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Behavioral patterns in broiler chickens monitored with a multi-view tracking system

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ABSTRACT

Understanding behavioral changes across the production cycle is essential for broiler welfare assessment. This study monitored three key broiler chicken behaviors over time: activity level (based on net displacement per second) and time spent at the feeder and drinker zones. It includes the analysis of activity dynamics (high, medium, and low activity level), distance traveled over time, the effect of time of day (morning: 9:00–12:00, midday: 13:00–16:00, and evening: 18:00–21:00) on behaviors, and behavior during periods of experimentally induced high environmental temperature (29,4 $\pm$ 1°C; from days 29 to 33 and 36 to 40). This study involved four production rounds, each with 280 as hatched Ross 308 broilers (1,120 total), housed in two climate-controlled pens (9×4 m) per round (140 birds/pen; 14 kg/m^2). A multi-camera system tracked broilers using a YOLOv11 model and the SORT algorithm. Tracklets (short segments of a moving object's trajectory) were projected onto ground-plane coordinates and merged across views to form unified movement paths. The system achieved high tracking accuracy (MOTA: 0.81; IDF1: 0.89). Video segments (n=1,641) of 3 minutes each were recorded between days 8 to 40. Broiler behaviors from 8 to 40 days of age were significantly influenced by high environmental temperature and age. Heat exposure increased time spent at the drinker and reduced time spent at the feeder zone, while overall activity levels were unaffected. Activity dynamics shifted across the production cycle, with high-intensity activity decreasing earlier and more rapidly than medium and low activity, leading to a progressive dominance of lower activity levels as broilers aged. Behavioral patterns also varied by time of day, with time at feeder zone and activity partially rebounding in the evening after the heat-challenge period. While the system offers valuable monitoring insights, it has only been tested under controlled conditions with low density, and validation under commercial conditions is still needed.

Introduction

Monitoring livestock behavior is fundamental to assessing its welfare, as deviations from normal or expected patterns of behaviors can help to quantify the impact of housing and management practices (Roos et al., 2019). In broiler production, behavioral changes are valuable indicators of illness, stress, or discomfort, enabling timely interventions that reduce both suffering and economic losses (Mohialdin et al., 2023). However, manual behavioral assessments are time-consuming and impractical given the scale of modern broiler systems.

The welfare of farmed animals is gaining recognition not only for ethical reasons but also due to its influence on production efficiency (UBA, 2008). Environmental challenges, such as high environmental temperature, can further compromise welfare by triggering subtle

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Fig. 1. Experimental compartment used for broiler behavioral tracking.

behavioral changes that might be difficult to detect without continuous monitoring (Duenk et al., 2024). In response, scientific opinions have highlighted the importance of individual animal monitoring through behavioral observation (EFSA, 2020). Continuous sampling is considered the gold standard for behavioral assessment, providing a complete record of behaviors and their durations over time (Lehner, 1992). Yet despite technological advances, most poultry studies still rely on human annotation. These manual methods are not only labor-intensive but also prone to observer bias and limited in scalability (Dell et al., 2014).

Precision Livestock Farming (PLF) presents a potential approach to address these limitations by automating real-time monitoring through advanced technologies (Wolfert et al., 2017). Precision livestock farming can help to optimize resource use, enhance farm management, and improve animal health and welfare (Pandorfi et al., 2005). One significant component of PLF in the context of animal welfare is the application of image analysis (Rios et al., 2020), which transforms visual data into actionable insights. However, most existing systems for broiler tracking focus on trajectory mapping without identifying specific behaviors (Zuerl et al. 2022; Evangelista et al. 2022; Okinda et al. 2019).

Tracking individual broilers remains technically challenging due to their uniform appearance and rapid growth (Ross, 2018; Li et al., 2021). As body size and activity patterns evolve throughout the production cycle, tracking systems must adapt to recognize behavior relative to each bird's developmental stage. To overcome these challenges, a multi-camera system capable of accurately localizing and tracking broilers from a top-down perspective within the pen was developed (Cardoen et al., 2025). Video-based broiler detection and tracking has largely been limited to single-camera systems, typically applied from two weeks of age onwards and often at discrete time points (Guo et al., 2020; Yang et al., 2022; Van der Eijk et al., 2022; Novas and Usberti, 2017; Li et al., 2022). Our Multi-View BROiler Tracking (MVBroTrack) dataset extends this age range to 5–38 days. Single-camera accuracy is reduced by frequent occlusions from other birds and feeding or drinking equipment (Guo et al., 2021; Okinda et al., 2020), whereas multi-camera setups reduce blind spots and occlusions with only modest additional hardware cost. The detection pipeline demonstrated robust performance, achieving a mean object detection accuracy of 83.8% and sustaining high accuracy throughout the six-week growth period, despite considerable changes in the birds' appearance over time.

