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# Goal-based action generalization does not increase incrementally with action prevalence: Evidence from event-related potentials and behavior

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ABSTRACT

Humans often rely on social group information to anticipate others' actions. While prior research suggests that group members' goals can be generalized to new individuals, it remains unclear whether this process scales incrementally with observed evidence or is constrained by prior beliefs. Across two experiments, we combined behavioral and EEG measures to examine whether the prevalence of observed actions enhances goal-directed actions generalization. In Experiment 1, participants observed animated groups performing goal-directed actions toward different targets while EEG was recorded. Both behavioral facilitation effects and contingent negative variation (CNV) amplitudes revealed stronger goal-based expectations for a group member when the group pursued a shared goal (i.e., high prevalence); medium and low prevalence conditions did not differ. Such a nongraded pattern indicates that statistical evidence is not the only factor shaping goal-based action generalization. In contrast, Experiment 2 showed that movement-based action generalization increases in a graded manner with action prevalence, highlighting the specific deviation from a graded pattern in goal-based action generalization. Together, these findings provide convergent behavioral and neural evidence that goal-based action generalization cannot be explained entirely by statistical evidence, but is instead constrained by shared-goal beliefs, underscoring the role of group-related beliefs in action prediction.

## 1. Introduction

Humans, as inherently social beings, are constantly engaged in interpersonal interactions (Miller, 2001). Effective social interactions require not only understanding others' actions but also anticipating and predicting their future behavior (Hauser and Wood, 2010; Quesque and Rossetti, 2020). Individuals often rely on cues or information, such as movement direction and goal states, to form expectations about others' actions (Ding et al., 2017; Quesque and Rossetti, 2020). However, the actions of an individual are often situated within a social group context. In many cases, observers lack specific knowledge about a person, making it difficult to anticipate their behaviors (Scott, 2017). As a result, they commonly rely on the individual's social group and use group information to guide their expectations (Vijayakumar et al., 2021).

Group information prompts social categorization (Gordon et al., 2020), leading individuals to view members of a social group not as distinct entities but as part of a shared category. This categorization fosters the perception that group members share attributes, creating expectations of similar behaviors among them (Duan et al., 2021; Yin et al., 2023). This phenomenon, known as action generalization within groups, involves extending the behaviors of familiar group members to those who have not yet been encountered. Such tendencies are not limited to adults but begin to emerge as early as infancy (Liberman et al., 2017; Rhodes and Chalik, 2013). Recent research offers clear support for action generalization within groups. Specifically, participants responded more quickly to actions aligned with the behaviors of two ingroup members than to actions that were inconsistent, reflecting their expectations of similar behaviors within the group (Duan et al., 2021; Xu et al., 2019). For object-directed actions, where the action goal (e.g., the target approached) as well as movement (e.g., the manner of reaching the goal) could be generalized, people generalize the underlying goals rather than the surface-level movements within group members, showing goal-based action generalization (Yin et al., 2022, 2023). Importantly, generalization arises from observing multiple group members engage in similar actions, not from repeated actions of a single person, highlighting the role of social groups in shaping evidence

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selection for action generalization.

As an instance of inductive generalization, the degree to which actions are generalized within social groups is generally shaped by how prevalent relevant behaviors are observed among group members (Hayes et al., 2019; Tentori et al., 2016). For instance, the likelihood of generalizing an action, such as choosing an apple instead of a banana, should theoretically correspond to the proportion of group members exhibiting that behavior. This suggests a graded (or monotonic[1]) relationship: as the prevalence with which a given action occurs increases, so should the extent to which it is generalized to others, which was confirmed by recent findings (Duan et al., 2021; Hu et al., 2023). However, beyond statistical evidence, people rely on prior knowledge or beliefs about the properties being generalized, reflecting a form of top-down modulation (Boyer, 2018; Shutts and Kalish, 2021). Recent findings suggest that group-related beliefs about shared goals—rooted in the social imperative for cooperative actions—play a significant role in shaping generalization (Brewer et al., 2004; Noyes and Keil, 2020; Sheikh and Hirschfeld, 2019). Thus, goal-based action generalization may be constrained by these shared-goal beliefs rather than strictly following statistical evidence, resulting in a nongraded relationship between action prevalence and generalization.

Preliminary evidence supports the above claim (Hu et al., 2023), showing that goal generalization to a new group member occurs only when all observed members display consistent goal-directed behavior. This finding indicates that the relationship between action prevalence and goal-based action generalization departs from strict monotonicity, instead exhibiting a nongraded pattern. The study utilized computer animations to simulate group actions and reaction times to assess goal-based action generalization. Specifically, when all group members are oriented toward a specific goal, participants expect a new group member to pursue this consistent goal, as reflected in a significantly faster recognition of their behavior compared to when the new member pursues an inconsistent goal (i.e., facilitation effect). This effect appears only when the goal is entirely consistent across all samples and does not show a monotonic increase in the effect with increasing goal prevalence. However, the measurement with reaction time in Hu et al. (2023) may not accurately capture goal-based action generalization, as it likely involves multiple cognitive processes. For instance, as observed in repetition priming (Race et al., 2010), encountering the same stimuli multiple times—such as observing known group members' actions—could lead to habituation, improving the representation of specific action features. This refinement may facilitate responses to group-consistent actions without necessarily reflecting genuine generalization. Thus, additional evidence is required to confirm the nongraded relationship between action prevalence and goal-based action generalization.

Hence, the present study investigated the issue using reaction times and event-related potentials (ERPs), which possess temporal resolution at the millisecond scale and are well-suited for monitoring neural activity associated with specific events (Luck, 2014). Among ERPs, the contingent negative variation (CNV) is closely linked to anticipatory attention, motivation, and action preparation, making it a key indicator for cognitive expectation (Gómez et al., 2007). The CNV typically increases in the thalamo-cortico-striatal areas showing increased activity about 300–450 ms after the event begins. Furthermore, amplitudes increase when definite expectations are established, relative to situations in which the expectations remain uncertain (Pfeuty et al., 2005; Mento, 2017). If individuals implicitly depend on shared goals for action generalization, when a novel agent belongs to the same group as previously observed members and a common goal is present, participants would be expected to form clear predictions about that agent's behavior; accordingly, the CNV component—associated with cognitive expectation, is expected to exhibit a larger amplitude compared to situations where group members pursue different goals. Additionally, based on Hu et al. (2023), we anticipated the behavioral facilitation effect to manifest, but, significantly, only for group members pursue the same goal (not pursue a different goal).

Based on the above discussion, two experiments were performed. First, we used reaction times and CNV to assess whether the goal-based action generalization among group members exhibits a nongraded relationship with statistical evidence (Experiment 1). To further investigate whether this relationship is specific to action goals, we established action generalization among group members based on the action movements (Experiment 2).

