

Delayed active swimmer in a velocity landscape

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Active systems in nature and synthetic environments commonly exhibit spatially heterogeneous activity patterns and time-delayed responses from internal feedback mechanisms, exemplified by bacterial chemotaxis. We study an idealized active gas where particles modulate their self-propulsion based on local environmental conditions with such delays. Through integrated theoretical, computational, and experimental approaches, we demonstrate that steady-state density distributions and collective polarization exhibit characteristic peaks and valleys as functions of response delay time. We find that delays can amplify polarization by nearly an order of magnitude and trigger complete polarization reversal when particle displacement during the delay period surpasses the persistence length. Multiparticle simulations incorporating interparticle interactions validate that these phenomena remain robust in sufficiently dilute collective systems. Since density and polarization determine the current in active matter, our findings show that temporally programming the delay time allows control over both static and dynamic states in active systems, with implications for biological microswimmers and engineered microrobots.

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Introduction. Active matter consists of particles operating far from equilibrium that convert energy into directed motion. These systems exhibit properties not possible in conventional materials that are constrained by thermal equilibrium symmetries, including persistent ring currents [1] and the breaking of mesoscopic action-reaction symmetry [2,3]. Microscopic organisms, particularly bacteria [4], represent fascinating examples of active matter as they navigate heterogeneous landscapes created by spatial gradients of chemicals, nutrients, or light [5–7], as well as physical obstacles [8]. Understanding these systems is critical to advance our fundamental knowledge of nonequilibrium physics and to guide the development of synthetic microrobots for applications such as targeted medical interventions [9].

The central hydrodynamic fields of polar microswimmers are the density and the polarization. Their dependence on noise and activity in force-free settings is as fundamental to active matter as the Boltzmann distribution of energy is in equilibrium statistical mechanics. For microswimmers responding instantaneously to activity landscapes with negligible translational diffusion, density and swim speed are inversely related, $\rho \sim 1/v$ [10], while polarization vanishes [11]. However, real systems exhibit two critical features that

complicate this picture: finite reaction times between sensing and response [12,13], and translational diffusion characterized by a coefficient D [14–17]. Biological examples demonstrate that organisms have evolved to exploit temporal delays as control parameters rather than limitations: from gene expression affecting pattern formation [18], to social amoebae using delays in intercellular signaling to coordinate collective behavior [19] and maintain directional chemotaxis [20], to green algae tuning phototactic steering through delays matched to their rotational period [21].

Previous theoretical work has explored the effects of these parameters separately. For negligible translational diffusivity, Refs. [22,23] showed that the product of a short time delay τ and rotational diffusivity D_θ modifies the density profile as $\rho \sim 1/v^{1+D_\theta\tau}$, increasing particle accumulation in low-speed regions. Conversely, for negligible delay, Refs. [11,24,25] demonstrated that translational diffusion introduces a nonzero decay length of polarization profiles near activity steps and substantially modifies density distributions. Despite these advances, a unified framework accounting for both finite delays and nonzero translational diffusion has remained elusive.

In this work, we examine single-particle dynamics to establish the fundamental effects of temporal delays and confirm their persistence in dilute many-body systems, leaving collective phenomena for future study. We derive analytical expressions for density and polarization profiles incorporating both nonzero translational diffusivity D and finite delay times τ . Our theoretical model reveals three key phenomena: (1) Short delays enhance density maxima in low-activity regions; (2) polarization profiles undergo sign inversion when swimming distance during the delay time, i.e., the reaction length, $L_\tau = v\tau$, exceeds the characteristic diffusion length, $L_D =$

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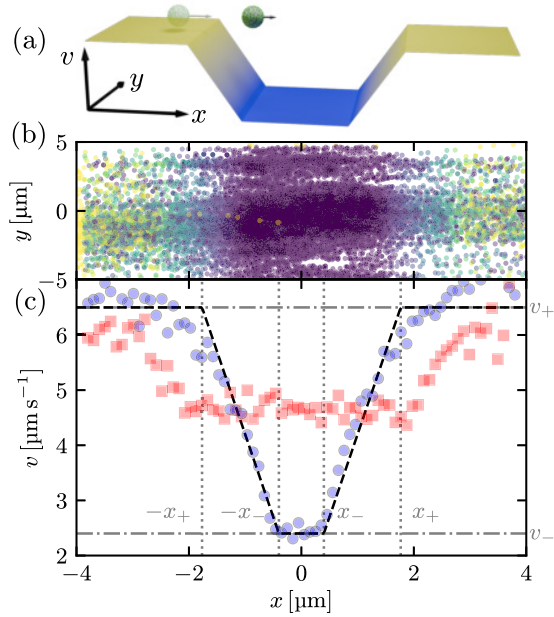