This study aimed to monitor three key behaviors in broiler chickens (activity and time spend around feeders and drinkers zone) over time and age. It includes the analysis of activity dynamics (high, medium, and low activity level; based on net displacement per second, that is, the change in an individual bird's position between consecutive time points) and distance traveled over time by the broilers, both using the multi-view detection and tracking system previously developed by our group (Cardoen et al., 2025). In addition, the effects of time of day (morning, midday, and evening) and periods of high environmental temperature on behavior were examined.

Materials and methods

The Ethics Committee of the Flemish Research Institute for Agriculture, Fisheries, and Food (ILVO) in Merelbeke-Melle, Belgium, approved the experimental protocol for this study under authorization number 2022/414.

Animals and treatments

The experiment consisted of four production rounds, each involving 280 male Ross 308 broiler chickens, totaling 1.120 birds. In each round, the barn was divided into two fully independent compartments, each equipped with its own automated climate control system. Between rounds, the compartment subjected to high environmental temperature was rotated to ensure unbiased treatment effects across pens (Soster et al., 2025). Each compartment contained one pen of 36 m^2 (9×4 m) (Fig. 1). The pens had concrete floors covered with wood shavings (2.5 kg/m^2). Each pen housed 140 broilers, resulting in a stocking density of 14 kg/m^2, equivalent to approximately 2.8 $birds/m^2$ at slaughter age. A lower stocking density than typically used in conventional broiler production was chosen in this trial to align with animal welfare standards required under experimental conditions (Directive 2010/63/EU), and to ensure the tracking system could reliably monitor the chickens.

On the day of the hatch, as hatched chicks were randomly assigned to each pen. All birds received the same starter (days 0 to 9), grower (days 10 to 22), and finisher (days 23 to 41) feed. Feed and water were provided *ad libitum* and were formulated according to the nutritional recommendations of Ross 308 broilers. Birds were kept on a 23 light (L):1 dark (D) in the first week, and on an 18L6D light schedule between days 7 and 41. During the first week, the dark period was from 5:00 to 6:00 am. From the second week onwards, the dark periods were from 10:00 to 11:00 pm, 12:00 am to 4:00 am, and 5:00 to 6:00 am, following typical commercial lighting programs used in Europe. A dawn–dusk program between light and dark period was not used; lighting transitions occurred abruptly according to the programmed schedule. To evaluate behavioral patterns throughout the day, the observation period was divided into three time blocks: morning (9:00 to 12:00), midday (13:00 to 16:00), and evening (18:00 to 21:00).

In the first week, the barn temperature was set at 32°C, after which it was gradually reduced by approximately 4°C per week until reaching 22°C at week 3, after which it was maintained through week 4. During the grower phase, and more specifically from days 29 to 33 and 36 to 40, high environmental temperature was applied in one of the compartments, while the control compartment remained under thermoneutral conditions. During the high environmental temperature period, the ambient temperature was gradually increased from 22°C to 32°C, rising by 2°C every 30 minutes to avoid stress from a sudden temperature shift. The peak temperature was maintained from 9:00 AM to 3:00 PM, after which it was gradually decreased back to 22°C at the same rate. Temperature and humidity were recorded every 2 hours. To evaluate the risk of birds experiencing high environmental temperature the temperature-humidity index (THI) was calculated using the formula proposed by Buffington et al. (1981). Between rounds, the compartment submitted to high environmental temperature was alternated to prevent possible room effects confounding treatment effects. The two compartments were separated by concrete wall and a closed door, ensuring that high environmental temperature could be applied in one pen without influencing the environmental conditions of the other.

Tracking system

The tracking system (Cardoen et al., 2025) employs a multi-camera setup with four synchronized cameras positioned around the pen that are fused together using calibration parameters to deliver a comprehensive view, minimizing occlusions from equipment such as feeders and drinkers. A fine-tuned YOLOv11 model analyzes footage from each camera (Jocher et al., 2023), detecting chickens and producing bounding boxes in every frame. These detections are linked across frames within each camera's view using the Simple Online and Real-time Tracking (SORT) algorithm (Bewley et al., 2016), generating partial tracks, or tracklets (short segments of a moving object's trajectory), for individual chickens. SORT was chosen for this system due to its reduced computational overhead.

Camera calibration parameters then transform 2D image coordinates into 3D world coordinates to map these tracklets to the ground plane. Accurate calibration parameters are essential for translating pixel-based detections into real-world spatial measurements, enabling precise localization of each chicken and allowing reliable estimation of movement patterns and distances traveled over time. Since chickens' feet are often hidden and hard to detect, a heuristic estimates their ground position using bounding box dimensions and their distance to the camera. Tracklets from all four cameras are fused to represent individual chickens across multiple views, forming a graph where tracklets are nodes connected by edges based on spatial and temporal proximity.

