European Journal of Psychological Assessment

Assessing Behavioral Dynamics in Group Interactions: A Focus on Expressiveness

Eva Bleckmann and Jenny Wagner

Online First Publication, October 29, 2025. https://dx.doi.org/10.1027/1015-5759/a000923

Brief Report

Assessing Behavioral Dynamics in Group Interactions

A Focus on Expressiveness

Eva Bleckmann and Jenny Wagner

Department of Psychology, Hamburg University, Germany

Abstract: A person's behavior in social interactions is shaped by both their individual characteristics and the social context. However, research on the processes that capture behavioral dynamics within social interactions is limited. This brief report focuses on short-term assessments of expressive behaviors in group interactions among adolescents (80 groups with N = 301 participants, M_{age} = 15.73, 60.08% girls). Specifically, we examined how trained observers can code nonverbal and verbal expressiveness through 30-second sequences in a 10-minute interaction. Our findings demonstrated the convergent validity of the behavioral expressiveness assessments with measures of extraversion and behavioral ratings during the interactions. Focusing on dynamics, results illustrated that participants varied substantially in their expressiveness during the interaction, revealing distinct patterns across behavioral channels. These first insights highlight the potential of short-term assessments to explore behavioral dynamics in social interactions, and we discuss future directions for research in this area.

Keywords: behavioral dynamics, behavior coding, personality, social interactions

Most contemporary researchers agree that people's behavior in social settings is determined by a complex interplay of stable person characteristics – how people typically think, feel, and behave – as well as their immediate social context, including their interaction partners (Back et al., 2023; Lewin, 1936; Mischel & Shoda, 1995). Despite this theoretical foundation, our understanding of processes within social interactions remains limited, since behaviors are often measured as static between-person differences rather than dynamic constructs that can change within persons during an interaction. To address this gap, short-term assessments of behavior are essential, as they can capture moment-to-moment fluctuations in individuals' behaviors, which are necessary to empirically test theories on personality and social interaction processes. In this brief report, we integrate three approaches to improve the conceptualization and assessment of interpersonal behaviors in social interactions.

First, we focus on within-person dynamics in behaviors during social interactions. This perspective allows for a richer understanding of how behaviors change in real time. Aligning with this perspective, interpersonal theory posits that individuals adapt their behaviors in response to their interaction partners (Sullivan, 1953). Such behavioral dynamics have been investigated in dyadic settings, revealing meaningful changes in people's agentic and communal behaviors over short interaction sequences (Halberstadt & Pincus, 2023; Kurzius et al., 2022). Second, we advocate shifting the focus from dyadic to group interactions. Although studying social behaviors in groups is well established in organizational research (Lehmann- Willenbrock & Allen, 2018), there has been limited attention to date on more complex social situations in the field of personality psychology. We argue that social groups are highly relevant contexts for daily interactions beyond the work context, where individuals express their personalities and form social connections. Finally, since interpersonal behaviors are multidimensional, we propose to assess them by distinct verbal and nonverbal channels (e.g., gestures, facial expressions). This approach can offer nuanced insights and a more comprehensive understanding of dynamic patterns: For example, while nonverbal movements change rapidly and more automatically in response to interaction partners (Arellano-Véliz et al., 2023), verbal behaviors may be more reflective and require longer timeframes to change.

Building on these insights, we adopt a dynamic perspective to assess behaviors within social group interactions. Specifically, we focus on expressive behaviors, which represent a key domain within the Interpersonal Circumplex (Wiggins, 1979) and are conveyed through observable nonverbal cues (e.g., smiling, nodding, and attentive movements) and verbal cues (e.g., sharing personal information; Grünberg et al., 2018). We selected expressive behaviors as a domain because it (1) can be readily observed by external coders, (2) is conceptually related to the pesonality

https://doi.org/10.1027/1015-5759/a000923

domain of extraversion, which provides means for validation, and (3) is highly relevant to various social outcomes (e.g., being liked; Bleckmann et al., 2024). Taken together, this brief report illustrates how short-term assessments of expressiveness can capture individuals' behavioral dynamics during group interactions.

