

Research Article

Active Matter Flocking via Predictive Alignment

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Understanding collective self-organization in active matter, such as bird flocks and fish schools, remains a grand challenge in physics. Alignment interactions are essential for flocking, yet alone, they are generally considered insufficient to maintain cohesion against noise, forcing traditional models to rely on artificial boundaries or added attractive forces. Here, we report the first model to achieve cohesive flocking using purely alignment interactions, introducing predictive alignment: agents orient based on the predicted future headings of their neighbors. Implemented in a discrete-time Vicsek-type framework, this approach delivers robust, noise-resistant cohesion without additional parameters. In the stable regime, flock size scales linearly with interaction radius, remaining nearly immune to noise or propulsion speed, and the group coherently follows a leader under noise. These findings reveal how predictive strategies enhance self-organization, paving the way for a new class of active matter models blending physics and cognitive-like dynamics.

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1. Introduction

From micrometer-sized bacteria to complex animals, biological organisms sense their environment, process directional cues, and adapt their motion accordingly^{[1][2][3]}. Similar feedback mechanisms are also indispensable in the control of autonomous robotic systems^[4]. Based on visual^[5], acoustic^[6], or chemical^[7] signals, these perception-reaction interactions result in the self-organization of large ensembles of cognitive individuals into cohesive spatiotemporal patterns, such as bird flocks^[8], fish schools^[9], and human crowds^[10]. The study of these collective behaviors falls within the domain of

active matter physics^{[11][12][3]}. Models of collective behavior in active matter span Reynolds-type ‘boid’ models^[13], Vicsek-type ‘alignment’ models^{[14][15]}, Couzin-type ‘zonal’ models^[16], ‘vision cone’ models^{[17][18]}, motivation-based models^{[19][20][21][22]}, vision-based models^{[5][23][24]}, energy-efficiency models^[25], and other biologically motivated models^[26], as well as models designed for controlling robotic swarms^[27].

Vicsek-type models, relying solely on alignment, struggle to maintain cohesion without artificial aids like periodic boundaries or added attractive forces^[28]. However, periodic boundaries can influence bulk behavior, particularly in the parameter regime associated with microphase separation, where density waves align with the symmetries of the periodic simulation box^[29]. Similarly, incorporating attractive interactions can induce swirling motion^[30], which was absent in the original model. Other models achieve cohesion through either direct attractive interactions^[31] or explicit mechanisms, such as active or passive reorientation and movement toward a local or global center of the group^{[13][16][17][18]}. Notable exceptions include models where cohesion is not explicitly built into the algorithm, such as the maximum path entropy model^{[21][22]} or vision-based models^[5]. However, these approaches do not restrict the agents’ sight range, effectively introducing long-range interactions. To our knowledge, no prior model achieves cohesive flocking with purely alignment interactions over a finite range.

Here, we introduce predictive alignment in a Vicsek-type framework with a limited interaction radius ζ . We interpret the alignment interactions as biologically motivated social behaviors based on individual decision-making. Specifically, we implement them using the sociological rule “copy the other”^[32], which is known to enhance the success of an individual in a group.

Our model reduces to a variation of the Vicsek model for simple agents that cannot anticipate future positions. However, when agents adopt the preferred orientation of their predicted future neighbors, they effectively optimize a tradeoff between alignment and proximity. To our knowledge, this results in the first cohesive flocking model that relies solely on alignment and does not have additional parameters or boundaries. The system undergoes a dynamical transition to an incoherent state with increasing noise and distance traveled per timestep over the interaction radius. In the flocking state, the stationary flock size is independent of agent speed, scales proportionally to the interaction radius, and linearly increases with noise—though with a very small slope. Additionally, the group efficiently follows a subgroup of maneuvering leaders. Our results reveal how predictive strategies enable robust self-organization akin to natural systems.

