Predicting group benefits in joint multiple object tracking

Short Title: Predicting group benefits

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Abstract

In everyday life, people often work together to accomplish a joint goal. Often in such tasks working together results in a higher performance compared to working alone – a so-called “group benefit”. While several factors influencing group benefits have already been investigated in a range of tasks, to date they have not been examined collectively with an integrative statistical approach such as linear modeling. To address this gap in the literature, we investigated several factors that are highly relevant for group benefits and used these factors as predictors in a linear model to predict group benefits. We found that predictors collectively account for half of the variance and make non-redundant contributions towards predicting group benefits, suggesting that they independently influence group benefits. The model also accurately predicts group benefits, suggesting that it could be used to predict group benefits for individuals that have not yet performed a joint task together. Given that the investigated factors are relevant for other joint tasks, our model provides a first step towards developing a more general model for predicting group benefits across several joint tasks.

Keywords: joint action; coordination; social cognition; multiple object tracking

Introduction

Many tasks of daily life require people working together. Common examples are preparing a meal, solving puzzles, searching people or objects, or carrying larger objects together. Often, in such tasks people attain a higher performance compared to performing the same task alone – a so-called “group benefit”. To date, several studies have investigated how group benefits come about in a wide range of joint tasks, and researchers have found a number of factors that influence whether group benefits are attained (or not) and also the extent of attained group benefits (for recent reviews, see Bang and Frith (2017); Wahn et al. (2018c)).

Two factors that have been shown to influence group performance across several joint tasks is the availability of information about other group member’s actions and performance feedback.

Regarding the former, receiving such action information has been shown to be beneficial to the group’s success in joint visual search tasks (Brennan et al., 2008; Wahn et al., 2020) and joint motor control tasks (Knoblich and Jordan, 2003) as such information can be used by group members to efficiently adapt to each other’s actions and thus facilitate interpersonal coordination. Regarding the latter, the availability of performance feedback has been shown to be critical for attaining a group benefit in a joint multiple object track (Wahn et al., 2017) and to boost already attained group benefits in a joint perceptual decision-making task (Bahrami et al., 2010) as group members tend to use the performance feedback to calibrate the accuracy of their performed actions.

Another often investigated factor is the degree to which group members perform similarly when performing the joint task alone (henceforth, "performance similarities"). Previous research on joint visual search (Wahn et al., 2018a), joint perceptual decision-making (Bahrami et al., 2010), and joint motor control (Wahn et al., 2016b) task has shown that performance similarities correlate positively with group performance.

If similar performance helps the group, then it is reasonable that social familiarity and personality traits relevant for social interactions (e.g., empathy) may also be beneficial. Indeed, previous research has found significant correlations between personality traits related to empathy, as assessed with the Interpersonal Reactivity Index (Davis et al., 1980), and joint performance (Ford and Aberdein, 2015; Czeszumski et al., 2019; Koban et al., 2012; Ruissen et al., 2018). However, the results for familiarity are more mixed. When comparing the joint performance of strangers and friends one study has reported a performance-enhancing effect of familiarity (Brennan and Enns, 2015a) while another has found no effects of familiarity (Ford and Aberdein, 2015).

In sum, several factors influencing group benefits have been investigated in a wide range of joint tasks. Yet, these factors have not been assessed simultaneously with a more integrative statistical approach. Such an approach, however, would be highly useful to address open questions with a

high theoretical as well as practical relevance. Linear modeling would represent such an integrative approach as it could go beyond the results provided by typical statistical analyses (e.g., ANOVAs) that often consider only a few factors at once. In particular, with linear modeling we can assess how much variance factors explain collectively and whether they are redundant or complementary in their influence on group benefits. Addressing these points would be informative with regard to whether factors actually reflect the same underlying mechanisms (i.e., are redundant in their influence on group benefits) or reflect different mechanisms (i.e., are complementary in their influence on group benefits). From a practical perspective, linear modeling can also be used to predict group benefits for group members who have not yet performed a task together. Addressing this point would help translate psychological research findings to more practical applications as such predictions have a high utility (e.g., they could be used to assemble more productive teams in real-life scenarios).

