and RIGHTEOUSNESS. Models reached MSE/MSE_{nul} ratios 0.292-0.405 (smaller better) in 10-fold cross-validation. All models were also significant at $p<0.0001$ against permutations. Raw Pearson correlation between valence and responses were 0.802 (x_8^r) and 0.813 (x^c), which accounted lots of the variation in the full models.

		Full		Reduced	
		Ind.	Pair.	Ind.	Pair.
	MSE/MSE_{null}	0.292	0.300	0.401	0.405
	FAMILIARITY	-0.64	2.03	1.37	3.52**
	TRUSTWORTHINESS	3.95**	3.92**	3.35*	3.29**
	RIGHTEOUSNESS	0.91	7.00**	2.40	7.69**
	NATIONAL_VALUE	2.64	-0.81	3.91**	1.61
	VALENCE	5.01**	7.20**		
	AROUSAL	0.59	-2.33	-0.40	-4.22**
	GENDER[male]	-0.40	2.60*	-1.72	-0.06
age :	FAMILIARITY	3.00*	0.07	2.51	0.41
	NATIONAL_VALUE	-3.05*	0.73	-4.06**	-1.03
	VALENCE	4.60**	0.98		
carelessness :	AROUSAL	-1.76	2.61*	-1.39	0.98
	CO-OPERATION	2.75	-0.57	2.89*	-0.06
	GENDER[male]	1.67	-1.42	0.17	-3.81**
	NATIONAL_VALUE	0.17	2.47	0.70	3.30**
conservativeness :	CO-OPERATION	0.77	2.94*	0.94	2.48*
	DECISIONMAKING	-0.22	2.20	0.56	3.93**
	FAMILIARITY	1.35	-1.34	-0.01	-3.55**
	GENDER[male]	1.27	-0.95	2.90*	1.98
	NATIONAL_VALUE	-0.40	0.61	1.36	3.26**
	RIGHTEOUSNESS	-0.52	-6.88**	-2.85	-8.23**
	VALENCE	1.43	3.43**		
discipline :	FAMILIARITY	-0.18	2.06	0.23	2.84*
	VALENCE	3.13*	4.25**		
gender[male] :	AROUSAL	-0.28	-6.19**	-1.62	-5.20**
	CO-OPERATION	-0.90	-0.71	-2.83	-4.75**
	FAMILIARITY	2.23	3.12*	2.68	4.32**
	GENDER[male]	-0.55	3.06*	2.25	5.19**
	NATIONAL_VALUE	2.88	4.21**	4.53**	4.88**
	VALENCE	2.13	-5.51**		
liberalness :	AROUSAL	0.12	-2.75*	-0.21	-2.34
	GENDER[male]	-0.62	-2.77*	-0.08	-1.72
	RIGHTEOUSNESS	0.31	-3.08*	0.03	-2.40
	VALENCE	2.10	2.93*		
openness :	CO-OPERATION	-0.03	2.26	0.06	2.72*
	DECISIONMAKING	0.13	1.54	0.84	2.53*
	FAMILIARITY	-2.25	-1.81	-3.02*	-2.71*
	RIGHTEOUSNESS	-1.50	-5.28**	-1.05	-4.44**
ordinality :	AROUSAL	-2.30	3.37**	-1.38	3.39**
	TRUSTWORTHINESS	-1.16	-2.90*	1.11	0.72
riskyinvestor :	GENDER[male]	0.09	0.98	1.48	2.98*
	VALENCE	-1.35	-2.57*		
SoMe_activity :	DECISIONMAKING	-1.76	-4.47**	-2.51	-4.25**
	RIGHTEOUSNESS	1.71	1.70	1.90	2.60*
	TRUSTWORTHINESS	-1.52	-3.19**	-1.47	-2.82*

Table 1: T-values of the linear mixed-effects model using individual (Ind.) and pairwise (Pair.) valuation for full and reduced models. The main effects are capitalized and interactions (if any) marked with "**:**". Here * and ** indicate $p<0.05$ and $p<0.01$ (both FDR adjusted).