For temporally overlapping tracklets, the Fréchet distance assesses trajectory similarity, linking them if the distance is below a threshold. For non-overlapping tracklets, Euclidean distance between endpoints connects them if they are close in space and time. Connected components in the graph group tracklets of the same chicken, averaging their positions into a unified ground-plane tracklet.

The system also adjusts projections based on tracklet dynamics to account for chicken movement, reducing double-detections and improving positional accuracy over static assumptions. The outcome is a set of precise ground-plane tracklets that capture individual chicken movements over time, supporting detailed behavioral analysis throughout the production cycle. The performance of the tracking system was evaluated using standard multi-object tracking metrics, with particular attention to Multiple Object Tracking Accuracy (MOTA) and IDF1. The MOTA score, which reflects the overall accuracy in 83.8% of the tracker by accounting for false positives, missed targets, and identity switches, reached 0.81 ± 0.01. This indicates a high level of tracking reliability across the experiments. In addition, the IDF1 score, which measures the consistency of object identities over time by comparing predicted and ground-truth trajectories was 0.89 ± 0.01 suggesting that the system maintained object identities with high fidelity. These strong performance indicators demonstrate that the system is well-suited for generating consistent, accurate tracklets across the multi-camera setup. A total of 1,641 video segments, each three minutes long and recorded at 25 fps, were processed at the same frame rate using the system. This produced 82.05 hours of ground-plane tracklets across four rounds, corresponding to 328.2 hours of single-view footage aggregated across the multiple camera feeds.

Table 1
Ethogram used for behavior classification in broiler chickens.

Behavior	Description
Time spent at feeder	Time spent at feeder zone. A bird was considered to be around the feeder when it was moving, standing, sitting, or resting within a defined detection zone. The feeder-zone radius was defined as the feeder radius plus one broiler diameter (feeder zone radius = feeder radius + one broiler diameter at the corresponding age).
Tome spent at drinker	Time spent at drinker zone. A bird was considered to be around the drinker when it was moving, standing, sitting, or resting within a defined detection zone. The drinker-zone radius was defined as one broiler diameter at the corresponding age.
Activity level	The broiler was considered to be moving: either standing, lying, or sitting. A track was classified as *active* when the net displacement over a one-second window exceeded 20% of the bird's body diameter. Active behavior was then categorized by intensity: low activity (20–40% of body diameter), visually characterized as slow walking; medium activity (40–60%), visually characterized as fast walking; and high activity (above 60%), visually characterized as running.

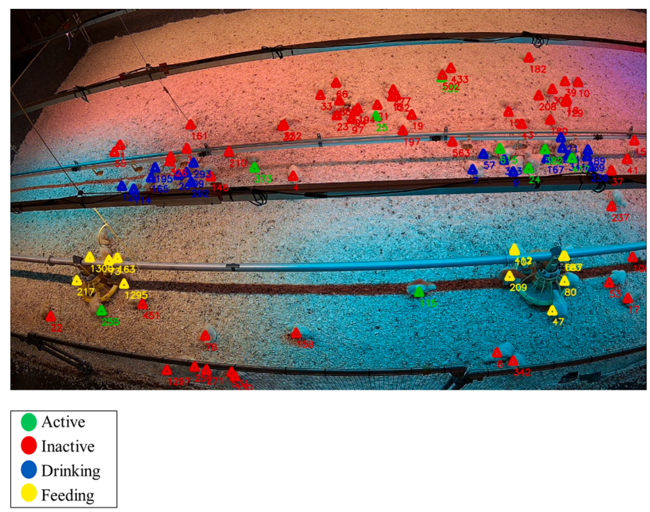

Fig. 2. Example of the post processed tracks at one timestamp. Green indicates active birds, red inactive, blue birds around drinkers, and yellow birds around feeders.

Tracklet post processing

From day 8 to 40, four cameras per pen recorded 3-minute video segments during the first 15 minutes of each hour (corresponding to three 5-minute segments) in the morning (9:00 to12:00), midday (13:00 to 16:00), and evening (18:00 to 21:00). Data was not recorded 24/7 because this would generate an extremely large dataset and be too heavy to store and process. Tracking started on day 8, because before this age the chicks were too small, which substantially reduced detection accuracy. The tracking data obtained from the video recordings underwent a systematic post-processing procedure to classify chicken behavior into