In the present study, we thus apply a linear modeling approach on our data from an extensive, eight experiment study, that examined the abovementioned factors' impact on group benefits (Wahn et al., 2021). In particular we assessed 1) how much variance factors explain collectively (**1st Modeling Objective**), 2) to what extent they are redundant or complementary in their explanatory power (**2nd Modeling Objective**), and 3) investigate the performance of the model in predicting group benefits on a separate test data set, which was not used when fitting the model, to assess the model's potential to predict future group benefits (**3rd Modeling Objective**).

Materials and methods

Participants

In eight experiments we collected data for 256 students (184 females, $M = 21.68$ years, $SD = 3.55$ years) at Osnabrück University and at the University of British Columbia. 32 students, grouped

in 16 pairs, participated in each experiment. Experiments 1, 3, 4, and 8 were conducted Osnabrück University and experiments 2, 5, 6, and 7 were conducted at University of British Columbia. We chose a sample size of 16 pairs for each experiment to equate the sample size to the sample sizes used in our previous studies on joint multiple object tracking (MOT) (Wahn et al., 2017; Wahn and Kingstone, 2020). We obtained written consent from all participants and they received credits or money for their participation.

Experimental setup

Each participant of a pair sat in front of a separate 24" monitor (screen resolution 1920 x 1020, refresh rate: 60 Hz) at a distance of 90 cm, wearing ear muffs. Each participant had a separate keyboard and computer mouse within easy reach. Participants sat at least 1.5 meters apart from each other and the monitor of each participant was concealed from the other participant by a divider.

Experimental procedure

Across our eight experiments we systematically varied the availability of individual performance feedback, team performance feedback, and information about the other pair member's target selections in a MOT task. The procedure for all experiments was the same except for the information that was received by the participants at the end of each trial.

In each trial participants were shown 19 white objects (0.56 visual degrees radius) in randomly selected positions for 2 seconds. Six objects (henceforth, referred to as "targets") then turned gray for 2 seconds. Objects then reverted to white again and commenced moving in random directions. The movement speed of each object was randomly chosen and varied between 0.90 and 1.21 visual degrees per second. While moving, objects repelled each other or the screen border in a physically plausible way (i.e., the angle of incidence was the same as the angle of reflection).

Participants were required to track the movements of the targets. After 11 seconds, the objects stopped moving and each participant was required to select the objects that they thought were the targets with the computer mouse. Participants were allowed to select as many objects as they wanted. After both participants confirmed their selections, depending on the experiment, participants would then either receive no information (Experiment 1), individual performance scores (Experiment 2), the team score (Experiment 3), selection information which objects were chosen by the other group member (Experiment 4), both the individual scores and team score (Experiment 5), the selection information and individual scores (Experiment 6), the selection information and the team score (Experiment 7), or all types of information (individual scores, team score, & selection information; Experiment 8; see Fig. 1 for an example trial).

Prior to the experiment, participants were first verbally instructed by the experimenter about the task procedure and were shown an example trial. Participants were also informed that each correct selection would add one point to their individual performance and each incorrect selection would deduct one point from their individual performance. Moreover, participants were informed that we would also keep track of a team performance score that combines the respective individual performance scores. For this team performance, an overlapping correct and incorrect selection only adds or deducts one point from their team performance. To give an example, in Fig. 1, the participant and the partner each made three correct selections, resulting in 3 points each for both participants (see Me and Partner in E). However, given that one selection was overlapping, the team score only results in 5 points (see Team in E). For all experiments, participants were instructed to maximize the team score.

In each experiment, participants performed 100 trials, which took about 1 hour to complete. All experiments were programmed in Python 2.7.3.

