Politics Speak Louder than Skills: Political Similarity Effects in Hireability Judgments in Multiparty Contexts and the Role of Political Interest

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Author Note

This study was preregistered; see https://aspredicted.org/4n3z5.pdf and https://aspredicted.org/kr5qk.pdf. The electronic supplementary is publicly available at the Open Science Framework, https://osf.io/hs39v/.

Franz W. Mönke and Philipp Schäpers thank the State of North Rhine-Westphalia’s Ministry of Economic Affairs, Industry, Climate Action, and Energy as well as the Exzellenz Start-up Center.NRW program at the REACH – EUREGIO Start-Up Center for their kind support of our work. The financial support for parts of the data collection was made possible through the Lee Kong Chian Fund for Excellence from the Lee Foundation. The authors also thank the SoSci-panel for granting access to their participant pool. Finally, the authors thank Manuel Voelkle, Manuel Arnold, Jan-Philipp Freudenstein, Michael Eid, and Marie Therese Bartossek for their helpful comments on this project.

Portions of this article are based on the master thesis of Franz W. Mönke and were presented at the 52nd Conference of the German Psychological Society (DGPs), the 12th International Meeting of Psychology Students at the Universidad de La Habana, and the 1st Science to Start-Up Convention at the REACH – EUREGIO Start-Up Center. Correspondence concerning this article should be addressed to Franz W. Mönke, University of Münster, Fliednerstraße 21, 48149 Münster, Germany. Email: franz.moenke@uni-muenster.de

This is the accepted version of the following paper: Mönke, F. W., Lievens, F., Hess, U., & Schäpers, P. (2023). Politics speak louder than skills: Political similarity effects in hireability judgments in multiparty contexts and the role of political interest. Journal of Applied Psychology. https://doi.org/10.1037/apl0001124

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Abstract

Recruiters increasingly cybervet job applicants by checking their social media profiles. Theory (i.e., the political affiliation model, PAM) and research show that during cybervetting, recruiters are exposed to job-unrelated information such as political affiliation, which might trigger similarity-attraction effects and bias hireability judgments. However, as the PAM was developed in a more polarized two-party political system, it is pivotal to test and refine the PAM in a multiparty context. Therefore, we asked working professionals from the United States (two-party context, \( N = 266 \)) and Germany (multiparty context, \( N = 747 \)) to rate an applicant’s hireability after cybervetting a LinkedIn profile that was manipulated in a between-subjects design (party affiliation by individuating information). Key tenets of the PAM could be transferred to multiparty contexts: The political similarity-attraction effect predicted hireability judgments beyond job-related individuating information, especially regarding organizational citizenship behavior. In addition, in a multiparty context, these biasing effects of political similarity and liking were not attenuated. Yet, there were also differences: In a multiparty context, political similarity had to be operationalized in terms of political value similarity, and recruiters’ political interest emerged as a significant moderator of the effects. So, this study refines the PAM by showing in multiparty contexts the importance of (1) a values-based perspective (instead of a behavioral political affiliation perspective) and (2) political interest (instead of identification). Accordingly, we provide a more nuanced understanding of when political affiliation similarity contributes to perceived overall similarity in affecting liking and hireability judgments in cybervetting.

*Keywords:* cybervetting, personnel selection, political ideology, similarity attraction, social media
Politics Speak Louder than Skills: Political Similarity Effects in Hireability

Judgments in Multiparty Contexts and the Role of Political Interest

As selection practices and personal branding now occur often online, recruiters have begun to scour applicants’ digital footprints on social media, also labeled as *cybervetting*. Cybervetting exposes recruiters not only to applicants’ job-related attributes like knowledge, skills, abilities, traits, and behaviors (i.e., individuating information; see McCarthy et al., 2010) but also to job-unrelated information. For instance, cues associated with applicants’ political affiliation (e.g., party membership or endorsement of issues) can be visible on social media (R. A. Hayes et al., 2015; Zhang et al., 2020). Given that such information might elicit negative affect among recruiters, it might affect their judgments and bias decisions (Roth et al., 2017).

To advance research in this area, Roth et al. (2017) developed the political affiliation model (PAM). As a central construct, similarity based on political ideology (i.e., beliefs concerning a society’s structure and its ideals; Jost et al., 2009; Swigart et al., 2020) is distinguished from similarity in terms of other features. This is because political ideology reflects a deep (vs. a surface) level of diversity and a deliberate choice (instead of being predetermined like gender or age, Roth et al., 2020). The PAM proposes that political affiliation similarity leads to perceived overall similarity, which elicits liking. The link between political affiliation similarity and overall similarity is posited to be stronger when recruiters identify more with a party. The PAM also suggests that these similarity perceptions influence hireability decisions more than job-related individuating information, thus leading to bias. Lately, Roth et al. (2020), Roulin et al. (2023), and Wade et al. (2020) found support for many of the PAM’s propositions.

Although the PAM provides a valuable theoretical underpinning for the emerging research base, its mechanisms were developed against the backdrop of the polarized two-party
system in the United States (US). Yet, most political systems differ from the US (LeDuc et al., 2010; Taylor et al., 2014) because proportional voting leads to multiparty parliaments, coalition governments, and more nuanced public discourse, thereby reducing polarization (Curini & Hino, 2012). Hence, it is unknown whether the PAM translates into multiparty systems. For instance, a binary match/mismatch notion of common party affiliation might be too coarse to capture political values in multiparty systems where one identifies less with a single party. The PAM’s identification component might also be less relevant in multiparty systems. So, although political affiliation based on voting behavior and an affect-based moderator (identification) fit in polarized systems, this might not be the case in multiparty systems.

This paper’s objectives are twofold. First, we test the effects of political affiliation cues (vs. individuating information) in cybervetting in both a two-party and a multiparty system. Second, to better understand when political value similarity exerts effects on perceived overall similarity, we examine not only the identification and disidentification moderators but also a moderator (political interest) that we posit to be especially relevant for multiparty systems. Hence, we contribute to prior research by (1) expanding the PAM from two-party to multiparty systems, (2) introducing political value similarity as a focal variable, and (3) highlighting political interest as a new moderator. The latter is based on identity theory because in less polarized systems this theory is more relevant than social identity theory (Stets & Burke, 2000; Stryker & Serpe, 1994): We posit that—for people with strong political interest—cybervetting a social media page with political affiliation cues makes their political identity more salient.

