

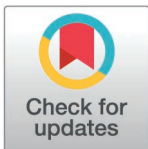
RESEARCH ARTICLE

Giving particles legs: How balance recovery may drive emergent collective dynamics in ultra-dense crowds

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Abstract

Ultra-dense crowds, in which physical contact between individuals cannot be avoided, pose major safety concerns. Nevertheless, the underlying dynamics driving their collective behaviours remain poorly understood. Existing dense crowd models, mostly two-dimensional and contact-based, overlook biomechanical mechanisms that govern human balance motion. In this study, we introduce a minimal two-level pedestrian model that couples upper body and legs dynamics, allowing us to capture how individuals continuously lose and recover balance under physical contact. This coupling generates emergent collective behaviours, such as self-organised waves and large-scale rotational motion, which prior modelling attempts failed to achieve. The model bridges basic individual biomechanical concepts and crowd-scale dynamics, offering a new interpretable framework for understanding collective dynamics in ultra-dense crowds.

Author summary

Ultra-dense crowds, with continuous inter-individual contacts have been commonly observed in mass events around the world. In these crowds, bodies are so tightly packed that involuntary movement may cascade into uncontrollable, and sometimes deadly, accidents. Despite the scale of these events, we still do not fully understand what drives the sudden, large-scale collective motions previously observed in this context. Existing models consider human bodies as single disks, and consistently fail to reproduce the rich spontaneous behaviours observed in real ultra-dense crowds. In this work, we propose that a key missing ingredient is the human balance recovery mechanisms. When people are pushed and set off balance, their legs and upper bodies are forced to move semi-independently: the upper body tends to topple due to gravity while the legs rush to maintain the upright position. We built a minimal mathematical model

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capturing this two-level coupling between legs and upper body. Despite its simplicity, our model spontaneously reproduces both propagating crowd waves and collective rotations, emerging purely from local physical interactions without any need for intentional coordination. Our findings suggest that individual balance control is a plausible engine driving complex collective behaviours observed in dense crowds.

1. Introduction

Ultra-dense crowds, i.e., crowds of 4–5 ped/m² and above where physical interactions between people cannot be avoided, are a major safety concern worldwide, with accidents reported every year [1]. Despite the potential hazards, the mechanisms underlying the collective dynamics of ultra-dense crowds remain poorly understood. As an example, most recent analysis of spontaneous density wave, transversal rushes, and rotational movements in ultra-dense crowds could not reveal its possible causes [2–4]. These collective dynamics are not intentional. What in pedestrian behaviour can explain such large and dangerous patterns? More precisely, could they arise from individual balance control mechanisms?

Early interpretations of crowd disasters commonly invoked the notion of *panic*, suggesting that individuals in emergencies lose rational control and behave selfishly or chaotically [5–7]. Building on these theories, simulation models have consistently sought to incorporate the propagation of emotional states and their effects on individual motion and interactions with neighbours [8–10]. However, numerous empirical studies and post-event analyses have since disproven this view [11–14]. Eyewitness accounts, video evidence, interviews and sociological investigations consistently show that people in extreme crowding conditions generally remain calm, cooperative, and even altruistic. Fatal outcomes may arise not from irrational behaviour, but from collective mechanical instabilities – when local pressures, force chains, and density waves propagate through the mass of pedestrians, leading to loss of balance, fainting, and even asphyxia [14].

This paradigm shift, integrating physical modelling with behavioural realism, reframes dense crowds as complex dynamical systems governed by biomechanical interactions rather than panic. Existing models, which primarily describe the passive transmission of motion between individuals through contact interactions and basic particle-like force exchanges, are not designed to capture additional active mechanisms. In particular, balance control behaviours can significantly influence the contact propagation dynamics, for example by amplifying, attenuating, or redirecting transmitted perturbations [15]. These active control processes constitute plausible explanatory factors for empirically observed phenomena that cannot be accounted for by passive propagation alone. Indeed, empirical studies have revealed a rich variety of collective patterns in dense pedestrian gatherings.

Pioneering observations in Mecca, Saudi Arabia, during the Hajj in 2006 identified stick-slip instabilities and turbulent-like flows, sometimes referred to as

earthquake-like *crowd turbulence*, where high-density pedestrian motions lead to sudden, large-scale ruptures [16]. Similar wave-like motions have been documented in large concert audiences, notably at the Oasis concert in 2005 in the United Kingdom [3], where propagating density waves emerge spontaneously. Transversal oscillating rushes have been documented experimentally in highly competitive, dense crowds in front of a bottleneck [2]. Collective chiral rotations have been observed in the Saint Fermín festival and the Love Parade in Duisburg, highlighting complex rotational and oscillatory modes in ultra-dense crowds [4]. These studies underline that ultra-dense crowds are far from static; even under extreme compression, they display rich self-organised collective behaviour that occur without clear triggers and require mechanistic understanding. Current models fail to predict how individual interactions translate into macroscopic crowd behaviour [17,18]. Understanding and modelling the collective dynamics of ultra-dense crowds is therefore critical not only for safety management but also for designing interpretable models capable of predicting and mitigating risky scenarios.

Classical microscopic pedestrian models, designed for low and intermediate densities at operational level, rely on concepts such as the fundamental diagram, social forces, collision avoidance, or trajectory optimisation [19–21]. These approaches have successfully described crowd behaviour under free and congested conditions, capturing flow, lane formation, and individual avoidance [22]. In these regimes, balance is maintained effortlessly through normal locomotion. However, physical contacts between pedestrians are continuous in ultra-dense situations and the dynamics changes fundamentally [4,23]. The contact forces can challenge postural control and standing balance must be actively maintained. Due to bio-mechanical constraints, the upper body and the legs can become constrained in different ways, preventing natural coordination and forcing pedestrians into potentially unbalanced postures. At such densities, pedestrian motion is primarily governed by physical forces and the bio-mechanical body response [4,16,24,25], rather than intentional navigation behaviour and locomotion-based balance maintaining: classical modelling frameworks become inadequate.