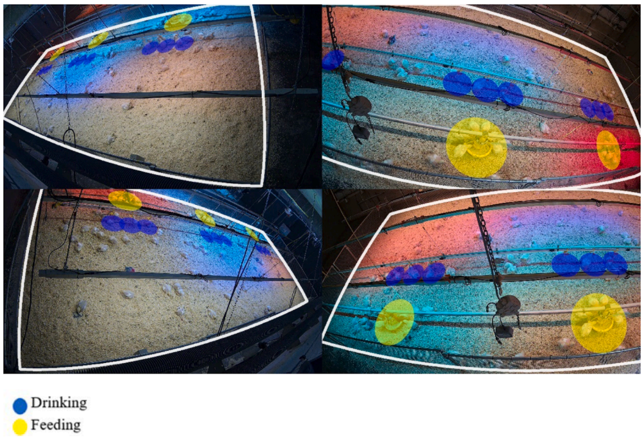

Fig. 3. Example of the masks used for determining the time spent at feeder and drinker zones. Yellow highlights the feeder zones, blue the drinking zones while white shows the pen boundaries.

three distinct categories: activity, time spent at feeder and drinker zones (Table 1). This classification relied on movement patterns (moving vs stationary) of individual chickens and spatial positioning (proximity to feeders or drinking nipples zones) (Fig. 2). Initially, the tracking data was filtered to ensure quality and reliability. Tracks shorter than 25 frames (equivalent to 1 second at 25 fps) were removed as they provided insufficient information for reliable behavioral analysis. Additionally, points falling outside the defined pen boundaries were excluded, see white mask in Fig. 3. To further enhance data quality, tracks with more than 30% missing detections were eliminated, ensuring that only continuous, reliable trajectories were analyzed.

For movement analysis, displacement vectors of the bird centroid (the geometric center of the detected bird body)were computed between consecutive frames and integrated over one-second windows. Activity classification was based exclusively on net center-of-mass displacement, providing an objective kinematic measure of locomotion independent of manual behavioral annotation. A track was classified as active when displacement exceeded 20% of the individual bird's body diameter, thereby normalizing movement thresholds to body size. Active behavior was further stratified by displacement magnitude into low (20–40%), medium (40–60%), and high (>60%) activity levels. These thresholds were selected to reflect increasing locomotor intensity and correspond approximately to slow walking, fast walking, and running, respectively. Non-locomotor behaviors (e.g., pecking or postural adjustments) result in minimal centroid displacement and therefore do not substantially contribute to activity classification. As activity classification relied on net spatial displacement, localized behaviors such as panting or wing stretching, which involve limited positional change, were categorized as inactive.

To correct for tracking errors and eliminate unrealistic movements, a threshold-based filtering method was applied, suppressing displacements exceeding 400 cm/s (Nääs et al., 2021). This approach effectively removed physically implausible movements while preserving genuine activity patterns. For each point in a track, cumulative displacement over the preceding 25 frames (1 second) was computed, providing a measure of effective movement. This method enabled differentiation between random jittering, characterized by minimal net displacement, and sustained directional movement. Activity classification was based on the net displacement per second and spatial location.

To estimate time spent at feeders and drinker zones, spatial proximity to these resources was used. Detection zones were defined separately for feeders and drinkers, accounting for bird age and positioning during use. For feeders, the feeder-zone radius was defined as the feeder radius plus one broiler diameter (feeder zone radius = feeder radius + one broiler diameter at the corresponding age), accounting for the space occupied by a bird standing at the feeder zone. For drinkers, the drinker-zone radius was defined as one broiler diameter (drinker zone radius = one broiler diameter at the corresponding age), as birds stand directly adjacent to the drinker.

The broiler radius (body diameter) was dynamically estimated based on the bird's age using the formula: radius = (0.3 × age in days) + 5 cm. Birds were positioned on a gridded cutting mat and gently held with a gloved hand to standardize posture and minimize movement. This approach accounts for growth over time and was experimentally determined N(Supplementary Fig. 1). Each experimental setup and pen configuration was calibrated to ensure accurate spatial measurements across different recording conditions. It is important to note that behaviors are not mutually exclusive. For example, when a chicken is exhibiting time spent at drinker zone, it may also be classified as active (moving around the feeder zone). The same applies to time spent at the feeder zone. However, a bird can be classified as active independently, without simultaneously engaging in time spent at feeder or drinker zones.

The linear radius model (r = 0.3 \times \text{age} + 5.0) cm was originally determined by physically measuring broilers at different ages (days: 7, 14, 21, 28, 35, and 42). To validate this equation, an independent image-based verification using the MVBroTrack dataset introduced in Cardoen et al., (2025) was performed. Individual broilers were segmented in all four camera views using the Segment Anything Model (Kirillov et al., 2023), and each segmentation mask was projected onto the ground plane via the calibrated camera parameters. In the next step, a circle was fitted within each ground-plane projection to estimate the body radius. Only broilers visible in at least three cameras with consistent, overlapping projections were retained. The resulting distribution of measured radii per age day (Fig. 4) clearly exhibits the same linear growth trend as the proposed equation, confirming its validity. The estimated radii are systematically slightly smaller than the physical

