Measuring Group Personality with Swarm AI

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***Abstract*—The aggregation of individual personality tests to predict team performance is widely accepted in management theory but has significant limitations: the isolated nature of individual personality surveys fails to capture much of the team dynamics that drive real-world team performance. Artificial Swarm Intelligence (ASI), a technology that enables networked teams to think together in real-time and answer questions as a unified system, promises a solution to these limitations by enabling teams to take personality tests together, whereby the team uses ASI to converge upon answers that best represent the group's disposition. In the present study, the group personality of 94 small teams was assessed by having teams take a standard Big Five Inventory (BFI) test both as individuals, and as a real-time system enabled by an ASI technology known as Swarm AI. The predictive accuracy of each personality assessment method was assessed by correlating the BFI personality traits to a range of real-world performance metrics. The results showed that assessments of personality generated using Swarm AI were far more predictive of team performance than the traditional survey-based method, showing a significant improvement in correlation with at least 25% of performance metrics, and in no case showing a significant decrease in predictive performance. This suggests that Swarm AI technology may be used as a highly effective team personality assessment tool that more accurately predicts future team performance than traditional survey approaches.**

Keywords—Group Personality, BFI, Group Performance, Swarm Intelligence, Artificial Swarm Intelligence, Collective Intelligence, Group Consensus.

I. INTRODUCTION

Most businesses strive to build high performing teams wherein the combination of skills, personality traits, and work habits of team-members drives effective execution towards organizational goals. One commonly used technique for predicting whether a team will be high performing is to administer a personality test to each individual member, aggregate the team's test results, and use those aggregated results to forecast whether the combined team is likely to work well together [1-4]. Prior research has shown a correlation between aggregated results on personality tests and resulting team performance [5]. The current study reviews these prior methods and explores whether improved forecasts of team performance can be attained using Artificial Swarm Intelligence—a unique AI technology that aims to more accurately assess team personality.

As further background, multilevel approaches to investigating organizational phenomena are critical, yet understudied [6]. Multilevel research often involves aggregating individual-level data (e.g., the personalities of individuals comprising a team) to measure group-level constructs (e.g., team performance). Typically, individual-level data are aggregated to measure group-level phenomena in one of four ways: by calculating a mean score of individual measures, by computing the highest (maximum) individual trait score, by computing the lowest (minimum) individual trait score, or by looking at the variance of individual trait scores within a team [7, 8]. Each of these four methods of aggregation have been found to capture unique information about the group [7]. For example, conscientiousness, an individual-level personality trait, is associated with high levels of organization and attention to detail. Averaging the conscientiousness scores of individuals comprising a team assumes that the amount of conscientiousness possessed by each individual team member contributes to the collective pool of conscientiousness available to the team, regardless of how the trait is distributed among team members. Alternatively, the lowest scoring individual on conscientiousness brings the rest of the group down on average, making the group minimum score the most appropriate way to aggregate individual scores. While each of these methods of aggregation provide unique insights, researchers continue to question the efficacy of using individual-level measures to assess group-level traits or phenomena.

An alternative aggregation method, group consensus, offers the potential to improve the accuracy of personality assessments. A consensus approach, whereby all members consider each question on an assessment and jointly agree on a collective score, has been advocated because it better captures the underlying and unique group dynamics present in teams [9, 10]. For example, a study of MBA students found that measuring team efficacy through a consensus approach was a better predictor of group performance than when measured through aggregated individual-level constructs [11]. While the

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consensus method offers a potentially superior way of aggregating individual-level constructs, it suffers from drawbacks. Specifically, the context of a group discussion allows for social influence to silence some members or to encourage conformity. Additionally, achieving consensus is costly in terms of time and logistical organization of participants. For these reasons, and despite the potential of group-level consensus personality measurement and calls to move away from the aggregation of individual-level data [12], researchers seldom use group-level consensus ratings.

Advances in networking technology and artificial intelligence have led to the development of Artificial Swarm Intelligence (ASI) systems that provides a way for groups of humans to quickly reach a consensus in a way that overcomes these limitations. ASI has been found to significantly amplify decision-making accuracy in human groups [13 - 19]. Indeed, groups can achieve consensus in less than 60 seconds, while also limiting social influence from group members through anonymous deliberation that capture group dynamics. ASI presents a promising method that answers the call for research using consensus-based aggregation approaches. Specifically, we focus on the potential of using ASI as a method of administering and composing group-level personality assessments, and in predicting team performance based on these personality assessments.