2. Results

2.1. Model

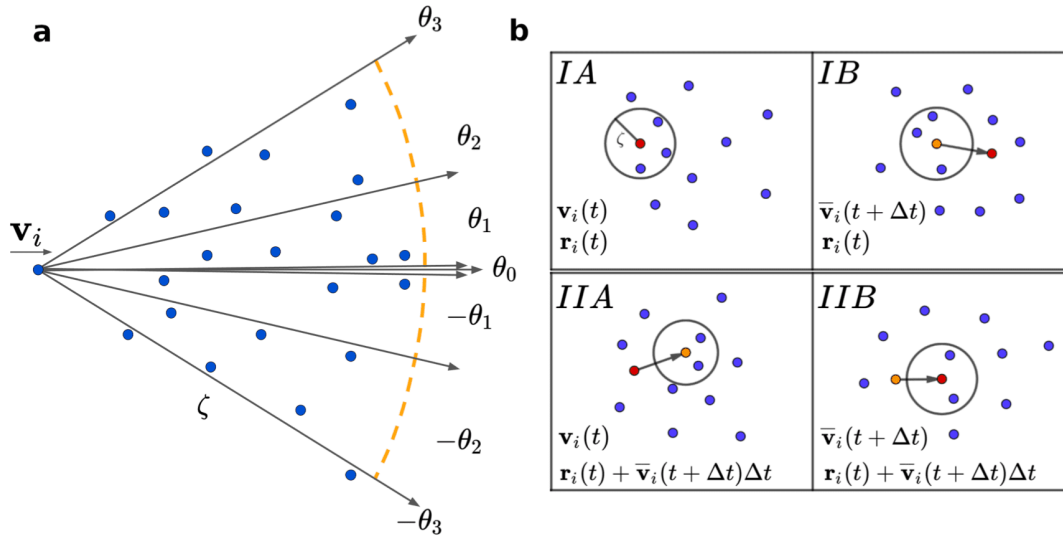


Figure 1. Model. **a** At each discrete time step, individual agents aim to align as closely as possible with the orientation of their neighbors within a circle of radius ζ . To achieve this, they select one of seven possible reorientations, $\Delta\theta_i^t \in \Omega_\theta = \pm\{0, 0.01, 0.2, 0.5\}$, that maximizes the correlation function in Eq. (3). All agents update their orientation in parallel. **b** We implemented four different strategies (IA–IIB) for evaluating the correlation function. In strategies I, the correlation is computed using the current neighbors ($\mathbf{r}_i = \mathbf{r}_i(t)$), whereas in strategies II, it is computed using predicted future neighbors [$\mathbf{r}_i = \mathbf{r}_i(t) + \bar{\mathbf{v}}_i(t + \Delta t)\Delta t$], as illustrated by the black circles. In strategies A, the agent’s own orientation is included inside the bracket of the correlation function ($\mathbf{v}_i = \mathbf{v}_i(t)$), introducing orientational inertia, which is absent in strategies B ($\mathbf{v}_i = \bar{\mathbf{v}}_i(t + \Delta t)$).

Biological active agents in nature follow evolutionarily adapted instincts and, in the case of higher animals, sometimes even learned or cognitively driven strategies to achieve specific goals such as collision avoidance or foraging. Similar mechanisms are also implemented in the development of autonomous robotic systems. These strategies are shaped by physical, biological, or technical constraints, which limit the range of possible dynamical and adaptive responses. We consider a system of N Vicsek-type agents self-propelling in discrete time in two dimensions with a constant velocity v_0 in the direction of their orientation vectors $(\cos \theta_i^t, \sin \theta_i^t)$, $i = 1, \dots, N$. At each discrete time step t , the agents reorient

by discrete angles $\Delta\theta_i^t \in \Omega_\theta = \pm\{0, 0.01, 0.2, 0.5\}$ rads to achieve maximum alignment with their neighbors, as shown in Fig. 1a. The agents thus have the ability to reorient more gradually or sharply depending on how far their desired orientation is from their current heading, which brings the model close to the original Vicsek model. Nevertheless, we show in the Supplementary information that a variant of the model with just three possible reorientation angles gives qualitatively the same results. The imperfections in reorientation and cognitive capabilities of the agents are reflected by a noise term ξ_i^t sampled from the interval $\eta[-\pi, \pi]$, added to chosen $\Delta\theta_i$. The resulting dynamical equations for the agents are given by:

$$\mathbf{r}_i^{t+\Delta t} = \mathbf{r}_i^t + \mathbf{v}_i^{t+\Delta t} \Delta t, \quad (1)$$

$$\theta_i^{t+\Delta t} = \theta_i^t + \Delta\theta_i^t + \xi_i^t. \quad (2)$$

What remains is to choose a strategy to determine the reorientation angle $\Delta\theta_i^t$ in Eq. (2). In the classical discrete-time Vicsek model, $\Delta\theta_i^t$ is chosen to align the i th agent's velocity with the average velocity $\mathbf{V}_i^t = \frac{1}{n_i^t} \sum_{j=1}^N H(|\mathbf{r}_i^t - \mathbf{r}_j^t| - \zeta) \mathbf{v}_j^t$ of its neighbors. To incorporate this effect, we define $\Delta\theta_i^t = \operatorname{argmax}_{\Delta\theta_i} C_i^t$, i.e., as the argument that maximizes the correlation function

$$C_i^t = \bar{\mathbf{v}}_i^{t+\Delta t} \cdot \left(\sum_{j=1}^N H(|\mathbf{r}_i - \mathbf{r}_j^t| - \zeta) \mathbf{v}_j^t - (\mathbf{v}_i^t - \mathbf{v}_i) \right) \quad (3)$$

which can be interpreted as the correlation between the agent's future desired velocity $\bar{\mathbf{v}}_i^{t+\Delta t} = v_0(\cos(\theta_i^t + \Delta\theta_i^t), \sin(\theta_i^t + \Delta\theta_i^t))$ and the non-normalized average velocity of its neighbors within the interaction radius. Since C_i^t is not normalized, it measures the degree of alignment of the i th agent with the prevailing orientation of its perceived neighbors. Thus, it serves as a natural objective function to maximize by agents aiming to 'copy' the prevalent orientation of their neighbors. The Heaviside step function H is modified such that $H(0) = 1$, ensuring that C_i^t properly accounts for all particles within the interaction radius ζ . The particle's i -th own velocity and position are included in the sum as \mathbf{v}_i and \mathbf{r}_i , respectively. This formula for C_i^t allows us to either take \mathbf{r}_i and \mathbf{v}_i at time t or their intended values at time $t + \Delta t$, which amounts to four of the many possibilities to define the correlation, depicted in Fig. 1b. If C_i^t vanishes for all possible reorientations, the agent updates its orientation purely by noise, i.e., $\Delta\theta_i^t = 0$ in Eq. (2).