Method

We report how we determined our sample size, all data exclusions (if any), all data inclusion/exclusion criteria, whether inclusion/exclusion criteria were established prior to data analysis, all measures in the study, and all analyses including all tested models. If we use inferential tests, we report exact *p*-values, effect sizes, and 95% confidence intervals.

Participants and Procedure

The Social Interaction and Adolescent Personality Study (SNAP; Wagner & Bleckmann, 2021) involved 301 adolescents (M_{age} = 15.73, *SD* = 1.28; 60.08% girls) recruited from across Germany who participated in a social group interaction. Ethical approval was granted by the local ethics committee at the University of Hamburg (protocol number: 2021_349). Details on the complete study design, recruitment strategy, and participant compensation can be found in the study codebook (Bleckmann & Wagner, 2021; https://osf.io/w4nmj). Most participants attended the highest level of education (81.23%) and stated German as their first language (84.98%). After completing an online questionnaire on sociodemographic variables and personality constructs, participants were randomly assigned to one of 80 groups of 3–5 people (*M* = 3.83, *SD* = 0.78) for a virtual interaction via ZOOM. This interaction consisted of three parts: a round of introductions, a roleplay, and a discussion. In the following, we focus on the roleplay, in which participants discussed who would take on specific tasks (e.g., task manager, timekeeper) in an imaginary school project and which lasted about 10 min. Participants rated their interaction partners' personality states and behaviors four times during the roleplay in a round-robin design.

Measures

Expressive behaviors were assessed by four trained coders (50% women) using a standardized procedure. We used an adapted version of the Münster Behavior Coding Scheme (Grünberg et al., 2018), focusing on meso-level observations that most closely resemble untrained raters' perceptions of group interactions (Burgoon & Dunbar, 2018). To capture the complexity of interpersonal behaviors, coders assessed different input channels, including gestures, facial expressions, and verbal content (see Supplement Table OS 1). After extensive training, coders first watched the muted interactions to rate nonverbal behaviors (facial expressions and gestures) and then rewatched the recordings with sound to rate verbal expressiveness.[1] To understand dynamics, all behaviors were rated every 30 s on a 6-point scale ranging from 1 (= *displays behavior not at all*) to 6 (= *displays behavior very strongly*). Interrater agreement (ICC [3, 4]; Koo & Li, 2016) across all 30-s intervals exceeded .75, except for two sequences for gesture ratings[2]. Table 1 shows an overview of personality and behavior self- and informant reports that were used to assess convergent validity.

Data Analysis

Data cleaning, structuring, and analyses were performed with R Version 4.0.2 (R Core Team, 2020). The analyses cover three major parts. As a first step, we estimated two types of intraclass correlation coefficients (ICC) to evaluate variance in expressive behaviors across and within individuals (Lüdtke & Trautwein, 2007). Specifically, ICC Type 1 quantifies the proportion of total variance in expressive behaviors attributable to between-group differences, with higher values indicating that a larger share of variance is due to systematic differences between groups (or persons), and lower values suggesting that most variance occurs within groups (or within persons across time). This can be estimated using an "empty" or unconditional multilevel model containing only a random intercept. We estimated the ICC(1) using two different nested structures. First, in a two-level model with timepoints nested within persons, we calculated the proportion of variance attributable to between-person differences. Second, we extended this to a three-level model with timepoints nested within persons nested within groups to additionally estimate the proportion of variance attributable to between-group differences (Hox et al., 2017). The structure of these models is illustrated in Supplement Table OS2. The ICC(1) coefficients were estimated with the *performance* package (Lüdecke et al., 2019). In addition, we calculated the ICC Type 2, which evaluates the reliability of aggregated scores when multiple measurements are averaged within persons.

[1] Instances without verbal contributions were recorded as zero; thus, the verbal expressiveness scores reflect the content expressiveness of a participant's engagement.

[2] Interrater agreement was determined on a subset of videos (25%) assessed by all four coders. Out of 5,727 coded sequences, 4,037 were rated by at least two raters.