## 2. Experiment 1

During the experiment, animated videos were displayed to participants, depicting two groups of agents engaging in synchronized movement, after which four ingroup agents sequentially demonstrated goal-directed actions toward one of two targets (an apple or a banana). The prevalence of these goal-directed actions varied across three levels: low, medium, and high. After the demonstration phase, the two targets exchanged positions, and a novel agent included within the same group acted to approach a target. During the action-expectation phase, the novel agent paused at the lower center of the screen while participants implicitly formed expectations about its upcoming behavior. Finally, this agent moved toward either the majority goal (consistent condition) or the minority goal (inconsistent condition), with participants tasked to rapidly identify the target approached by the agent. If participants expect group members to share common goals, they should exhibit faster responses when the new agent approaches the majority goal (consistent condition) compared to the minority goal (inconsistent condition). This facilitation effect is expected to emerge only in the high prevalence condition, in which all demonstrators converge on the same goal. Moreover, the CNV amplitude during the action-expectation phase is predicted to be greater in the high prevalence condition than in the medium and low prevalence conditions, where no such effect is expected. This pattern would reflect a nongraded relationship with statistical evidence, indicating that goal-based action generalization depends on the perception of a common group goal rather than the mere accumulation of goal prevalence.

### 2.1. Methods

Thirty compensated participants were recruited (17 males and 13 females; mean age 22 years, range 17–31 years). Participants were in good neurological health and exhibited vision that was normal or appropriately corrected. Two additional participants were tested but not included because of excessive motion-related noise. The determination of the sample size was guided by specific considerations. Given that the primary inquiry focused on whether the action generalization effect (i.e., facilitation effect) depended on prevalence, a statistical power analysis was run via the G*Power package (version 3.1; Faul et al., 2009). Sample size was determined based on a medium effect ($\eta_p^2 = 0.06$), $\alpha = 0.05$, and power $= 0.80$, for three within-subject levels of prevalence. The analysis suggested at least 28 participants. To address the expected variability in EEG measurements, we conservatively retained 30 participants. This chosen sample size aligns with the sample used in a prior study using comparable procedures to assess action expectations, albeit exclusively relying on behavioral measurements (Hu et al., 2023).

This study received approval from the Research Ethics Committee of the Department of Psychology at Ningbo University and conducted in compliance with applicable ethical standards and regulations. All

[1] We define "graded relationship/generalization" as a strictly monotonic association between how prevalent actions are observed and the degree of generalization. If the generalization pattern levels off or does not increase with rising prevalence, we describe this as a deviation from graded generalization, sometimes "nongraded" for brevity.

participants gave written informed consent in accordance with the Declaration of Helsinki prior to the commencement of any study procedures. Experiment designs were not preregistered. Data, analysis code, and supplementary videos are publicly accessible via OSF at https://osf.io/pnkmh/?view_only=b43a60e0b1354fb2ad0e3b24cd2ca3bc.

### 2.1.1. Apparatus and stimuli

The experimental stimuli were rendered on a 15.6-in. LCD monitor (LED-backlit; resolution: 1920 × 1080; refresh rate: 120 Hz) with a gray background, positioned 60 cm from participants. Presentation was implemented through Python-based custom software employing PsychoPy libraries.

The visual stimuli comprised computer-animated events generated using the open-free software Blender 2.81a. The events presented two groups of visually distinct cartoon agents and two targets (an apple and a banana). The agents were chosen at random from a pool of six animated figures characterized by unique distinctive geometric forms and colors. Each character was designed to include a pair of eyes functioning as primary facial cues, subtending dimensions of 1.5° × 1.5°.

### 2.1.2. Procedure and design

At the beginning of each trial, a fixation cross (1.5° × 1.5°) appeared at the screen center for 500 ms. Following this, two groups of agents were presented, with each group containing five members. At trial onset, agents belonging to each group were presented in close proximity within the two upper corners of the screen. Following this initial arrangement, the agents engaged in a synchronized series of movements along a circular trajectory lasting 830 ms (refer to Fig. 1 and supplementary videos; "Introducing social groups"). Following the introductory phase, all agents were displayed ascending to the platforms' upper surface. Four ingroup agents, serving as demonstrative examples, then followed a prescribed order from the center to the periphery, sequentially executing goal-directed actions. This entire sequence spanned 6200 ms (shown in Fig. 1; "Group members' actions"). In particular, each agent first descended to the bottom area of the display. Subsequently, the agent oriented itself either leftward or rightward—counterbalanced across participants, to approach one of the two objects designated as targets. The agent then moved back to its original location. The apple and banana were positioned in the bottom-left and bottom-right regions of the display, with their locations balanced among different participants.

Following this, the two targets were covered by a plate, after which the objects exchanged locations. This stage, labeled as "Plate loading" in Fig. 1, was presented for a duration of 600 ms. Following this, a new agent positioned at the outermost location replicated the initial actions of the exemplars. But, when this agent reached the lower section of the screen, it came to a halt, and a black question mark was presented above the agent, remaining visible for 1000 ms (refer to Fig. 1; "Action expectation"). The question mark served as an implicit cue for participants to anticipate the upcoming action, but no overt response was required during this interval. At the end, the final agent resumed movement toward an object positioned on either side of the display. After 750 ms, this agent reached the target object. Participants were instructed to make rapid and accurate responses about the agent's movement, pressing the 'F' key if the agent approached the left object and the 'J' key if it approached the right object (see Fig. 1; "Response"). When participants failed to make a response in 1000 ms, the trial proceeded automatically.

The study used within-subjects design incorporating two variables: goal prevalence and goal consistency. Goal prevalence, referring to the extent to which exemplars approached an identical target, and was manipulated at three levels: low, medium and high. *Low prevalence* was defined as a scenario where two exemplars approached one target, and two exemplars approached the other target. *Medium prevalence* occurred when three exemplars approached a target, with the remaining one approaching the other target. *High prevalence* was characterized by all exemplars converging on the same target. Goal consistency indicated whether the last agent's approached target aligned with the prevalent goal and consisted of two levels: consistent and inconsistent. For the low-prevalence manipulation, the prevalent goal was randomly chosen prior to the experimental session, as no specific target consistently served as the dominant goal. Since the locations of the two targets were swapped prior to response collection, a participant's accurate goal identification corresponded to what would be classified as an inconsistent movement, and conversely. Consequently, the experimental design followed a 3 × 2 repeated-measures framework, crossing prevalence (low, medium, high) with goal consistency (consistent vs. inconsistent) as within-subject variables. The videos showing how each condition is designed in all experiments can be accessed at https://osf.io/pnkmh/?view_only=b43a60e0b1354fb2ad0e3b24cd2ca3bc.