After the experiment was completed, participants were asked to fill out two questionnaires. The first questionnaire required a participant’s demographic data and asked how well they knew their partner on a 5-point scale (1 = “not at all”, 5 = “very well”). The second questionnaire was the interpersonal reactivity index questionnaire by Davis et al. (1980), which includes four major

Figure 1: **Example trial from the perspective of one participant.** (A) Object presentation: 19 white objects in randomly selected positions were shown for 2 seconds. (B) Target indication: Six target objects turned gray for 2 seconds. (C) Object Movements: Objects reverted to all look white again and commenced moving in random directions for 11 seconds. (D) Target selections: Participants selected the objects that they thought were the targets with the computer mouse. Participants were allowed to select as many objects as they wanted and confirmed their selections by clicking on the central dot. There was no time limit. (E) Selection information: Participants saw the selections by the other group member. Overlapping selections were shown in both colors. (F) Performance feedback: Participants saw individual performance scores of themselves (Me), the other group member (Partner), and the team performance score (Team). Note, presentations in E and F had no time limit and participants could move to the next screen by pressing space. Presentations for all experiments are the same for A - D but differ for parts E and F. In particular, in Experiment 1 (No Information), participants did not see the information given in E and F. In Experiment 2 (Individual Scores), participants only saw the individual scores given in F. In Experiment 3 (Team Score), participants only saw the team score given in F. In Experiment 4 (Selections), participants only saw the selection information given in E. In Experiment 5 (Team Score + Individual Scores), participants only saw the performance feedback given in F. In Experiment 6, participants saw the selection information given in E and only the individual scores given in F. In Experiment 7, participants saw the selection information given in E and only the team score given in F. In Experiment 8, participants saw all types of information (E & F).

factors (7 items rated on a 5-point Likert scale per factor). These factors are: 1) Fantasy items: A tendency to identify with conceived characters (e.g., from movies or books), 2) Perspective-taking items: A tendency to adopt the view of other people, 3) Empathic concern items: A tendency to feel compassion/concern for others with negative experiences, and 4) Personal distress items: A tendency to feel discomfort/anxiety when witnessing negative experiences of others.

Methods of data analysis

Dependent variables

As the dependent variables for our linear models, we will use two commonly used criteria of group benefits – the collective benefit (Bahrami et al., 2010; Wahn et al., 2018a) and the collaborative benefit (Brennan and Enns, 2015b; Wahn et al., 2017) criterion. The collective benefit criterion is used to assess whether a group benefit is attained at all and the collaborative benefit criterion is used to assess whether a group benefit is attained due to a collaboration (i.e., group members devised a division of labor strategy). Using two criteria has been shown to be necessary for the MOT task given that a collective benefit can be attained without any collaboration (Wahn et al., 2021). That is, the mere statistical facilitation of working on the same task has been shown to be sufficient for attaining a collective benefit but not sufficient to attain a collaborative benefit (Wahn et al., 2021). In other words, if group members independently pick their targets in the MOT task (i.e., without following a labor division strategy), the overlap between target selections is still sufficiently low to attain a collective benefit.

A collective benefit is attained by a group if it outperforms its best member’s individual performance. As in our earlier studies (Wahn et al., 2017; Wahn and Kingstone, 2020), we computed this criterion by dividing the pair’s team performance by the better member’s performance for each trial. If this ratio is above one, a pair attained a collective benefit for a given trial. We then applied a moving average window (size 20 trials) to the data of each pair, extracted the peak value, and used this measure as our dependent variable in our linear models.

A collaborative benefit is attained by a group if it outperforms a simulated group performance of group members that do not collaborate (i.e., divide the labor). We simulated this hypothetical performance by randomly distributing the hits and false alarms for each group member in a given trial and calculating the resulting team score. We repeated this procedure a 1000 times for each trial and computed the average team score. The reasoning for this procedure is that we assume

that object selections of group members will not be systematically related to each other. They only would be related to each other if group members collaborate by dividing the labor (e.g., one member tracks the leftmost and the other member tracks the rightmost targets). In earlier studies we found that such a simulation approximates the team score of group members of a non-collaborative group accurately (Wahn et al., 2017, 2018a, 2021). As for the collective benefit, we again computed ratios by dividing the actual team score for each trial by the simulated team score. A ratio of above one would indicate whether a collaborative benefit is attained or not. We again applied a moving average window (size 20 trials) to the data of each pair, extracted the peak value, and used this measure as our dependent variable in our linear models.