In the literature, the representation of physical interactions in dense crowds relies on two tightly coupled components: the spatial representation of the crowd and the modelling of interaction effort [23]. At the largest scale, macroscopic approaches treat the crowd as a continuum and model focus on the overall dynamics. Such formulations have recently been used to capture rotational chiral oscillations without resolving individual interactions at the local level [4]. Hybrid micro–macro approaches based on kernel continuum formulations can be seen as a bridge between individual-level dynamics and macroscopic flows, offering a clearer separation between social and physical interactions while capturing density-dependent patterns and flow heterogeneities [26–28]. Microscopic pedestrian models for dense crowds include individual interactions arising from body contact, such as normal repulsion and tangential friction, modelled by quadratic and higher-order nonlinear potentials [29,30]. For instance, the repulsive force is hyperbolic in the *asocial* pedestrian model [24]. In [31], the authors employ a Vicsek-like model with algebraic body contact and passive/active pedestrians to reproduce the dense crowd behaviour observed during concerts. Another example is the work in [32] that extended velocity-based collision avoidance models by incorporating contact, pushing, and resistive forces to represent balance recovery strategies. Despite their differences, microscopic pedestrian models for dense crowds remain grounded in simplified two-dimensional, disk-like, representations of individual agents. Beyond this simple isotropic approach, submicroscopic body representations have also been proposed. In [33], a representation featuring three circles for each agents is used in order to account for pedestrians shoulders. This approach have recently been augmented to proposed multi-circles agent body shapes fitted on an anthropometric database [34]. Humanoid limbed representation have also recently been proposed to simulate pedestrians. However, this approach uses limited physical interaction modelling without consideration for balance recovery mechanism, hence similar to former approaches [35]. The study [25] addresses cascading loss of balance following external perturbations—known as the *domino effect*. However, this approach remains restricted to perturbation propagation along a one-dimensional line of individuals and cannot, in its current form, be applied for dense crowd modelling.

None of the existing refined modelling paradigms for dense crowds explicitly incorporate balance-control mechanisms arising from the coupled motion of the upper body and the legs during physical interactions. In fact, current dense-crowd

models largely neglect the biomechanical coupling that governs how pedestrians maintain balance under contact. However, this coupling is essential for reproducing large-scale instabilities and emergent collective patterns driven by balance-control dynamics. Rather than further increasing the complexity of existing microscopic models through ad hoc contact forces, we introduce in this study an original dense-crowd model grounded in minimalist biomechanical principles, which explicitly accounts for the coupling between the legs and the upper body during physical interactions. Numerical simulations demonstrate that the model naturally reproduces several empirically observed collective phenomena within an interpretable submicroscopic framework.

2. Two-level pedestrian model

In this work, our main hypothesis is that the loss and the recovery of standing balance are dominant factors explaining the mechanisms of individual absorption and transmission of perturbation forces, and therefore explaining the collective motion of ultra-dense crowds. To test this hypothesis, we introduce a minimal two-level pedestrian model in which each agent consists of an upper body and a leg subsystem. We consider the relative positions, in the horizontal plane, of the upper body on the one hand and the legs on the other (see Fig 1). These positions, denoted in the following $\mathbf{x}_n(t)$ for the upper body and $\mathbf{x}_n^l(t)$ for the legs of the n -th pedestrian at time t , can be interpreted respectively as the ground-projected position of the body's center of mass and the center position of the support area containing the feet. The interaction between the upper body and the legs relies on two antagonistic mechanisms:

- First, when the upper body position moves away from the legs, it becomes affected by an “Unbalancing” force. This increases the relative velocity of the upper body with respect to the legs and further amplifies this displacement. This *unbalancing mechanism*, unintentionally endured by the pedestrian, is modelled by the term $\mathbf{u}$ in Fig 1.
- Second, in response, the legs move to ensure a stabilisation role: a rebalancing force increases their velocity to bring them back under the upper body, compensating for the destabilizing dynamics. This *balancing mechanism*, intentionally produced by the pedestrian, corresponds to the term $\mathbf{b}$ in Fig 1.

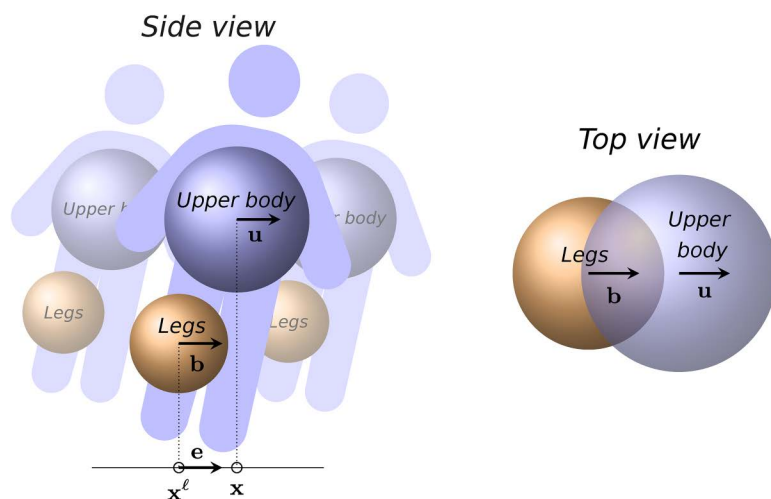


Fig 1. Scheme for the two-level pedestrian model with two antagonistic mechanisms. The force $\mathbf{u}$ acting on the upper body is an endured unbalancing mechanism whereby vertical displacements between the body and the legs induce instability due to the gravity. Conversely, the force $\mathbf{b}$ displays an intentional balancing mechanism whereby the legs relax to the upper body to maintain the body's upright posture.

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These mechanisms dynamically couple the upper body and leg layers, forming a quasi-three-dimensional paradigm that integrates vertical and horizontal interactions without explicitly simulating full 3D body dynamics.

Beside the kinematic relationships between projected positions and velocities of the pedestrian bodies and legs, namely $\dot{\mathbf{x}}_n(t) = \mathbf{v}_n(t)$ and $\dot{\mathbf{x}}_n^\ell(t) = \mathbf{v}_n^\ell(t)$, the dynamics of the two-level pedestrian model are given by

$$\dot{\mathbf{v}}_n(t) = \underbrace{\lambda_u(\mathbf{u}_n(t) - \mathbf{v}_n(t))}_{\text{Unbalancing}} - \underbrace{\lambda \mathbf{v}_n(t)}_{\text{Damping}} - \underbrace{\sum_{m \neq n} \nabla V(\mathbf{x}_n(t) - \mathbf{x}_m(t))}_{\text{Upper body interaction}} \quad (1)$$

for the upper body and

$$\dot{\mathbf{v}}_n^\ell(t) = \underbrace{\lambda_b(\mathbf{b}_n(t) - \mathbf{v}_n^\ell(t))}_{\text{Balance recovery}} - \underbrace{\sum_{m \neq n} \nabla V_\ell(\mathbf{x}_n^\ell(t) - \mathbf{x}_m^\ell(t))}_{\text{Legs interaction}} \quad (2)$$

for the legs, where

$$\mathbf{b}_n(t) = v_b(t) \mathbf{e}_n(t) \quad (3)$$

is the intentional balance recovery force acting on the legs with $v_b \geq 0$ the balance recovery speed, while

$$\mathbf{u}_n(t) = v_u(t) \mathbf{e}_n(t) \quad (4)$$

is the unintentionally endured unbalancing force acting on the upper body with $v_u \geq 0$ the unbalancing speed. Here $\mathbf{e}_n(t) = (\mathbf{x}_n(t) - \mathbf{x}_n^\ell(t)) / |\mathbf{x}_n(t) - \mathbf{x}_n^\ell(t)|$ is the unit vector that points from the legs to the upper body. Note that the model is well-defined as long as $\mathbf{x}_n(t) \neq \mathbf{x}_n^\ell(t)$ for all n and t , i.e., as long as the upper body and legs of each pedestrian remain spatially distinct. When $\mathbf{x}_n(t) = \mathbf{x}_n^\ell(t)$, the unit vector $\mathbf{e}_n(t)$ is undefined and the dynamics (1)–(2) become singular. Physically, this degenerate configuration corresponds to a perfectly balanced pedestrian with no postural lean, which is a measure-zero event in the dynamics.