The strategies IA and IB calculate the correlation C_i^t with the current neighbors of the agent i , $\mathbf{r}_i = \mathbf{r}_i^t$. Strategy IA further takes the agent's current velocity $\mathbf{v}_i = \mathbf{v}_i^t$ inside the sum, and IB uses the interpolated velocity $\mathbf{v}_i = \bar{\mathbf{v}}_i^{t+\Delta t}$ instead. In both cases, $C_i^t = n_i^t \bar{\mathbf{v}}_i^{t+\Delta t} \cdot \mathbf{V}_i^t + C_0$, where C_0 is a constant, n_i^t the

number of neighbors of agent i at time t and \mathbf{V}_i^t their average velocity. For IA, $C_0 = 0$ and the agent i is counted in n_i^t and \mathbf{V}_i^t , so that $n_i^t = \sum_{j=1}^N H(|\mathbf{r}_i^t - \mathbf{r}_j^t|)$ and $\mathbf{V}_i^t = \sum_{j=1}^N H(|\mathbf{r}_i^t - \mathbf{r}_j^t|) \mathbf{v}_j^t / n_i^t$. For IB, $C_0 = v_0 n_i^t$ and the agent i is not counted in the definition of n_i^t and \mathbf{V}_i^t ($j \neq i$ in the sums above). Nevertheless, in both cases, n_i^t and C_0 are independent of $\Delta\theta_i^t$ and thus the intended velocity that maximizes C_i^t is the one best aligned with the average velocity \mathbf{V}_i^t . Notably, considering the agent's own velocity in \mathbf{V}_i^t introduces slight orientational inertia in IA, as agents take their own heading into account. These two strategies correspond to two variants of the Vicsek model: Vicsek model A, which includes the agent's own velocity in the average velocity calculation, and Vicsek model B, which does not (see Methods).

The strategies IIA and IIB, use the neighbors corresponding to the intended future position of agent i at time $t + \Delta t$, $\mathbf{r}_i = \mathbf{r}_i^t + \bar{\mathbf{v}}_i^{t+\Delta t} \Delta t$, and thus require calculating the correlation C_i^t using different neighbors for each value of the realignment angle. From now on, we will call these two strategies predictive and the corresponding models as predictive models. As above, strategy IIA further takes the agent's current velocity $\mathbf{v}_i = \mathbf{v}_i^t$ inside the sum, and IIB the interpolated velocity $\mathbf{v}_i = \bar{\mathbf{v}}_i^{t+\Delta t}$. Also in these cases, $C_i^t = n_i^t \bar{\mathbf{v}}_i^{t+\Delta t} \cdot \mathbf{V}_i^t + C_0$. Nevertheless, the number of neighbors of i , n_i^t , and their average velocity, \mathbf{V}_i^t , are now calculated with respect to its intended position $\mathbf{r}_i(t) + \bar{\mathbf{v}}_i(t + \Delta t) \Delta t$ and thus they depend on the reorientation angle. For IIA the agent i is counted in n_i^t and $C_0 = 0$. For IIB, $C_0 = v_0 n_i^t$ and the agent i does not contribute to the averages. Importantly, in both these strategies, the optimal reorientation angle follows from a tradeoff balancing the number of nearest neighbors and alignment with the average velocity, resulting in an attractive alignment interaction. Different from IIB, IIA, in addition, has some positional inertia.

The time step Δt affects only the relaxation times and does not alter the stationary state. Upon rescaling particle positions by the interaction radius ζ , the stationary behavior of this model is controlled by two parameters: the ratio of the distance traveled per timestep to the interaction radius, $v_0 \Delta t / \zeta$, and the noise-induced orientation change per time step, quantified by η . In the following, we consider groups of $N = 200$ agents initially positioned randomly within a square of side length $L = 4\zeta$, with $\zeta = 1$ and $\Delta t = 1$. In the Supplementary Information, we show that using a larger $N = 500$ produces qualitatively the same results. A more physically grounded, continuous-time variant of the model is described in the Methods section.