As in our earlier studies (Wahn et al., 2017, 2020, 2021), to assess the degree of collaboration between group members, we also calculated for each trial the fraction of overlapping selections (henceforth, referred to as “overlap”) between group members (i.e., divided the number of selections that both group members selected by the total number of selections). We will use the overlap as another predictor in our models.

As a point of note, in our earlier paper (Wahn et al., 2021) we analyzed the collective and collaborative benefit ratios, the overlap, and whether group members collaborated or not. If group members collaborated, we also analyzed how they collaborated. To briefly summarize these earlier results, we found that groups can already attain a collective benefit without receiving any information (Experiment 1: No Information) or only receiving the individual scores (Experiment 2: Individual Scores). A collaborative benefit is attained if participants receive feedback about their team performance (Experiment 3: Team Score & Experiment 5: Team Score + Individual Scores) or each other’s actions (Experiment 4: Selections). In these experiments, group members devised division of labor strategies. If both types of information are received (Experiment 7: Team Score + Selections & Experiment 8: Team Score + Individual Scores + Selections), groups are faster in creating efficient labor divisions. To create labor divisions, group members used the screen center as a reference to divide the labor into a left and right side such that one group member tracks the left targets and the other group member tracks the right targets.

Results: Modeling and predicting group benefits

Collective benefits

We first test how much variance is explained by our experimental manipulations (**1st Modeling Objective**) and assess the degree to which they are redundant or complementary in their explanatory power (**2nd Modeling Objective**). For the step-wise multiple regression, we thus included all factors that varied across experiments (i.e., the availability of the target selections of co-actors, the team performance feedback, and individual performance feedback) as categorical predictors (henceforth referred to as “experimental factors”). The different experiments were translated into three categorical predictors for the model (see Fig. 2, for an overview). We found that the multiple regression including our experimental factors was significant ($F(3,120) = 12.85$, $p < .001$), explaining 24% of the variance (see Table 1 column “Model 1” for an overview and Fig. 3). Comparing the normalized regression weights of our predictors (all variables were z-scored prior to running the model), we find that only the weights for the Team Score and Selections are significant predictors and similar in size; whereas the Individual Scores predictor is not significant. These results suggest that the type of information group members receive already accounts for about one quarter of the variance and that this variance is primarily explained by the Team Score and Selections predictors. When adding all possible interaction effects between our experimental factors as predictors to the regression and running a model comparison, we found that they did not significantly explain additional variance ($F(4,116) = 1.71$, $p < .153$).

Expanding our multiple regression further, in a second step, we added the performance similarities as another predictor to the model. As noted in the introduction, earlier studies (Bahrami et al., 2010; Wahn et al., 2016b, 2018a) have found that the similarities between individuals’ performances correlate with the extent of an attained group benefit in several joint tasks (i.e., the higher the similarities between the individual performances, the higher the collective benefit). This predictor was computed by dividing the better individual’s mean

Table 1: Collective benefit step-wise regression results. Standardized regression weights are shown for each predictor along with the standard errors in brackets, separately for each regression step.