FIG. 1. Experimental setup. (a) A spherical thermophoretic microswimmer undergoes active Brownian motion in a spatially varying laser intensity profile that controls the self-thermophoretic propulsion of the swimmer using a feedback loop (see the Supplemental Material [26]). (b) Sample trajectory of the microswimmer over 15 min in an $8\,\mu\text{m} \times 10\,\mu\text{m}$ chamber, exhibiting rotational diffusion $D_\theta = 2.9\,\text{rad}^2\,\text{s}^{-1}$, translational diffusion $D = 0.04\,\mu\text{m}^2\,\text{s}^{-1}$, and delay time $\tau = 0.46\,\text{s}$. Colors indicate instantaneous velocity (scale: blue = $2\,\mu\text{m}\,\text{s}^{-1}$, red = $7\,\mu\text{m}\,\text{s}^{-1}$). (c) Velocity profiles induced by the spatially varying laser intensity: imposed profile with slope $m = \pm 3\,\text{s}^{-1}$ (dashed line), instantaneous velocity profile measured at $\tau = 0.46\,\text{s}$ (squares), and imposed profile reconstructed from trajectory measurements (circles).

$\sqrt{2D\tau}$; and (3) long delays randomize dynamics, leading to flat density profiles and zero polarization. These predictions, validated through experiments with thermophoretic microswimmers and Brownian dynamics simulations, establish time delay as a crucial control parameter for particle transport and organization in active matter. Our findings have implications for understanding biological navigation strategies, the evolution of sensory systems, and the design of synthetic microrobots with programmable responses to heterogeneous environments.

Experimental setup. Our experimental system employs active particles consisting of melamine resin spheres (diameter $d = 2.19\,\mu\text{m}$) partially coated with gold nanoparticles ($d_{\text{Au}} = 10\,\text{nm}$, surface coverage 10%) suspended in water between parallel glass plates separated by $h = 4\,\mu\text{m}$ [Fig. 1(a)]. The particles were propelled via self-thermophoresis induced by focusing a $532\,\text{nm}$ laser ($w_0 = 0.5\,\mu\text{m}$) to the edge of the particle (displaced by distance d from the center of the particle [27]), where plasmonic heating generates local temperature gradients and thermo-osmotic flows that propel the particle [28,29].

The particles were tracked using dark-field microscopy with light-emitting diode (LED) illumination and a high numerical aperture (NA) oil-immersion darkfield condenser (1.2

NA) integrated into an Olympus IX-71 microscope. Scattered light was collected through an Olympus $100\times/1.35\,\text{NA}$ objective (aperture set to $0.6\,\text{NA}$) and focused onto an Andor iXon EMCCD camera, which imaged a $50 \times 50\,\mu\text{m}^2$ field of view at 20 frames per second. Particle positions were analyzed at video rate during the experiment to control the laser position and power to adjust the particle speed with an acousto-optic deflector system (AA Optics). The feedback control loop has an intrinsic delay of $\tau_0 = 0.046\,\text{s}$. To explore the influence of time delay, we introduce an additional programmed delay, obtaining delay times of $\tau = n\tau_0$ ($n = 1, 4, 7, 10, 13$) such that the current particle speed depends on an earlier position.

We imposed a spatially varying velocity profile $v(x)$ composed of three regions [Fig. 1(c)]: a low-speed central region ($|x| \leq x_- = x_m - 2v_-/m$) with $x_m = 2\,\mu\text{m}$ and constant velocity $v_- = 2.4\,\mu\text{m}\,\text{s}^{-1}$; transition regions ($x_- < |x| \leq x_+ = x_m + (v_+ - 3v_-)/m$), where the velocity increases linearly with slope m (the rate of change of velocity with position), from v_- at $|x| = x_-$ to $v_+ = 6.5\,\mu\text{m}\,\text{s}^{-1}$ at $|x| = x_+$; and high-speed outer regions ($|x| > x_+$) with constant velocity v_+ . In symbols,

$$v(x) = v_- I_{0,x_-} + [3v_- + m(|x| - x_m)] I_{x_-,x_+} + v_+ I_{x_+, \infty}, \quad (1)$$

where $I_{ab}(x)$ is the indicator function, equal to 1 for $|x| \in [a, b]$ and 0 otherwise, effectively selecting the relevant spatial regions.