**Study Background**

**Cybervetting: Use of Candidates’ Social Media Information in Personnel Selection**
The term *cybervetting* refers to the gathering of online information about applicants, mainly by inspecting professional (e.g., LinkedIn) or social media profiles (e.g., Facebook, Twitter; Berkelaar, 2014; Berkelaar & Harrison, 2017). According to recent surveys, at least two out of three recruiters use such social media assessments (Hartwell & Campion, 2020; Roth et al., 2019; Smith, 2017). This practice is controversial (see Mönke & Schäpers, 2022; Wilcox et al., 2022): Although several studies reported that cybervetting judgments converge with self-reports regarding personality traits and hireability based on information in Facebook (e.g., Kluemper et al., 2012; see Tskhay & Rule, 2014) and LinkedIn (Roulin & Levashina, 2019); however, the only longitudinal study addressing cybervetting judgments and job applicants’ performance by Van Iddekinge et al. (2016) found that Facebook-based evaluations “correlate essentially zero” (p. 1832) with job performance. Moreover, there is consensus that cybervetting risks increasing recruiters’ exposure to job-irrelevant information about the applicant (e.g., political affiliation, religion, sexual orientation; Zhang et al., 2020). Such job-irrelevant elements threaten to influence hireability judgments, even when recruiters underwent bias training (Hartwell & Campion, 2020; Zhang et al., 2020).

**Politics in Cybervetting: Refinements to the Political Affiliation Model (PAM)**

Although the PAM provides a theoretical underpinning for why and how information on applicants’ political affiliation might affect recruiters’ cybervetting judgments and bias their decisions, it was developed and tested against the backdrop of the US political system (Roth et al., 2020; Roulin et al., 2023; Wade et al., 2020). Given its two-party and polarized political landscape (Iyengar & Westwood, 2015; Pew Research Center, 2014), the US is a unique context for testing theories on political similarity. Such a majoritarian electoral system, which results in polarization, is established only in approximately 20% of democracies: In fact, most democracies
favor proportional representation (e.g., European Parliament; national parliaments in Mexico, Israel, Germany, Argentina, Indonesia, South Africa, or New Zealand; Carter & Farrell, 2010), which typically leads to multiparty parliaments and coalition governments, making the political landscape substantially different from the US. Thus, considering these significant differences “it is not clear how [the PAM’s] results translate to other countries” (Roth et al., 2020, p. 483). So, below we address the question: Should parts of the PAM be refined to fit multiparty systems?

**The Construct of Political Affiliation Similarity**

We start by positing that there is a difference in the operationalization of the PAM’s focal variable (i.e., political affiliation similarity). Swigart et al.’s (2020) hierarchical framework distinguishes various lenses of political ideology. At the top, they placed a behavioral perspective (political ideology as party affiliation), which can be observed in the party that one votes for. Conversely, at the bottom (political ideology as values), political ideology represents a schema of related values that are not directly observable. In a more polarized two-party context, Swigart et al.’s (2020) behavioral perspective is relevant because people typically have a clear party affiliation, which is reflected in their voting behavior. For instance, in 2020, 62% of registered US voters identified with one of the two major parties: 33% as Democrats and 29% as Republicans (Pew Research Center, 2020). That is also the reason why prior studies in a two-party context used common party affiliation (CPA) as a focal variable, which is assessed “by coding participants who reported the same political affiliation as the […] applicant as 1 […] and […] a different political affiliation as 0” (Roth et al., 2020; p. 477). This operationalization is based on social identity theory (dynamics of in- vs. outgroups; e.g., Stets & Burke, 2000).

However, in multiparty contexts, we argue that the notion of having a common party affiliation is less relevant for several reasons. First, few people are members of a political party
(e.g., in Germany, the latest estimate is 1.7%; Niedermayer, 2020). Second, parties’ ideological standpoints often depend on the topic and not on ideological blocs (Linhart & Shikano, 2009; Urban Pappi & Seher, 2009). Third, people’s political affiliation is less clear because voting behavior is sometimes inconsistent with political ideology (Swigart et al., 2020): For instance, people might not vote according to their party affiliation but according to which coalition they prefer. Therefore, we propose that, in multiparty systems, the values-based perspective of political ideology (Swigart et al., 2020) is more relevant. Accordingly, political similarity should be measured via a conceptually aligned measure, namely perceived political value similarity (PVS). Hence, in this study, PVS is measured as a continuum that reflects the degree to which one’s political values correspond with those of the applicant’s party. Given that this study deals with both two-party and multiparty systems, we included both CPA and PVS. We expect that CPA induces similarity bias in two-party systems, whereas PVS does so in multiparty systems.

**The Link between Political Affiliation Similarity and Perceived Overall Similarity**

The PAM proposes the similarity-attraction effect (see Byrne, 1971) as the mechanism at play when recruiters are exposed to information about applicants’ political views (Roth et al., 2017). If the recruiter and applicant share similar views, this leads to attraction, resulting in positively biased hireability judgments. Montoya et al.’s (2008) meta-analysis confirmed a strong association between similarity and attraction, especially for evaluating strangers. This matches well with cybervetting because recruiters use it to obtain a first impression (Berkelaar, 2017). Hence, given that similarity-attraction is a fundamental effect and is relevant in cybervetting, we expect it to transfer to multiparty systems. Thus,

*(H1)* **Political affiliation similarity (CPA in a two-party system vs. PVS in a multiparty system) between applicant and recruiter positively predicts perceived overall similarity.**
(H2) Perceived overall similarity positively predicts liking.

Party (Dis)Identification as Moderator

In the seminal work of Campbell et al. (1960/1980), identification refers to the “affective orientation to an important group-object in [the] environment” (p. 121). Identification has its roots in social identity theory, which posits people make categorizations between in-group and out-group members (Stets & Burke, 2000). Roth et al. (2017) proposed that, in polarized contexts, the degree of (dis)identification with the applicants’ party moderates the link between political affiliation similarity and overall similarity perceptions. They posited that identification invokes feelings of “hostility and loathing for outgroup party members” (p. 1293). So, when recruiters with a strong party identification are exposed to political affiliation cues on social media opposite to theirs, their interpersonal reaction (dislike) will be stronger; the reverse (liking) is expected when exposed to political affiliation cues similar to theirs. Thus,

(H3a) Party identification moderates the relationship between political similarity and overall similarity such that higher levels of recruiters’ identification with the applicant’s party, the stronger the relationship between political similarity and overall similarity.

(H3b) This moderation effect is stronger in two-party contexts.