We can distinguish three main types of mechanisms at play in the two-level pedestrian model (1)–(4) of dense crowds:

- (a) **Unbalancing and balance recovery mechanisms:** On the one hand, the unbalancing term accounts for the ability of the pedestrians to lean away from their base of support. It directly reflect the fact that an upper body displaced from its base of support naturally tends to “fall”. In other words, this force could be seen as the linearised effect of gravity on pedestrians’ upper bodies. On the other hand, the balance recovery terms represent the ability of the pedestrians to move their feet to change the location of their base of support in order to maintain upright standing balance. For simplicity, both the balancing and unbalancing processes are modelled using linear relaxations, which are dominated in magnitude by the repulsive interaction forces at short distances. These mechanisms are controlled by the balancing and unbalancing rates λ_b and λ_u . In addition, the balancing and unbalancing speeds, v_b and v_u , are assumed to be constant and equal. In principle, they could differ or dynamically depend on the distance between the legs and the upper body or their respective velocities.
- (b) **Interaction behaviour: Two-layer upper body and leg repulsions** We assume that upper bodies and legs interact independently on the two layers through purely repulsive, radially symmetric potentials V and V_ℓ , which monotonically vanish with increasing distance. These pairwise interaction forces describe repulsion and exclusion between the bodies and the legs respectively. They are nonlinear and dominate the upper body/leg coupling mechanisms at short distance. In the following, the interaction potentials are the exponential (short-range) functions [36]

$$V(x) = AB \exp\left(\frac{-|x|}{B}\right) \quad \text{and} \quad V_\ell(x) = AB_\ell \exp\left(\frac{-|x|}{B_\ell}\right), \quad A, B, B_\ell > 0. \quad (5)$$

Other repulsive interaction potentials, such as algebraic and power-law repulsion potentials as in [24,31], can be used instead. In fact, the collective dynamics of the model are mainly governed by the balance/unbalance mechanisms and related parameters, provided that the interaction potentials are nonlinear and repulsive. Because the pedestrian upper body is wider than the ground support area, we assume a larger repulsive distance at upper body level than at leg level, i.e., $B_\ell < B$, which naturally makes the legs more mobile and able to adjust more freely under dense-contact conditions.

(c) **Damping: or individual will to remain still in position** The damping term of the upper body $-\lambda v_n$, where $\lambda > 0$ is the damping rate, represent pedestrian's active resistance to external perturbations. Very much like classical force models, this term may include an external desired velocity v^* via the relaxation term $\lambda(v^* - v_n)$, to provide a direction of motion to the pedestrians. In the current version of the model, the desired velocity is null, and this term can therefore be seen as an internal will to remain still at the same position.

Having defined the motion mechanisms and interactions, it is instructive to clarify the qualitative behaviour expected from such a system. Each pedestrian can be viewed as a mechanically coupled body-leg unit, analogous to an inverted pendulum: the upper body provides inertia and is inherently destabilised by gravity when displaced from its base of support, while the legs act as an active control element that attempts to restore standing balance. The inverted pendulum is widely used as a conceptual model of individual pedestrian balance control [37,38]. When many such units interact through short-range exclusion forces, perturbations experienced by one pedestrian are transmitted mechanically to others thanks to the interaction layers, allowing local balance corrections or instabilities to propagate through the crowd. From this perspective, the model constitutes a many-body system of interacting inverted pendula, where energy injected by imbalance and dissipated through balance recovery is continuously exchanged between neighbouring pedestrians. The explicit two-layer structure further introduces internal degrees of freedom that naturally favour oscillatory responses and feedback loops, creating the conditions for collective modes to emerge at the system scale. These considerations motivate a systematic exploration of the model's dynamical regimes in simulation, where macroscopic organisation can arise from the interplay between individual balance control and mechanical coupling.

3. Simulation results

The duality between stabilizing and destabilizing forces generates a rich repertoire of individual behaviours, giving rise not only to crystallization but also to density waves and collective chiral motion. Beyond visualising the evolution of pedestrian upper body and leg positions over time, two main order parameters are used to quantify the collective behaviour:

- *System kinetic energy*

$$\mathcal{E} = \sum_{n=1}^N |\mathbf{v}_n|^2 \geq 0. \quad (6)$$

The kinetic energy $\mathcal{E}$ characterises the *magnitude of fluctuations* in pedestrian velocities.

- *Local velocity correlation*

$$C = \frac{1}{N} \sum_{n=1}^N \frac{1}{N_n} \sum_{m \in D_n} \frac{\mathbf{v}_n \cdot \mathbf{v}_m}{|\mathbf{v}_n||\mathbf{v}_m|} \in [-1, 1], \quad (7)$$

where $D_n = \{m, |\mathbf{x}_n - \mathbf{x}_m| < r\}$ is the set of neighbouring pedestrians within a radius $r=2$ m, and $N_n = \text{card}(D_n)$ is the number of neighbours. The velocity correlation $\mathcal{C}$ quantifies the *local alignment of motion*, indicating how coherently pedestrians move together [2].

In the following, we consider a square periodic system and two sets of parameters. The first set, presented in Section 3.1, promotes the formation of density waves, while the second set, presented in Section 3.2, gives rise to collective chiral oscillations and coherent rotational motion. Finally, the phase diagram of the model as a function of the balance and unbalance parameters is presented in Section 3.3. Details on the simulation setup and numerical scheme are given in Section 5.

3.1. Density wave pattern

When the unbalancing rate and the balance/unbalance speed are set to intermediate values, the system exhibits a density-wave pattern. Pedestrians move collectively, forming coherent diagonal waves across the domain, while maintaining local alignment. The propagation speed of these waves is of the order of 4–5 m/s, which is consistent with the propagation speeds of self-sustained wave observed during the Oasis concert [3] or of frontward impulses through standing crowds reported in [15]. The time evolution of pedestrian upper body and leg positions at discrete times $t=0, 10, 20, 30$ and 40 s is shown in Fig 2, illustrating the emergence and propagation of stationary density wave propagating in diagonal. The parameter values are the following: $\lambda_u = 0.5 \text{ s}^{-1}$, $\lambda_b = 1 \text{ s}^{-1}$, and $v=1 \text{ m/s}$. The values of the remaining parameters are given in Section 5.