We aimed the laser either to the left or right of the particle's center along the x axis, causing the microspheres to persistently move along the horizontal axis besides their Brownian motion [Fig. 1(b)]. The microspheres underwent rotational Brownian motion, but since the laser focus remained fixed and the heated gold nanoparticles experienced almost instantaneous temperature relaxation, this motion did not affect the temperature field or the propulsion direction. To simulate the rotational diffusion inherent in microorganisms, we introduced an artificial angular variable $\theta(t)$ through Brownian dynamics simulation of Eq. (3) to modulate the velocity as $v(x(t - \tau)) \cos(\theta(t))$ [30]. Throughout all experiments, the rotational diffusion coefficient was fixed at $D_\theta = 2.9\,\text{rad}^2\,\text{s}^{-1}$.

This setup mimics, for example, bacteria adjusting their speed in response to a chemical gradient with a finite perception-reaction delay. Importantly, this situation differs fundamentally from externally forcing particles through the fluid: Dragging particles violates the overall momentum conservation of the agent-fluid system, whereas self-propulsion preserves it.

Figure 1(b) illustrates an example of the trajectory observed for a delay $\tau = 10\tau_0$ and a speed profile with a slope of $m = 3\,\text{s}^{-1}$, as depicted by the dashed black line in Fig. 1(c). The delayed response of microswimmers to the velocity profile leads to a mixing of high- and low-activity regions. Consequently, the mean instantaneous velocity profile $\langle \delta(x(t) - x) | x(t + \tau_0) - x(t) | / \tau_0 \rangle$ experienced by the microswimmer (red squares) deviates from the imposed one. The imposed velocity profile can be reconstructed from the trajectories as $\langle \delta(x(t - \tau) - x) | x(t + \tau_0) - x(t) | / \tau_0 \rangle$ (blue circles).

Results. To describe the delayed adaptation of microswimmers to environmental changes, we employ a single-particle active Brownian particle model incorporating time-delayed speed adjustments. The time evolution of the particle position

and orientation is governed by the following coupled stochastic equations:

$$\dot{\mathbf{x}}(t) = v[x(t - \tau)]\mathbf{n}(t) + \sqrt{2D}\boldsymbol{\xi}(t), \quad (2)$$

$$\dot{\theta}(t) = \sqrt{2D_\theta}\xi_\theta(t). \quad (3)$$

Here, $\mathbf{x}(t) = [x(t), y(t)]$ represents the position and $\mathbf{n}(t) = [\cos \theta(t), \sin \theta(t)]$ the orientation of the microswimmer. The speed $v[x(t - \tau)]$ depends on the particle's position at an earlier time $t - \tau$, while D and D_θ denote translational and rotational diffusivities. The terms $\boldsymbol{\xi}$ and ξ_θ represent independent, normalized, unbiased Gaussian white noises. Importantly, for homogeneous velocity profiles ($v(x) = v$), the dynamics is independent of the time delay. The effects discussed below therefore arise solely from the interplay of delay with spatial inhomogeneities in velocity.

For *short delay times* (where $\tau \ll D/v^2, 1/D_\theta$), we have derived analytical expressions describing two key properties of the system: the marginal density ρ (the probability of finding a particle at position x) and polarization p (the average orientation at position x , with positive values indicating rightward bias and negative values indicating leftward bias) [30], which read

$$\rho = \rho_0 \left(\frac{1}{v^2 + 2DD_\theta} \right)^{\frac{1+D_\theta\tau}{2}}, \quad (4)$$

$$p = \frac{v^2\tau^2 - 2D\tau}{v^2 + 2DD_\theta} \frac{\rho}{2\tau} v', \quad (5)$$

where ρ_0 normalizes the density profile and $v' = \frac{dv}{dx}$. Equations (4) and (5) are derived in the Supplemental Material [26], assuming smooth velocity profiles together with short-delay and small-diffusivity approximations. For constant velocity ($v' = 0$), they correctly predict uniform density and vanishing polarization. Beyond this regime, their validity can be confirmed through Brownian dynamics simulations (Figs. 2–4) as well as by direct comparison with experiments [Figs. 2(c) and 2(d)].