Political Interest as Moderator

We extend the PAM by arguing that political interest serves as a key moderator in less polarized multiparty systems. Political interest refers to how centrally one values politics in life¹ and is considered the best predictor of political behavior (Prior, 2010). It is, thus, a trait-based

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¹ Lent et al. (1994) explained how interest and identity development influence each other. According to Lent et al., interests (e.g., in politics) lead to activity involvement (e.g., political activity) through goals and choices, which then feedback into interests (through experiences). So, they posited that political activity (instead of party identification per se) might result in more political interest (although such political activity might in the end also result in party identification).
interest that reflects a relatively “stable, underlying disposition activated in particular situations” (Harackiewicz et al., 2016, p. 221). We posit that political interest is activated via cues in social media profiles and might strengthen the link between political affiliation similarity and overall similarity. Our rationale for its moderating role is based on identity theory’s notion of identity salience (i.e., the likelihood that a given identity will be invoked in situations; Brenner et al., 2014; Stets & Burke, 2000; Stryker, 1968; Stryker & Serpe, 1994). This means people have several identities/selves (e.g., in terms of race, political ideology). These are ranked by differences in salience, with identities being more likely to be enacted when they are higher on the salience hierarchy. When one has an interest in politics, one’s political identity will be ranked higher. Thus, for recruiters interested in politics, there is a higher likelihood that a political affiliation cue on social media will invoke their political identity. Due to the higher salience of politics, they will ascribe more value to information about applicants’ political affiliation.

We also propose that political interest will be of more effect in multiparty systems: Due to lower polarization, political cues will activate one’s political identity, especially for people with high political interest. In contrast, in two-party systems, deep-level differences in political values are ever-present in society. Thus, potential (dis)agreement with an applicant’s ideology is salient independently from one’s political interest. In sum:

**(H4a)** Political interest moderates the relationship between political similarity and overall similarity such that higher levels of recruiters’ political interest, the stronger the relationship between political similarity and overall similarity.

**(H4b)** This moderation effect is stronger in multiparty contexts.

**Effects on Hireability Judgments**
As a result of similarity attraction, the PAM posits that recruiters evaluate values or beliefs as important applicant characteristics and, thus, weigh them more in hireability decisions. As mentioned by Roth et al. (2017, 2020), political affiliation cues might also lead recruiters to extrapolate political party stereotypes (e.g., “Republicans make firmer decisions”) to potential job behaviors, which might further overshadow individuating information and invoke biases.

A common thread running through our above discussion is that in multiparty systems, political polarization and division are tempered. Hence, political party stereotypes might be less clear, and it might be more difficult to extrapolate them to anticipated workplace behaviors. So, we expect that this attenuates the political similarity-attraction effects on hireability. Thus,

(H5a) Liking predicts hireability judgments over and beyond individuating information.

(H5b) Political similarity effects are smaller in multiparty than in two-party systems.

Method

Transparency and Openness

We adhered to the Journal of Applied Psychology methodological checklist; we conducted all analyses in R (Version 4.2.2) and RStudio (Version 2022.07.2). The ethics committee of the Department of Psychology at the Humboldt-University Berlin approved our procedure (Decision 2021-13). Our hypotheses, study designs, and analyses were preregistered; see https://aspredicted.org/4n3z5.pdf and https://aspredicted.org/kr5qk.pdf. Data, analysis code, and materials are publicly available in the electronic supplementary (ES), https://osf.io/hs39v/.

Sample

Our final sample consisted of 266 US and 747 German working professionals. As all participants were gathered via online samples, we followed suggestions by Ward and Meade (2023) and thus excluded participants who showed indications of careless responding (self-
report, instructed responses), failed to recognize the applicant’s party affiliation, or were multivariate outliers (Mahalanobis distances) to obtain these final samples (for details, see ES 07).

US participants (Prolific panel) were on average 40.6 years old ($SD = 11.3$, range 18–76), 49.2% identified as women, 48.8% as men, and 1.9% as non-binary or preferred not to say. The US sample was well educated, with 74.1% having a university degree. A majority of 85.3% had hiring experience; 55.6% used social media at least once a week.

German participants (SoSci panel; Leiner, 2016) were on average 45.8 years old ($SD = 11.2$, range 23–71), 58.9% identified as women, 39.6% as men, and 1.5% as non-binary or preferred not to say. They were also well educated (74.4% had a university degree); 51% indicated hiring experience; 65.3% used social media at least once a week. Germany is well suited for testing the PAM in a multiparty context due to its proportional mixed-member system, six-party federal parliament, and tradition of coalition governments (see Zittel, 2017).

**Procedure and Design**

Similar to earlier research (Roth et al., 2020; Wade et al., 2020), we instructed each participant to act as a recruiter for a job offer (business administration: about project management) with the typical job requirements (e.g., a degree in a related field, computer skills, and prior experience; see posting in ES 01). We asked participants to inspect the applicant’s LinkedIn profile, judge the applicant’s hireability, and answer the scales described below. The profiles were manipulated in a between-subjects design; for the US group 2 (major US parties) x 2 (high vs. low individuating information); for the German group 6 (major German parties) x 2 (high vs. low individuating information). Participants were randomly assigned to one of the
conditions, resulting in 56 to 69 participants per group. German participants were offered a raffle draw of bookstore vouchers (20 x 10€); US participants received $1.80.

Experimental Materials: LinkedIn Profiles and Pilot Studies

We presented LinkedIn profiles because this platform is most often used in cybervetting (Smith, 2017; Society for Human Resource Management, 2016). In these profiles, we manipulated the fictitious applicant’s political affiliation through (1) a political statement, (2) a job in the parliament group (Germany) or party headquarters (US), and (3) party campaigning. High individuating information was operationalized via job-related information: (1) being the employee of the month, (2) prior job-related experience, (3) a master’s degree, and (4) stellar grades and short study duration. Conversely, less qualified candidates lacked these attributes.