2.2. Flocking from predictive alignment

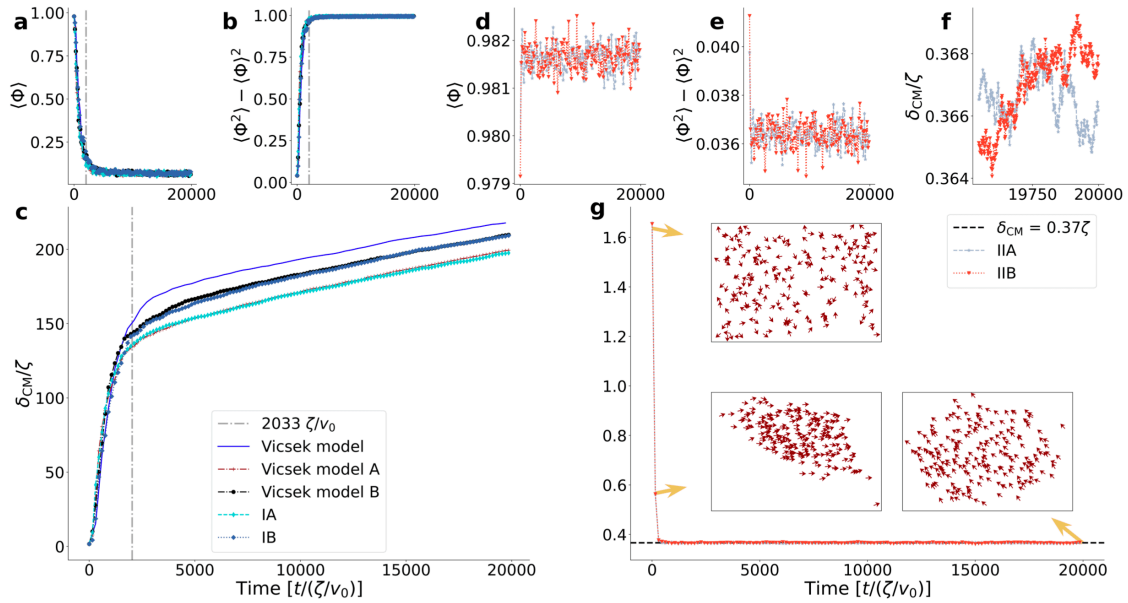


Figure 2. Comparison between Vicsek-like and predictive models. The agents started with uniformly distributed orientations and evolved according to the standard time-discrete Vicsek model, its modifications A and B (see Methods), as well as the decision-based models IA–IIB defined in the main text. For all models, we set the reduced speed to $v_0/\zeta = 0.0076$, noise intensity to $\eta = 0.1$, and averaged the shown data over 25 replicas with different noise realizations. **a–c**, The Vicsek-type models exhibit a rapid loss of cohesion, indicated by **a** a sharp decrease in the average polarization $\langle \Phi \rangle$, **b** an increase in its fluctuation $\langle \Phi^2 \rangle - \langle \Phi \rangle^2$, and **c** a rapid growth of the average agent-to-center-of-mass distance, δ_{CM} . These effects occur before $t \approx 2033\zeta/v_0$, predicted from diffusive spreading analysis of Vicsek model (vertical dashed lines). **d–g**, The predictive models IIA and IIB yield nearly identical stable flocking behaviors, with **d** a consistently high average polarization fluctuating weakly around 0.98, **e** low polarization variance, and **f** a closely packed system configuration, where the average agent-to-center-of-mass distance fluctuates around 0.366. **g** The system size self-adjusts as the initially square-shaped flock transitions through an elongated intermediate state before settling into a final circular configuration (insets). The system size relaxation time, defined as the point when δ_{CM} drops to half of its initial value, is approximately $100\zeta/v_0$. Analogously defined relaxation times for $\langle \Phi \rangle$ and $\langle \Phi^2 \rangle - \langle \Phi \rangle^2$ are shorter than ζ/v_0 (see the Supplementary Information).

Models with purely alignment interactions, such as the Vicsek model, fail at maintaining group cohesion even under arbitrarily weak noise due to the diffusive spreading of agents. The time it takes for two particles, initially at the same position, to ‘diffuse’ further away than one interaction radius can be

estimated as $\left(\frac{1}{5} + \frac{3}{2\pi^2\eta^2}\right) \frac{\zeta^2}{v_0^2}$ (see Methods). It is reasonable to expect that as the number of agents increases, the Vicsek flock will break up into subgroups more quickly. For $\eta = 0.1$ and $v_0/\zeta = 0.0076$ as used in Fig. 2, our estimate suggests that flock coherence is lost before $t \approx 2033\zeta/v_0$. For Vicsek-like models IA, IB, and for the standard Vicsek model, this prediction aligns remarkably well with the saturation point where (a) the average polarization, $\langle\Phi\rangle$, halts its rapid decrease, and (b) the polarization variance, $\langle\Phi^2\rangle - \langle\Phi\rangle^2$, halts its rapid increase. It also marks the end of the initial sharp rise in the average agent-to-center-of-mass distance, δ_{CM} (c). Beyond this point, the system size expands ballistically as the single flock fragments into multiple sub-flocks, indicated by the vanishing polarization and peak variance in (a) and (b). (For precise definitions of the order parameters, see Methods.) On the other hand, the predictive models IIA and IIB form highly polarized, closely packed, coherent flocks with self-adjusted $\delta_{CM} \approx 0.4\zeta$ corresponding to flock radius of roughly 0.6ζ (see Methods). Their order parameters fluctuate only slightly and remain stable over time, at least for simulation durations on the order of ten diffusive spreading times we tested.