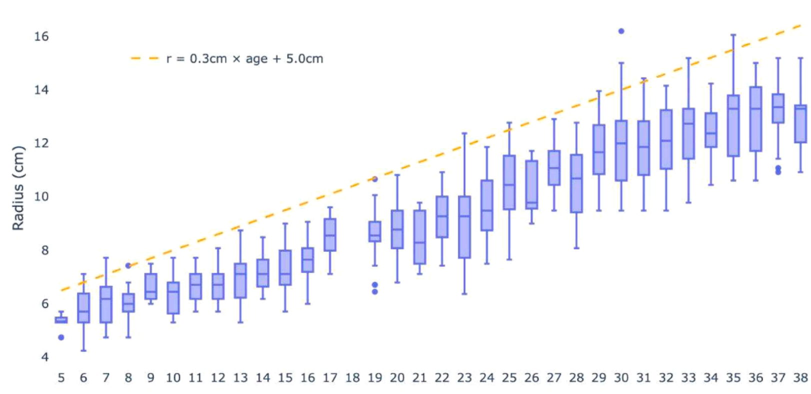

Fig. 4. Distribution of estimated broiler chickens body radii derived from image-based segmentation for each day of age (5–38 days).

Fig. 5. Example of broiler segmentation used to estimate body radius. The detected bird mask (blue) is projected onto the ground plane, from which the centroid and corresponding radius used for movement and spatial analyses are derived.

Table 2
Effects of high environmental temperature (HET; 29,4 ± 1°C, from days 29 to 33 and 36 to 40) and age of broiler chickens from 8 to 40 days-old on broiler behavioral time budgets.

Outcome	Term	Estimate	SE	P>|z|
Time spent at feeder	Intercept	14.838	1.256	<0.001
	High environment temperature	-3.028	0.27	<0.001
	Age	0.077	0.012	<0.001
Time spent at drinker	Intercept	10.079	1.117	<0.001
	High environment temperature	3.68	0.301	<0.001
	Age	0.277	0.013	<0.001
Activity	Intercept	9.053	0.497	<0.001
	High environment temperature	0.229	0.202	0.257
	Age	-0.168	0.009	<0.001

measurements, which is expected since the inscribed circle within a projected mask does not necessarily capture the full width of the bird. The tracking method proposed by Cardoen et al. (2025) operates on the ground plane, so the radius estimate naturally reflects the bird's footprint, regardless of whether it is sitting or standing.

Data analysis

Separate linear mixed models were fitted for time in drinker, feeder zone, and activity using the mixedlm function from the stats models library in Python. Data were aggregated at the pen level for each time point, thereby averaging over individual broilers within the same pen prior to modelling. Production round was included as a random intercept to account for the correlation of repeated measurements within rounds. In the main behavioral dynamics models, high ambient temperature condition (categorical: high environment temperature vs. thermoneutral) and age (continuous, zero-centered at the minimum observed age) were included as fixed effects; no interaction term was fitted. To assess the effect of time of day, the 24-h cycle was partitioned into three categorical periods: morning (00:00–12:00), midday (12:00–16:00), and evening (16:00–24:00). Time of day was first modelled as a fixed effect under high environment temperature conditions only. Subsequently, the interaction between time of day and high environment temperature condition (time of day × high environment temperature) was tested on data from both pens, restricted to ages occurring during the high environment temperature period. Statistical significance was set at $P < 0.001$. Where tendencies are reported, the corresponding exact P-values are provided in the text.

Results

Behavioral dynamics

Behavioral dynamics of broiler chickens from 8 to 40 days of age are presented in Fig. 5 and Table 2, while differences in THI between treatments are provided in Supplementary Table 1. Across the 10-day period of high environmental temperature phase, THI values were consistently higher in the high-temperature treatment than under thermoneutral conditions. High environment temperature significantly affected broiler behavior, but the effects differed depending on the activity measured (time spent at drinker or feeder zones).

Time spent at drinker zone increased under high environment temperature, with challenged birds showing higher drinking compared to control birds (linear mixed-effects model; $\beta = 3.68 \pm 0.30$ SE, $p < 0.001$). In contrast, time spent at feeder zones decreased under high environment temperature, with heat-stressed birds showing reduced