To test the profiles’ internal and external validity, we conducted three pilot studies. Via our first study (ES 02, German sample of \( N = 16; 62.5\% \) women, 31.3\% men, 6.3\% non-binary; \( M_{\text{age}} = 34.5 \) years, \( SD_{\text{age}} = 15 \) years, \( \text{range} \ 20–63 \) years) we ensured that the LinkedIn profiles did not contain unintended political affiliation cues, which might counter the manipulation. That is, we asked whether the applicant’s picture, name, and activities induced political affiliation beliefs. Further, we pre-tested the statements: We set a 66\% threshold as a minimum for agreeing with the manipulation (Schubert et al., 2008). We then used the pre-tested characteristics to construct the profiles. Our second pilot study (ES 03) validated the LinkedIn profiles with 15 German LinkedIn users (53\% women, 47\% men; \( M_{\text{age}} = 25 \) years, \( SD_{\text{age}} = 3.9 \) years, \( \text{range} \ 20–35 \) years) who rated the profiles. They rated the profiles as authentic (5-point scale: \( M = 4.0, SD = 0.9 \)) and the candidate with the more-qualified profile was indeed perceived as better qualified for the job (Wilcoxon \( W = 86.5, p = .003 \)). Finally, we transferred these LinkedIn profiles to the US context. The third pilot study (ES 04) was, thus, conducted with 19 US full-time employed
LinkedIn users (47% women, 53% men; \(M_{age} = 33\) years, \(SD_{age} = 9.7\) years, range 23–52 years). They rated the profiles high in authenticity (5-point scale: \(M = 4.0, SD = 1.3\)) and hireability higher for the more qualified profiles (Wilcoxon \(W = 73.5, p = .002\)), and detected the applicant’s intended party affiliation (range 84%–95%). Detailed results and final profiles are available in ES 02 to ES 05.

**Measures**

*Common Party Affiliation (CPA)*

We used each participant’s political affiliation (“To which of the following parties do you lean (most likely) toward?”) to model the dichotomous CPA variable. As suggested by Roth et al. (2020), 1 represented a match between the participant’s and the applicant’s party affiliation as indicated on the LinkedIn profile, whereas 0 indicated a differing party preference.

*Political Value Similarity (PVS)*

We asked participants to indicate the degree to which their political ideology was shared by the applicant’s party: We provided a visual analog scale (“To what degree do your political affiliation, views, and values correspond with those of the [party, e.g., Democrats/SPD]?”). The scale’s slider position was transformed into a metric 0 (not at all) to 100 (fully) scale. Given PVS’s range was much higher than for the other scales, it was standardized for the model test.

*Political Interest*

To assess how much the participant was interested in politics, we used a 4-point scale (“Generally speaking: How much are you interested in politics?”; 1 = not at all, 4 = very strongly interested). One-item measures are the most established scales for measuring political interest (e.g., American National Election Study, British Election Study, Swiss Household Panel, German Socio-Economic Panel Study, Jennings Panel; Prior, 2010; see also ES 08).
Perceived Overall Similarity

We assessed perceived overall similarity with the applicant via five items on a 7-point scale (Roth et al., 2020; Tepper et al., 2011), e.g., “The job applicant and I are similar in terms of our outlook, perspective, and values” (1 = strongly disagree, 7 = strongly agree).

Identification and Disidentification

To capture the influence of both positive and negative affect and following the two-dimensional rationale of organizational identification (Kreiner & Ashforth, 2004; Roth et al., 2020), we assessed the degree of party identification (Mael & Ashforth, 1992) as well as the degree of disidentification (Kreiner & Ashforth, 2004) with two 5-point scales (1 = strongly disagree, 5 = strongly agree; 5 items each). Sample items are “I am very interested in what others think about X” (identification) and “I find X to be disgraceful.” (disidentification). Due to non-invariance, we excluded one item from the disidentification scale (see Table 2).

Liking

We used the liking scale as amended by Roth et al. (2020) from Wayne and Ferris (1990). Four items (e.g., “I would likely get along well with this job applicant”) were presented on a 5-point scale (1 = strongly disagree, 5 = strongly agree).

Hireability: Expected Task Performance and Organizational Citizenship Behavior (OCB)

We measured hireability with two 7-point scales (1 = strongly disagree, 7 = strongly agree), as amended by Roth et al. (2020) from Williams and Anderson (1991): Three items concerned expected task performance (e.g., “The job applicant can be expected to adequately complete assigned duties”), and three items referred to organizational citizenship behavior (OCB; e.g., “The job applicant can be expected to help others who have heavy workloads”).

Results
Descriptive Statistics and Correlations

Descriptive statistics and correlations are provided in Table 1. In both groups, expected task performance was rated higher for applicants with high individuating information versus low individuating information (US: Wilcoxon $W = 5654.5$, $p < .001$; German: $W = 41176$, $p < .001$); this was not the case for expected OCB (US: $W = 7946$, $p = .15$; German: $W = 66151$, $p = .23$).

Measurement Assessment: CFA, Reliability, and Measurement Invariance

We used the following criteria for acceptable model fit (Browne & Cudeck, 1992; Hu & Bentler, 1998; McDonald & Ho, 2002): Comparative fit index (CFI) $\geq .90$, root-mean-square error of approximation (RMSEA) $\leq .10$, and standardized root-mean-square residual (SRMR) $\leq .08$. A confirmatory factor analysis (CFA) supported the expected factor structure; see Table 2. To address concerns about the high correlation of overall similarity with liking, we tested a model in which we collapsed both into one factor: Model fit was significantly worse, $\Delta \chi^2(5) = 227.99$, $p < .001$; $\Delta$ CFI = .026, $\Delta$ RMSEA = .017, $\Delta$ SRMR = .002 in the US and $\Delta \chi^2(5) = 387.11$, $p < .001$; $\Delta$ CFI = .029, $\Delta$ RMSEA = .016, $\Delta$ SRMR = .004 in the German sample. The fit was also worse for a model with PVS and the identification variables as one factor, $\Delta \chi^2(28) = 666.30$, $p < .001$; $\Delta$ CFI = .068, $\Delta$ RMSEA = .039, $\Delta$ SRMR = .011 in the US and $\Delta \chi^2(28) = 1468.01$, $p < .001$; $\Delta$ CFI = .098, $\Delta$ RMSEA = .045, $\Delta$ SRMR = .034 in the German sample. For reliability, we used the weighted McDonald’s $\omega$ (i.e., the amount of true variance of the latent factor to the total variance, Bacon et al., 1995; Brunner & Süß, 2005). The $\omega$ of all scales’ ratings was good, ranging between .89 and .98; see Table 2. Importantly, there was metric invariance, see Table 3. So, correlations and regressions could be compared across samples (Chen, 2007).

Hypotheses Testing
We tested a multigroup structural equation model (SEM). Overall model fit was good, \( \chi^2(658) = 2229.60, p < .001; \) CFI = .936, RMSEA = .069 (90% CI [.066, .072]), SRMR = .053. \(^2\)

We used the residual-centering approach to model latent interaction variables (Little et al., 2006) and calculated robust confidence intervals to test group differences and indirect effects (Monte Carlo method; see MacKinnon et al., 2004; Preacher & Selig, 2012). Results of the structural model are presented in Table 4 and Figures 1a and 1b.