The corresponding time series of system kinetic energy and velocity correlation (upper panel) and velocity autocorrelation in the stationary state (lower panel) are shown in Fig 3. Across the density-wave domain, the velocity correlation and wave speed remain approximately constant (see Fig 6), while the kinetic energy increases with the unbalancing rate and speed, reflecting waves of varying amplitude. The full video of the density-wave experiment is available in the repositories provided in Section “Data and code availability”.

3.2. Chiral rotation pattern

Under conditions where the unbalancing rate exceeds the balancing rate and the balance/unbalance speed is low, the system exhibits a global collective chiral rotations. In this regime, pedestrians describe individual circular trajectories while maintaining synchronised motion. The time evolution of pedestrian positions at discrete times $t=0, 20, 40, 60$, and 80 s is illustrated in Fig 4, while the corresponding dynamics of system kinetic energy, velocity correlation, and velocity autocorrelation in stationary states are shown in Fig 5. The parameter values are $\lambda_u = 1 \text{ s}^{-1}$, $\lambda_b = 0.5 \text{ s}^{-1}$, and $v=0.2 \text{ m/s}$. After a short transient, pedestrians walk in circles at a period of approximately 12 s (see Fig 5, right panel). Their velocity varies synchronously and their spatial correlation is close to one (see Fig 5, left panel). The full video of the chiral rotation experiment is available in the repositories provided in Section “Data and code availability”.

This large-scale coherent rotational dynamics are strikingly reminiscent of the spontaneous chiral rotation recently documented at the St. Fermín festival in Pamplona by Gu et al. [4], with a typical rotational period of approximately 18 s. Notably, the rotational period is tunable through the model parameters: periods of 15 s and 19 s are obtained for $(\lambda_u, \lambda_b) = (0.6, 0.3) \text{ s}^{-1}$ and $(0.4, 0.2) \text{ s}^{-1}$, respectively (keeping $v=0.2 \text{ m/s}$), indicating that the ratio λ_u/λ_b primarily controls the timescale of collective rotation. The amplitude of the rotations can be further adjusted through the balance/unbalance speed v .

3.3. Phase diagram

We systematically explore the dynamics of the two-level pedestrian model by varying the unbalancing rate λ_u and the balance/unbalance speed $v = v_u = v_b$, while keeping the balancing rate fixed at $\lambda_b = 1 \text{ s}^{-1}$. Fig 6 shows the system kinetic energy (left panels) and local velocity correlation (right panels) in the stationary state, used to characterise the different system phases. The kinetic energy quantifies the amplitude of pedestrian motion, while the velocity correlation measures

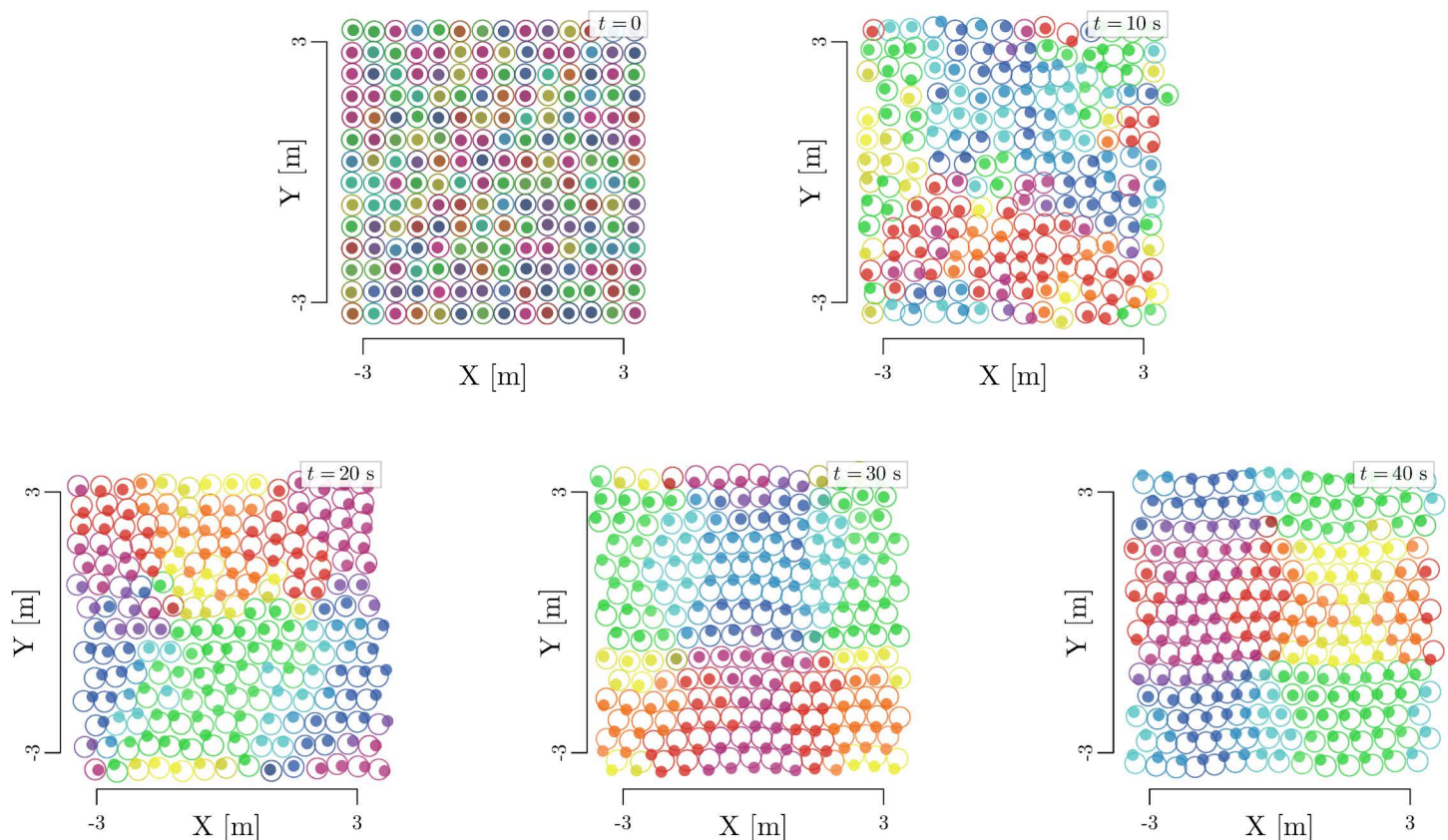


Fig 2. Time evolution of pedestrian body and leg positions under the density-wave parameter setting (B), see Fig 6. A diagonal density wave rapidly emerges and propagates through the system. Colour encodes pedestrian direction, and brightness indicates velocity magnitude. The full video of the experiment is available in the repositories provided in Section “Data and code availability”.