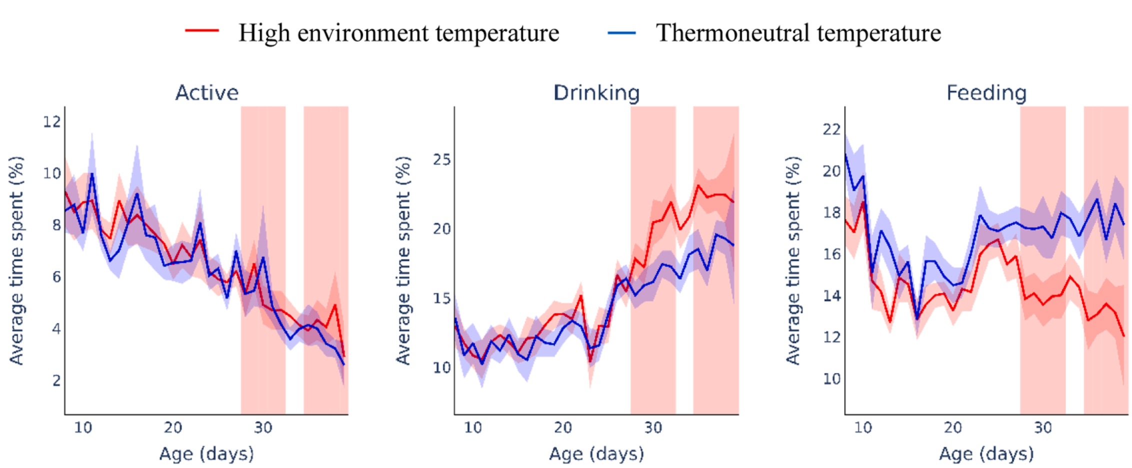

Fig. 6. Behavioral dynamics (overall activity, time spent at feeder and drinker zones) of broiler chickens from day 8 to 40 of age. Birds were exposed to high environmental temperature and thermoneutral conditions from day 29 to 33 and 36 to 40 (both periods are indicated as red in the figure). Estimated behaviors represent the average amount of time the broilers spend doing that activity. Activity, time spent at feeder and drinker zones represent the percentage of birds that are moving, or located in close proximity to the drinker or feeder, respectively. For instance, on approximately day 10, 12% of the broilers were located near a drinking nipple during the observation periods across the day.

Table 3
Effect of age on activity intensity categories of broiler chickens from 8 to 40 days-old.

Activity level	Term	Estimate	SE	P>|z|
Low	Intercept	6.783	0.39	<0.001
	Age	-0.037	0.004	<0.001
Medium	Intercept	3.346	0.178	<0.001
	Age	-0.038	0.003	<0.001
High	Intercept	5.752	0.312	<0.001
	Age	-0.134	0.006	<0.001
Difference (low – high level)	Intercept	1.034	0.263	<0.001
	Age	0.096	0.004	<0.001

feeding compared to controls ($\beta = -3.03 \pm 0.27$ SE, $p < 0.001$). Age had a significant positive effect on both time spent at drinker ($\beta = 0.277 \pm 0.013$ SE, $p < 0.001$) and feeder ($\beta = 0.077 \pm 0.012$ SE, $p < 0.001$) zones, although time spent at feeder zone showed peaks around days 10 and 23. Activity levels, however, were not significantly affected by high environment temperature ($\beta = 0.229 \pm 0.202$ SE, $p = 0.257$), though age was associated with a decrease in overall activity ($\beta = -0.168 \pm 0.009$ SE, $p < 0.001$).

Activity dynamics and distance traveled over time

While broiler activity levels changed with age (Fig. 6), the patterns differed across activity categories (Table 3). Initial analyses fitting separate mixed models for low, medium, and high activity suggested that high activity declined faster with age than medium or low activity, as indicated by steeper negative slopes (high: $\beta = -0.134 \pm 0.006$ SE, medium: $\beta = -0.038 \pm 0.003$ SE, low: $\beta = -0.037 \pm 0.004$ SE; all $p < 0.001$). To formally test this observation, the difference between low and high activity were calculated and modeled it as a function of age. This confirmed that the difference increased significantly with age ($\beta = 0.096 \pm 0.004$ SE, $p < 0.001$), demonstrating that high activity declines more rapidly than low activity as broilers grow older. High activity, characterized by running, began declining around day 15 and showed the most pronounced decrease over time. Medium and low activity levels started to decline around day 30, with low activity, primarily slow walking, remaining the most frequent but still gradually reducing.

Birds performing the high activity consistently showed the highest levels of locomotion, with average distances per pen often exceeding 1,200 cm during 3-minute recordings. This activity peaked around days 15 to 17, followed by a marked decline from day 30 onward. The medium activity behavior displayed a more stable and gradual increase in distance traveled, reaching a plateau between 600 and 900 cm up to approximately day 28, followed by a slight decline. The low activity behavior consistently showed the shortest distances traveled, rarely exceeding 600 cm. From around day 30 onward, all groups showed a progressive decline in activity, most notably in the high activity group, whose distance began to converge with that of the medium activity behavior. It is important to note that these distance values reflect the total locomotion of all chickens in the pen ($n = 140$) within the standardized recording duration, and should be interpreted as a relative measure of group-level activity rather than individual displacement.