In line with H1, political similarity was related to perceived overall similarity: In the US sample, both CPA (\( \beta = 0.18, p = .049 \)) and PVS (\( \beta = 0.30, p = .008 \)) predicted perceived overall similarity with the applicant. In the German sample, as expected, only PVS predicted perceived overall similarity (\( \beta = 0.28, p < .001 \)), whereas CPA did not (\( \beta = 0.04, p = .17 \)). Next, perceived overall similarity strongly predicted liking in both samples (US: \( \beta = 0.96, p < .001 \); German: \( \beta = 0.83, p < .001 \)). This supports H2.

Concerning H3a, the path between PVS and overall similarity was not moderated by (dis)identification. That is, (dis)identification with the applicant’s party had no significant effect on the value of PVS in perceptions of overall similarity. These effects were also not different between the samples for both identification (\( \Delta b = -0.02, 95\% CI [-0.22, 0.19] \)) and disidentification (\( \Delta b = -0.07, 95\% CI [-0.51, 0.36] \)), thus not supporting H3b.

Regarding H4a, political interest was a significant moderator between PVS and perceived overall similarity in the German sample, \( \beta = 0.10, p = .001 \): The higher a recruiter’s political interest, the greater the value of PVS in similarity perceptions; see Figure 2 for an interaction plot. Conversely, political interest was not a significant moderator in the US sample, \( \beta = 0.11, p = .11 \). In addition, the moderator’s indirect effect on the hireability criteria was significant in the

\(^2\) We report indices for a model without interaction variables to avoid biased fit estimates (Schoemann & Jorgensen, 2021).
German sample (task performance: $b = 0.04$, 95% CI [0.02, 0.07]; OCB: $b = 0.06$, 95% CI [0.02, 0.11]) but not in the US sample (task performance: $b = 0.08$, 95% CI [-0.02, 0.18]; OCB: $b = 0.12$ [-0.03, 0.27]). Yet, the difference tests of the coefficients between groups were not significant (e.g., $\Delta b = 0.10$, 95% CI [-0.21, 0.41]). Thus, there was only partial support for H4b.

H5a stated that liking influences hireability judgments beyond individuating information. First, we found that liking predicted expected task performance in both samples (US: $\beta = 0.61$, $p < .001$; German: $\beta = 0.52$, $p < .001$) and OCB (US: $\beta = 0.82$, $p < .001$; German: $\beta = 0.64$, $p < .001$). Second, and in support of H5a, liking accounted for a substantial amount of variance in the hireability judgments over and beyond individuating information (as determined via T. Hayes, 2021): In the US sample, we found an incremental $\Delta R^2 = .16$ for expectations of task performance and $\Delta R^2 = .28$ for OCB, and in the German sample, we found $\Delta R^2 = .14$ for expected task performance and $\Delta R^2 = .24$ for OCB. Interestingly, liking was a stronger predictor for expected OCB than for task performance (US: $\Delta b = 0.32$ [0.19, 0.45], German: $\Delta b = 0.30$, 95% CI [0.17, 0.44]). Overall, these results support H5a.

H5b posited political similarity effects to be smaller in multiparty than in two-party systems. To this end, we tested whether the relevant path coefficients differed. Yet, political similarity was an equally important predictor of overall similarity in both contexts (CPA: $\Delta b = 0.58$, 95% CI [-0.21, 1.39]; PVS: $\Delta b = 0.23$ [-0.27, 0.73]). Relatedly, there was no difference regarding the effect of overall similarity on liking, $\Delta b = 0.09$, 95% CI [0.00, 0.18]. Finally, liking predicted hireability judgments equally in both groups (task performance: $\Delta b = -0.05$, 95% CI [-0.25, 0.14]; OCB: $\Delta b = -0.04$, 95% CI [-0.24, 0.16]). So, we found no support for H5b.

The PAM also implies indirect effects of political similarity on the hireability criteria: In the US sample, both CPA (task performance: $b = 0.23$, 95% CI [0.004, 0.50]; OCB: $b = 0.37$
[0.007, 0.77]) and PVS (task performance: $b = 0.20$, 95% CI [0.05, 0.37]; OCB: $b = 0.31$ [0.08, 0.56]) had the proposed indirect effect on hireability (mediated via perceived overall similarity and liking). In the German group, only PVS had an indirect effect on expected task performance ($b = 0.12$, 95% CI [0.06, 0.17]) and OCB ($b = 0.17$, 95% CI [0.10, 0.26]); but CPA did not (task performance: $b = 0.05$, 95% CI [-0.02, 0.13], OCB: $b = 0.08$ [-0.03, 0.20]). This further suggests that in a multiparty context, PVS is the key variable driving the similarity effects.

**Effect of Control Variables and Exploratory Analyses**

To assess the influence of control variables (age, gender, prior selection experience) we conducted individual parameter contribution regression (IPCR) analyses. That is, a SEM parameter was regressed on a covariate, after which one can test whether the magnitude of the parameter is predicted by a control variable (Arnold et al., 2021). Control variables had no substantial influence (see ES 06). As a robustness check, we also ran additional analyses (e.g., including outliers, participants who failed the manipulation check, or only participants with prior hiring experience). One exception in each of these analyses notwithstanding, the results were similar to the results presented above. Detailed results of these additional analyses are available in the electronic supplementary, ES 12.

**Discussion**

Cybervetting is a growing but controversial practice (Landers & Schmidt, 2016; Mönke & Schäpers, 2022; Roth et al., 2016; Wilcox et al., 2022). Given that social media risk exposing recruiters to job-unrelated applicant information (e.g., political affiliation; Zhang et al., 2020), the PAM (Roth et al., 2017, 2020) serves as an important conceptual capstone to better understand similarity-attraction effects in cybervetting. Yet, the PAM and its assumptions were developed in a two-party context, which is inherently more polarized than a multiparty context.
Therefore, we sought to refine this model and tested it in a multiparty context wherein political (dis)similarity is more fine-grained. Our results add to the current knowledge of cybervetting and the PAM in several ways.