2.3. Noise induced dynamical transition

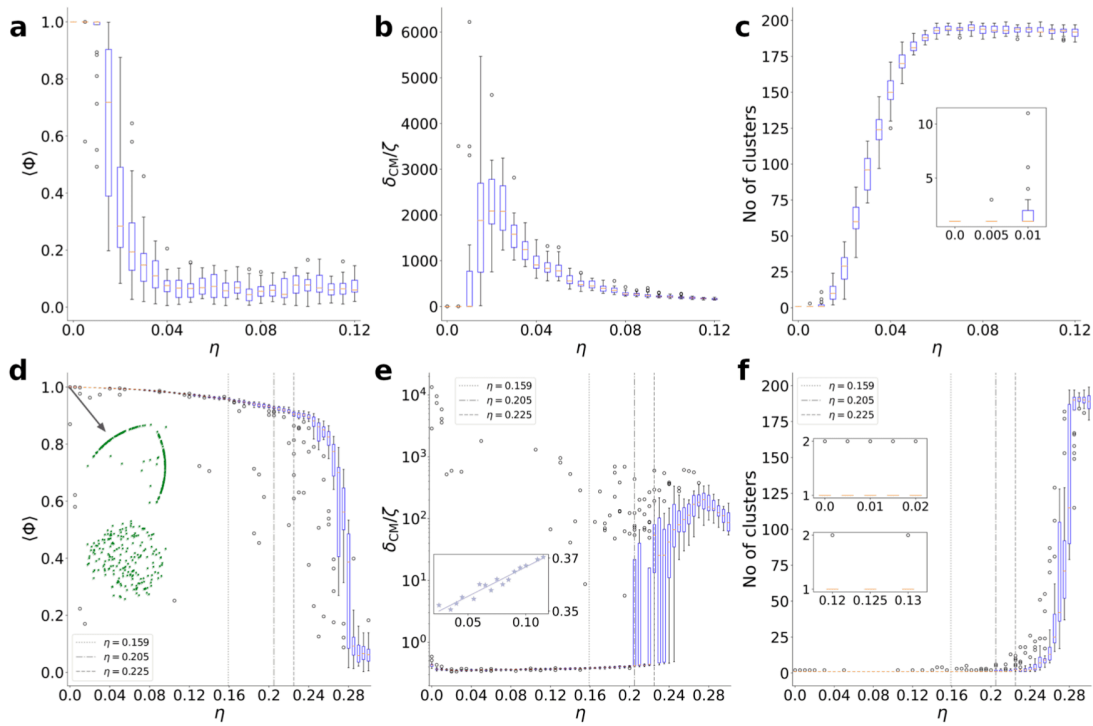


Figure 3. Effects of noise in Vicsek model and the predictive model IIA. Boxplots represent results from 25 independent simulations with different noise realizations, where orange lines indicate the median, boxes span the interquartile range, whiskers extend to data points within 1.5 times the interquartile range, and outliers are shown as individual circles. **a–c** In the Vicsek model, for noise levels $\eta \gtrsim 0.005$, flock cohesion is lost, with fragmentation increasing at higher noise levels, as reflected by **a** reduced average polarization $\langle \Phi \rangle$, **b** an increased average agent-to-center-of-mass distance δ_{CM} , and **c** a greater number of clusters. **d–f** In contrast, the predictive model IIA maintains stable flocking in over half of the replicas for $\eta \lesssim 0.225$. Here, **d** polarization gradually decreases from 1, with agents forming V-shaped flocks at zero noise and round flocks at nonzero noise (insets). **e** The average agent-to-center-of-mass distance initially decreases but subsequently increases linearly for $0.015 \lesssim \eta \lesssim 0.225$ and coherent replicas, following $\delta_{CM} \approx (0.35 + 0.19\eta)\zeta$ (inset). **f** The system predominantly consists of a single cluster of communicating agents for $\eta \lesssim 0.225$, with more than one outlier for $0.015 \lesssim \eta$ and $0.159 \lesssim \eta \lesssim 0.205$. At high noise levels, system size (**b**, **e**) decreases due to the interplay between noise-induced alignment destabilization and suppression of system growth by the diffusive motion of individual subclusters. The models were simulated under the same conditions as in Fig. 2 unless otherwise specified in the figure. The order parameters were evaluated at time $2 \times 10^4 \zeta / v_0$.

The predictive strategies IIA and IIB yield nearly identical results, while strategy IA exhibits slightly better coherence than IB. We attribute this to the slight orientational inertia introduced by the definition of the correlation function in strategies A. In the following, we analyze the behavior of the IIA model under variations in the two key parameters: noise intensity, η , and scaled velocity, v_0/ζ .

With periodic boundary conditions^[14], the Vicsek model undergoes a discontinuous phase transition^[33] from an ordered to a disordered state. Without periodic boundaries, coherent polarized flocks form only at vanishing noise. When initialized with randomly oriented agents uniformly distributed within a rectangle of side length 4ζ , the model exhibits a monotonic decrease in average polarization (Fig. 3a) and a corresponding increase in the number of communicating clusters (Fig. 3c) as noise intensifies, consistent with this expectation. Notably, the average agent-to-center-of-mass distance reaches a maximum at an intermediate noise level (Fig. 3b). This nonmonotonic behavior arises because, at low noise, the flock expands ballistically, whereas at high noise, the motion of individual subflocks becomes diffusive on the relevant timescale. In this regime, subflocks undergo an effective random walk, slowing the overall expansion of the system.

Under the same conditions and for noise intensities $\eta \lesssim 0.225$, the predictive model IIA produces coherent flocks consisting of a single cluster of communicating particles (Fig. 3f) with polarization $\langle \Phi \rangle \approx 1$ (Fig. 3d) in most of the 25 replicas used in our simulations. The inset shows that, in the absence of noise, the coherent flocks adopt a V-shaped formation, reminiscent of those observed in migrating birds, where this arrangement reduces energy expenditure. At nonzero noise levels, the flocks transition to a rounded shape, similar to the formations observed in foraging bird flocks, where cohesion and flexibility are prioritized over aerodynamic efficiency. For videos showing the relaxation of flock shapes and an analysis of the corresponding relaxation times, see the Supplementary Information.

For $\eta \lesssim 0.015$, the average agent-to-center-of-mass distance decreases with increasing noise. This ‘noise stabilization effect’ arises from the discrete set of allowed reorientations, which, unlike the classical Vicsek model with arbitrary reorientation per timestep, prevents the system from fully polarizing at zero noise. A similar effect has been observed in Ref. ^[22]. For $0.015 \lesssim \eta \lesssim 0.225$, the average agent-to-center-of-mass distance in stable replicas increases linearly with noise (inset of Fig. 3e). Beyond $\eta \approx 0.225$, all order parameters undergo a transition for the majority of replicas: polarization $\langle \Phi \rangle$ vanishes, δ_{CM} grows by two orders of magnitude within the given simulation time, and the number of clusters approaches the total number of agents. At higher noise levels, both δ_{CM} and the number of clusters slightly decrease, consistent with the diffusive motion of subclusters described above.

In the 25 replicas of the system with different noise realizations obtained from our simulations, a few exceptions to the described behavior appear as empty circles in Fig.3, representing individual outliers from the typical trend, depicted by the orange lines inside the boxes. The higher number of outliers observed for $\eta \approx 0$ in Fig.3e, compared to Fig.3f, arises because each replica contributing to the system size outliers consisted of two separate subflocks, leading to overlapping circles in Fig.3f. In the Supplementary Information, we show that the same phenomenology (except for the weak noise instability) can also be observed when the system is initially perfectly aligned, demonstrating the robustness of the described dynamic phases.