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the degree of coherence among pedestrians. In the crystallization state (A), see Figs A and B in [S1 Appendix](#), energy and correlation are both low. In the density-wave state (B), see [Figs 2](#) and [Fig 3](#), energy is intermediate and correlation is high, reflecting coherent wave propagation. In the chiral-oscillation state (C), see [Figs 4](#) and [Fig 5](#), energy remains low while correlation is high, corresponding to slow, coordinated rotational motion. Finally, in the disordered state (D), upper-bodies and legs decouple, the system does not appear to have a stationary state, although it is not diverging either. However, no clear pattern seems to be emerging, see Figs C and D in [S1 Appendix](#).

As either λ_u or v cross specific thresholds, the system transitions from a crystallised state to a density-wave pattern, forming a diagonal boundary beyond which the dynamics become disordered. In addition, in the bottom-right region of the parameter space, where λ_u is high and v is low, the system exhibits collective chiral rotations. Notably, the velocity correlation remains approximately constant across the entire density-wave domain, whereas the system kinetic energy increases with both λ_u and v . To assess the robustness of the four dynamical regimes identified in [Fig 6](#), we have systematically varied the system size, the initial conditions, and the model parameters (see [S1 Appendix](#)). Reducing the crowd size preserves the overall structure of the phase diagram, although the wave regime (B) tends to shrink while the rotation regime (C) expands as the system becomes more confined ([Fig E](#) in [S1 Appendix](#)). Introducing positional noise on the initial conditions (up to $\sigma_{IC} = 0.2$ m) or drawing the relaxation rates λ , λ_u , and λ_b independently for each pedestrian from a normal distribution with standard deviation up to $\sigma_\lambda = 0.2$ s⁻¹ leaves the phase diagram essentially unchanged (see [Figs G](#)

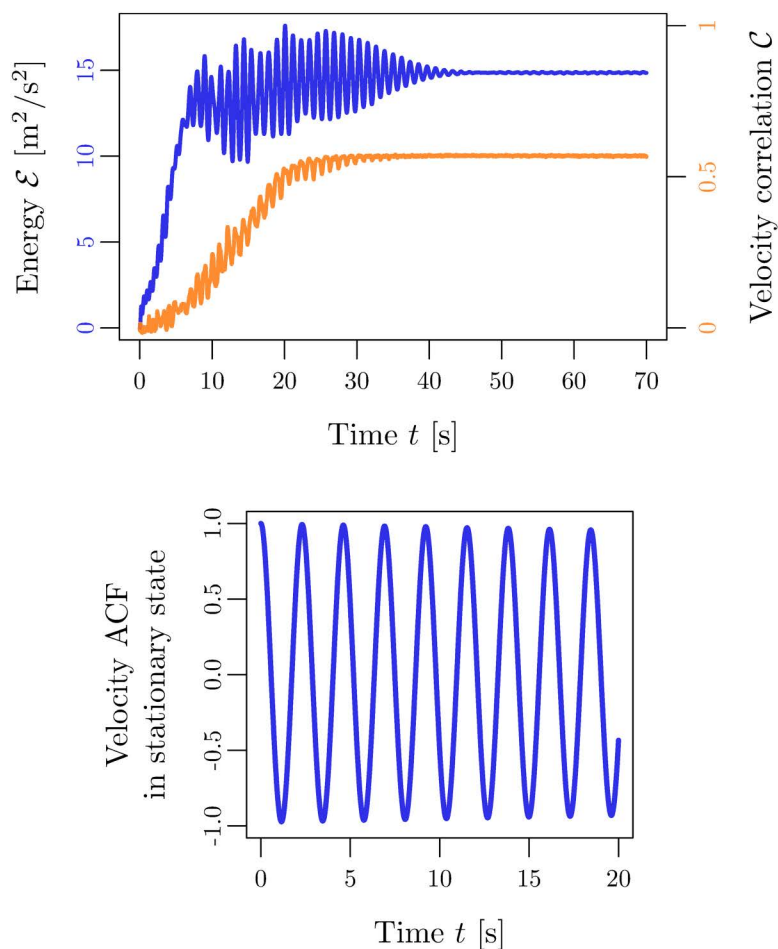


Fig 3. System kinetic energy and velocity correlation time-series (upper panel) corresponding to the sequence shown in Fig 2, and velocity time autocorrelation function (ACF) in stationary state (lower panel). The system converges to a stationary state featuring a density wave and pedestrians exhibiting periodic velocity fluctuations at high frequency.

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and I in S1 Appendix). Taken together, these results demonstrate that the emergent collective behaviours are robust features of the two-level model, persisting across a wide range of perturbations. In addition, further simulation results show that similar collective dynamics of density waves and chiral rotations arise when using the algebraic repulsive interaction potentials

$$V(x) = \frac{AB}{|x|} \quad \text{or} \quad V(x) = AB \left(1 - \frac{|x|}{B}\right)_+^{5/2} \quad (8)$$

where $A, B > 0$. In fact, the main mechanisms governing the emergence of collective motions are the balance and unbalance dynamics, and related parameters λ_b and λ_u . The interaction potentials appear to be secondary, as long as they are repulsive. Collective dynamics also emerge in the absence of potential leg interactions V_ℓ , although synchronisation is more difficult to achieve in this case. Furthermore, emerging dynamics appear to be relatively insensitive to the damping rate λ , provided that it is strictly positive.