Bayesian network models In the Bayesian network analysis we found no major differences between search methods (HC or Tabu). AIC scoring, which tends to add more edges, resulted in generally smaller classification losses (i.e., better models). In general, higher edge density (bootstrapping frequencies <50%) resulted in higher classification accuracies. Here we present results obtained with Tabu and AIC. Results of bootstrapping are depicted in Fig. 2. Fig. 2a show all (undirected) edges with at least 5% frequency (i.e., 0.05) where upper triangular part is for individual and lower triangular for pairwise valuation. Weight 1.00 indicates very strong causal connection. The difference of the two triangular matrices is depicted in Fig. 2b (no thresholding), where all positive values correspond to higher frequency obtained for the pairwise valuation. The results indicate that most direct connections were within main effects (20 and 28) and subject-dependent characteristics (38 and 41), than between the two (only 6 and 14). While the individual valuation resulted in more subject-to-candidate edges (14 vs. 6), the edges were generally weaker (<0.5) than those for the pairwise valuation (three edges with weight 1.0).

Finally, an example DAG for the SELECTION response is depicted in Fig. 3 with edge weight threshold 0.5 (with AIC and Tabu). The edge line weight corresponds to frequencies between 0.5 and 1.0 (thicker line = higher value). Node size indicates total number of incoming and outgoing edges (here between 2 and 9). The classification accuracy loss for this network was 0.581, while the (adjusted) baseline accuracy loss was 0.828. The *Markov blanket* for SELECTION included eight variables: gender, age, conservativeness, GENDER, VALENCE, TRUSTWORTHINESS, CO-OPERATION and RIGHTEOUSNESS. In other words, the SELECTION had direct causal connection with three background variables.

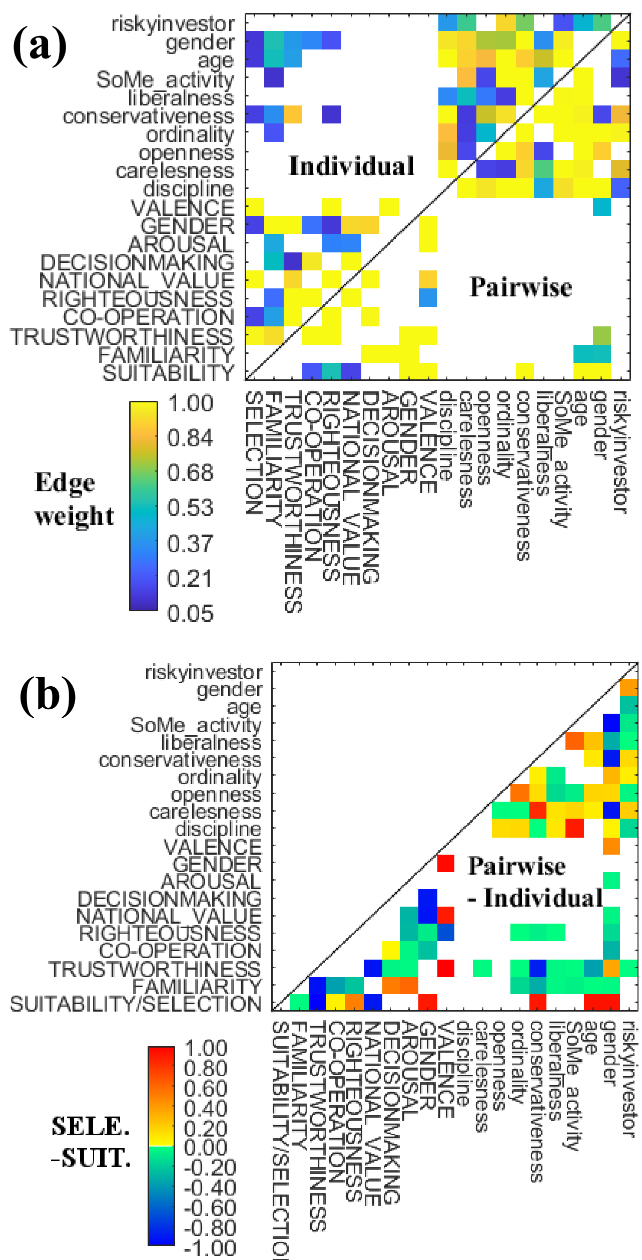

Figure 2: Bayesian network bootstrapping results for individual and pairwise valuation. **(a):** Occurrence rate of edges for individual (upper triangular) and pairwise valuation (lower triangular), only edges with at least 0.05 frequency are shown. **(b):** Difference of the two matrices (both unthresholded).