First, this study supports the PAM (Roth et al., 2017) in that political similarity-attraction effects also biased cybervetting judgments outside the US context. Thus, our study underlines the fundamental nature of similarity attraction in the PAM (Byrne, 1971; Montoya et al., 2008). Importantly, at the same time, we also discovered that in multiparty contexts the PAM’s key variable is better conceptualized as a deep-level similarity in political values than mere affiliation with the applicant’s preferred party: In Germany, only PVS had a significant effect, whereas CPA had not. This shows that, in multiparty systems, the PAM needs to be refined from the two-party systems’ behavioral lens to a values-based lens of political ideology (Swigart et al., 2020). In the US sample, CPA and PVS were highly correlated and played a similar PAM role. 3

Second, we also refined the PAM by introducing recruiters’ political interest as a key albeit so-far ignored moderator in multiparty systems. So, we shifted the focus from only “affect-based” (identification) to “interest-based” moderators. Contrary to the (dis)identification variables that in our study seem to be rather independent variables instead of moderators (see also Roth et al., 2020; Figure 3), political interest strengthened the role of political similarity as a facet of perceived overall similarity—the higher a recruiter’s political interest, the greater their political ideology influenced their general similarity perceptions. Hereby, we introduced identity theory in the PAM by positing that for people with strong political interest, cybervetting a social

3 In a two-party context, both CPA and PVS capture the concept of political similarity, but PVS captures the concept better in a multiparty context. This notion was supported by (1) a CFA showing that PVS and CPA are indicators of a common latent factor only in the US and (2) model tests that omitted either CPA or PVS: In the US, both variables explained similar variance in overall similarity, whereas in Germany PVS explained more (see ES 12d).
media profile with a political affiliation cue makes their political identity more salient. We suggest that future studies also rely on identity theory as the basis for their theorizing (instead of using only social identity theory, see Stets & Burke, 2000; Stryker & Serpe, 1994).

Third, similar to prior PAM work (Roth et al., 2020; Wade et al., 2020), political similarity outperformed applicants’ individuating information in cybervetting judgments: Liking predicted expected task performance and OCB beyond individuating information. Importantly, in the multiparty context, the perception of PVS triggered this bias (not the mere affiliation with the applicant’s party, CPA). At a practical level, these results send an important signal to organizations that endorse cybervetting. If recruiters use cybervetting, they might be prone to make biased decisions and, thus, to potential legal action from applicants. As another practical implication, this study suggests that organizations should consider interventions to make cybervetting more systematic and standardized (e.g., providing bias training to recruiters, and scraping protected information from social media pages before providing them to recruiters).

Finally, the similarity-attraction bias occurred especially for judgments of expected OCB (as compared to task performance). A plausible explanation is that OCB refers here to the expected contextual behavior of a future colleague (e.g., helping; Borman & Motowidlo, 1997; Williams & Anderson, 1991), which might reinforce the importance of sympathy, increasing the risk that liking biases hireability judgments. As in selection it is more difficult to obtain tangible cues of OCB (as compared to task performance), stereotypes might more easily slip into recruiters’ judgments of expected OCB: Thus, the incremental effect of liking beyond individuating information might be best observed in hireability judgments of OCB.

In terms of limitations, we acknowledge our sample of working professionals is not representative of recruiting practice. That said, more than half of the sample had prior hiring
experience and such prior experience did not reduce the effects found. Further, we acknowledge
the high intercorrelations of some variables (e.g., liking and overall similarity, see also Roth et
al., 2020). In part, this might be due to common method variance (Podsakoff et al., 2003): For
instance, PVS shares method variance with perceived overall similarity because both ask about
similarity judgments. Conversely, CPA minimizes method variance between party affiliation and
perceived overall similarity because it is a function of the applicant’s party (manipulated) and the
participant’s actual party affiliation. In addition, our study, as have prior studies, tested the PAM
in the context of White, male MBA applicant profiles. We need to investigate whether different
applicant characteristics (e.g., gender, profession) moderate the effects. Given cybervetting’s
widespread use (Hartwell & Campion, 2020; Roth et al., 2019), we also call to further investigate
its validity and adverse impact. Along these lines, we should scrutinize the effectiveness of
standardization strategies (Hartwell et al., 2022) and machine learning (see, e.g., Guilfoyle et al.,
2016; Langer et al., 2021; Park et al., 2015) to reduce human biases in cybervetting. Finally, the
role of political ideology in other selection procedures (e.g., assessment centers, interviews) and
HR decisions (e.g., promotions) should be explored (Swigart et al., 2020).

Conclusion

Overall, this study showed that political affiliation similarity can affect recruiters’
hireability judgments in cybervetting. Hereby key tenets of the PAM (Roth et al., 2017, 2020)
could be transferred to multiparty contexts. In addition, by introducing political value similarity
(rather than common party affiliation) as the PAM’s focal variable and recruiters’ political
interest (rather than party identification) as a moderator, we refined this theory’s propositions to
multiparty contexts. Thereby, we provide a more nuanced understanding of when political
similarity affects recruiters’ judgments in cybervetting.
References


https://doi.org/10.1080/10705510701301834


https://doi.org/10.1017/S0022381611001721


Smith, M. (2017). *Disgracebook: One in five employers have turned down a candidate because of social media.* YouGov. https://yougov.co.uk/topics/politics/articles-reports/2017/04/10/disgracebook-one-five-employers-have-turned-down-c


Table 1

Descriptive Statistics and Correlations of Study Variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>$M_{USA}$ (SD)</th>
<th>$M_{GER}$ (SD)</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. CPA $^a$</td>
<td>—</td>
<td>—</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>2. PVS</td>
<td>40.39 (35.80)</td>
<td>36.72 (28.94)</td>
<td>.50$^*$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3. Political Interest</td>
<td>2.96 (0.80)</td>
<td>2.91 (0.72)</td>
<td>.04</td>
<td>.05</td>
<td>—</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4. Overall Similarity</td>
<td>3.76 (1.75)</td>
<td>3.27 (1.26)</td>
<td>.38$^*$</td>
<td>.69$^*$</td>
<td>.05</td>
<td>—</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5. Identification</td>
<td>2.00 (1.01)</td>
<td>1.64 (0.69)</td>
<td>.40$^*$</td>
<td>.53$^*$</td>
<td>.14$^*$</td>
<td>.45$^*$</td>
<td>—</td>
<td></td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>6. Disidentification</td>
<td>2.98 (1.38)</td>
<td>2.99 (1.29)</td>
<td>— .44$^*$</td>
<td>— .81$^*$</td>
<td>.02</td>
<td>— .65$^*$</td>
<td>— .41$^*$</td>
<td>—</td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>7. Liking</td>
<td>3.01 (1.31)</td>
<td>2.72 (0.87)</td>
<td>.33$^*$</td>
<td>.62$^*$</td>
<td>.05</td>
<td>.79$^*$</td>
<td>.40$^*$</td>
<td>— .65$^*$</td>
<td>—</td>
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<td>8. Task Performance</td>
<td>5.58 (1.12)</td>
<td>5.27 (1.05)</td>
<td>.16$^*$</td>
<td>.18$^*$</td>
<td>— .01</td>
<td>.40$^*$</td>
<td>.17$^*$</td>
<td>— .17$^*$</td>
<td>.37$^*$</td>
<td>—</td>
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<td></td>
</tr>
<tr>
<td>9. Org. Citizenship</td>
<td>4.79 (1.35)</td>
<td>4.68 (1.22)</td>
<td>.18$^*$</td>
<td>.41$^*$</td>
<td>— .01</td>
<td>.60$^*$</td>
<td>.28$^*$</td>
<td>— .39$^*$</td>
<td>.57$^*$</td>
<td>.42$^*$</td>
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<td>10. Ind. Information $^a$</td>
<td>—</td>
<td>—</td>
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</tbody>
</table>