Within each experiment, the design included six experimental conditions formed by crossing prevalence with consistency. Each condition contained 40 trials, producing an overall total of 240 trials for the 3 × 2 repeated-measures design. Within each condition, two spatial factors were counterbalanced: (a) the initial position of the exemplar group, namely whether the group whose members performed the demonstrated actions appeared on the left or right side of the display; and (b) the location of the target approached by the majority of the first four agents, namely whether the majority-approached target was located on the left or right side of the display. Thus, there were four possible spatial combinations, and each combination appeared equally often, with 10 trials per combination within each condition. In addition, the initial spatial positions of the two target objects, namely the apple and banana, were counterbalanced across participants. To enhance the manipulation of social groups, 12 additional trials featuring an outgroup-identified agent were included as filling trials, emphasizing the presence of social groups but were not subjected to analysis. Consequently, each participant completed a total of 252 trials. To mitigate the potential impact of the presentation order of deviants (i.e., how the minority was presented), the exemplars deviating from the majority were randomly determined. Before the formal task began, participants completed at least two minutes of practice. A break was provided after every 50 trials, and the full experiment was completed within a 55-min timeframe for each participant.

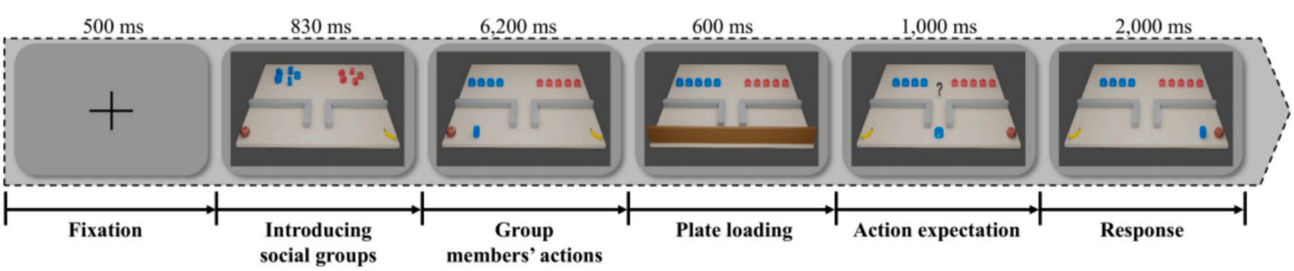


**Fig. 1.** Representative sequences of trials used in Experiment 1. The CNV was evaluated in the action-expectation phase, and reaction time was recorded in the response phase.

### 2.1.3. EEG recordings and analyses

Continuous EEG was recorded using 64 electrodes (actiCAP) in combination with an actiCHamp Plus amplifier (Brain Products GmbH, Gilching, Germany), sampled at 500 Hz and low-pass filtered at 200 Hz. The EEG data were first recorded with a TP9 (left mastoid) reference and later offline re-referenced to the mean of the two mastoid electrodes, TP9 and TP10. Interelectrode impedances remained below 10 kΩ.

Processing and analysis of EEG data were conducted with MATLAB (R2025a) and the EEGLAB toolbox (v2025; Delorme and Makeig, 2004). EEG signals were offline filtered using a 0.1–50 Hz band-pass finite impulse response (FIR) filter. The filter was implemented with the fir1 method in EEGLAB and applied using EEGLAB's two-way FIR filtering procedure. The filter order was not manually specified and therefore followed EEGLAB's default setting, corresponding to a filter length of 15,000 points at the 500-Hz sampling rate. Because the transition bandwidth was not manually specified, the roll-off characteristics were determined by EEGLAB's default fir1 implementation. Epochs with accurate behavioral performance were chosen for subsequent analyses. Epochs were defined to start 0.2 s before the action-expectation phase onset, prior to the new agent performing the goal-directed action, and this period served as the baseline. The epoch extended until 1 s following the action-expectation phase, resulting in an overall duration of 2.2 s. This period allowed for the examination of different expectations and their corresponding contingent negative variation (CNV) amplitudes. Subsequently, independent component analysis (ICA) was performed to identify and remove artifacts such as eye movements and muscle activity. Artifacts resulting from eye movements and blinks were identified using an automated procedure with the ADJUST toolbox (v1.1.1; Mognon et al., 2011), manually inspected to ensure accuracy, and then excluded from the EEG recordings. To ensure data quality, additional rejection procedures targeted epochs containing excessive activity, identified as amplitudes greater than 1000 μV or probability scores more than 5 SD above the mean. In Experiment 1, this procedure rejected, on average, 4 trials in the low prevalence condition, 4 trials in the medium prevalence condition, and 5 trials in the high prevalence condition. In Experiment 2, the corresponding averages were 5 trials in the low prevalence condition, 4 trials in the medium prevalence condition, and 5 trials in the high prevalence condition. Finally, averaged event-related potentials (ERPs) were averaged across trials for three prevalence conditions. Notably, when computing ERPs for the action-expectation phase, the factor of goal consistency was not included, as it only became significant during the response phase.

The CNV has been observed to exhibit a more pronounced presence at frontal electrodes compared to other electrode locations. It is particularly prominent within a time interval of roughly 500–1000 ms after the event. Accordingly, the CNV was calculated by averaging the activity across frontal, frontocentral, and central electrodes (F1, F2, Fz, FC1, FC2, FCz, Cz, C1, and C2) during the interval between 500 and 1000 ms