To provide further insight into the behavior of individual replicas, Fig. 4a shows the logarithm of the average agent-to-center-of-mass distance. Dark red-colored replicas indicate a small stationary system size and thus stability, whereas blue and faint red mark unstable replicas. The reduced number of blue points beyond $\eta \leq 0.015$ illustrates the aforementioned noise-induced stabilization effect. The figure also shows that for $0.159 \lesssim \eta \lesssim 0.205$, the number of unstable replicas sharply increases. For $0.205 \lesssim \eta \lesssim 0.225$, unstable replicas are no longer mere outliers, and for $\eta \gtrsim 0.225$, the system becomes unstable in the majority of replicas. Interestingly, the very onset of the transition at $\eta \approx 0.159$ corresponds to the parameter regime when the maximum ‘intentional’ reorientation of the agents, 0.5 rad, matches the maximum reorientation due to noise, $\eta\pi$.

2.4. Role of speed and interaction radius

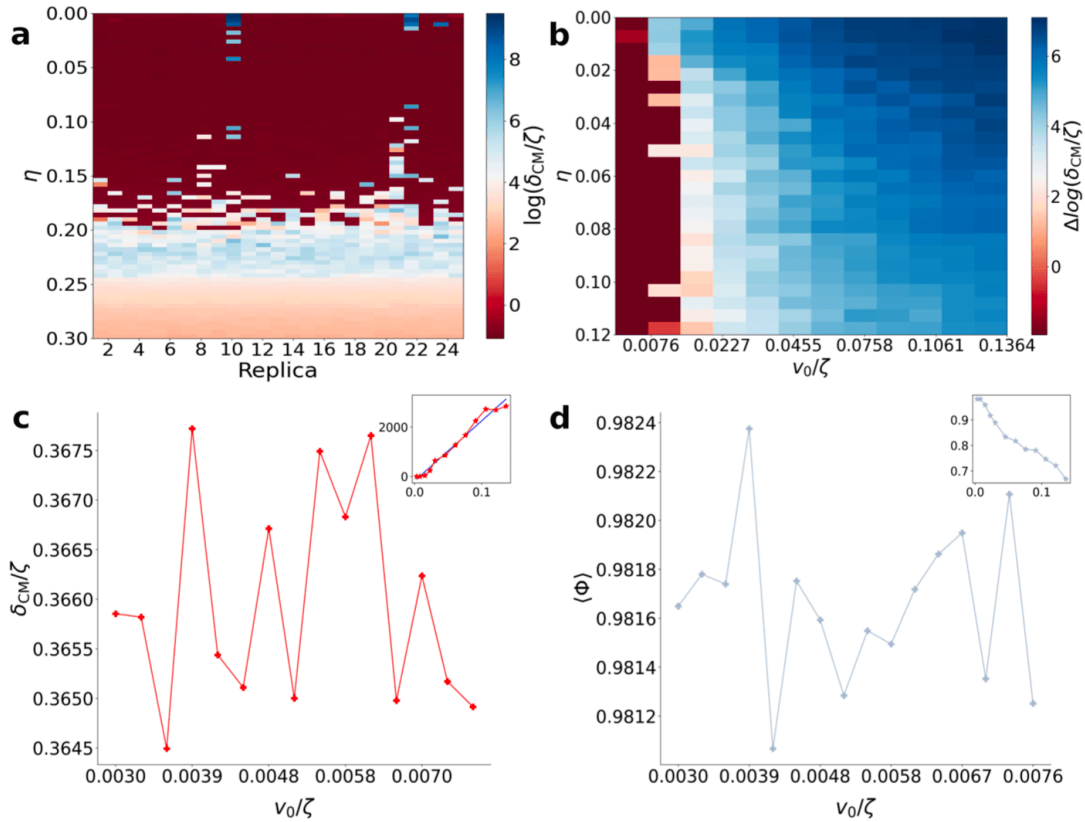


Figure 4. Effects of noise, speed, and interaction radius in the predictive model IIA. **(a)** The logarithm of the average agent-to-center-of-mass distance, $\log(\delta_{CM}/\zeta)$, for individual replicas as a function of noise intensity, η . **(b)** Change in $\log(\delta_{CM}/\zeta)$ between the final simulation time, $2 \times 10^4\zeta/v_0$, and an earlier time, $2 \times 10^4(\zeta/v_0 - 1)$, as a function of η and the fraction of the interaction radius traveled per time step, v_0/ζ . **(c)** The average agent-to-center-of-mass distance as a function of the reduced speed, v_0/ζ , in the regime where the model forms stable flocks (taking out outliers). The insets in **(c)** and **(d)** show δ_{CM} and the average polarization, $\langle\Phi\rangle$, as functions of v_0/ζ outside the stable regime. The models were simulated under the same conditions as in Fig. 2, with $\eta = 0.1$ and $v_0/\zeta = 0.0076$, unless otherwise specified in the figure. The order parameters were evaluated at time $2 \times 10^4\zeta/v_0$.

In Fig. 4b-d, we analyze the distance traveled per timestep over the interaction radius, v_0/ζ , on the system dynamics. The system forms a stable flock if the fraction is small enough so that each agent has enough time to align with its neighbors before it changes them. The threshold value of v_0/ζ increases with noise intensity from roughly 0.008 at $\eta \lesssim 0.02$ to almost 0.024 at $\eta = 0.12$ (Fig. 4b), highlighting

once more the stabilizing effect of the noise discussed above. In the stable regime, the average agent-to-center-of-mass distance reduced by ζ (Fig. 4c) and the average polarization (Fig. 4d) are independent of v_0/ζ . Hence, the system size is proportional to the interaction radius. Beyond the stable regime, $\langle \Phi \rangle$ drops and δ_{CM} increases with both v_0/ζ and the simulation time.