Figures 2(a) and 2(b) show the density and polarization profiles for $\tau = 0$, which is not accessible in current experiments but was realized in Ref. [25]. Comparing the graphs in Figs. 2(c) and 2(d) with those in Figs. 2(a) and 2(b) reveals that adding delay enhances the maximum density and, more strikingly, reverses and drastically enhances the polarization. All these effects are captured by Eqs. (4) and (5). The quantitative agreement between theory and experiment is generally good, though systematic deviations are visible. These likely arise from our short-delay approximations ($\tau D_\theta \rightarrow 0$, $\tau D/L^2 \rightarrow 0$, where L is the characteristic length scale of the velocity gradient), finite experimental trajectory lengths, and differences between the piecewise-linear experimental profiles and smooth theoretical assumptions. The density enhancement follows from the exponent $1/2 + D_\theta\tau/2 < 1$ in Eq. (4) [22,23]. According to Eq. (5), the polarization is controlled by the competition between reaction length ($L_\tau = v\tau$) and the characteristic diffusion length ($L_D = \sqrt{2D\tau}$). When $L_D > L_\tau$, the polarization is positive as activity decreases ($v' < 0$), matching previous findings without delay [11,24,25]. As τ increases, the polarization decreases, vanishes when the two lengths match, flips sign when the delay

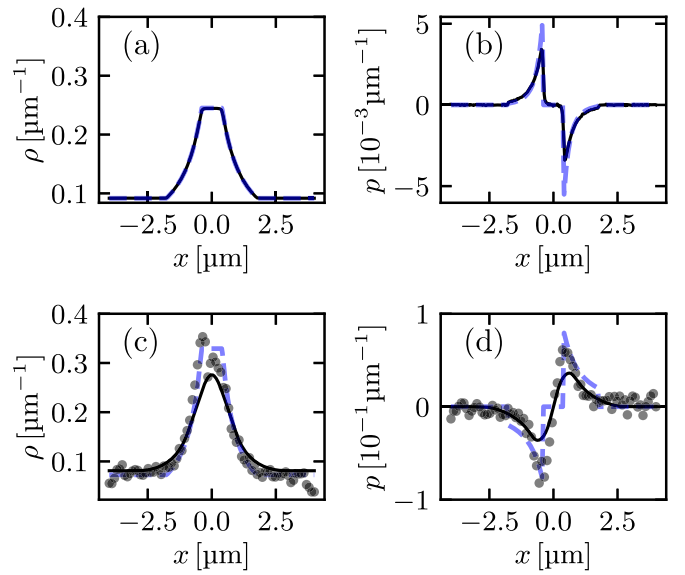


FIG. 2. Effect of short time delays on density [panels (a) and (c)] and polarization [panels (b) and (d)] profiles for the velocity profile in Fig. 1. Results are shown for $D_\theta = 2.9 \text{ rad}^2 \text{ s}^{-1}$, $D = 0.04 \mu\text{m}^2 \text{ s}^{-1}$, and $\tau = 0 \text{ s}$ (top) or $\tau = 0.184 \text{ s}$ (bottom). Solid black: simulations; blue dashed: theory [Eqs. (4) and (5)]; black circles: experiments.