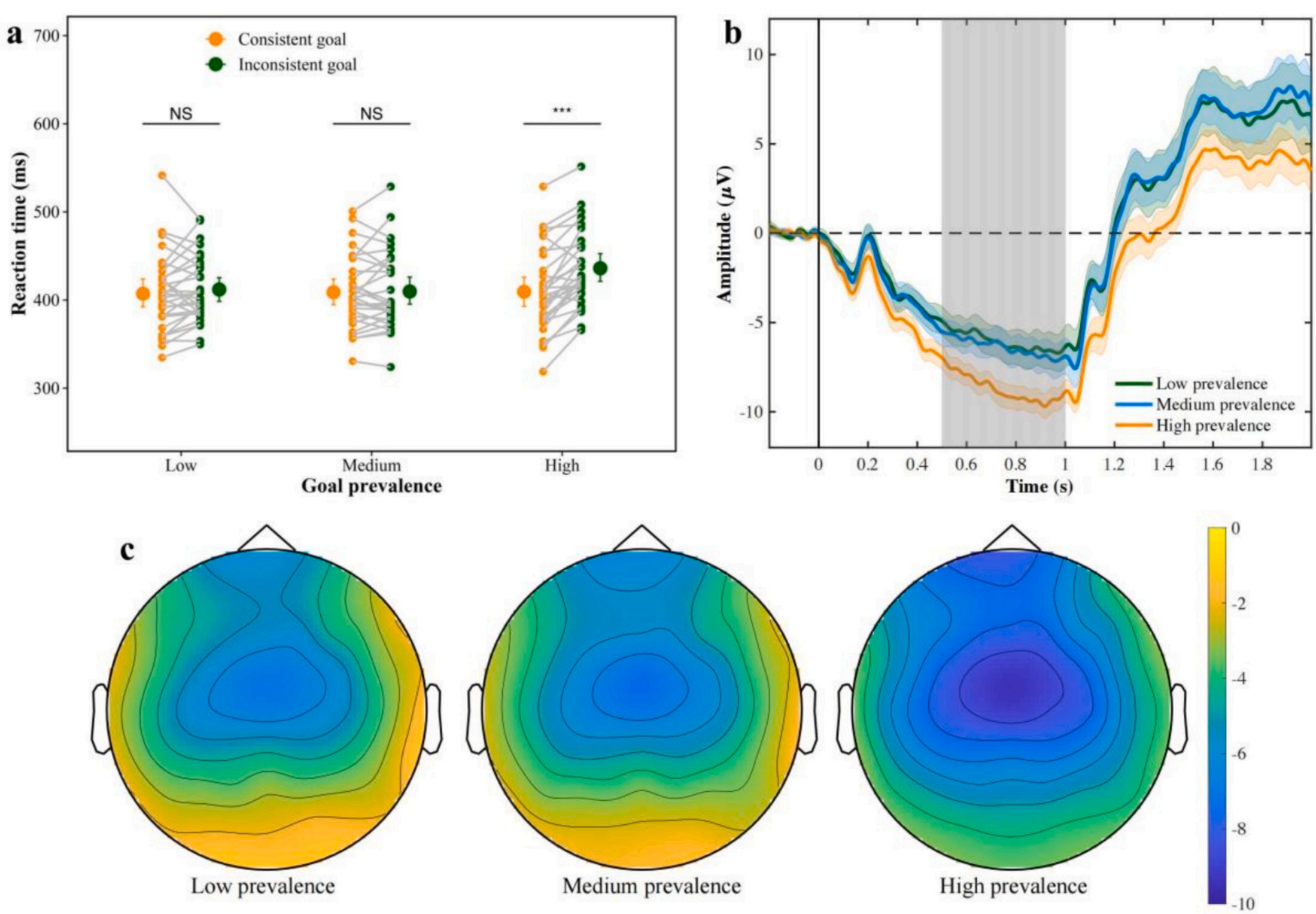


**Fig. 2.** Results of behavioral performance and ERP analyses in Experiment 1. (a) Mean reaction time (RT) for correct trials depending on both prevalence and goal consistency. Each small dot represents the mean RT of an individual participant in a specific condition, with connected lines indicating data from the same participant. Large circles denote the average RT for each group within each condition, while black vertical lines represent the 95% bootstrapping confidence intervals (CIs) of these means. (b) The averaged ERPs for the three prevalence conditions, derived by averaging activity across electrodes of interest. The gray-masked time windows highlight periods where significant differences in amplitude were observed across conditions. (c) The spatial distribution of the averaged CNV amplitude across the scalp for each prevalence condition within the time window spanning from 500 ms to 1000 ms.

in the goal prevalence condition.

Statistical analyses were conducted in R version 4.5.1 (R Core Team, 2025), with the packages bruceR (version 2025.8; Bao, 2025), lme4 (version 1.1.37; Bates et al., 2015), and ggplot2 (version 4.0.1; Wickham, 2016).

### 2.2. Results and discussion

#### 2.2.1. Behavioral results in the response phase

The primary focus of the analyses centered on the RT data, given its emphasis on participant reaction times and relevance to our hypothesis. The average RT for each participant under each condition (refer to Fig. 2a) was calculated by omitting incorrect trials, resulting in an exclusion rate of 2.58%. A repeated-measures ANOVA was conducted on the RTs, incorporating a 3-level factor of prevalence (low, medium, high) and a 2-level factor of goal consistency (consistent, inconsistent). For all repeated-measures ANOVAs reported below, the sphericity assumption was assessed using Mauchly's test for effects involving factors with more than two levels. When sphericity was violated, Greenhouse–Geisser corrections were applied to adjust the degrees of freedom (the uncorrected degrees of freedom were presented for simplicity); post hoc tests were corrected using Holm's procedure. A significant effect of prevalence was observed ($F(2, 58) = 21.85$, $p < 0.001$, $\eta_p^2 = 0.430$, 95% CI of $\eta_p^2 = [0.264, 0.552]$), showing that participants exhibited slower responses under the high prevalence condition ($M = 423$ ms, $SE = 8$) compared to medium ($M = 409$ ms, $SE = 8$; $t(29) = 5.31$, $p < 0.001$, Cohen's $d = 0.659$, 95% CI of Cohen's $d = [0.344, 0.974]$) and low ($M = 410$ ms, $SE = 7$; $t(29) = 5.17$, $p < 0.001$, Cohen's $d = 0.645$, 95% CI of Cohen's $d = [0.328, 0.962]$). However, the comparison between medium and low prevalence conditions showed no significant difference ($t(29) = -0.16$, $p = 0.876$, Cohen's $d = -0.014$, 95% CI of Cohen's $d = [-0.241, 0.212]$). Moreover, goal consistency exerted a significant effect ($F(1, 29) = 17.41$, $p < 0.001$, $\eta_p^2 = 0.375$, 95% CI of $\eta_p^2 = [0.151, 0.555]$); participants were quicker in the consistent condition ($M = 408$ ms, $SE = 8$) relative to the inconsistent condition ($M = 419$ ms, $SE = 7$). Furthermore, the two factors showed a significant interaction effect ($F(2, 58) = 13.96$, $p < 0.001$, $\eta_p^2 = 0.325$, 95% CI of $\eta_p^2 = [0.159, 0.459]$).

Simple effects analysis showed that under the high prevalence condition, participants were significantly quicker to respond when agents followed a consistent goal ($M = 409$ ms, $SE = 9$) compared to an inconsistent goal ($M = 436$ ms, $SE = 8$; $t(29) = -6.56$, $p < 0.001$, Cohen's $d = -1.308$, 95% CI of Cohen's $d = [-1.716, -0.901]$). This facilitation effect, termed the "goal-based action generalization effect," was calculated separately for each prevalence condition by subtracting the mean RT in the consistent condition from the mean RT in the inconsistent condition, with larger positive values indicating stronger goal-based action generalization. Notably, this facilitation effect did not emerge under the medium prevalence condition (consistent goal: $M = 409$ ms, $SE = 8$; inconsistent goal: $M = 410$ ms, $SE = 8$; $t(29) = -0.25$, $p = 0.803$, Cohen's $d = -0.043$, 95% CI of Cohen's $d = [-0.392, 0.306]$), or in the low prevalence condition (consistent goal: $M = 407$ ms, $SE = 8$; inconsistent goal: $M = 412$ ms, $SE = 7$; $t(29) = -1.10$, $p = 0.284$, Cohen's $d = -0.234$, 95% CI of Cohen's $d = [-0.672, 0.204]$). Furthermore, pairwise comparisons showed that the facilitation effect under high prevalence ($M = 27$ ms, $SE = 4$) exceeded that observed in both medium ($M = 1$ ms, $SE = 3$; $t(29) = 4.73$, $p < 0.001$, Cohen's $d = 0.863$, 95% CI of Cohen's $d = [0.489, 1.236]$) and low ($M = 5$ ms, $SE = 4$; $t(29) = 4.39$, $p < 0.001$, Cohen's $d = 0.801$, 95% CI of Cohen's $d = [0.427, 1.174]$) prevalence. Interestingly, comparisons between medium and low prevalence conditions revealed no significant statistical difference ($t(29) = -0.73$, $p = 0.471$, Cohen's $d = -0.133$, 95% CI of Cohen's $d = [-0.507, 0.240]$). Hence, the effect of goal prevalence on goal-based action generalization does not follow strict monotonicity, and this property is generalized to an unknown agent who shares group membership with the exemplars only when all sampled agents have a common goal, supporting the hypothesis that goal-based action generalization is constrained by the group-related belief about sharing a goal.