II. Foundations of Swarm Intelligence

In the natural world, Swarm Intelligence (SI) enables social organisms to aggregate their collective insights rapidly and to converge in synchrony on optimal decisions by forming real-time closed-loop systems. Swarm Intelligence has been deeply studied across many social species, from schools of fish and flocks of birds to swarms of honey bees and even slime molds. Unlike birds, bees and fish, humans have not evolved the natural ability to form real-time swarms, as we lack the innate mechanisms used by other species to form closed-loop systems. Schooling fish detect vibrations in the water around them. Flocking birds detect high-speed motions propagating through the group formation. Swarming bees generate complex body vibrations called a “waggle dance” that encode assessment information. To enable networked human groups to form similar closed-loop systems, a cloud-based platform called “swarm.ai” was developed. It enables human groups, connected from remote locations, to make collective predictions, decisions, and assessments by working together as closed-loop swarms.

When using the swarm.ai platform, networked human teams answer questions by collaboratively moving a graphical pointer to select from a set of answer options. Each participant provides their individual input by manipulating a graphical magnet with a mouse, touchpad, or touchscreen. By adjusting the position and orientation of their magnet with respect to the moving puck, participants express their real-time intent. The input from each user is not a discrete vote, but a stream of vectors that varies freely over time. Because all members of the group can adjust their intent continuously in real-time, the swarm explores the decision-space, not based on the input of any individual member, but based on the emergent dynamics of the full system. This enables a complex behavioral interaction among all members of the population, empowering the group to collectively consider the options and synchronously converge on the most agreeable solution.

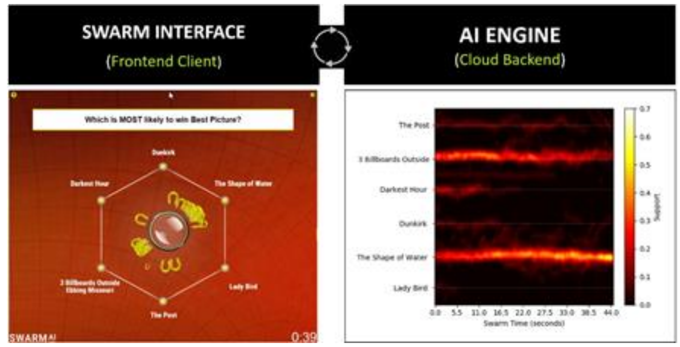

Fig. 1. Architecture of the swarm.ai platform with graphical client and cloud-based AI engine

It is important to note that participants not only vary the direction of their intent but also modulate the magnitude of their intent by adjusting the distance between their magnets and the pointer, which is commonly represented as a graphical puck. Because the graphical puck is in continuous motion across the decision-space, users need to move their magnets continually so that they stay close to the puck’s rim. This is significant for it requires that all participants, regardless of group size or composition, be engaged continuously throughout the decision process, evaluating and re-evaluating their intent in real-time. If a participant stops adjusting their magnet with respect to the changing position of the puck, the distance grows and the participant’s influence on the group’s decision wanes.

Thus, like bees vibrate their bodies to express sentiment in a biological swarm or neurons fire to express conviction levels within a biological neural-network, the participants in an artificial swarm must continuously update and express their changing preferences during the decision process or lose their influence over the collective outcome. This is generally referred to as a “leaky integrator” structure and common to both swarm-based and neuron-based systems. In addition, intelligence algorithms monitor the behaviors of swarm members in real-time, inferring their relative conviction based on their actions and interactions over time. This reveals a range of behavioral characteristics within the population and weights their contributions accordingly.

Just as ASI provides an effective way for groups to reach a consensus around decision-making, it is a promising method for reaching a consensus around responses to psychometric assessments like a personality test. Through ASI, a question can be answered in less than 60 seconds, participants are anonymous and less subject to dysfunctional social influence, and consensus is achieved through interactions as participants deliberate visually through the interface.

III. Method

To assess the ability of ASI technology to function as an accurate assessment tool of team personality, a large study was conducted across a set of 94 working groups (i.e. teams), each comprising 3 to 6 members. Each of these teams were engaged in a 10-week group project. In total, 384 human subjects participated in this study. All were college students enrolled in business, communication studies, or engineering courses, for which a team project was a significant component. Participants first completed the personality assessment individually by themselves, then they completed a personality test collectively as a group using ASI. The individual results were used to compose group-level team personality through typical aggregation approaches (mean, max, min, and variance). The results from the ASI represent a consensus-based team personality. Finally, at the conclusion of the group project, an outcome survey was administered individually to participants to measure group outcomes (e.g., performance).