Effect of time of day

Behaviors also varied by time of day (Fig. 7; Table 4). Within the high

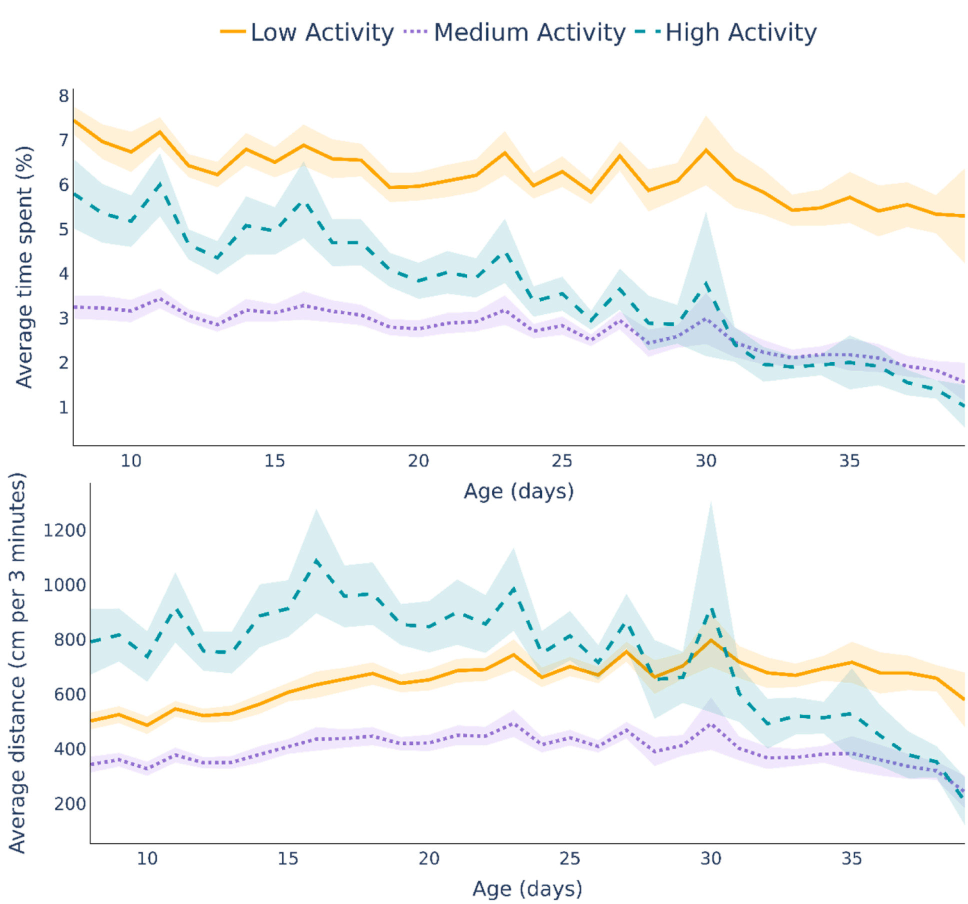

Fig. 7. Progression of three levels of activity behavior (low, medium, and high activity) in broiler chickens from day 8 to day 40 of age, shown both in terms of activity level and total distance traveled. Activity level denotes the average time per pen spent in each activity across all birds. Distance traveled represents the total distance per pen covered by all chickens in the pen (140 birds combined) during the 3-minute tracking windows.

Table 4
Effects of time of day (morning: 9:00–12:00, midday: 13:00–16:00, and evening: 18:00–21:00) and its interaction with high environmental temperature treatments (targeting 30°C; from days 29 to 33 and 36 to 40) on broiler behavioral time budgets during high environmental temperature periods.

Outcome	Term	Estimate	SE	z	P>|z|
Time spent at feeder	Intercept	13.263	1.07	12.391	<0.001
	Midday vs morning	-0.308	0.434	-0.71	0.4776
	Evening vs morning	1.995	0.46	4.339	<0.001
	High environment temperature	-4.851	0.472	-10.287	<0.001
Time spent at drinker	Intercept	20.726	1.76	11.779	<0.001
	Midday vs morning	-0.279	0.666	-0.419	0.675
	Evening vs morning	-1.305	0.707	-1.847	0.0647
	High environment temperature	3.644	0.679	5.367	<0.001
Activity	Intercept	5.703	0.927	6.151	<0.001
	Midday vs morning	-0.277	0.383	-0.723	0.4694
	Evening vs morning	-0.563	0.406	-1.387	0.1653
	High environment temperature	0.095	0.407	0.234	0.815
Time spent at feeder (time x HS, HS-period ages)	Intercept	17.809	1.333	13.363	<0.001
	Midday vs morning	-0.981	0.445	-2.203	0.0276
	Evening vs morning	-0.013	0.475	-0.028	0.9778
	Midday x Heat stress	0.694	0.63	1.102	0.2706
	Evening x Heat stress	2.053	0.67	3.064	0.0022
Time spent at drinker (time x HS, HS-period ages)	Intercept	17.255	1.18	14.627	<0.001
	Midday vs morning	-0.463	0.641	-0.722	0.4702
	Evening vs morning	-1.001	0.683	-1.464	0.1432
	Midday x Heat stress	0.099	0.907	0.109	0.9132
	Evening x Heat stress	-0.364	0.965	-0.377	0.7062
Activity (time x HS, HS-period ages)	Intercept	5.512	0.751	7.336	<0.001
	Midday vs morning	-0.358	0.384	-0.933	0.3508
	Evening vs morning	-1.187	0.409	-2.9	0.0037
	Midday x Heat stress	0.069	0.544	0.127	0.8987
	Evening x Heat stress	0.631	0.578	1.091	0.2751