Accuracy was defined as the ratio of correct responses (see Table 1). Because accuracy was not the primary dependent variable, the accuracy analysis was conducted mainly to examine whether the RT results could be explained by a potential speed–accuracy trade-off. Similar to the analysis of reaction times, a repeated-measures ANOVA was conducted on the accuracy data. Only the main effect of prevalence was significant ($F(2, 58) = 3.30$, $p = 0.044$, $\eta_p^2 = 0.102$, 95% CI of $\eta_p^2 = [0.002, 0.224]$), showing that participants demonstrated higher accuracy in the medium prevalence condition ($M = 0.981$, $SE = 0.006$) compared to the high prevalence condition ($M = 0.968$, $SE = 0.008$; $t(29) = 2.98$, $p = 0.017$, Cohen's $d = 0.370$, 95% CI of Cohen's $d = [0.054, 0.685]$), and no other significant differences were observed between conditions ($ps > 0.330$, Cohen's $d < 0.200$). Notably, neither the main effect of goal consistency ($F(1, 29) < 0.01$, $p = 0.907$, $\eta_p^2 < 0.001$, 95% CI of $\eta_p^2 = [0.000, 0.041]$) nor the interaction between prevalence and goal consistency ($F(2, 58) = 2.10$, $p = 0.131$, $\eta_p^2 = 0.068$, 95% CI of $\eta_p^2 = [0.000, 0.177]$) reached significance. We reanalyzed the trial-level accuracy data using logistic mixed-effects models with a binomial distribution and logit link function, which yielded a pattern consistent with the original ANOVA results (see the Supplementary Material). Thus, the RT facilitation effect observed in the high-prevalence condition was not accompanied by reduced accuracy, providing no evidence for a speed–accuracy trade-off.

#### 2.2.2. ERP results in the action-expectation phase

To investigate the impact of prevalence on the CNV within the expectation phase, we performed a repeated-measures ANOVA compared the mean CNV amplitudes across prevalence conditions. We observed a statistically significant impact of prevalence ($F(2, 58) = 3.46$, $p = 0.038$, $\eta_p^2 = 0.107$, 95% CI of $\eta_p^2 = [0.003, 0.230]$). In addition, point-by-point repeated-measures $F$ analyses were conducted using the FieldTrip toolbox (version 20,210,122) within the predefined 500–1000 ms CNV window after averaging the signal across the electrodes of interest. Bonferroni correction was applied to the statistical comparisons within this predefined interval. These tests revealed significant differences in CNV amplitudes across all three prevalence conditions within the gray-highlighted period shown in Fig. 2b ($ps < 0.050$). Post hoc contrasts further demonstrated that participants under the high prevalence condition ($M = -8.71$ μV, $SE = 0.60$) exhibited a significantly greater CNV response compared to both the medium prevalence condition ($M = -6.38$ μV, $SE = 0.81$; $t(29) = 2.68$, $p = 0.036$, Cohen's $d = 0.490$, 95% CI of Cohen's $d = [0.116, 0.863]$) and the low prevalence condition ($M = -6.07$ μV, $SE = 0.89$; $t(29) = 2.48$, $p = 0.038$, Cohen's $d = 0.454$, 95% CI of Cohen's $d = [0.080, 0.827]$). No statistically meaningful difference emerged between the medium and low prevalence conditions ($t(29) = 0.37$, $p = 0.712$, Cohen's $d = 0.068$, 95% CI of Cohen's $d = [-0.305, 0.441]$).

## 3. Experiment 2

Findings from Experiment 1 indicate that goal-based action generalization exhibits a nongraded pattern, as facilitation effects were observed only under high prevalence condition. This raises the question of whether this nongraded pattern is specific—that is, whether it is limited to goal representations or also applies to movement-based action generalization within a group. To investigate this, Experiment 2 modified the movements of agents: when approaching an external target, target information was replaced by action movements information, and the efficiency of the agents' movements was manipulated (jumping vs. straight). If participants expect group members to generalize actions in a graded manner, then when a new group member carries out a movement matching the majority (consistent condition), their reaction times should be faster than when the agent carries out a movement matching the minority (inconsistent condition). This facilitation effect was expected primarily under high and medium prevalence conditions. Furthermore, during the action-expectation phase, the CNV amplitude

**Table 1**
Accuracy in each condition across all experiments.

| | Experiment 1 (goal) | | | Experiment 2 (movement) | | |
|---|---|---|---|---|---|---|
| | Low prevalence | Medium prevalence | High prevalence | Low prevalence | Medium prevalence | High prevalence |
| Consistent | 0.970 (0.010) | 0.980 (0.006) | 0.972 (0.008) | 0.953 (0.008) | 0.957 (0.006) | 0.960 (0.007) |
| Inconsistent | 0.978 (0.008) | 0.982 (0.007) | 0.964 (0.010) | 0.965 (0.005) | 0.965 (0.006) | 0.959 (0.008) |

Note. Results are shown as mean (standard error; SE).

was expected to be larger under high prevalence condition than under medium and low conditions, and larger under medium than low condition. These results indicate that movement-based action generalization exhibits a graded increasing pattern, thereby supporting the specificity of the nongraded pattern observed in goal-based action generalization.

### 3.1. Methods

Thirty compensated participants were recruited (16 males and 14 females; mean age 22 years, range 19–25 years). Two individuals were excluded due to excessive movement artifacts. Given that the current experiment's design closely resembled Experiment 1, with the difference being the replacement of expected content with action movements, the same sample size of 30 participants was employed for this experiment.