Note. The US sample above the diagonal, $n_{USA} = 266$; the German sample below the diagonal, $n_{GER} = 747$. CPA. = Common party affiliation with the applicant. PVS = Political value similarity with the applicant’s party. Task Performance = Expected task performance. Org. Citizenship = Expected organizational citizenship behavior. Ind. Information = Individuating information. $^a$This variable is binary (1 = match, 0 = mismatch), and point-biserial correlation is reported. Also, this variable was based on the experiment’s manipulation. Thus, descriptive statistics are not reported.

$p < .05$. $^{*}p < .001$
Table 2

Results from the CFA and Reliability Estimates, separated per Sample

<table>
<thead>
<tr>
<th>Factor / Items</th>
<th>US sample</th>
<th>German sample</th>
<th></th>
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<tr>
<td></td>
<td>λ (std.)</td>
<td>ω</td>
<td></td>
</tr>
<tr>
<td></td>
<td>λ (std.)</td>
<td>ω</td>
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<td>Perc. Overall Similarity</td>
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</tr>
<tr>
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<td>.91</td>
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<td>.94</td>
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<td>Exp. Task Performance</td>
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<tr>
<td>Exp. Org. Citizenship</td>
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<td>.97</td>
<td>.93</td>
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</tr>
<tr>
<td>Item 3</td>
<td>.91</td>
<td>.81</td>
<td></td>
</tr>
</tbody>
</table>

Note. N = 266 (US sample), N = 747 (German sample). Standardized λ in brackets. ω = weighted McDonalds ω.

*Removed due to non-invariance. All loadings were significant, p < .001. For items, see Roth et al. (2020).

As Mardia’s test showed that our data did not follow a multivariate normal distribution, we used the robust maximum likelihood estimator for all analyses (MLR; see Bentler & Yuan, 1999; Yuan & Bentler, 1997). Fit indices for the US sample: χ²(237) = 713.23, p < .001; CFI = .94, RMSEA = .087 (90% CI [.008, .094]), SRMR = .046. Fit for the German sample: χ²(237) = 800.03, p < .001; CFI = .96, RMSEA = .056 (90% CI [.052, .061]), SRMR = .039.
### Table 3

**Results from Tests of Measurement Invariance**

<table>
<thead>
<tr>
<th>Model</th>
<th>( \chi^2 ) (df)</th>
<th>CFI</th>
<th>RMSEA [90% CI]</th>
<th>SRMR</th>
<th>Model comp.</th>
<th>( \Delta \chi^2 ) (( \Delta ) df)</th>
<th>( \Delta ) CFI</th>
<th>( \Delta ) RMSEA</th>
<th>( \Delta ) SRMR</th>
<th>Decision</th>
</tr>
</thead>
<tbody>
<tr>
<td>M1: Configural Invariance</td>
<td>2229.59 (658)*</td>
<td>.936</td>
<td>.069 [.066, .072]</td>
<td>.053</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>Accept</td>
</tr>
<tr>
<td>M2: Metric Invariance</td>
<td>2368.56 (676)*</td>
<td>.931</td>
<td>.070 [.067, .073]</td>
<td>.062</td>
<td>M1</td>
<td>138.96 (18)*</td>
<td>.005</td>
<td>.001</td>
<td>.009</td>
<td>Accept</td>
</tr>
<tr>
<td>M3: Scalar Invariance</td>
<td>2647.34 (697)*</td>
<td>.920</td>
<td>.074 [.071, .077]</td>
<td>.070</td>
<td>M2</td>
<td>278.78 (21)*</td>
<td>.011</td>
<td>.004</td>
<td>.008</td>
<td>Reject</td>
</tr>
<tr>
<td>M3a: Partial Scalar Invariance</td>
<td>2476.81 (696)*</td>
<td>.927</td>
<td>.071 [.068, .074]</td>
<td>.062</td>
<td>M2</td>
<td>108.25 (20)*</td>
<td>.004</td>
<td>.001</td>
<td>.000</td>
<td>Accept</td>
</tr>
</tbody>
</table>

*Note. \( N = 1013 \), group 1 \( n = 747 \) (German sample); group 2 \( n = 266 \) (US sample). All \( \chi^2 \) and fit indices are Yuan-Bentler-corrected (robust-scaled). We excluded one item from the disidentification scale (“I have been ashamed of what goes on in X”), due to substantially different loadings in the German (\( \lambda = .41 \)) and the US group (\( \lambda = .89 \)). In M3a, the intercept of common party affiliation was released. We used established criteria to evaluate measurement invariance (Chen, 2007; Chen et al., 2005; Sass, 2011): non-significant \( \chi^2 \)-test or \( \Delta \)CFI < .01, \( \Delta \)RMSEA < .015 for every level of invariance testing, and \( \Delta \)SRMR < .03 for metric invariance.