	Model 1	Model 2	Model 3	Model 4
Intercept	−0.00 (0.08)	−0.00 (0.07)	−0.00 (0.07)	−0.00 (0.05)
Individual Scores	−0.04 (0.08)	−0.02 (0.07)	0.00 (0.07)	0.07 (0.05)
Team Score	0.33*** (0.08)	0.33*** (0.07)	0.30*** (0.07)	0.02 (0.06)
Selections	0.36*** (0.08)	0.35*** (0.07)	0.38*** (0.07)	0.13* (0.06)
Performance Similarities		−0.39*** (0.07)	−0.39*** (0.07)	−0.32*** (0.05)
Empathic Concern (mean)			0.03 (0.07)	0.02 (0.05)
Empathic Concern (difference)			−0.11 (0.07)	−0.02 (0.06)
Personal Distress (mean)			−0.14 (0.07)	−0.08 (0.05)
Personal Distress (difference)			−0.20** (0.07)	−0.08 (0.06)
Overlap				−0.65*** (0.07)
R ²	.24	.39	.47	.71
Adj. R ²	.22	.37	.44	.68
Pairs	124	124	124	124

*** $p < .001$, ** $p < .01$, * $p < .05$

		Categorical predictors		
Experiments		Individual Scores	Team Score	Selections
	Experiment 1: No information	0	0	0
	Experiment 2: Individual Scores	1	0	0
	Experiment 3: Team Score	0	1	0
	Experiment 4: Team Score + Individual Scores	1	1	0
	Experiment 5: Selections	0	0	1
	Experiment 6: Individual Scores + Selections	1	0	1
	Experiment 7: Team Score + Selections	0	1	1
	Experiment 8: Team Score + Individual Scores + Selections	1	1	1

Figure 2: **Overview how the experiments are translated into three categorical predictors for our linear regression models to predict group benefits.**

performance (across trials) by the worse individual’s mean performance (across trials) for each pair. We find that this addition is significant ($F(1,119) = 29.51$ $p < .001$) and that this predictor explains an additional 15% of the variance (total: variance explained: 39%, see Table 1 column “Model 2” for an overview). These results suggest that performance similarities are also a predictor of collective benefits in the current joint task, and that this predictor explains additional variance on top of the variance explained by the other predictors already included in the model (i.e., it is not redundant to the other predictors).

Next, we assessed whether the four factors of the interpersonal reactivity index questionnaire (Davis et al., 1980) and participants’ rating how well they know each other may explain additional variance. Prior to including the interpersonal reactivity index factors, we assessed their

Figure 3: **Collective benefit step-wise regression results.** The variance explained (in %) is shown as a function of the models and their relative increase in explained variance (in green).

internal consistency by computing Cronbach's alpha for the items of each factor. We found that the computed Cronbach's alphas are high and in a similar range (.71 - .78; Fantasy items: .75; Perspective-taking items: .78; Empathic Concern items: .76; Personal Distress Items: .71) to those obtained by Davis et al. (1980) (.68 - .79). For each set of items of each dimension, we reversed the inverted items and then added up the ratings to obtain scores for each questionnaire dimension. As a point of note, for four pairs the questionnaire data were incomplete or missing (1 in Experiment 4; 1 in Experiment 6; 2 in Experiment 8). We did not include these four pairs for all regressions to make model comparisons possible for all our analyses.

Given that our regression predicts collective benefits for *pairs* while questionnaires were filled out by each *individual* participant, we included two predictors for each questionnaire dimension of the interpersonal reactivity index questionnaire to avoid a potential loss of information by averaging

scores across the ratings of group members. One predictor was the mean score for each pair, and the other predictor was the absolute difference between the two scores for each pair. We added these two predictors for each questionnaire dimension separately to the model and tested for each of these additions whether they significantly explain additional variance when comparing models. We found a significant effect only for the empathic concern ($F(2,117) = 3.09$, $p = .049$, additional variance explained: 3%) and personal distress scores ($F(2,117) = 7.44$, $p < .001$, additional variance explained: 7%).

Adding both these sets of predictors simultaneously to the model resulted in an 8% increase of explained variance (total: variance explained: 47%, see Table 1 column “Model 3” for an overview). These results suggest that the empathic concern and personal distress scores explain additional non-redundant variance in collective benefits. When inspecting the regression weights for this model, the only significant predictor is the personal distress difference score predictor. Given that this regression weight is negative, our findings suggest that the lower the difference between personal distress scores, the higher the collective benefit.