The Big Five Inventory (BFI) assessment [20] was used to measure personality for both individual and ASI conditions. Qualitics was used to administer the assessment to individuals and the Swarm® software platform was used for measuring ASI consensus. The BFI test is commonly used in literature and industry as a personality assessment tool, and a wide body of research has validated that individual and group scores on this test are correlated with performance on real-world tasks [21-28]. The questions that were included in Individual and Swarm versions of the BFI test are listed in Appendix A. When answering the BFI individually, participants were asked about their own personalities (e.g., Are you talkative?). When group were asked questions through ASI, the referent shifted to the group-level (e.g., Is this group talkative?).

The swarms were attended by 297 (77.3%) participants, and any group in which fewer than 2 individuals participated in the swarm was eliminated from the dataset. The swarms had one minute to answer each question, and if they failed to reach a consensus in that time (referred to as a Brain Freeze), the question was repeated only once. No swarm experienced a brain freeze during the second round.

The individual personality assessments were aggregated in post-processing into a group personality assessment using each of four different methods: (1) average score, (2) minimum score, (3) maximum score, and (4) the variance of individual scores. In this way, the traditional method for assessing group personality (i.e. statistically aggregating individual BFI scores) and a new method for assessing group personality (i.e. enabling teams to take the BFI test together as a unified swarm intelligence) could be directly compared.

Several team outcome variables were measured at the conclusion of the group project, which occurred several days or weeks after the swarm assessment. Several performance related self-assessments were administered to each team member:

- Cohesiveness--degree of bonding towards the team, team members, and the task [29].
- Conflict--the degree of relational, task, and process-based conflict experienced in the group [30]
- Psychological Safety--the degree to which group members feel like they can be vulnerable and speak up with other group members [31]
- Potency--general perception of the group's confidence and capability [32]
- Satisfaction--the degree to which group members are pleased with group members and the team [33]
- Viability--the degree to which the group desires to work together again in the future [34]
- Transactive memory--the degree to which group members know about the skills, emotions, and tasks of other group members [35]
- Team Effectiveness—a self-rating of how well the group accomplished it's task [36]

Prior studies have established connections between group-level personality and these performance outcome variables. For each group, the aggregated scores (average, min, max, variance) and the swarm scores for the BFI were correlated with the six performance indicators with Pearson's correlation coefficient. The resulting R^2 values were compared and used for statistical tests in analysis.

IV. Analysis

The correlation between each personality assessment method and the performance of each team was calculated using a linear regression. The Pearson coefficient of determination (R^2 value) between each BFI Dimension and performance metric was calculated for each of the five group personality measurement methods. The study originally measured 17 performance metrics, which have been averaged by category down to 9 metrics for ease of viewing.

The R^2 values for each personality measurement method are shown in Appendix A, and the Survey Average vs Swarm Correlations with the performance metrics are shown in figure 2 below. Immediately, these plots show that, on average, swarm-based assessments of group personality have a higher correlation with team performance than the survey-based assessments of group personality.

Fig. 2. Heat map of Pearson R^2 values between Swarm or Survey Average Personality Measurement and Performance Metrics

A bootstrapped significance test was performed to measure whether the swarm could have outperformed the survey methods in this test due to random chance alone. In this process, the observed groups (including the personality assessment by each method and performance metrics) were randomly resampled with replacement 1000 times, and the 90% confidence interval of the difference in R^2 values between the survey and swarm assessments of group personality was calculated. This process was repeated for each group performance metric and each surveying method.

A table of confidence intervals generated using this approach is shown in Appendix B, with the cells in which the swarm's assessment was found to correlate with the performance metric significantly more than the survey's assessment highlighted in yellow, and the cells in which the reverse is true highlighted in green. Table 1 below gives an overview of this statistical significance test: out of the 85 comparisons made between each survey assessment method and the swarm, the swarm significantly outperformed the survey in at least 25.9% of cases, while the survey never significantly outperformed the swarm.

TABLE I. SUMMARY OF BOOTSTRAPPED CORRELATION DIFFERENCES BETWEEN SWARM AND SURVEY ASSESSMENTS OF TEAM PERSONALITY

Survey Assessment Method	**Percentage of Comparisons Where…**		
	Swarm Significantly Outperforms the Survey	***Survey Significantly Outperforms the Swarm***	***Average R^2 Increase***
Average	30 (35.3%)	0 (0%)	0.0654
Maximum	25 (29.4%)	0 (0%)	0.0687
Minimum	22 (25.9%)	0 (0%)	0.0484
Variance	24 (28.2%)	0 (0%)	0.0684

V. CONCLUSION

The group personality of 94 small teams was assessed by asking the teams to respond to a standard set of 45 Big Five Inventory questions using both traditional surveys of individual personality and a real-time collaboration interface (Swarm AI) to establish a group consensus of the team's own personality. Four different multilevel approaches to aggregating the team member's answers to the survey BFI questions were studied: the average, variance, minimum, and maximum of the team's answers.