2.5. Leadership

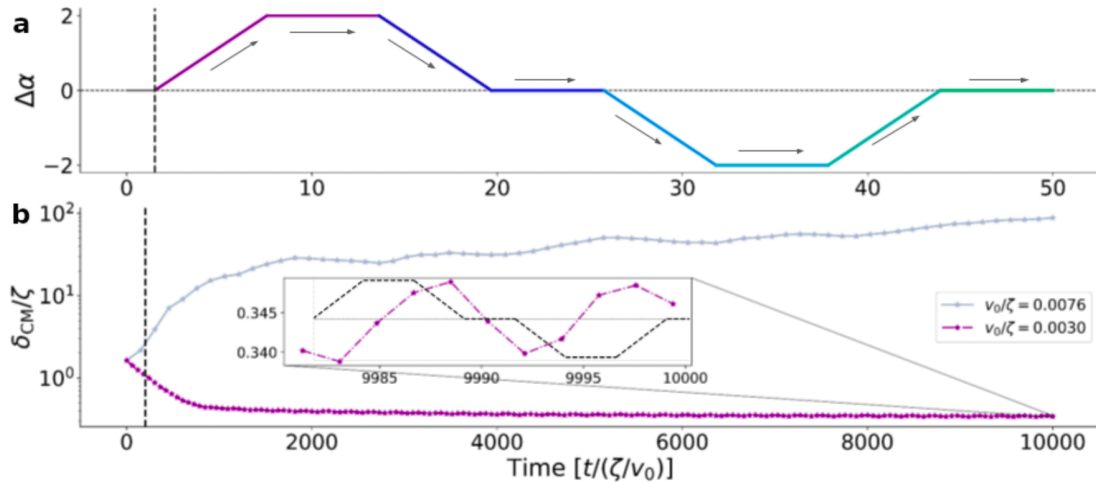


Figure 5. Leadership in the predictive model IIA In this numerical experiment, the agents were initially perfectly aligned. After an equilibration period of 200 timesteps, a subgroup of 20 leaders was selected to change orientation deterministically according to the oscillatory protocol shown in a, with $v_0/\zeta = 0.0076$. The leaders reoriented with an angular velocity of $\Delta\alpha = 0.0025$ rad/timestep for 800 timesteps, interspersed with relaxation periods of 800 timesteps. b Under this protocol, for $v_0/\zeta = 0.0076$ and noise intensity $\eta = 0.04$, the flock disperses, as indicated by the increase in the average agent-to-center-of-mass distance, δ_{CM} . In contrast, stable flocking is maintained in the absence of leaders. However, when the reduced speed is decreased to $v_0/\zeta = 0.003$, the agents successfully follow the leaders, forming a characteristic pattern where maxima in system size lag behind the leaders' turning events. This behavior is highlighted in the inset, which magnifies a single oscillation of δ_{CM} at the time marked by the vertical dashed line (pink dash-dotted line). As a visual reference, the inset also includes the corresponding angular variation of the leaders from a (black dashed line).

In nature, bird flocks often involve a subgroup of leaders who are best informed about the target position and who are followed by the rest of the flock^{[16][26]}. Figure 5 shows that the predictive model IIA can form

cohesive flocks also in the scenario when a subgroup of leaders perform an oscillator deterministic motion, albeit for slightly lower v_0/ζ than without the perturbation by leaders. For a video showing the stationary flock following the leaders, see the Supplementary Information.

3. Discussion

We have presented the first cohesive flocking model based solely on alignment interactions, achieved by replacing the Vicsek model's Ising-like alignment with predictive alignment. Agents that can predict the future positions of their neighbors optimize a tradeoff between aligning with neighbors' headings and maintaining proximity, yielding cohesion and order without the need for boundaries or added forces. This fundamentally departs from prior models, which rely on such aids^[28]. From a technical perspective, the dynamical equations feature a reorientation 'force' that does not follow the gradient of a potential, which would typically lead to stable orientations at local minima. Instead, it is governed by an $\arg \max$ function, which reorients agents toward the deepest minimum of a utility function (negative orientation correlation with neighbors) that is accessible in the next timestep. This process is constrained by the agent's field of view, reorientation capabilities, and motility. The model is scalable, and the resulting flock shapes resemble those observed in nature. However, further investigation is needed to assess how closely the resulting flocks resemble those observed in nature, in terms of internal dynamics, correlations, and finite-size scaling^[34].

Our algorithm provides a plausible strategy that intelligent agents with given physical and cognitive abilities might employ to efficiently align with their neighbors. As such, it falls within the class of intrinsically motivated^{[19][20][21]} and cognitive^{[17][18]} active matter algorithms. The algorithm can also be integrated into the broader framework of active inference^[35], a general theory of decision-making. However, unlike typical active inference models, our approach does not rely on the assumption that the system state is near the global optimum of a utility function, allowing forces to be described as gradients of generalized potentials. Instead, it enables agents to dynamically adapt the most preferable configuration they perceive.

Future extensions of the model could explore modifications to agents' cognitive abilities such as predictive capabilities, perception^[8], or delays in decision-making processes^[36]. Another possibility is to study agents with different physics, e.g., where inertia or more general non-Markovian effects play a role.

To conclude, our findings open the door to new directions in active matter research by introducing a biologically plausible, prediction-based alignment mechanism that naturally leads to cohesive flocking states. By bridging the gap between simple alignment rules and decision-making strategies inspired by cognitive processes, this work provides a foundation for exploring collective behavior in intelligent systems and offers a new framework for modeling real-world flocking dynamics. Additionally, this model could be applicable to other collective behaviors, such as the swarming of insects, the movement of robotic swarms, or even the coordination in human crowds.