Up to this point, all predictors included in the model could in principle be known before group members actually perform the MOT task together. Specifically, one could know in advance an individual’s solo tracking performance, their interpersonal reactivity index questionnaire results, and what type of information they will receive when they are teamed up with another participant. Hence, the current regression model could potentially be used to *predict* the extent of collective benefits of group members *before* they actually perform the MOT task together (**3rd Modeling Objective**). To test how well our regression model can predict collective benefits, or, in other words, how well it generalizes to unseen data, we performed a cross validation approach. We repeatedly fitted the model with one pair left out of the dataset and used the fitted regression weights to predict the extent of the collective benefit of the excluded pair. To assess the prediction error, we computed the root-mean-square error (RMSE) for each excluded pair. As a point of note, standard deviations is the unit of this error measure as all the data are z-scored. We find a RMSE of 0.79 for our cross validated data, which is an error increase of only 9% compared to the RMSE of 0.72, which we obtain if the model fitting procedure includes all pairs.

These results suggest that the model generalizes well to unseen data.

In a final modeling step, we included the overlap as a measure of the collaboration between group members as another predictor in the model. This enables us to assess the predictors in the model that are redundant with regard to a direct measure of the collaboration in the MOT task (i.e., how well co-actors divided the labor) (**2nd Modeling Objective**). We find that the overlap explains an additional 24% of the variance in the data ($F(1,114) = 90.55, p < .001$) (total: variance explained: 71%, see Table 1 column “Model 4” for an overview). We also observe that the regression weights of our experimental factors are considerably reduced after adding the overlap predictor, suggesting that these predictors are redundant with regard to a direct measure of the collaboration between co-actors.

To summarize, our multiple regression model including several predictors of collective benefits explains about half of the variance in the data (**1st Modeling Objective**) and contains non-redundant predictors (**2nd Modeling Objective**). Moreover, the model generalizes well and likely could be used to also accurately predict future collective benefits (**3rd Modeling Objective**).

Collaborative benefits

We repeated the above regression analyses to assess how the contributions of our predictors anticipate collaborative benefits compared to collective benefits. When again first including only our experimental factors, we again find a significant effect ($F(3,120) = 23.06, p < .001$). Specifically, it explains 37% of the variance, which is 13% more than the 24% explained in the initial collective benefit model. Comparing the normalized regression weights of our predictors (see Table 2 column “Model 1” for an overview and Figure 4), we find that the team score and selection predictors have high weights and are both significant. When adding all possible interaction effects between these factors as predictors to the model, we find that these additions are significant ($F(4,116) = 2.57, p = .04$). When extending this model with the performance

similarities predictor, we find that this addition is not significant ($F(1,115) = 0.77, p = .38$). With regard to the predictors from our questionnaire, we only find that adding the personal distress scores results in a significant addition ($F(2,118) = 4.65, p = .01$; all other $ps > .11$).

Figure 4: **Collaborative benefit step-wise regression results.** The variance explained (in %) is shown as a function of the models and their relative increase in explained variance (in green).

We performed the same cross validation approach as above also for this model including the categorical predictors (and their interactions) and the personal distress predictors. To assess the prediction error, we again computed the RMSE for each left out pair. We found a RMSE of 0.79, which is an increase of about 9% compared to the RMSE of 0.72 obtained if the model includes all pairs. These results suggest that this model also generalizes well to unseen data (i.e., could potentially be used to predict future collaborative benefits).

In a final modeling step, we again added the overlap measure as a predictor to the model, and found that this addition is significant ($F(1,113) = 220.16, p < .001$), explaining an additional

Table 2: Collaborative benefit step-wise regression results. Standardized regression weights are shown for each predictor along with the standard errors in brackets, separately for each model.