Table 1. Self- and informant reports of personality and behavioral measures

Construct	Measure	Scale	Informant	Content
Trait extraversion	BFI-2	1–7	Self	
State extraversion	Bipolar item	1–10	Self Other	Reserved, quiet – enthusiastic, sociable
Talkativeness	Bipolar item	1–10	Other	Reclusive – talkative
Assertiveness	Bipolar item	1–10	Other	Unassertive – assertive

Note. BFI-2 = Big Five Inventory 2 (German version; Danner et al., 2016). Measures for state extraversion and behaviors were adapted from previous interaction studies (Wagner et al., 2021) and assessed directly after the roleplay in a round-robin.

In the present case, ICC(2,*k*) assesses the reliability of mean expressive behavior calculated across *k* sequences within each person, treating sequences as repeated measures. This coefficient indicates how consistently sequences capture individual differences in expressive behavior and whether averaging across sequences yields a stable and reliable indicator of each participant's typical expressive behavior pattern. ICC(2,*k*) coefficients were estimated with the *psych* package (Revelle, 2007).

As a second step, we assessed the convergent validity of the behavioral ratings by investigating their bivariate associations with between-person expressiveness (i.e., aggregated across sequences), trait extraversion, state measures of extraversion during the interaction, and peer reports of behavior during the interactions. As a final step, to gain insights into behavioral dynamics, we investigated how expressiveness within a single interaction sequence correlated with: (1) an individual's behavior in the preceding sequence, (2) the group's average expressiveness during the same sequence, and (3) the group's expressiveness in the preceding sequence.

Results

The ICC(1) coefficients revealed that for each behavioral channel, a substantial amount of variance was located within persons (> 49%, see Table OS 3). Additionally, the three-level model showed that behavioral channels displayed considerably more variance at the person level than at the group level. That is, randomly selected gestures of different people in the same group were moderately correlated (0.20); expressive facial expressions and verbal content were even less similar within groups (0.04–0.12). The mean scores of observer-coded expressive behaviors across interaction sequences indicated good reliability (ICC[2,k] >.89).

Next, we explored the associations between aggregated expressive behaviors per person and extraversion as a conceptually related construct (Table 2). The correlational patterns aligned with our expectations: Individuals who viewed themselves as generally more outgoing and sociable (trait extraversion), and those who perceived themselves as more extraverted during the interaction (state extraversion), tended to behave more expressively during the interaction. Further supporting the convergent validity of the behavioral ratings, talkativeness rated by interaction partners strongly correlated with behavioral codings of verbal expressiveness.[3] As an indicator of how much people varied in their expressiveness, we explored the within-person standard deviation of expressiveness. For expressive gestures and facial expressions, people with higher average expressiveness exhibited greater variability. However, this pattern did not hold for variability in verbal expressiveness, which showed no correlation with average verbal expressiveness or any other personality or behavioral constructs. Interestingly, variability across behavioral channels was substantially correlated: people who varied more in their expressive gestures also varied more in facial expressions and verbal content.

Focusing on within-person behavioral dynamics, Figure 1 illustrates the trajectories for expressiveness within individuals of three randomly selected groups. Across the behavioral channels, changes in expressiveness often appear nonlinear and show significant interindividual differences in terms of strength and direction. Thus, some individuals exhibit greater variability in their expressiveness during interactions than others, leading to distinctive dynamic behavior patterns.

Three findings stand out regarding the situational correlations of expressive behaviors (Table OS 4): First, correlations between a distinct sequence and the preceding sequence showed moderate stability for expressive gestures, facial expressions and verbal content within individuals (.31–.58). Second, individual's and others' facial expressions within the same 30-second sequence were moderately correlated (.44), suggesting that people might immediately adapt nonverbal facial expressions in response to other group members. Third, expressive verbal content was not correlated with others' average verbal

[3] The strong correlations between interaction partners' ratings of state extraversion, talkativeness, and assertiveness (.73 to .83) likely reflect both the genuine conceptual overlap among these related constructs and potential challenges interaction partners are faced with in making fine-grained distinctions between similar behavioral aspects during a brief interaction.