The performance of the surveying methods was compared to the swarming methods by correlating the BFI dimensions, as calculated by each method, to various metrics of the team's self-reported performance. The swarming methods significantly outperformed each of the survey aggregation methods at predicting a wide range of performance metrics (at least 25.9%, n=85), and were never significantly outperformed by the survey aggregation methods.

This result suggests that ASI can be used to evaluate team personality, and predict team performance, more accurately than traditional individual surveying methods. There are several advantages to this approach. First, it overcomes concerns about both time and social influence of the consensus-based approach to aggregation. The average time to reach a consensus was 18.8 seconds. The anonymity provided by the platform enables participants to interact and deliberate visually, while protecting the identities of team members. Second, the analysis reveals that the BFI results of the ASI-based group consensus was a stronger predictor of important group outcomes, such as performance, viability, and cohesion. In doing so, it provides a response to calls for consensus-based aggregation and support for consensus being a superior method of aggregating group-level variables [9]. Future research is needed to replicate and extend these findings to new contexts and different group-level variables.

This research was limited by the availability and participation rate of participants, as 72.9% of participants did not take the pre-swarm survey, and 77.3% did not participate in the swarm. This research also did not investigate whether the presentation of the question itself contributed to the higher success rate of the swarm in predicting team performance, since participants were asked directly about the team's personality in the swarm, but were asked about their own personality in the surveys.

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REFERENCES

[1] Kichuk, S. L., Wiesner, W. H., The big five personality factors and team performance: implications for selecting successful product design teams, Journal of Engineering and Technology Management,Volume 14, Issues 3–4, 1997, Pages 195-221

[2] Peeters, M., van Tuijl, H., Rutte, C., & Reymen, I. (2006). Personality and team performance: A meta-analysis. European Journal of Personality, 20(5), 377.

[3] Digman, J. M. (1990). Personality structure: Emergence of the five-factor model. Annual Review of Psychology, 41, 417–440.

[4] De Raad, B. (2000). The Big Five personality factors. The psycholexical approach to personality. Gottingen, Germany: Hogrefe & Huber Publishers.

[5] Kichuk, S. L.; Wiesner, W.H.: "Personality and Team Performance: Implications for Selecting Successful Product Design Teams". Innovation Research Centre Working Paper#51, 1996.

[6] Paruchuri, S., Perry-Smith, J. E., Chattopadhyay, P., & Shaw, J. D. (2018). New ways of seeing: Pitfalls and opportunities in multilevel research.

[7] Hollenbeck, J. R., DeRue, D. S., & Guzzo, R. (2004). Bridging the gap between I/O research and HR practice: Improving team composition, team training, and team task design. Human Resource Management, 43(4), 353-366.

[8] Barrick, M. R., Stewart, G. L., Neubert, M. J., & Mount, M. K. (1998). Relating member ability and personality to work-team processes and team effectiveness. Journal of applied psychology, 83(3), 377-391.

[9] Bar-T&l D. (1990). Group beliefs. New York: Springer-Verlag

[10] Campion MA, Medsker GJ, Higgs AC. (1993). Relations between work group characteristics and effectiveness: Implications for designing effective work groups, PERSONNEL PSYCHOLOGY, 46,823-850.

[11] Gibson CB, Randel AE, Earley AE. (2000). Understanding group efficacy: An empirical test of multiple assessment methods. Group and Organization Management, 25, 67-97.

[12] Kirkman, B. L., Tesluk, P. E., & Rosen, B. (2001). Assessing the incremental validity of team consensus ratings over aggregation of

individual ‐ level data in predicting team effectiveness. Personnel Psychology, 54(3), 645-667.

[13] Rosenberg, L.B., “Human Swarms, a real-time method for collective intelligence.” Proceedings of the European Conference on Artificial Life 2015, pp. 658-659

[14] Rosenberg, Louis. “Artificial Swarm Intelligence vs Human Experts,” Neural Networks (IJCNN), 2016 International Joint Conference on. IEEE. J. Clerk Maxwell, A Treatise on Electricity and Magnetism, 3rd ed., vol. 2. Oxford: Clarendon, 1892, pp.68–73.

[15] Rosenberg, Louis. Baltaxe, David and Pescetelli, Nicollo. "Crowds vs Swarms, a Comparison of Intelligence," IEEE 2016 Swarm/Human Blended Intelligence (SHBI), Cleveland, OH, 2016, pp. 1-4.

[16] Baltaxe, David, Rosenberg, Louis and N. Pescetelli, “Amplifying Prediction Accuracy using Human Swarms”, Collective Intelligence 2017. New York, NY ; 2017.