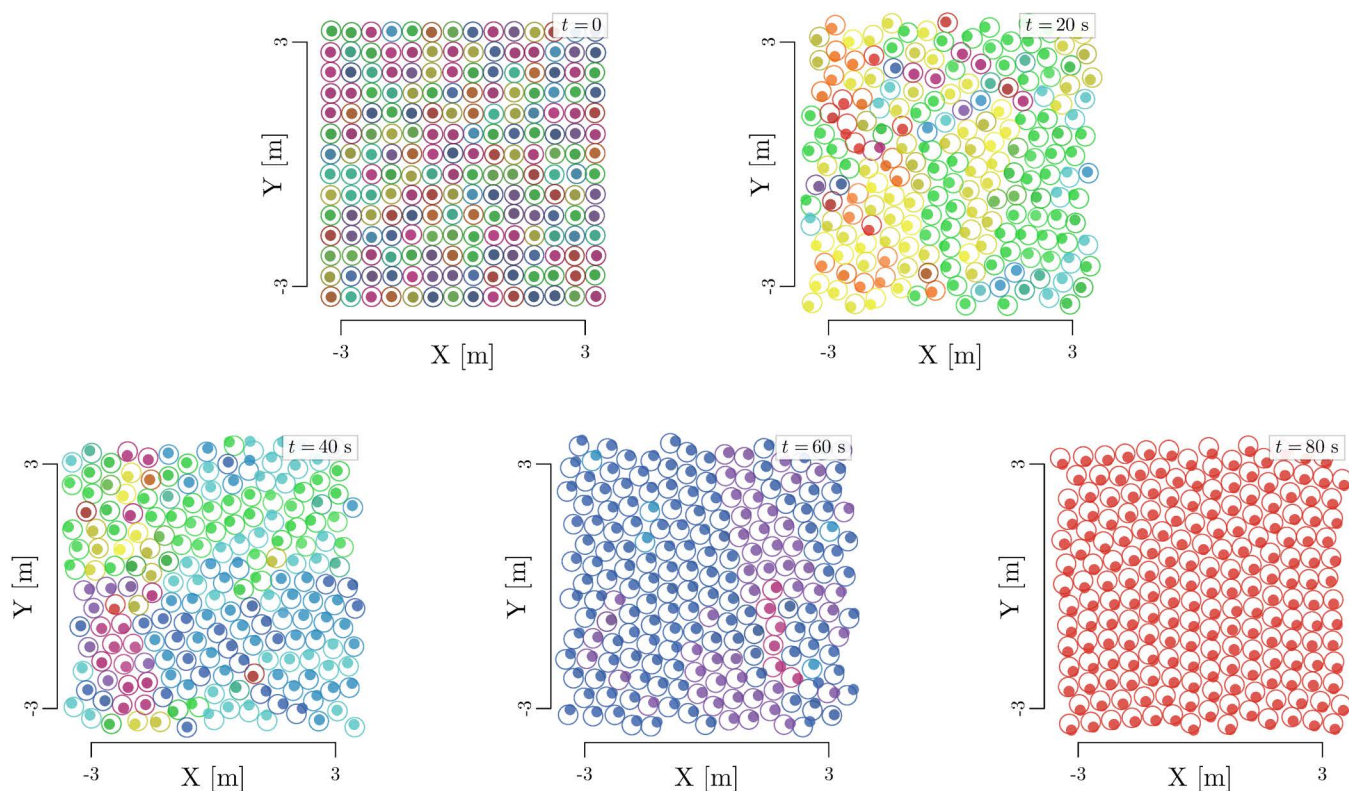


Fig 4. Time evolution of pedestrian body and leg positions under the chiral-oscillation parameter setting (C), see Fig 6. Pedestrians self-organise into a collective rotational motion. Colour encodes pedestrian direction, and brightness represents velocity magnitude. The full video of the experiment is available in the the repositories provided in Section “Data and code availability”.

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4. Discussion

Although deliberately minimalist, the present two-level model reveals a qualitative advance with respect to existing approaches to dense crowd dynamics. Classical two-dimensional models based solely on contact forces or velocity alignment successfully reproduce congestion, jamming, or stop-and-go motion, but they fail so far to account, within a single and interpretable framework, for the coexistence of distinct instability-driven collective modes that are directly relevant for safety of dense crowds. In contrast, by explicitly introducing an internal body–leg degree of freedom and balance-related feedback at the individual scale, the present model is able to reproduce propagating density waves and coherent chiral rotations, emerging from purely local interactions.

Importantly, the large scale behaviours observed here arise without fine-tuning or ad hoc global rules. Systematic exploration of the parameter space reveals well-structured dynamical regimes and robust phase boundaries, indicating that the observed collective states are intrinsic characteristics of the model. This robustness, together with the minimal and physically interpretable nature of the balance and unbalance mechanisms, strongly supports the relevance of biomechanical coupling as a missing ingredient in previous dense crowd models. In addition, the precise functional form of the repulsive interaction potentials appears to be secondary for the emergence of collective dynamics, provided that interactions remain short-ranged, repulsive, and offer more mobility to the legs. This further

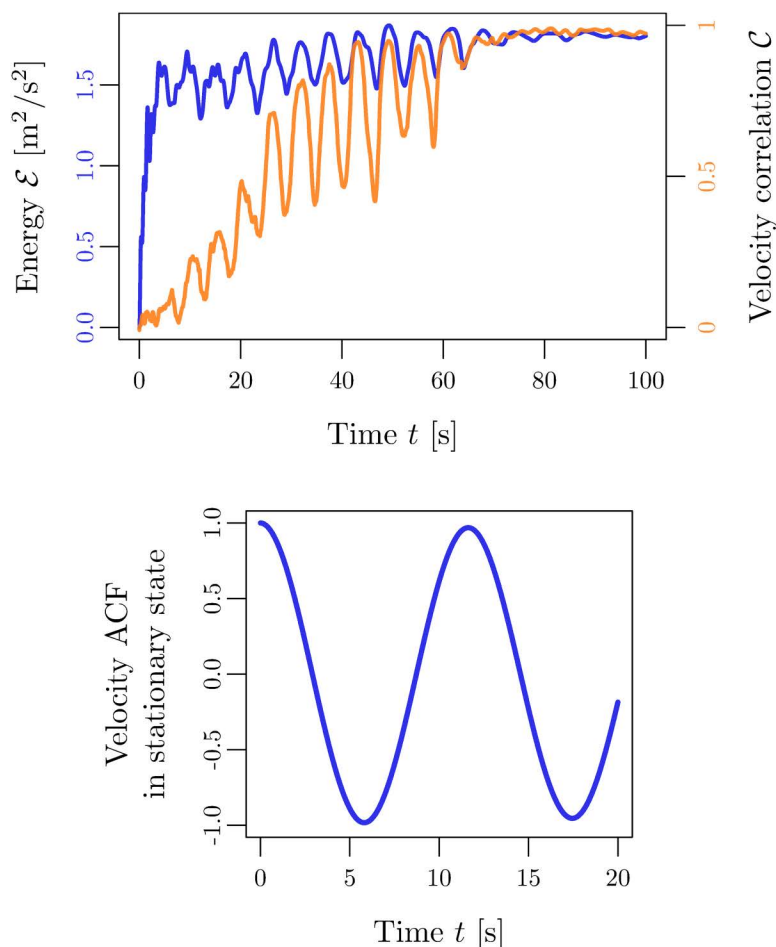


Fig 5. System kinetic energy and velocity correlation time-series (upper panel) corresponding to the sequence shown in Fig 4, and velocity time autocorrelation function (ACF) in stationary state (lower panel). The system converges to a stationary state exhibiting a global collective behaviour with chiral rotations, where pedestrians display periodic velocity fluctuations at low frequency.

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emphasises that the dominant organising principle lies in the internal balance dynamics rather than in the details of contact modelling.