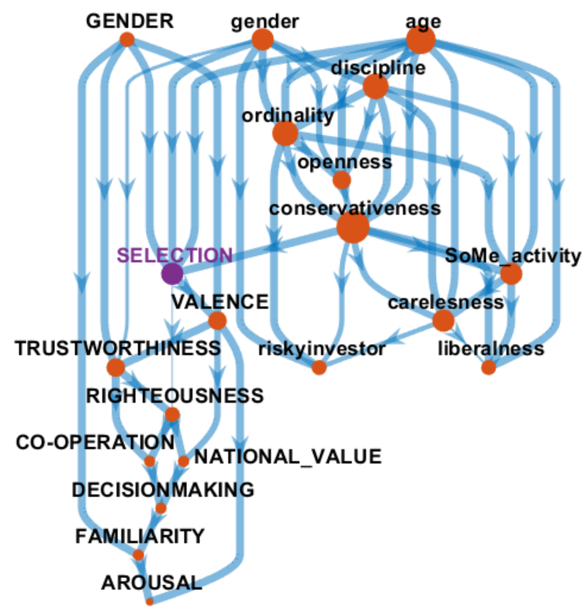

Figure 3: An example of a directed acyclic graph with 50 ed ges (at density >0.50) estimated using pairwise valuations of candidates. Line widths correspond to bootstrapping strength and node size to total number of connections.

Discussion

We collected behavioral questionnaire data on how voters valuate and judge politicians and their presumed suitability to serve as Prime Ministers. Aim was to pinpoint candidate and subject dependent factors that influence the valuation. We used linear mixed-effects models and Bayesian networks to analyze the data. We build two flavors of models; one for direct candidate valuation and the other for indirect valuation based candidate pairwise comparison. Although the average valuation scores of candidates were similar between direct and indirect approaches (Fig. 1), the models revealed differences in how the subjects arrived in their valuations.

In linear models, the pairwise valuation emphasized between individual- and candidate -related interactions with higher t-values magnitudes (Table 1). While the results for the main effects were similar (both highlighted trustworthiness, righteousness and valence), pairwise analysis resulted in more interaction terms surpassing significance (by the factor 3). While this can partly result from differences in number of samples (20 pairwise vs. 11 individuals per subject), it also reflects the difference in valuation processing when forced to choose between two choices. In particular, the interactions associated to emotion (valence and arousal) and gender (both candidate and subject) had high impact in pairwise comparisons. Male responders favored male candidates and national value score of the candidate.

In order to complement our linear models, we also applied Bayesian network analysis. This framework allowed building full (nonlinear) probabilistic models for the data; however, here, we mainly used it as an exploratory tool to pinpoint causal connections between variables. The analysis also resulted in notable differences between individual and pairwise valuation (Fig. 2). In comparison to linear models, the candidate-related variable valence had direct causal effect only with electorate-related gender, but only for pairwise valuation. For individual valuation, causal connection between candidate valuation and electorate-related variables were more numerous (14 vs. 6), but were generally weaker. The strongest causal connection with the valuation score were found with conservativeness, age and gender of the electorate. These three had direct connections also with various other candidate-related properties, e.g., trustworthiness and familiarity.

In conclusion, we found that the background factors with strongest effect on the valuation of candidates were conservativeness, gender, age, ordinality and activity in social media of the voter. Emotion, especially valence, was strongly associated with valuation both directly and via interactions with voters' conservativeness, gender and ordinality. For males, higher arousal and valence strongly reduced the valuation. Emotion was found generally more important in pairwise candidate valuation.

Our results highlight the importance of how one measures the valuation of candidates (individual vs. pairwise) and how one analyzes such data (linear vs. nonlinear). Multiple views related to the data and methods are needed in pinpointing the most relevant effects. Previous studies have shown, that stimuli which trigger positive arousal increases the probability that people will behave according to the stimuli's suggestions in the future. Our results suggest that pairwise comparison – which is typical in USA elections – could enhance emotional and gender-related valuation of candidates.

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