	Model 1	Model 2	Model 3	Model 4
Intercept	0.00 (0.07)	-0.00 (0.07)	-0.00 (0.07)	0.00 (0.04)
Individual Scores	-0.06 (0.07)	-0.06 (0.07)	-0.04 (0.07)	0.04 (0.04)
Team Score	0.44*** (0.07)	0.44*** (0.07)	0.43*** (0.07)	0.07 (0.05)
Selections	0.41*** (0.07)	0.41*** (0.07)	0.43*** (0.07)	0.12* (0.05)
Individual Scores x Team Score		0.00 (0.07)	-0.03 (0.07)	-0.01 (0.04)
Individual Scores x Selections		-0.02 (0.07)	-0.02 (0.07)	0.03 (0.04)
Team Score x Selections		-0.23** (0.07)	-0.22** (0.07)	-0.09* (0.04)
Individual Score x Team Score x Selections		0.03 (0.07)	0.02 (0.07)	0.02 (0.04)
Personal Distress (mean)			-0.14* (0.07)	-0.07 (0.04)
Personal Distress (difference)			-0.16* (0.07)	0.00 (0.04)
Overlap				-0.80*** (0.05)
R ²	0.37	0.42	0.46	0.82
Adj. R ²	0.35	0.38	0.42	0.80
Pairs	124	124	124	124

*** $p < .001$, ** $p < .01$, * $p < .05$

36% of the variance (total: variance explained: 81%, see Table 2 column “Model 2” for an overview). We also found that the regression weights of our experimental factors are reduced, suggesting that they are redundant with respect to the added overlap predictor.

Overall, we find a similar pattern of results as above when predicting the collective benefits. Again, our experimental factors make major contributions towards explaining variance also for the collaborative benefit (**1st Modeling Objective**). When expanding the model, the performance similarities predictor is now redundant with regard to our experimental factors. The personal distress questionnaire predictor, however, still explains additional variance (**2nd Modeling Objective**). Again, the model again generalizes well to unseen data (**3rd Modeling Objective**).

Discussion

In this paper, we addressed three modeling objectives. We assessed 1) how much variance factors explain collectively (**1st Modeling Objective**), 2) to what extent they are redundant or complementary in their explanatory power (**2nd Modeling Objective**), and 3) the performance of the model in predicting group benefits on a separate test data set, which was not used during model fit, to assess the model’s potential to predict future group benefits (**3rd Modeling Objective**)

For the first and second objective, we find that several predictors (i.e., our experimental factors, performance similarities, questionnaire data) make non-redundant contributions, collectively explaining about half of the variance. These regression models only included predictors that could be measured *prior* to performance. This allowed us to also test the usefulness of our models to predict future group benefits by applying a leave-one-out cross-validation approach (3rd modeling objective). We found that the models predict the left-out data accurately. In the following, we discuss each of our modeling findings in more detail.

In our models, we first added the experimental factors alone (i.e., the different types of information received by the group members depending on the experiment) and found that they already explain sizeable portions of the variance, with significant contributions from both selection information and team performance feedback predictors. These findings suggest that the availability of these types of information independently influence group benefits, supporting the view that they are particularly important for group benefits in joint spatial tasks (Brennan et al., 2008; Wahn et al., 2020).

When extending the models with the performance similarities predictor, we found that this predictor significantly explains additional variance. These findings suggest that this predictor accounts for a complementary set of variance relative to the performance feedback and selection information. We thus suggest that it likely accounts for variance in group benefits related to the individual performance capabilities, which are independent of the co-actors’ abilities to

collaborate with each other. Adding the performance similarities predictor to the collaborative benefit model, however, did not significantly increased the explained variance. To explain this difference in our results between our two models, we suggest that the simulated independent performance used to assess collaborative benefits may already account for the similarities in the individual performances. That is, given that the simulated independent performance is based on repeatedly sampling trials from the individual selections of both group members, differences in the individual performances were likely already incorporated when assessing collaborative benefits.