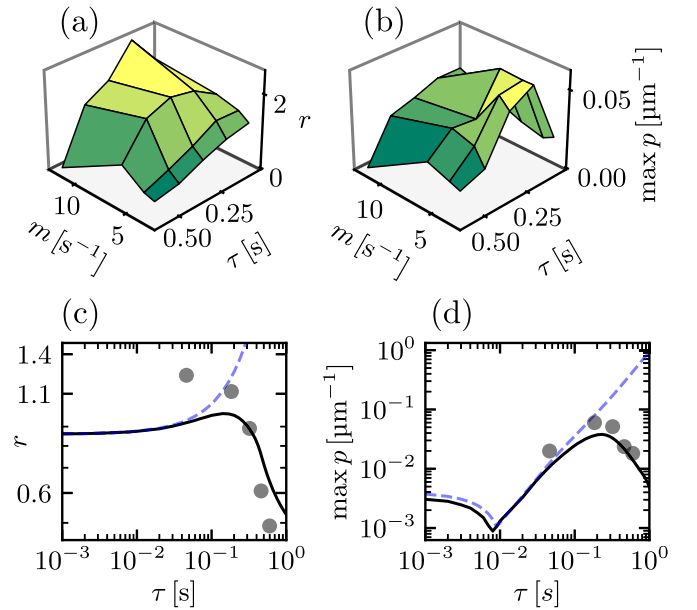


FIG. 3. Effect of longer delays on density and polarization for $D_\theta = 2.9 \text{ rad}^2 \text{ s}^{-1}$, $D = 0.04 \mu\text{m}^2 \text{ s}^{-1}$. Each data point in the first row corresponds to a single measurement with a given delay τ and slope m of the velocity profile. (a) Experimentally obtained ratio r of the weights of trajectory points inside the region from -2 to $2 \mu\text{m}$ vs those outside. (b) Corresponding maximum polarization. Panels (c) and (d) show the density ratio r and maximum polarization as functions of delay for the velocity profile in Fig. 1(c). Circles: experiment; blue dashed lines: theoretical predictions from Eqs. (4) and (5); black solid lines: Brownian dynamics simulations. The systematic deviations between theory and experiment at longer delays reflect the breakdown of the short-delay approximation used in our analytical treatment.

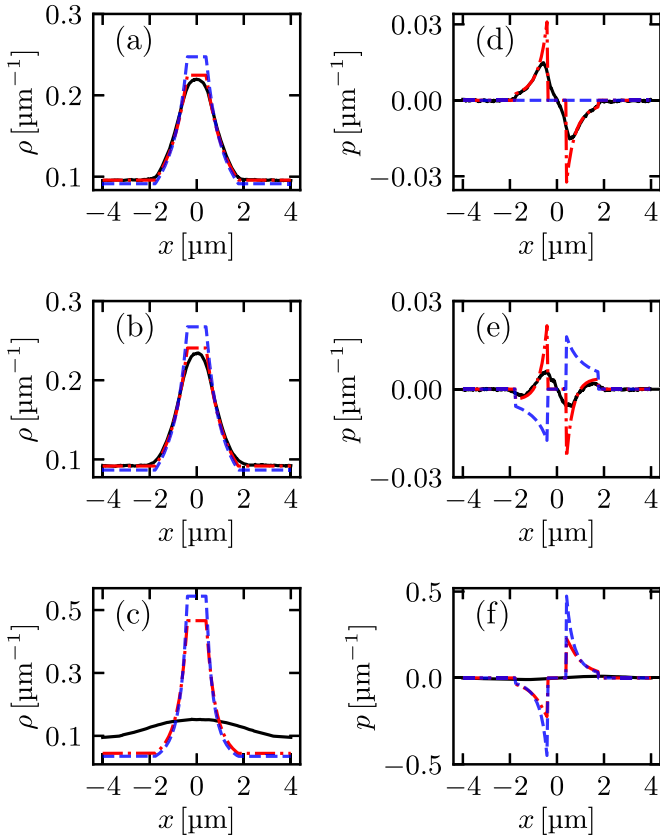


FIG. 4. Effects of translational diffusion on density and polarization. Data were obtained for $D_\theta = 2.9 \text{ s}^{-1}$, the velocity profile in Fig. 1, and a translational diffusion coefficient $D = 0.4 \mu\text{m}^2 \text{ s}^{-1}$, which is ten times larger than in experiments. The individual rows correspond to time delays $\tau = 0, 0.046$, and 0.598 s , respectively. Black solid lines: Brownian dynamics simulations; blue dashed and red dot-dashed lines: theoretical predictions from Eqs. (4) and (5) for $D = 0 \mu\text{m}^2 \text{ s}^{-1}$ and $D = 0.4 \mu\text{m}^2 \text{ s}^{-1}$, respectively.

exceeds a critical value ($\tau > 2D/v^2$), and subsequently, its absolute value increases almost linearly with τ . These predicted behaviors are verified by simulations in Figs. 3(c) and 3(d).