* \( p < .001 \)
Table 4
Results from the Multigroup SEM for the Structural Model

<table>
<thead>
<tr>
<th>Variable</th>
<th>US sample</th>
<th></th>
<th></th>
<th>German sample</th>
<th></th>
<th></th>
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</thead>
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<tr>
<td>Overall Similarity</td>
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<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>CPA</td>
<td>0.76 (0.39)</td>
<td>1.97*</td>
<td>0.18</td>
<td>0.19 (0.14)</td>
<td>1.37</td>
<td>0.04</td>
</tr>
<tr>
<td>PVS</td>
<td>0.64 (0.24)</td>
<td>2.67*</td>
<td>0.30</td>
<td>0.41 (0.09)</td>
<td>4.51*</td>
<td>0.28</td>
</tr>
<tr>
<td>Political Interest (PI)</td>
<td>0.28 (0.16)</td>
<td>1.69</td>
<td>0.13</td>
<td>0.11 (0.05)</td>
<td>2.36*</td>
<td>0.07</td>
</tr>
<tr>
<td>PI x PVS</td>
<td>0.25 (0.15)</td>
<td>1.60</td>
<td>0.11</td>
<td>0.15 (0.05)</td>
<td>3.18*</td>
<td>0.10</td>
</tr>
<tr>
<td>PI x CPA</td>
<td>-0.35 (0.31)</td>
<td>-1.15</td>
<td>-0.11</td>
<td>-0.15 (0.14)</td>
<td>-1.11</td>
<td>-0.04</td>
</tr>
<tr>
<td>Identification</td>
<td>0.17 (0.13)</td>
<td>1.31</td>
<td>0.07</td>
<td>0.34 (0.07)</td>
<td>4.61*</td>
<td>0.17</td>
</tr>
<tr>
<td>Identification x PVS</td>
<td>-0.04 (0.07)</td>
<td>-0.55</td>
<td>-0.01</td>
<td>-0.02 (0.07)</td>
<td>-0.32</td>
<td>-0.01</td>
</tr>
<tr>
<td>Disidentification</td>
<td>-0.76 (0.20)</td>
<td>-3.77*</td>
<td>-0.35</td>
<td>-0.64 (0.10)</td>
<td>-6.13*</td>
<td>-0.35</td>
</tr>
<tr>
<td>Disident. x PVS</td>
<td>0.23 (0.12)</td>
<td>1.88</td>
<td>0.05</td>
<td>0.30 (0.18)</td>
<td>1.70</td>
<td>0.13</td>
</tr>
<tr>
<td>Liking</td>
<td>0.57 (0.04)</td>
<td>14.60*</td>
<td>0.96</td>
<td>0.48 (0.03)</td>
<td>18.33*</td>
<td>0.83</td>
</tr>
<tr>
<td>Per. Overall Similarity</td>
<td>-0.22 (0.13)</td>
<td>-1.67</td>
<td>-0.09</td>
<td>-0.03 (0.07)</td>
<td>-0.42</td>
<td>-0.01</td>
</tr>
<tr>
<td>CPA</td>
<td>0.06 (0.09)</td>
<td>0.65</td>
<td>0.05</td>
<td>0.06 (0.04)</td>
<td>1.69</td>
<td>0.07</td>
</tr>
<tr>
<td>Exp. Task Performance</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Liking</td>
<td>0.54 (0.08)</td>
<td>7.05*</td>
<td>0.61</td>
<td>0.59 (0.06)</td>
<td>9.21*</td>
<td>0.50</td>
</tr>
<tr>
<td>Ind. Information</td>
<td>0.53 (0.12)</td>
<td>4.55*</td>
<td>0.24</td>
<td>0.52 (0.07)</td>
<td>7.12*</td>
<td>0.26</td>
</tr>
<tr>
<td>CPA</td>
<td>-0.55 (0.21)</td>
<td>-2.59*</td>
<td>-0.25</td>
<td>0.22 (0.10)</td>
<td>2.18*</td>
<td>0.07</td>
</tr>
<tr>
<td>PVS</td>
<td>0.10 (0.11)</td>
<td>0.87</td>
<td>0.09</td>
<td>-0.15 (0.05)</td>
<td>-2.63*</td>
<td>-0.14</td>
</tr>
<tr>
<td>Exp. Org. Citizenship</td>
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<td></td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Liking</td>
<td>0.86 (0.08)</td>
<td>11.24*</td>
<td>0.82</td>
<td>0.90 (0.07)</td>
<td>13.18*</td>
<td>0.65</td>
</tr>
<tr>
<td>Ind. Information</td>
<td>0.01 (0.11)</td>
<td>0.05</td>
<td>0.00</td>
<td>-0.04 (0.07)</td>
<td>-0.59</td>
<td>-0.02</td>
</tr>
<tr>
<td>CPA</td>
<td>-0.02 (0.18)</td>
<td>-0.09</td>
<td>-0.01</td>
<td>-0.13 (0.12)</td>
<td>-1.11</td>
<td>-0.04</td>
</tr>
<tr>
<td>PVS</td>
<td>-0.10 (0.10)</td>
<td>-0.99</td>
<td>-0.08</td>
<td>0.01 (0.06)</td>
<td>0.20</td>
<td>0.01</td>
</tr>
</tbody>
</table>

Note. N = 266 (US), N = 747 (German). β = standardized path coefficient. Predictors are indented, dependent variables are not indented. The boldface indicates significant predictors. *p < .05 (two-tailed).
Figure 1a

*Results from Multigroup SEM for the Structural Model: US group*

Note. \( N = 266 \). Standardized path coefficients are reported, covariances in italics. Dotted paths indicate non-significance. CPA = Common party affiliation. PVS = Political value similarity. Fit of the multigroup SEM, without interaction variables (to avoid biased estimates, as suggested by Schoemann & Jorgensen, 2021): \( \chi^2 (658) = 2229.60, p < .001; \text{CFI} = .936, \text{RMSEA} = .069 \text{ (90\% CI [.066, .072])}, \text{SRMR} = .053. \)

* * \( p < .05 \)
Figure 1b

Results from Multigroup SEM for the Structural Model: German group

Note. \( N = 747 \). Standardized path coefficients are reported, covariances in italics. Dotted paths indicate non-significance. CPA = Common party affiliation. PVS = Political value similarity. Fit of the multigroup SEM, without interaction variables (to avoid biased estimates, as suggested by Schoemann & Jorgensen, 2021):

\[ \chi^2(658) = 2229.60, \ p < .001; \ CFI = .936, \ RMSEA = .069 \ (90\% \ CI \ [.066, .072]), \ SRMR = .053 \]

* \( p < .05 \)
Figure 2

Interaction Plot: Influence of Political Interest on the Relation between PVS and Perceived Overall Similarity in the German sample

Note. $N = 747$. PI = Political interest. PVS = Political value similarity. Low levels of the variable represent values one standard deviation below its mean, high levels represent values one standard deviation above its mean value. PVS and PI were scaled.