Table 2. Between-person correlations among expressive behaviors, personality, and behavior measures

Variables	Mean (*SD*)	1	2	3	4	5	6	7	8	9	10
1. Expressive gestures	2.72 (0.73)										
2. Expressive facial exp.	2.64 (0.79)	**.79**									
3. Expressive verbal content	2.74 (0.68)	**.61**	**.62**								
4. *SD* expressive gestures	0.65 (0.25)	**.47**	**.36**	**.31**							
5. *SD* expressive facial exp.	0.73 (0.29)	**.34**	**.47**	**.21**	**.55**						
6. *SD* expressive verbal content	0.90 (0.28)	**.16**	**.15**	.10	**.25**	**.21**					
7. Trait extraversion SR	4.53 (0.94)	**.28**	**.27**	**.24**	**.23**	**.14**	.02				
8. State extraversion SR	7.07 (2.15)	**.22**	**.27**	**.25**	.09	.09	.04	**.44**			
9. State extraversion OR	6.71 (1.85)	**.39**	**.37**	**.40**	**.23**	**.25**	.10	**.19**	**.28**		
10. Talkativeness OR	6.86 (1.97)	**.44**	**.43**	**.51**	**.25**	**.25**	.08	**.21**	**.27**	**.83**	
11. Assertiveness OR	6.79 (1.86)	**.37**	**.35**	**.41**	**.17**	**.21**	.08	**.16**	**.24**	**.73**	**.79**

Note. Expressive gestures, facial expressions, and verbal content are averaged across sequences per person. OR = other-report of interaction partners after interactive roleplay; *SD* = Within-person standard deviation; SR = self-report. Correlations in bold font significant at $p < .05$.

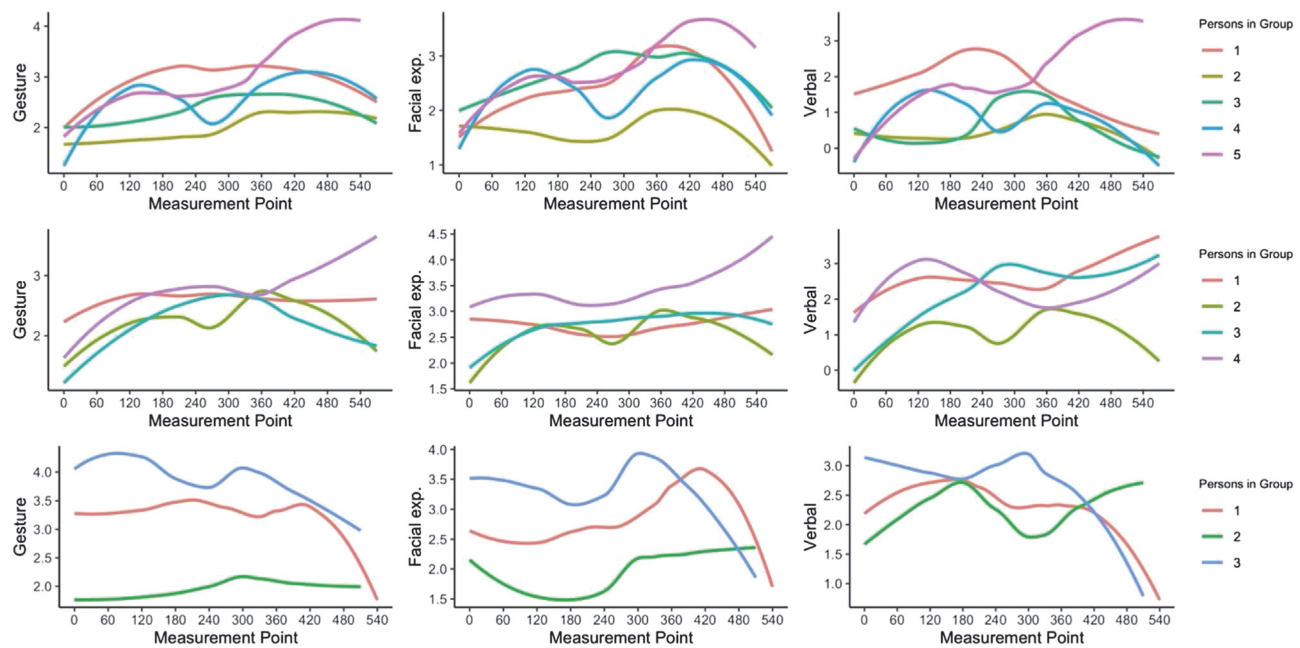

Figure 1. Within-person trajectories of expressive behaviors of participants in three randomly selected groups. *Y*-axes represent time in seconds.