When further extending our models by adding predictors from our empathy questionnaires (Davis et al., 1980) to our models, we found that adding personal distress scores led to significant increases in the explained variance, indicating that this predictor also explains additional non-redundant variance. These personal distress scores have been interpreted as a measure of feeling discomfort or anxiety when witnessing negative experiences of others (Davis et al., 1980). When interpreting the regression weights, our findings suggest that the more similar personal distress scores are, the higher the group benefit. Our findings thus suggest that members with more similar personal distress scores may more easily converge on an effective collaboration strategy, resulting in higher group benefits. Yet, we acknowledge that this interpretation is speculative and given that we had no concrete hypothesis or prediction with regard to our questionnaire predictors, we suggest that further studies are needed to confirm whether personal distress scores reliably contribute towards predicting group benefits.

After adding the predictors described above, we also tested how well the models generalize to data that is not part of the model fitting procedure. That is, we tested how well the models would predict group benefits for group members prior to performing the MOT task together. We found that the prediction error was only marginally increased for data that was not part of the fitting procedure. Thus, the collective and collaborative benefit models have potential to also predict future group benefits. These findings suggest that such models may prove to have a high utility as they could also be used to specifically assemble individuals in teams that are predicted to perform well together. Future studies could expand on the list of predictors relevant to group benefits to further improve such predictive models. For instance, other potential predictors could

be physiological measures relevant to attentional selection such as event related potentials (Drew et al., 2009; Sternsheim et al., 2011) or pupil size (Wahn et al., 2016a) as a correlate of attentional effort.

In a final modeling step, we also included the overlap measure – a direct measure of the collaboration between group members in the MOT task – to assess which predictors are redundant with regard to this variable. We found that the regression weights of our categorical predictors representing our different experimental manipulations were considerably reduced, suggesting that these factors are redundant with regard to the overlap measure, and thus directly related to co-actors’ collaborative behavior. With regard to devising a model that can predict future group benefits, these results suggest that a direct measure of the actual collaboration between group members can at least in part be replaced by predictors indicating which information group members will receive when working together. In other words, one can predict, to a degree, how well the group members will collaborate based on the information that the group members will receive.

Finally, a critical and open question for future investigations is whether the same or a similar set of predictors as used in the present study would also predict group benefits in other joint tasks. We already partially addressed this question in a different study when we applied a regression model with a similar set of predictors to a joint visual search task and found comparable results (Wahn et al., 2020). This suggests that at least for spatial joint tasks a similar set of predictors is highly relevant for predicting group benefits. With regard to other tasks, previous research on joint motor control tasks found that performance similarities are a predictor of group benefits (Wahn et al., 2016b) and that the availability of selection information is highly important for coordination (Knoblich and Jordan, 2003). These findings suggest that a similar model as used in the present study may also predict group benefits in joint motor control tasks (for a recent review on group benefits in joint motor tasks, see Wahn et al. (2018b)). Apart from joint motor control tasks, the present set of predictors could also be applied, for instance, to joint memory tasks. In joint memory tasks (for general reviews, see Bietti and Sutton (2015); Rajaram and Pereira-Pasarin (2010)), in which co-actors need to jointly memorize a list of words, there are a

number of similarities between such a task setting and the present joint MOT task. For instance, co-actors may divide the labor by having each co-actor memorize a complementary subset of words and differences in the individual abilities to memorize words may also influence the extent of group benefits. Ultimately, testing whether the set of predictors used in the present study also predicts group benefits in other joint tasks could lead to constructing a more general model for the prediction of group benefits across many different types of joint tasks. This would not only enable researchers to extract commonalities and differences in the factors, which are relevant to group benefits for different joint tasks, but also help to predict future group benefits using one general model for several joint tasks.

Open Practices Statement:

The study has not been pre-registered. All data is available in the following repository:

https://osf.io/ve6fh/?view_only=caea135057634a6a84e9f95bcf846a4b. Experimental code and analysis scripts are available on request.

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