In contrast, *long delay times* randomize the dynamics, producing flat density profiles ($\rho \sim 1$) and zero polarization ($p = 0$). These long delay regimes can be characterized by $\tau \gg \tau_c$, where $\tau_c \sim \max(1/D_\theta, L^2/D)$ represents a critical delay time beyond which the particle's motion becomes decorrelated from its position at the time of sensing.

The transition between short and long delay regimes thus necessarily features peaks in the maximum density and polarization. These predictions are verified in Fig. 3. Specifically, we depict the maximum polarization, $\max_x p$, and the localization in the density measured by the parameter $r = \langle I_{02}[x(t)] \rangle / \langle I_{2\infty}[x(t)] \rangle$, which represents the ratio of the weights of trajectories in the central and outer regions of the arena (with higher values indicating stronger particle accumulation in the central region). Figures 3(a) and 3(b) show r and $\max_x p$ obtained from experiments for various delays, τ , and speed profile slopes, m . Figures 3(c) and 3(d) present the same quantities obtained from simulations (solid black lines), experiments (circles), and analytical calculations using Eqs. (4)

and (5) (dashed blue lines) for $m = 3 \text{ s}^{-1}$. Finally, in Fig. 4, we illustrate the interplay of delay, τ , and translation diffusivity, D , on the density and polarization profiles. Since D is fixed at a small value of $D = 0.04 \mu\text{m}^2 \text{ s}^{-1}$ in the experiments, we present results for a tenfold larger translational diffusivity, $D = 0.4 \mu\text{m}^2 \text{ s}^{-1}$, obtained from simulations (solid black lines) and theoretical predictions (4) and (5) (red dot-dashed lines). Neglecting D in the theoretical predictions (dashed blue lines) systematically underestimates the maximum density for short delays [Figs. 4(a) and 4(b)]. Moreover, for $\tau = 0$, Eq. (5) incorrectly predicts vanishing polarization [Fig. 4(d)], and for $\tau = \tau_0$, it produces a polarization profile with the wrong sign [Fig. 4(e)]. For a long delay $\tau = 13\tau_0$, the short-delay theory fails to predict both density and polarization, regardless of D [Figs. 4(c) and 4(f)]. In Figs. S3 and S4 of the Supplemental Material [26], we show that the single-particle effects described above persist in dilute systems (packing fraction ~ 0.15) of identical active Brownian particles interacting via short-range harmonic repulsive or attractive forces.

In summary, we theoretically predicted that microswimmers sensing an activity profile with a delay exhibit maxima in both localization and polarization as functions of the delay time, and demonstrated the phenomenon of delay-induced polarization inversion. The demonstrated polarization sign inversion represents a phenomenon not possible with instantaneous responses, offering a mechanism for switchable transport control through temporal rather than spatial programming. These predictions were validated through Brownian dynamics simulations and confirmed experimentally using thermophoretic microswimmers. Our experimental realization, the first of its kind at the microscale in the low Reynolds number regime, enables precise control of activity-rotational diffusivity landscapes and interaction delays. Our findings demonstrate how temporal delays in response to activity landscapes can shape both density and polarization, and our preliminary work [31] further shows that these effects can generate transport mechanisms in force-free active particle systems [32]. This principle extends beyond our experimental system to diverse biological contexts, potentially explaining how microorganisms optimize their response times for competitive advantages in heterogeneous environments. Future research could leverage these insights to design adaptive microrobotic systems capable of navigating complex landscapes for targeted medical interventions. Moreover, the demonstrated interplay between delay time and diffusion opens avenues for understanding cellular decision-making processes, where sensory delays may serve not as limitations but as evolutionary advantages that filter environmental noise and enhance collective behavior. Our current framework focuses on single-particle dynamics and provides a foundation for future investigations. Key extensions include (1) many-body interactions. In dense suspensions, delayed responses could create memory-driven clustering where particles accumulate based on historical rather than instantaneous local densities. This temporal non-locality could fundamentally alter the onset and structure of motility-induced phase separation [33], potentially creating dynamical phases with oscillatory or traveling wave characteristics; (2) study of the effects of delay and polarization on pattern formation [34]; (3) development of coarse-graining

techniques to bridge microscopic delay dynamics to macroscopic continuum descriptions; and (4) optimization protocols to actively control delay parameters for specific transport objectives. These directions represent natural next steps toward realizing the full potential of temporal programming in active matter.

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Data availability. The data that support the findings of this article are openly available [36]; embargo periods may apply.

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