expressiveness in the same sequence. However, there was a weak lagged relationship: when the group showed higher verbal expressiveness, individuals tended to slightly increase their own verbal expressiveness in the following sequence.

Discussion

We highlight two key insights from the short-term assessment of expressive behaviors in social group interactions. First, by coding behaviors across 30-second intervals within individuals, we gain unique insights into people's behavioral trajectories, which often exhibit nonlinear patterns and show substantial variability. This finding aligns with the theoretical perspective that although being partly driven by stable tendencies captured in personality, interpersonal behaviors are highly adaptive and depend on the social context (e.g., the interaction partners' behaviors within the group; Back, 2021; Roche & Cain, 2021). Additionally, our findings illustrate the value of differentiating among different behavioral channels, underscoring the multidimensionality of behavior.

Looking ahead, short-term assessments of behaviors during group interactions can provide crucial insights into group dynamics, including whether (and how strongly) individuals adapt their expressiveness in response to others and whether a particular person acts as a "leader" driving the behaviors of fellow group members. Additionally, we can probe the patterns and functionality of behavioral variability: in which social situations does changing one's behavior indicate that a person is either successfully adapting to their environment, or reflect inconsistency that harms social outcomes (e.g., being liked) and group dynamics?

Moving forward, two conceptual questions regarding behavioral dynamics remain. First is the question of granularity: At what level do we need to study behavioral dynamics within social interactions? While we focused exclusively on behavioral cues at the meso-level (i.e., neither very global nor very detailed cues), understanding dynamics may (or may not) require a focus on more fine-grained behavior cues (e.g., a smile, a nod) and how these play into complex behavioral patterns. Second, what is the adequate time axis to study behavioral dynamics? Few existing theories explicitly address the role of time, particularly regarding what constitutes meaningful intervals for examining dynamics within social interactions.

Beyond addressing these conceptual questions, future research should tackle several methodological shortcomings of the current work. First, our coding procedure, which involved coders analyzing all participants and sequences chronologically, may have inflated correlations among sequences. This was a practical choice given the resource-intensive nature of behavioral coding and the limited number of coders. Future studies can mitigate potential order effects by randomizing the individual video sequences prior to coding or by randomizing how observers code participants across groups. To reduce the burden on coders, exploring continuous assessment techniques, such as using joysticks to track real-time behavior changes (Hopwood et al., 2020), offers a promising avenue. Additionally, interdisciplinary collaborations could train machine learning models to automate manual coding processes. Successful implementation of such models hinges on collecting diverse samples and producing meticulously annotated data, enabling researchers to develop, evaluate, and refine effective tools for subsequent studies.

Second, the generalizability of our findings is an important consideration, as our data were collected in an online interaction setting. While behaviors were clearly visible and we observed both within- and between-person differences, these findings may not directly transfer to face-to-face lab settings or naturalistic interactions outside the lab (but see Buss et al., 2024). Therefore, future research should aim to replicate these findings in more diverse settings, such as controlled environments or real-world in-person interactions to explicitly compare and understand potential differences in expressive behaviors across online and offline interactions.