[17] Willcox G., Rosenberg L., Askay D., Metcalf L., Harris E., Domnauer C. (2020) Artificial Swarming Shown to Amplify Accuracy of Group Decisions in Subjective Judgment Tasks. In: Arai K., Bhatia R. (eds) Advances in Information and Communication. FICC 2019. Lecture Notes in Networks and Systems, vol 70. Springer, Cham

[18] L. Rosenberg, N. Pescetelli and G. Willcox, "Artificial Swarm Intelligence amplifies accuracy when predicting financial markets," 2017 IEEE 8th Annual Ubiquitous Computing, Electronics and Mobile Communication Conference (UEMCON), New York City, NY, 2017, pp. 58-62.

[19] L. Rosenberg and G. Willcox, "Artificial Swarm Intelligence vs Vegas Betting Markets," 2018 11th International Conference on Developments in eSystems Engineering (DeSE), Cambridge, United Kingdom, 2018, pp. 36-39

[20] John, O. P., Naumann, L. P., & Soto, C. J. (2008). Paradigm Shift to the Integrative Big-Five Trait Taxonomy: History, Measurement, and Conceptual Issues. In O. P. John, R. W. Robins, & L. A. Pervin (Eds.), Handbook of personality: Theory and research (pp. 114-158). New York, NY: Guilford Press.

[21] Bell, S. T. (2007). Deep-level composition variables as predictors of team performance: a meta-analysis. Journal of applied psychology, 92(3), 595.

[22] Bradley, B. H., Klotz, A. C., Postlethwaite, B. E., & Brown, K. G. (2013). Ready to rumble: How team personality composition and task conflict interact to improve performance. Journal of Applied Psychology, 98(2), 385.

[23] O'Neill, T. A., & Allen, N. J. (2014). Team task conflict resolution: An examination of its linkages to team personality composition and team effectiveness outcomes. Group Dynamics: Theory, Research, and Practice, 18(2), 159.

[24] Gregory, R. J. (2004). Psychological testing: History, principles, and applications. Allyn & Bacon.

[25] Judge, Timothy A., and Cindy P. Zapata. "The person–situation debate revisited: Effect of situation strength and trait activation on the validity of the Big Five personality traits in predicting job performance." Academy of Management Journal 58, no. 4 (2015): 1149-1179.

[26] Howard, Pierce J., and Jane Mitchell Howard. Owner's Manual for Personality at Work. Bard Press (Austin, TX), 2001.

[27] Judge, Timothy A., Chad A. Higgins, Carl J. Thoresen, and Murray R. Barrick. "The big five personality traits, general mental ability, and career success across the life span." Personnel psychology 52, no. 3 (1999): 621-652.

[28] Boudreau, John W., Wendy R. Boswell, and Timothy A. Judge. "Effects of personality on executive career success in the United States and Europe." Journal of vocational behavior 58, no. 1 (2001): 53-81.

[29] Carless, S. A., & De Paola, C. (2000). The measurement of cohesion in work teams. Small group research, 31(1), 71-88.

[30] Jehn, K. A., & Mannix, E. A. (2001). The dynamic nature of conflict: A longitudinal study of intragroup conflict and group performance. Academy of management journal, 44(2), 238-251.

[31] Edmondson, A. (1999). Psychological safety and learning behavior in work teams. Administrative Science Quarterly, 44(2), 350-383

[32] Guzzo, R. A., Yost, P. R., Campbell, R. J., & Shea, G. P. (1993). Potency in groups: Articulating a construct. British journal of social psychology, 32(1), 87-106.

[33] Vegt, G. S., Emans, B. J., & Vliert, E. (2001). Patterns of interdependence in work teams: A two ‐ level investigation of the relations with job and team satisfaction. Personnel Psychology, 54(1), 51-69.

[34] Hackman, J. R. 1987. The design of work teams. In J. W. Lorsch (Ed.), Handbook of organizational behavior: 315-342. Englewood Cliffs, NJ: Prentice-Hall.

[35] Lewis, K. (2003). Measuring transactive memory systems in the field: Scale development and validation. *Journal of applied psychology*, *88*(4), 587-603.

[36] Alper, S., Tjosvold, D. and Law, S. A. (2000). ‘Conflict management, efficacy, and performance in self-managing work teams. *Personnel Psychology*, 53, 625–42.