The stimuli and procedures closely followed those of Experiment 1, with the following exceptions. During the “Group members' actions” phase, exemplars initially moved downward to the bottom of the display before turning left or right (counterbalanced across participants) toward one of two target objects. Two movement types were employed: an inefficient “jumping” movement or an efficient “straight” movement. After reaching the object, the exemplar returned to its starting point using a straight movement. The jumping movement commenced approximately 45 milliseconds after the turn and reached its peak at approximately 210 milliseconds. While the horizontal velocity of the jumping movement matched that of the straight movement, the target was reached 750 milliseconds after the turn for both types of movements. This implementation would make the reaction times in this experiment longer compared to Experiment 1, as movement discrimination would not be possible until later in the animations. This display

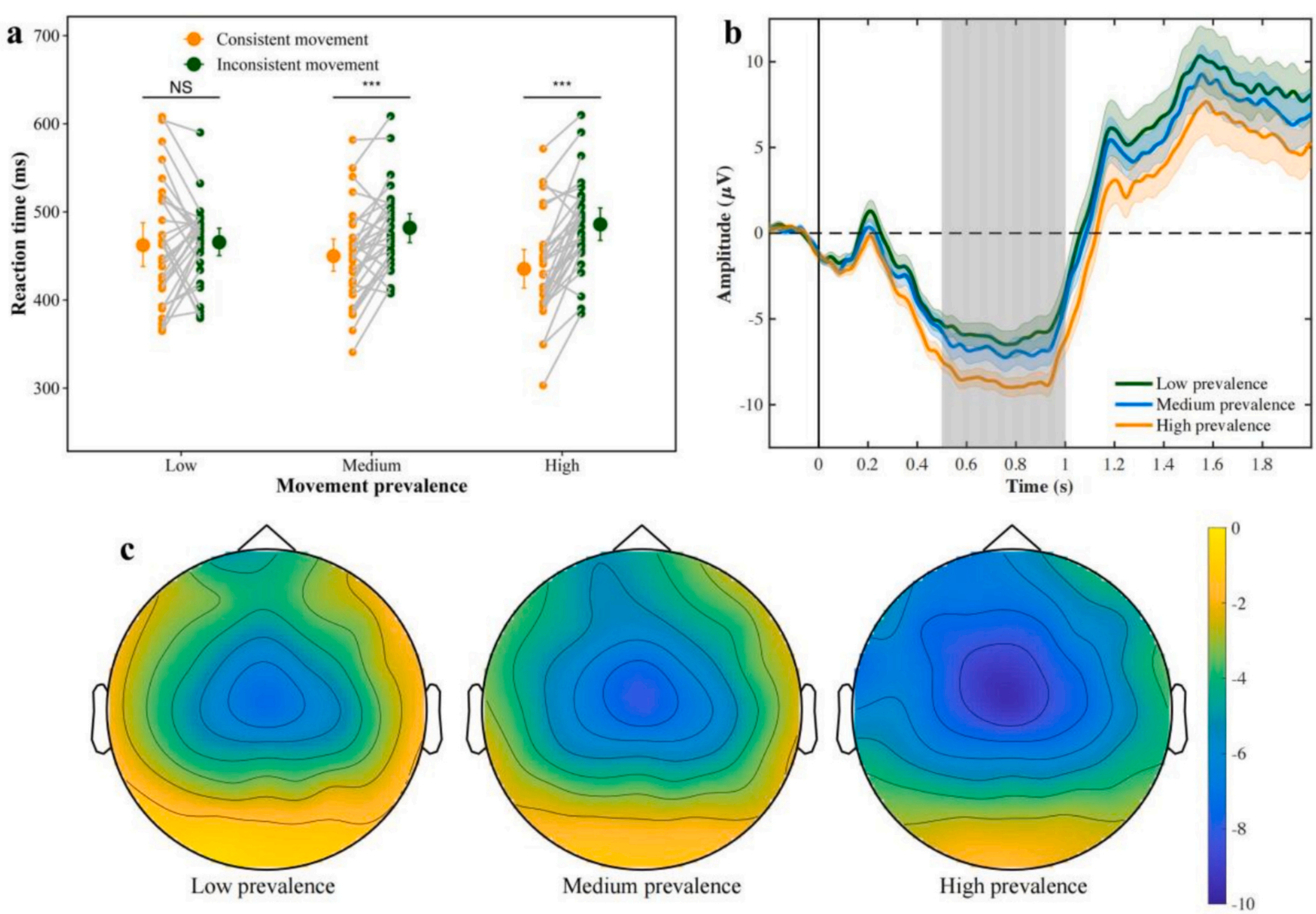


**Fig. 3.** Results of behavioral performance and ERP analyses in Experiment 2. (a) Mean reaction time (RT) for correct trials depending on both prevalence and movement consistency. Each small dot represents the mean RT of an individual participant in a specific condition, with connected lines indicating data from the same participant. Large circles denote the average RT for each group within each condition, while black vertical lines represent the 95% bootstrapping confidence intervals (CIs) of these means. (b) The averaged ERPs for the three prevalence conditions, derived by averaging activity across electrodes of interest. The gray-masked time windows highlight periods where significant differences in amplitude were observed across conditions. (c) The spatial distribution of the averaged CNV amplitude across the scalp for each prevalence condition within the time window spanning from 500 ms to 1000 ms.

was intentional because the response-relevant information in Experiment 2 was movement form rather than action goal. The final agent's left/right orientation indicated only the trajectory along which the action would unfold and did not indicate whether the upcoming movement would be straight or jumping. This procedure followed the logic of previous studies using similar animated action-generalization paradigms (Yin et al., 2022; Yin et al., 2023; Hu et al., 2023).

Based on the movement choices of four exemplars, three movement-based prevalence conditions were created: *low prevalence* (two exemplars jumped, two went straight), *medium prevalence* (three exemplars jumped, one went straight), and *high prevalence* (all exemplars jumped). Participants judged whether the identified agent moved straight or performed a jump, responding with “F” or “J,” respectively. The identified agent then performed the selected movement, which was either consistent with the majority (except in the low prevalence condition, where the agent's movement was randomly chosen) or inconsistent. Therefore, this experiment employed a 3 (prevalence: low vs. medium vs. high) × 2 (movement consistency: consistent vs. inconsistent) repeated-measures design.

### 3.2. Results and discussion

#### 3.2.1. Behavioral results in the response phase

Fig. 3a presents the average RTs across conditions, excluding incorrect trials (exclusion rate = 4.01%). Using repeated-measures ANOVA, we observed a significant main effect of movement consistency ($F(1, 29) = 25.01$, $p < 0.001$, $\eta_p^2 = 0.463$, 95% CI of $\eta_p^2 = [0.237, 0.624]$), demonstrating that participants responded more quickly when the agent's movement was consistent with the majority ($M = 449$ ms, $SE = 11$) compared to inconsistent ($M = 478$ ms, $SE = 8$). The main effect of prevalence was not significant ($F(2, 58) = 1.33$, $p = 0.273$, $\eta_p^2 = 0.044$, 95% CI of $\eta_p^2 = [0.000, 0.139]$). However, prevalence and movement consistency significantly interacted ($F(2, 58) = 8.88$, $p < 0.001$, $\eta_p^2 = 0.234$, 95% CI of $\eta_p^2 = [0.081, 0.372]$).