References

Arellano-Véliz, N. A., Jeronimus, B. F., Kunnen, E. S., & Cox, R. F. A. (2024). The interacting partner as the immediate environment: Personality, interpersonal dynamics, and bodily synchronization. *Journal of Personality, 92*(1), 180–201. https://doi.org/10.1111/jopy.12828

Back, M. D. (2021). Social interaction processes and personality. In J. F. Rauthmann (Ed.), *The handbook of personality dynamics and processes* (pp. 183–226). Elsevier. https://doi.org/10.1016/B978-0-12-813995-0.00008-X

Back, M. D., Branje, S., Eastwick, P. W., Human, L. J., Penke, L., Sadikaj, G., Slatcher, R. B., Thielmann, I., van Zalk, M. H. W., & Wrzus, C. (2023). Personality and social relationships: What do we know and where do we go. *Personality Science, 4*, Article e7505. https://doi.org/10.5964/ps.7505

Bleckmann, E., Rau, R., Carlson, E. N., & Wagner, J. (2024). I think you might like me: Emergence and change of meta-liking in initial social interactions. *Journal of Personality and Social Psychology, 127*(4), 901–919. https://doi.org/10.1037/pspp0000496

Bleckmann, E., & Wagner, J. (2025, September 2). *Assessing Behavioral Dynamics in Group Interactions: A Focus on Expressiveness* [Code, Data, Materials]. https://osf.io/f65nx

Burgoon, J. K., & Dunbar, N. E. (2018). Coding nonverbal behavior. In E. Brauner, M. Boos, & M. Kolbe (Eds.), *The Cambridge handbook of group interaction analysis* (1st ed., pp. 104–120). Cambridge University Press. https://doi.org/10.1017/9781316286302.007

Buss, M., Wagner, J., Bleckmann, E., & Wieczorek, L. L. (2024). Popularity at first sight: Dominant behaviors mediate the link between extraversion and popularity in face-to-face and virtual group interactions. *British Journal of Social Psychology, 63*(3), 1226–1253. https://doi.org/10.1111/bjso.12720

Danner, D., Rammstedt, B., Bluemke, M., Treiber, L., Berres, S., Soto, C., & John, O. (2016). Die deutsche Version des Big Five Inventory 2 (BFI-2) [The German version of the Big Five Inventory 2 (BFI-2)]. *Zusammenstellung sozialwissenschaftlicher Items und Skalen (ZIS)*. https://doi.org/10.6102/ZIS247

Grünberg, M., Mattern, J., Geukes, K., Küfner, A. C. P., & Back, M. D. (2018). Assessing group interactions in personality psychology: The Münster Behavior Coding-System (M-BeCoSy). In E. Brauner, M. Boos, & M. Kolbe (Eds.), *The Cambridge Handbook of Group Interaction Analysis* (1st ed., pp. 602–611). Cambridge University Press. https://doi.org/10.1017/9781316286302.042

Halberstadt, A. L., & Pincus, A. L. (2023). The impact of personality traits on interpersonal dynamics at zero acquaintance. *International Journal of Personality Psychology*, *9*, 61–77. https://doi.org/10.21827/ijpp.9.40271

Hopwood, C. J., Harrison, A. L., Amole, M., Girard, J. M., Wright, A. G. C., Thomas, K. M., Sadler, P., Ansell, E. B., Chaplin, T. M., Morey, L. C., Crowley, M. J., Emily Durbin, C., & Kashy, D. A. (2020). Properties of the continuous assessment of interpersonal dynamics across sex, level of familiarity, and interpersonal conflict. *Assessment, 27*(1), 40–56. https://doi.org/10.1177/1073191118798916

Hox, J., Moerbeek, M., & Schoot, R. van de (2017). *Multilevel analysis: Techniques and Applications* (3rd ed.). Routledge. https://doi.org/10.4324/9781315650982

Koo, T. K., & Li, M. Y. (2016). A guideline of selecting and reporting intraclass correlation coefficients for reliability research. *Journal of Chiropractic Medicine, 15*(2), 155–163. https://doi.org/10.1016/j.jcm.2016.02.012

Kurzius, E., Borkenau, P., & Leising, D. (2022). Spontaneous interpersonal complementarity in the lab: A multilevel approach to modeling the antecedents and consequences of people's interpersonal behaviors and their dynamic interplay. *Journal of Personality and Social Psychology, 122*(2), 244–264. https://doi.org/10.1037/pspi0000347