APPENDIX A: CORRELATION HEAT MAPS

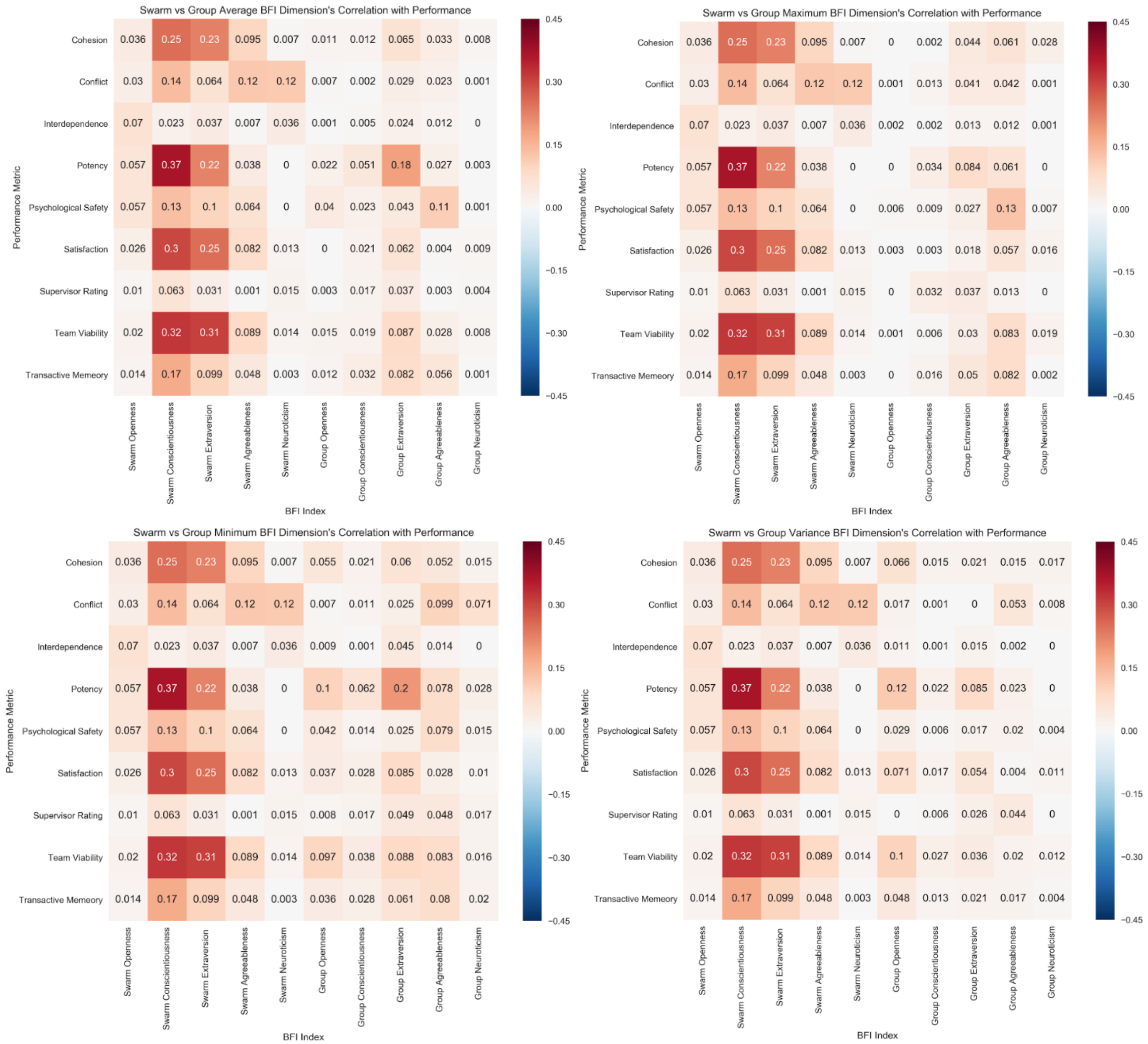

Figure A1: Swarm and Survey Correlation with Performance Metrics (Reported as R^2). From top left clockwise: Swarm vs Survey Average, Swarm vs Survey Maximum, Swarm vs Survey Minimum, Swarm vs Survey Variance