Analysis of simple effects indicated that, under high prevalence, participants responded more slowly when agents performed an inconsistent movement ($M = 486$ ms, $SE = 9$) than when they performed a consistent movement ($M = 435$ ms, $SE = 11$; $t(29) = 7.03$, $p < 0.001$, Cohen's $d = 1.257$, 95% CI of Cohen's $d = [0.891, 1.622]$), as well as in the medium prevalence condition (inconsistent movement: $M = 482$ ms, $SE = 9$; consistent movement: $M = 450$ ms, $SE = 10$; $t(29) = 4.61$, $p < 0.001$, Cohen's $d = 0.796$, 95% CI of Cohen's $d = [0.443, 1.150]$). However, this facilitation effect was absent under the low prevalence condition (inconsistent movement: $M = 466$ ms, $SE = 8$; consistent movement: $M = 462$ ms, $SE = 13$; $t(29) = 0.30$, $p = 0.766$, Cohen's $d = 0.084$, 95% CI of Cohen's $d = [-0.487, 0.654]$). Furthermore, pairwise comparisons showed that the facilitation observed under high prevalence ($M = 51$ ms, $SE = 7$) exceeded the facilitation under both medium ($M = 32$ ms, $SE = 7$; $t(29) = 2.74$, $p = 0.021$, Cohen's $d = 0.500$, 95% CI of Cohen's $d = [0.126, 0.873]$) and low ($M = 3$ ms, $SE = 11$; $t(29) = 3.78$, $p = 0.002$, Cohen's $d = 0.689$, 95% CI of Cohen's $d = [0.316, 1.063]$) prevalence, and facilitation under medium prevalence exceeded that observed under low prevalence ($t(29) = 2.14$, $p = 0.041$, Cohen's $d = 0.390$, 95% CI of Cohen's $d = [0.017, 0.764]$).

The repeated-measures ANOVA on the accuracy data indicated that only movement consistency produced a significant main effect ($F(1, 29) = 4.76$, $p = 0.037$, $\eta_p^2 = 0.141$, 95% CI of $\eta_p^2 = [0.005, 0.441]$), showing that participants' accuracy was lower in the consistent condition ($M = 0.957$, $SE = 0.005$) than in the inconsistent condition ($M = 0.963$, $SE = 0.004$). Notably, neither the main effect of prevalence ($F(2, 58) = 0.04$, $p = 0.960$, $\eta_p^2 < 0.001$, 95% CI of $\eta_p^2 = [0.000, 0.000]$) nor the interaction between prevalence and movement consistency ($F(2, 58) = 0.60$, $p = 0.554$, $\eta_p^2 = 0.020$, 95% CI of $\eta_p^2 = [0.000, 0.091]$) reached significance. The logistic mixed-effects analyses yielded a pattern consistent with the original ANOVA results and provided no evidence for a speed–accuracy trade-off (see the Supplementary Material).

#### 3.2.2. ERP results in the action-expectation phase

Similar with Experiment 1, we performed a repeated-measures ANOVA compared the mean CNV amplitudes across prevalence conditions. Results indicated a significant effect of prevalence ($F(2, 58) = 9.82$, $p < 0.001$, $\eta_p^2 = 0.253$, 95% CI of $\eta_p^2 = [0.096, 0.391]$). Similar with Experiment 1, point-by-point repeated-measures $F$ analyses revealed significant differences in CNV amplitudes across all three prevalence conditions within the gray-masked time window in Fig. 3b ($ps < 0.050$). Post hoc contrasts further revealed that the high prevalence condition ($M = -8.44$ μV, $SE = 0.49$) elicited a significantly greater CNV response compared to both the medium prevalence condition ($M = -6.65$ μV, $SE = 0.76$; $t(29) = 2.39$, $p = 0.048$, Cohen's $d = 0.435$, 95% CI of Cohen's $d = [0.062, 0.809]$) and the low prevalence condition ($M = -5.82$ μV, $SE = 0.74$; $t(29) = 4.20$, $p < 0.001$, Cohen's $d = 0.767$, 95% CI of Cohen's $d = [0.393, 1.140]$). Moreover, CNV amplitude under medium prevalence exceeded that observed under low prevalence ($t(29) = 2.19$, $p = 0.048$, Cohen's $d = 0.400$, 95% CI of Cohen's $d = [0.027, 0.774]$).

## 4. General discussion

The present study investigated whether goal-based action generalization increases incrementally with rising action prevalence, using both the behavioral facilitation effect and the CNV component. Experiment 1 demonstrated that behavioral facilitation effect was greater in the high prevalence condition compared with medium and low conditions, which did not differ, and the expectation-related CNV exhibited a similar trend. The present results indicate that goal-based action generalization follows a nongraded pattern relative to statistical evidence. In contrast, Experiment 2 showed that both the behavioral facilitation effect and CNV amplitude were largest in the high prevalence condition, intermediate in the medium prevalence condition, and smallest in the low prevalence condition. Thus, movement-based action generalization increased in a graded manner with observed evidence, underscoring the specificity of the nongraded pattern observed in goal-based action generalization.

Conceptually, the nongraded pattern observed in Experiment 1 is more consistent with a categorical-like interpretation than with a purely linear accumulation of statistical evidence. This interpretation was further supported by the further model-comparison analyses, which showed that the behavioral and electrophysiological patterns in Experiment 1 were better characterized by a high prevalence driven nongraded model than by a graded linear model (see Supplementary Material, Table S3). Participants may have treated the high prevalence condition, in which all observed group members pursued the same goal, as qualitatively distinct from the low and medium prevalence conditions. The high prevalence condition may have supported the representation of the group as having a shared goal, whereas the low and medium prevalence conditions may have indicated that the group goal was ambiguous or not fully shared. Thus, the low and medium prevalence conditions may not simply have functioned as weaker versions of the high prevalence condition; rather, they may have fallen into a different psychological category in which a shared goal was not sufficiently established. We use the term categorical-like cautiously, because the present findings support a high prevalence driven nongraded pattern but do not establish a strict categorical or all-or-none mechanism.

The present findings align with prior research demonstrating that people generalize the behaviors of familiar group members to unfamiliar members of the same group (Sheehy-Skeffington and Thomsen, 2023; Yin et al., 2023). This study further replicated goal-based action generalization, measured via behavioral facilitation effects, and demonstrated that such generalization follows a nongraded pattern with increasing statistical evidence of prevalent actions (Hu et al., 2023). Crucially, this conclusion was supported by CNV data, which capture neural activity underlying action expectations and complement behavioral judgments (Gómez et al., 2007; Mento, 2017). Together, these results suggest that people do not rely solely on evidence strength to generalize actions across group members; rather, top-down knowledge constrains this process. Consistent with prior accounts (Cimpian et al., 2010; Hayes and Heit, 2018; Voorspoels et al., 2015), generalization occurs only when prior beliefs align with observed data. In the present case, the violation of a graded pattern indicates that the relevant belief concerns group members' shared goals. Specifically, the property of pursuing a common goal was generalized only when all observed members acted commonly with it. These findings highlight that action generalization is not primarily evidence-driven but is shaped by prior beliefs as a form of top-down modulation.