At a mechanical level, the two-level pedestrian representation can be interpreted as a system of interacting inverted pendulums. Each pedestrian consists of an upper body acting as a mass subject to gravity-driven destabilisation, supported by a leg subsystem that plays the role of an actively controlled base providing elastic and dissipative stabilisation. The relative displacement between legs and upper body defines a local tilt, so that the unbalancing term mimics the linearised gravitational torque of an inverted pendulum, while the balancing term represents active postural control that repositions the base of support to maintain standing balance. This representation is classical to model individual pedestrian posture control [37,38]. When embedded in a dense crowd, the individual inverted pendulums are mechanically coupled through short-range repulsive interactions, allowing energy, momentum, and perturbations to be transmitted across the system.

In our model the crowd can thus be viewed as a spatially extended network of coupled inverted pendulums or mass–spring–damper units, whose collective dynamics are governed by both internal balance control and inter-agent

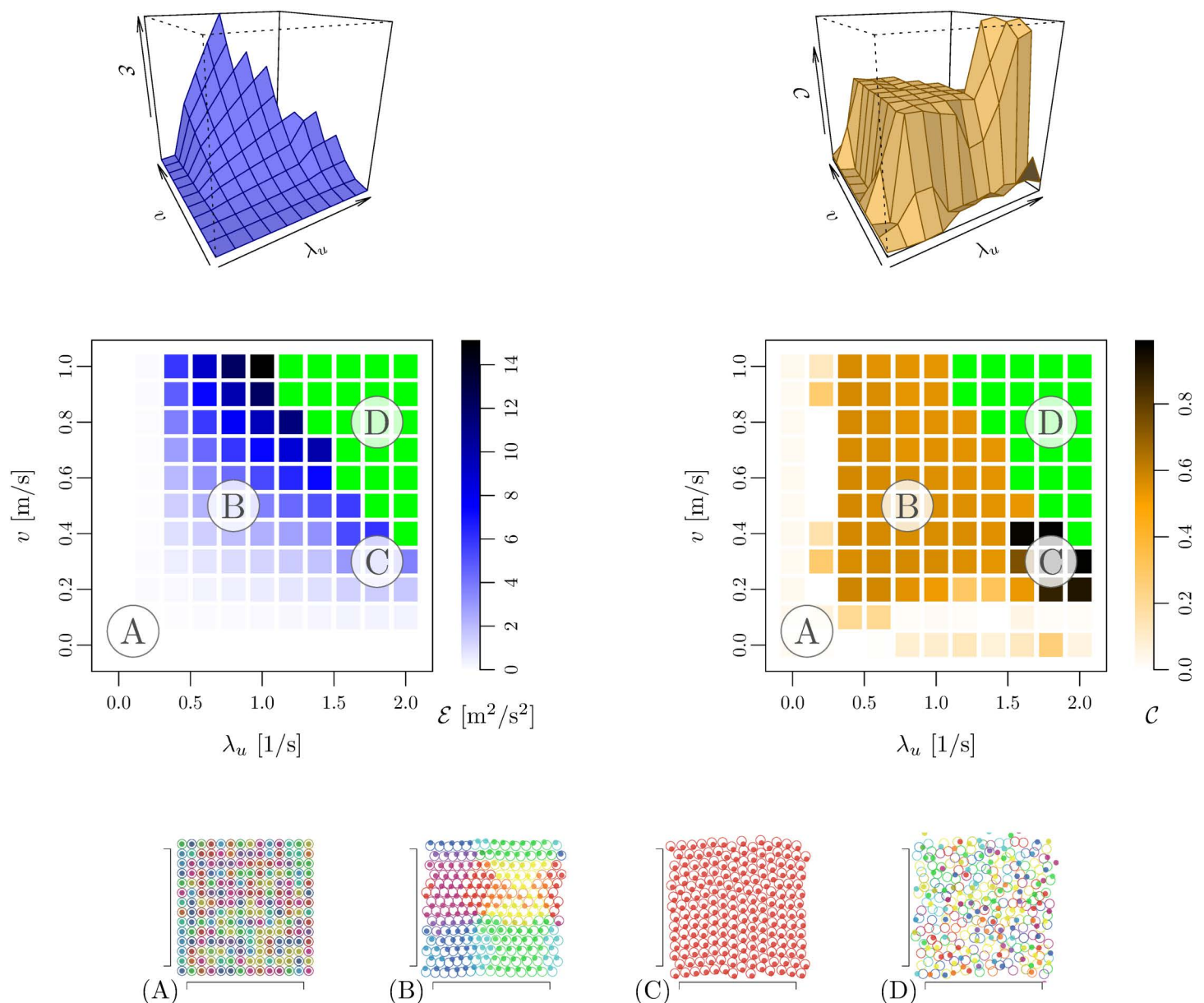


Fig 6. Phase diagram of the two-level pedestrian model as a function of unbalancing rate λ_u and balance/unbalance speed $v = v_u = v_b$ ($\lambda_b = 1 \text{ s}^{-1}$). Four main states emerge with increasing λ_u and v : (A) a crystallization state with low energy and correlation, see Figs A and B in [S1 Appendix](#); (B) a density wave state at relatively low unbalancing rate with intermediate correlation, see [Figs 2](#) and [Fig 3](#); (C) a chiral oscillating state at high unbalancing rate with high correlation, see [Figs 4](#) and [Fig 5](#); and (D) a disordered state where leg and body behaviours decouple (shown in green, see Figs C and D in [S1 Appendix](#)).

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mechanical (exclusion) constraints. This mechanical interpretation naturally connects the balance–unbalance feedback to the theory of coupled oscillatory systems, multi-layer systems, and Kuramoto-type systems. Within this framework, stability and synchronisation theory [39–42] provides a powerful conceptual lens to understand how local balance controls can self-organise into macroscopic patterns and system-wide coordinated motion.

Nonetheless, important steps remain before the model can serve as a predictive tool. We would like to emphasise that the work proposed here is an explanatory model rather than a predictive one. Its purpose is to demonstrate that integrating simple mechanisms to account for loss and recovery of pedestrian standing balance is sufficient to observe emergent patterns comparable to the ones reported from real ultra-dense crowds. However, the complete human body dynamic at stake in ultra-dense crowds is much more complex and beyond the scope of this work. The minimal mechanistic hypothesis presented in this contribution has to be further discussed in regard to future experimental studies of physical interaction and balance recovery of individuals in ultra-dense crowds.

First, the model must be regularised to ensure it is well-defined at equilibrium: the imbalance direction $\mathbf{e}_n$ is singular whenever upper body and legs coincide ($\mathbf{x}_n = \mathbf{x}_n^\ell$), and a natural fix is to replace the exact normalisation by a smooth approximation $\mathbf{e}_n = (\mathbf{x}_n - \mathbf{x}_n^\ell) / \sqrt{\|\mathbf{x}_n - \mathbf{x}_n^\ell\|^2 + \varepsilon^2}$, for a small $\varepsilon > 0$. More physically, replacing the propulsive unbalancing force by a conservative gravitational-like potential (e.g., an inverted-spring term $\kappa \|\mathbf{x}_n - \mathbf{x}_n^\ell\|^2$) would simultaneously eliminate this singularity and ground the individual dynamics in established biomechanical principles. Beyond this, the model must be extended with non-linear coupling terms and state-dependent parameters (e.g., making relaxation rates depend on body-leg separation or relative velocities) that recover the observed collective behaviour without adjusting parameter values. It should also be generalised to heterogeneous anisotropic populations with individual-specific biomechanical parameters, and augmented with frictional forces and rupture/falling mechanisms that capture discontinuous loss-of-balance events.