Appendix B: Bootstrapping Results

	Swarm R^2 - Survey Average R^2				
	Openness	Conscientiousness	Extraversion	Agreeableness	Neuroticism
Cohesiveness Task Attraction	-0.041:0.27	0.125:0.374	0.039:0.314	-0.062:0.171	-0.042:0.105
Interpersonal Cohesiveness	-0.06:0.091	0.074:0.341	0.065:0.381	-0.081:0.238	-0.067:0.108
Task Commitment	-0.037:0.137	0.139:0.432	0.021:0.263	-0.003:0.288	-0.067:0.081
Cohesiveness Total	-0.047:0.195	0.146:0.439	0.063:0.386	-0.043:0.258	-0.064:0.124
Relationship Conflict	-0.049:0.118	0.042:0.334	-0.051:0.09	-0.073:0.317	-0.017:0.293
Task Conflict	-0.09:0.068	0.006:0.233	-0.089:0.088	-0.01:0.177	0.0:0.21
Process Conflict	-0.041:0.125	0.007:0.233	-0.013:0.147	-0.064:0.228	-0.028:0.242
Conflict Total	-0.065:0.107	0.029:0.307	-0.051:0.123	-0.03:0.279	-0.002:0.286
Team Specialization	-0.104:0.111	-0.012:0.107	-0.128:0.086	-0.129:0.033	-0.081:0.043
Team Credibility	-0.057:0.085	0.037:0.263	-0.053:0.118	-0.157:0.083	-0.055:0.028
Team Coordination	-0.032:0.093	0.116:0.36	-0.094:0.114	-0.018:0.212	-0.031:0.183
Team Transactive Memory Total	-0.05:0.137	0.07:0.296	-0.105:0.136	-0.103:0.11	-0.049:0.053
Psychological Safety	-0.067:0.18	0.032:0.223	-0.031:0.161	-0.178:0.051	-0.027:0.04
Team Viability	-0.058:0.094	0.158:0.434	0.098:0.373	-0.048:0.199	-0.072:0.097
Team Satisfaction	-0.038:0.153	0.139:0.434	0.057:0.355	-0.01:0.257	-0.075:0.114
Team Potency	-0.055:0.18	0.206:0.477	-0.108:0.176	-0.049:0.113	-0.061:0.054
Team Effectiveness by Member	-0.015:0.225	0.174:0.455	-0.009:0.272	0.004:0.255	-0.05:0.069

Table B1: Bootstrapped difference in Pearson R values between the Swarm and the Survey Average methods of team personality assessments

	Swarm R2 - Survey Maximum R2				
	Openness	Conscientiousness	Extraversion	Agreeableness	Neuroticism
Cohesiveness Task Attraction	-0.001:0.317	0.132:0.421	0.062:0.344	-0.098:0.148	-0.077:0.088
Interpersonal Cohesiveness	-0.023:0.109	0.073:0.36	0.081:0.396	-0.121:0.179	-0.123:0.079
Task Commitment	-0.017:0.154	0.146:0.446	0.018:0.29	-0.029:0.261	-0.075:0.076
Cohesiveness Total	-0.008:0.217	0.142:0.467	0.074:0.401	-0.098:0.24	-0.089:0.094
Relationship Conflict	-0.038:0.128	0.046:0.312	-0.149:0.084	-0.061:0.308	-0.011:0.284
Task Conflict	-0.049:0.074	0.001:0.208	-0.072:0.126	-0.031:0.169	0.005:0.214
Process Conflict	-0.011:0.141	0.004:0.217	-0.076:0.164	-0.097:0.22	-0.004:0.237
Conflict Total	-0.027:0.104	0.027:0.28	-0.095:0.138	-0.071:0.265	0.006:0.289
Team Specialization	-0.041:0.159	-0.024:0.118	-0.126:0.117	-0.156:0.03	-0.121:0.043
Team Credibility	-0.025:0.081	0.043:0.285	-0.097:0.153	-0.195:0.064	-0.082:0.029
Team Coordination	-0.028:0.092	0.144:0.39	-0.067:0.191	-0.078:0.177	-0.032:0.18
Team Transactive Memory Total	-0.013:0.14	0.086:0.33	-0.105:0.187	-0.177:0.091	-0.044:0.065
Psychological Safety	-0.008:0.221	0.039:0.249	-0.036:0.173	-0.211:0.038	-0.046:0.038
Team Viability	-0.019:0.123	0.172:0.457	0.126:0.429	-0.098:0.159	-0.087:0.083
Team Satisfaction	-0.027:0.173	0.136:0.465	0.085:0.41	-0.078:0.171	-0.065:0.117
Team Potency	-0.009:0.207	0.202:0.505	-0.018:0.292	-0.103:0.09	-0.047:0.054
Team Effectiveness by Member	-0.036:0.213	0.168:0.476	0.02:0.324	-0.067:0.201	-0.052:0.076

Table B2: Bootstrapped difference in Pearson R values between the Swarm and the Survey Maximum methods of team personality assessments