In the context of action perception, such top-down modulation refers to the influence of prior knowledge and higher-level beliefs on how observed actions are interpreted. Observers do not interpret actions solely from visible movement features or action frequency; instead, they often use prior knowledge to infer the goals and intentions underlying observed actions (Blakemore and Decety, 2001; Gergely and Csibra, 2003). Predictive accounts similarly suggest that higher-level assumptions about an actor's goal can shape expectations about upcoming actions (Kilner et al., 2007; Bach and Schenke, 2017). In the present study, this top-down influence was reflected in how participants interpreted the observed frequency information in relation to group members' shared goals. The critical issue was not simply how many agents approached the same target, but whether the observed pattern was sufficient to support the higher-level interpretation that the group was organized around a common goal.

Social-cognitive perspectives emphasize that a key basis for the existence of groups is the cooperative relationship among members to achieve common goals (Brewer et al., 2004; Noyes and Keil, 2020). This structural feature shapes individuals' default expectations regarding goal commonness within the group. Such expectations extend beyond observed behaviors, constituting a metacognitive belief about the very nature of the group: perceiving “us” as a unified entity rests on the assumption that members share and pursue collective goals (Liberman et al., 2017; Rhodes and Chalik, 2013). Within this framework, only when observed behaviors fully conform to the presupposed shared goal (i.e., all observed group members approach a common target) is this belief activated and validated, allowing individuals to confidently generalize the goal attribute to previously unobserved members.

Notably, when the movement of the action is predominant, the extent of action generalization follows the graded increasement with the evidence strength. Namely, movements, as concrete means to achieve goals, exhibit different generalization patterns as goal attribute, indicating that movement-based action generalization predominantly relies on statistical evidence. Existing theories propose that action understanding and prediction rely on two complementary reasoning systems: agentic reasoning and social reasoning (Spelke, 2016). Agentic reasoning infers specific action goals based on principles of instrumental rationality (Gergely and Csibra, 2003), whereas social reasoning ascribes shared or ritualized significance to actions, thereby fostering group cohesion and normative regulation (Rakoczy, 2015). When an action violates rational principles (e.g., jumping to reach a target), making it difficult to explain through agentic reasoning, social reasoning is recruited, leading observers to interpret the behavior as reflecting group norms or conventionalized practices. The present findings extend this framework by showing that, within social groups, actions deviating from rational explanations highlight the significance of action movements—how the target is approached. Moreover, as the prevalence of group members performing the same movement increases, such movements may be increasingly represented as group-specific conventionalized practices.

Importantly, this interpretation still depends on statistical evidence extracted from the observed action stream. Prior work has shown that observers are sensitive to statistical structure in dynamic human actions, that such structure can support the segmentation of continuous action streams, and that learned regularities in action sequences can guide predictions about upcoming actions (Baldwin et al., 2008; Monroy et al., 2017; Monroy et al., 2018). More recent work further suggests that people can use knowledge about transition probabilities between actions to predict which action is likely to occur next (Thornton and Tamir, 2021). From this perspective, as more group members performed the same movement, participants could form progressively stronger expectations that a new ingroup member would perform that movement as well. This explains why both behavioral facilitation and CNV amplitude increased from low to medium to high prevalence in Experiment 2. The contrast between Experiments 1 and 2 therefore does not argue against the role of statistical evidence in action prediction. Rather, it suggests that statistical evidence is interpreted differently depending on the action property being generalized. For concrete movement forms, observed evidence provided a relatively direct basis for graded action expectation. For action goals, however, the same observed information may have been interpreted in light of group-level prior expectations about whether group members were likely to pursue a common goal. Thus, the present findings extend statistical-learning accounts of action expectation by showing that, in goal-based action generalization, statistically based action expectations are constrained by prior beliefs about shared goals. Taken together, convergent behavioral and electrophysiological evidence suggest that movement-based action generalization is primarily governed by a statistically driven, inductive process, in sharp contrast to the belief-driven mechanism underlying goal-based action generalization.

The present study demonstrated that under high prevalence condition, participants exhibited significantly stronger action expectations toward ingroup members, as indexed by greater CNV amplitudes relative to medium and low prevalence conditions, with no significant difference between the latter two. This electrophysiological pattern was consistent with the behavioral findings, further supporting the CNV component as a sensitive index of action expectation. Although RT differences between consistent and inconsistent actions may partly involve expectancy-violation processing after the final action was revealed, the prevalence-related CNV differences were measured before the final movement unfolded. Thus, the CNV results provide clear evidence that participants had already formed differential action expectations during the expectation phase. Importantly, the CNV amplitude enhanced during the expectation interval preceding the response stage, the magnitude of action expectation was already discernible. Such evidence suggests that action expectation for group members is not entirely dependent on explicit task demands, but involves a certain degree of automaticity. Beyond aligning with prior research on expectancy-related cognitive mechanisms during the cue and action phases of the CNV (Tecce, 1972; Mento, 2013; Jiang et al., 2025), our findings extend this literature by showing that anticipatory neural activity can be modulated by expectations of action generalization among group members, even before overt behavior occurs.

Previous research has classified meaningful social groups into intimate groups (e.g., friends and family), task groups (e.g., project teams), and social categories (e.g., gender, race; Johnson et al., 2006; Lickel et al., 2000). In the present study, the synchronous movements of group members most closely resembled the structure of task groups. However, it is still unclear whether the current findings generalize to intimate groups or broader social categories, an issue that future research should address. Moreover, for the purpose of presenting two groups simultaneously on a single screen, each group in our study was limited to five members. Given that group size is a critical determinant of group-related processing (Luhmann and Rajaram, 2015), future work should examine larger and more complex groups to better understand how group size shapes expectations about members' actions.

In summary, goal-based action generalization does not increase incrementally with action prevalence; instead, a goal is generalized to a new group member only when all observed members pursue the same goal. This nongraded pattern is specific to goal generalization and does not occur for action movements. Such findings likely reflect the impact of assuming a shared goal among group members, suggesting that action generalization is not solely driven by statistical evidence but is constrained by group-related beliefs.

## CRediT authorship contribution statement

**Yueyang Huang:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation. **Qinglu Xiao:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Formal analysis. **Xinyu Tang:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Formal analysis. **Jun Yin:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

## Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work, we used ChatGPT-3.5 in order to improve the readability and language of the manuscript. After using this tool, we reviewed and edited the content as needed and take full responsibility for the content of the published article.

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## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ijpsycho.2026.113432.

## Data availability

Data, analysis code, and supplementary videos are publicly accessible via OSF at https://osf.io/pnkmh/?view_only=b43a60e0b1354fb2ad0e3b24cd2ca3bc.

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