Additionally, the current model assumes that balance recovery is primarily achieved through motion of the legs. Here, repulsion of the upper body corresponds to continuous passive contacts between individuals. We acknowledge that pedestrians may also use their upper body and arms to exert forces onto other individuals beyond simple leaning. However, evidence from crowd disasters indicates that suffocation by thoracic compression is a leading cause of death [43], and eyewitness reports describe individuals struggling to even position their arms to protect their chest [14]. These observations show that upper-limb actions play a critical protective role, yet it remains unclear whether individuals generate active pushing forces or only use their upper limbs to protect their thorax and thus only passively transmit and redistribute the load. In addition, large-scale collective motions are observed under conditions where voluntary movement is reported to be extremely difficult. Our results suggest that active arm pushing is also not required to reproduce the collective motion observed under ultra-dense conditions. However, disentangling the contributions of balance recovery, upper-body contacts, active pushing, and passive force transmission will require further dedicated experimental measurements of whole-body contact forces.

Similarly, the relevant characteristic length of the inverted pendulum representation is yet to be investigated. In single-individual balance studies [44] the leg length serves as a natural estimate of the distance from the base of support to the centre of mass. In a crowd, interactions occur predominantly at the upper-body level [45], above the centre of mass, which may introduce an additional coupling length. Our minimal model deliberately absorbs these length scales into the rates λ_u and λ_b and the speed v ; a more detailed resolution of the spatial coupling mechanisms would be required for future model applications.

Beyond model extensions, systematic calibration and validation against experimental and naturalistic datasets, e.g., video analysis of large scale events, as well as controlled laboratory experiments including motion capture, are required to estimate parameters, test predictive capabilities of future models, and evaluate safety-relevant diagnostics. These developments will determine whether the two-level paradigm can be elevated from a qualitative mechanistic framework to a quantitatively reliable model for forecasting and mitigating hazards in ultra-dense crowds.

5. Materials and methods

We consider in the simulations a square system of length $L = 7$ meters with periodic boundaries (i.e., a horn torus of 49 m^2) and 196 pedestrians. The model [equation \(9\)](#) is simulated using the numerical scheme

$$\left\{ \begin{array}{l} \mathbf{v}_n(t + \delta t) = \mathbf{v}_n(t) + \delta t \left[\lambda_u (\mathbf{v}_n(t) - \mathbf{v}_n(t)) - \lambda \mathbf{v}_n(t) - \sum_{m \neq n} \nabla V(\mathbf{x}_n(t) - \mathbf{x}_m(t)) \right] \\ \mathbf{v}_n^\ell(t + \delta t) = \mathbf{v}_n^\ell(t) + \delta t \left[\lambda_b (\mathbf{v}_n(t) - \mathbf{v}_n^\ell(t)) - \sum_{m \neq n} \nabla V_\ell(\mathbf{x}_n^\ell(t) - \mathbf{x}_m^\ell(t)) \right] \\ \mathbf{x}_n(t + \delta t) = \mathbf{x}_n(t) + \delta t \mathbf{v}_n(t + \delta t) \\ \mathbf{x}_n^\ell(t + \delta t) = \mathbf{x}_n^\ell(t) + \delta t \mathbf{v}_n^\ell(t + \delta t) \end{array} \right. \quad (9)$$

where the position of the legs and upper body are computed using an implicit Euler scheme while the velocities are computed using an explicit scheme. The repulsive potentials for upper bodies and legs, V and V_ℓ , are the exponential functions [36]

$$V(x) = AB \exp\left(\frac{-|x|}{B}\right) \quad \text{and} \quad V_\ell(x) = AB_\ell \exp\left(\frac{-|x|}{B_\ell}\right). \quad (10)$$

The parameter values are the following. The damping rate λ is set to 1 s^{-1} . The repulsion rate is set to $A = 5 \text{ m/s}^2$ for both leg and body repulsive potential while the characteristic repulsion distance is higher for the body, $B = 0.5 \text{ m}$, than for the legs, $B_\ell = 0.3 \text{ m}$. For the sake of simplicity, the balance and imbalance speed are assumed to be constant and equal to v . The values of the parameters used in the two-level pedestrian model for the different scenarios of the simulations are given in Table 1.

The time step δt is set to 0.01 s in Figs 2, 3, 4, and 5, while δt is set to 0.1 s in the simulations of the phase diagram in Fig 6. In addition, the system performance in stationary states shown in Figs 3 and 5, right panels, and in Fig 6 is obtained after a simulation time of 500 s and 1000 s , respectively. In addition, 1000 attempts are carried out in Fig 6 before stating that the system is disordered with incoherent leg and body behaviours. The initial conditions are identical across simulations, consisting of an upright square lattice perturbed by independent, normally distributed noise with an amplitude of 1 cm .

5.1. Data and code availability

The videos of the simulations for the wave formation shown in Figs 2 and 3, and for the formation of collective chiral rotations in Section 3.2, see Figs 4 and 5, are available in [46]. An online simulation module of the system with periodic boundaries and 196 pedestrians is available at

<https://antoinetordeux.github.io/Two-Level-Pedestrian-Model/>

Table 1. Parameters settings of the two-level pedestrian to obtain the dynamics described in Section 3.1, see Figs 2 and 3, Section 3.2, see Figs 4 and 5, and Section 3.3, see Fig 6. As a remainder, λ_b is the balancing rate, λ_u the unbalancing rate and v is the balance and imbalance speed.

	$\lambda_b [\text{s}^{-1}]$	$\lambda_u [\text{s}^{-1}]$	$v [\text{m/s}]$
Density wave – Sec. 3.1, Figs 2 and 3	1	0.5	1
Chiral rotation – Sec. 3.2, Figs 4 and 5	0.5	1	0.2
Phase diagram – Sec. 3.3, Fig 6	1	$0 \rightarrow 2$	$0 \rightarrow 1$

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Supporting Information

S1 Appendix. This appendix contains supplementary information regarding the model and the robustness of the emergent collective dynamics under different conditions. Detailed illustrations of the crystallised and disordered states of the model are provided, including time evolutions of pedestrian positions, kinetic energy, and velocity autocorrelation functions. The robustness of the phase diagram is then detailed with respect to system size, random initial conditions, and heterogeneity within agents' parameters.
(PDF)

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