	Swarm R^2 - Survey Minimum R^2				
	Openness	**Conscientiousness**	**Extraversion**	**Agreeableness**	**Neuroticism**
Cohesiveness Task Attraction	-0.072:0.24	0.112:0.362	0.035:0.33	-0.059:0.176	-0.079:0.071
Interpersonal Cohesiveness	-0.169:0.054	0.051:0.32	0.094:0.415	-0.118:0.192	-0.087:0.104
Task Commitment	-0.092:0.111	0.13:0.402	0.016:0.279	-0.056:0.245	-0.081:0.057
Cohesiveness Total	-0.109:0.125	0.121:0.414	0.059:0.387	-0.08:0.23	-0.089:0.094
Relationship Conflict	-0.083:0.094	0.033:0.334	-0.023:0.103	-0.102:0.28	-0.122:0.252
Task Conflict	-0.049:0.065	-0.006:0.227	-0.091:0.104	-0.171:0.099	-0.067:0.172
Process Conflict	-0.03:0.116	-0.012:0.222	-0.006:0.158	-0.134:0.191	-0.141:0.194
Conflict Total	-0.055:0.096	0.016:0.303	-0.04:0.136	-0.14:0.203	-0.122:0.234
Team Specialization	-0.109:0.119	-0.037:0.098	-0.129:0.052	-0.132:0.02	-0.068:0.046
Team Credibility	-0.108:0.049	0.046:0.285	0.004:0.185	-0.123:0.11	-0.157:0.025
Team Coordination	-0.069:0.078	0.095:0.343	-0.028:0.188	-0.127:0.128	-0.066:0.141
Team Transactive Memory Total	-0.104:0.112	0.066:0.289	-0.022:0.175	-0.156:0.086	-0.125:0.026
Psychological Safety	-0.067:0.198	0.024:0.231	0.015:0.195	-0.114:0.081	-0.099:0.024
Team Viability	-0.191:0.036	0.132:0.418	0.095:0.396	-0.16:0.162	-0.065:0.102
Team Satisfaction	-0.098:0.104	0.125:0.414	0.038:0.335	-0.077:0.214	-0.056:0.134
Team Potency	-0.147:0.101	0.192:0.444	-0.077:0.177	-0.163:0.071	-0.097:0.04
Team Effectiveness by Member	-0.092:0.15	0.112:0.391	-0.017:0.238	-0.133:0.177	-0.063:0.059

Table B3: Bootstrapped difference in Pearson R values between the Swarm and the Survey Minimum methods of team personality assessments

	Swarm R^2 - Survey Variance R^2				
	Openness	**Conscientiousness**	**Extraversion**	**Agreeableness**	**Neuroticism**
Cohesiveness Task Attraction	-0.079:0.254	0.111:0.395	0.052:0.395	-0.022:0.21	-0.06:0.092
Interpersonal Cohesiveness	-0.195:0.04	0.03:0.312	0.098:0.488	-0.062:0.229	-0.084:0.12
Task Commitment	-0.076:0.135	0.137:0.431	0.013:0.333	-0.002:0.305	-0.071:0.076
Cohesiveness Total	-0.111:0.152	0.124:0.431	0.067:0.465	-0.03:0.308	-0.073:0.101
Relationship Conflict	-0.114:0.091	0.04:0.352	-0.016:0.111	-0.083:0.301	-0.039:0.268
Task Conflict	-0.09:0.059	-0.005:0.236	-0.026:0.152	-0.115:0.133	0.009:0.21
Process Conflict	-0.024:0.129	0.003:0.263	0.0:0.185	-0.047:0.202	-0.008:0.248
Conflict Total	-0.07:0.096	0.022:0.319	-0.004:0.177	-0.075:0.248	-0.0:0.276
Team Specialization	-0.082:0.134	-0.056:0.114	-0.072:0.157	-0.051:0.064	-0.136:0.05
Team Credibility	-0.122:0.035	0.048:0.321	-0.007:0.203	-0.011:0.194	-0.099:0.021
Team Coordination	-0.114:0.064	0.113:0.394	-0.016:0.246	-0.054:0.186	-0.046:0.157
Team Transactive Memory Total	-0.11:0.09	0.07:0.343	-0.008:0.263	-0.044:0.17	-0.05:0.068
Psychological Safety	-0.052:0.216	0.022:0.251	-0.011:0.219	-0.028:0.165	-0.046:0.045
Team Viability	-0.202:0.058	0.127:0.448	0.093:0.46	-0.05:0.199	-0.063:0.101
Team Satisfaction	-0.127:0.087	0.117:0.446	0.022:0.396	-0.027:0.237	-0.045:0.14
Team Potency	-0.167:0.126	0.209:0.49	-0.015:0.342	-0.073:0.12	-0.053:0.047
Team Effectiveness by Member	-0.13:0.143	0.141:0.452	0.021:0.345	-0.036:0.254	-0.028:0.077

Table B4: Bootstrapped difference in Pearson R values between the Swarm and the Survey Variance methods of team personality assessments