Lehmann-Willenbrock, N., & Allen, J. A. (2018). Modeling temporal interaction dynamics in organizational settings. *Journal of Business and Psychology, 33*(3), 325–344. https://doi.org/10.1007/s10869-017-9506-9

Lewin, K. (1936). *Principles of topological psychology*. (F. Heider & G. M. Heider, Trans.). McGraw-Hill. https://doi.org/10.1037/10019–000

Lüdecke, D., Makowski, D., Ben-Shachar, M. S., Patil, I., Waggoner, P., Wiernik, B. M., & Thériault, R. (2019). *Performance: Assessment of regression models performance* (p. 0.14.0) [Dataset]. https://doi.org/10.32614/CRAN.package.performance

Lüdtke, O., & Trautwein, U. (2007). Aggregating to the between-person level in idiographic research designs: Personal goal research as an example of the need to distinguish between reliability and homogeneity. *Journal of Research in Personality, 41*(1), 230–238. https://doi.org/10.1016/j.jrp.2006.03.005

Mischel, W., & Shoda, Y. (1995). A cognitive-affective system theory of personality: Reconceptualizing situations, dispositions, dynamics, and invariance in personality structure. *Psychological Review, 102*(2), 246–268. https://doi.org/10.1037/0033-295X.102.2.246

R Core Team. (2020). *R: A language and environment for statistical computing* [Computer software]. R Foundation for Statistical Computing. https://www.R-project.org

Revelle, W. (2007). *psych: Procedures for psychological, psychometric, and personality research* (p. 2.5.6) [Dataset]. https://doi.org/10.32614/CRAN.package.psych

Roche, M. J., & Cain, N. M. (2021). Interpersonal theory and personality processes. In J. F. Rauthmann (Ed.), *The Handbook of Personality Dynamics and Processes* (pp. 669–688). Elsevier. https://doi.org/10.1016/B978-0-12-813995-0.00025-X

Sullivan, H. S. (1953). *The interpersonal theory pf psychiatry*. W. W. Norton & Co.

Wagner, J., & Bleckmann, E. (2021). *SNAP – Social interaction and adolescent personality* [Dataset]. OSF. https://doi.org/10.17605/OSF.IO/W4NMJ

Wagner, J., Mueller, S., & Wieczorek, L. L. (2021). *SELFIE – Personality and self-esteem in everyday life* [Dataset]. https://doi.org/10.17605/OSF.IO/4GNZ9

Wiggins, J. S. (1979). Circumplex models of interpersonal behavior. *Review of Personality and Social Psychology, 1*, 265–294.

History
Received March 6, 2025
Revision received July 7, 2025
Accepted July 28, 2025
Published online October 29, 2025
EJPA Section / Category Personality

Publication Ethics
Ethical approval was granted by the local ethics committee at the University of Hamburg (protocol number: 2021_349). Details on the complete study design, recruitment strategy, and participant compensation can be found in the study codebook (Bleckmann https://osf.io/w4nmj).

Open Science
Open Analytic Code: We confirm that all the scripts, code, and outputs needed to reproduce the results are provided (https://osf.io/f65nx/; Bleckmann & Wagner, 2025).
Open Data: We confirm that there is sufficient information for an independent researcher to reproduce all of the reported results, including codebook if relevant (https://osf.io/f65nx/).
Open Materials: We confirm that there is sufficient information for an independent researcher to reproduce all of the reported methodology (https://osf.io/f65nx/).
Preregistration of Analysis Plans: This study was not preregistered.

Funding
The data used in this project originate from a research project for which Jenny Wagner received funding from the Landesforschungsförderung Hamburg (LFF-GV 79-2019; P4). We have no known conflicts of interest to disclose. Open access publication is enabled by Hamburg University Libraries, Germany.

ORCID
Eva Bleckmann
https://orcid.org/0000-0003-2942-3114
Jenny Wagner
https://orcid.org/0000-0002-6605-0313

Eva Bleckmann
Hamburg University
Institute for Psychology
Educational Psychology and Personality Development
Von-Melle-Park 5
20146 Hamburg
Germany
eva.bleckmann@uni-hamburg.de