4. Methods

4.1. Variants of the Vicsek model

In the original discrete-time variant of the Vicsek model^[14], agent positions are updated according to Eq. (1), while their velocities \mathbf{v}_i^{t+1} are determined by the average velocity of their neighbors at time t , $\mathbf{V}_i = \sum_{j=1}^N H_x(|\mathbf{r}_i^t - \mathbf{r}_j^t| - \zeta) \mathbf{v}_j^t$, where \mathbf{V}_i is then randomly rotated by an angle ξ_i^t , as described in Eq. (2). Here, H_x (with $x = A, B$) are Heaviside theta functions modified at the origin such that agent i 's own velocity is included ($H_A(0) = 1$) or excluded ($H_B(0) = 0$) in the averaging, yielding variants of the model with slight orientational "inertia" or no inertia, respectively.

We compare the 'predictive' models defined in the main text with the original Vicsek model using H_A . However, this comparison is not entirely fair, as the predictive models do not allow for arbitrary reorientation within a single time step. To ensure a fair comparison, we also compare the predictive models with variants of the Vicsek model using H_A or H_B , where agents reorient by the angle in the set Ω_θ that makes their velocity closest to \mathbf{V}_i before undergoing random reorientation due to noise. We call these variants of the Vicsek model as Vicsek model A and B, respectively. They are identical to the models corresponding to strategies IA and IB defined in the main text.

4.2. Time-continuous model

Physically, the algorithmic discrete-time model in Eqs. (1) and (2) is reasonable when agents travel only a fraction of the interaction radius per time step, i.e., $v_0 \Delta t \ll \zeta$, ensuring that they do not switch neighbors at each step. This condition is fulfilled in all our numerical experiments. In this parameter regime, one can readily take the continuous-time limit $\Delta t \rightarrow 0$ in Eq. (1) to obtain

$$\dot{\mathbf{x}}_i(t) = \mathbf{v}_i(t). \quad (4)$$

Introducing a reorientation angular velocity, ω_0 , and rotational diffusion, D_r , the continuous-time variant of Eq. (2) can be formulated as

$$\dot{\theta}_i(t) = \omega_0 \Delta\theta_i(t) + \sqrt{2D_r} \xi_i(t), \quad (5)$$

where $\xi_i(t)$, $i = 1, \dots, N$, are normalized, unbiased, and mutually independent Gaussian white noises.

4.3. Order parameters

We characterize the studied systems using the average polarization $\langle \Phi \rangle$, polarization variance $\langle \Phi^2 \rangle - \langle \Phi \rangle^2$, the average agent-to-center-of-mass distance [37], δ_{CM} , which serves as a proxy for system size, and the number of clusters of communicating particles. These variables are calculated as

$$\langle \Phi \rangle = \frac{1}{v_0} |\langle \mathbf{v} \rangle| = \frac{1}{v_0 N} \left| \sum_{i=1}^N \mathbf{v}_i \right|, \quad (6)$$

$$\langle \Phi^2 \rangle - \langle \Phi \rangle^2 = \frac{1}{v_0^2 N} \sum_{i=1}^N (\mathbf{v}_i - \langle \mathbf{v} \rangle)^2, \quad (7)$$

$$\delta_{CM} = \sqrt{\frac{1}{N} \sum_{i=1}^N |\mathbf{x}_i(t) - \langle \mathbf{x}(t) \rangle|^2}, \quad (8)$$

with the flock center of mass position vector $\langle \mathbf{x}(t) \rangle = \frac{1}{N} \sum_{i=1}^N \mathbf{x}_i(t)$. The number of clusters is calculated by iteratively identifying all particles that can be connected through a path where each step links particles separated by a distance smaller than the interaction radius ζ .

For a homogeneous circular flock with radius R , $\delta_{CM} = \frac{1}{\pi R^2} \int_0^{2\pi} d\phi \int_0^R r dr = \frac{2}{3} R$. This result can be used to estimate the flock radius from the easily calculable δ_{CM} .

4.4. Diffusive spreading in Vicsek model

To estimate the speed of the inevitable noise-induced spreading of agents in the Vicsek model, we consider two particles interacting via a perfect, infinite-range alignment interaction. At each time step, they align their velocities, and each adds a noise term drawn from the uniform distribution $\eta \in [-\pi, \pi]$ to their orientation. Consequently, after each time step, the velocities of the two particles are given by $\mathbf{v}_i = v_0(\cos \theta_i, \sin \theta_i)$ for $i = 1, 2$. Per time step, the distance between the two particles increases by $\Delta d = |\mathbf{v}_1 - \mathbf{v}_2|$. Since these individual distance increments are independent by construction, the probability density of the distance between the two particles after a large number of time steps t can be well approximated by a Gaussian distribution with zero mean and variance

$$\langle \Delta d^2 \rangle_t = \frac{v_0^2 (2\pi^2 \eta^2 - 1 + \cos(2\pi\eta))}{\pi^2 \eta^2},$$

where the average is taken over the noise. This result provides an estimate for the expected distance between the two particles after t time steps as $\sqrt{\langle \Delta d^2 \rangle_t}$. Similarly, the time at which the distance between the two particles exceeds the interaction radius ζ — marking the loss of coherence in the system — can be estimated as $t \approx \frac{\zeta^2}{\langle \Delta d^2 \rangle}$.

Statements and Declarations

Data availability

Supplementary information, videos, materials, and data are promptly available for all readers.

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Author contributions

VH conceptualized and designed the research, while JGB conducted the numerical experiments and analyses. Both authors discussed the results and contributed to writing and revising the manuscript.

Conflicts of interest

The authors declare no competing interests.

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Declarations

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