environment temperature period, time spent at feeder zone varied across the day (Fig. 8). Feeding did not differ significantly at midday compared to the morning ($\beta = -0.308 \pm 0.434$ SE, $p = 0.478$), but increased significantly in the evening ($\beta = 1.995 \pm 0.460$ SE, $p < 0.001$), after the high environment temperature period ended (applied 9:00 AM–3:00 PM). Similarly, activity tended to remain higher in the evening under high environment temperature compared to thermoneutral conditions, although the interaction between time period and high environment temperature was not statistically significant (evening × high environment temperature: $\beta = 0.631 \pm 0.578$ SE, $p = 0.275$; Supplementary Fig. 2).

Discussion

This study provides a comprehensive analysis of broiler behavior across developmental stages and under high environmental temperature, using a scalable, multi-view computer vision system. The results demonstrate how both intrinsic (age) and extrinsic factors (temperature and time of day) shape key behaviors, time spent at feeder and drinker zones, and activity in broiler chickens. Recent advances in computer vision have enabled automated detection and monitoring of broilers under commercial conditions using single-camera YOLO-based frameworks (Elmessery et al., 2023; Guo et al., 2023) and resource-use assessment approaches (van der Eijk et al., 2022). However, most rely on single-view systems and short observation windows, limiting their capacity to reconstruct continuous individual trajectories in dense commercial settings.

For instance, Li et al. (2020) used top-view imaging to detect time spent at feeder and drinker zones based on posture and proximity but were limited by occlusions and manual annotations. Guo et al. (2022) applied a deep learning model (DenseNet-264) to classify four discrete behaviors with high accuracy, though only in short observation windows. Nasiri et al. (2024) focused on estimating individual time spent at drinker zone using an action recognition pipeline but restricted their analysis to a single behavior. In contrast, the present system fuses synchronized multi-camera views into unified ground-plane tracklets, mitigating occlusion and enabling longitudinal assessment of locomotion across age, diurnal periods, and thermal conditions, supporting intensity-based activity quantification and cumulative group-level distance estimates over extended monitoring windows, improving generalizability.

Behavioral trends revealed effects of age, temperature, and time of day, with implications for broiler welfare. As birds aged, locomotor activity declined, particularly in high-intensity movements, consistent with previous reports showing that broilers spend over 70% of their day inactive toward the end of the production cycle (Weeks et al., 2000; Tickle et al., 2018). Although gait score data are not presented in the current manuscript, gait assessment was performed within the same experimental cohort (Carvalho et al., 2026), demonstrating lameness and impaired bone health at day 40 of age. Thus, the observed reductions in movement intensity likely reflect emerging locomotor limitations associated with rapid growth, which compromises skeletal integrity and mobility (Knowles et al., 2008; Soster et al., 2025).

In our trial, high activity declined progressively, while medium activity showed a moderate reduction, and low activity remained relatively stable. Distance traveled mirrored these trends: high-activity distance decreased steadily with age, whereas medium and low activity levels showed temporary increases, peaking around days 23 and 29. This brief rise likely reflects the physical development phase in which birds grow rapidly and take longer steps. As growth continues, the combination of increasing body weight and limited skeletal support (Aviagen, 2018; Santos et al., 2024; Fernandes et al., 2012), together with literature-reported effects of litter deterioration (Peña Fernández et al., 2018; Riber et al., 2024), likely contributes to the overall reduction in movement, particularly for high-intensity activity, over time affecting also medium and low activity levels. However, given the low stocking density in our setup, large litter-related effects would be less expected. Tickle et al. (2018) provide important mechanistic insight into this phenomenon: their work demonstrates that as broilers age they increasingly divert energy from locomotion to growth. With rising body mass, movement becomes disproportionately costly and less biomechanically efficient, leading to more sitting/resting and fewer voluntary movements such as walking and feeder visits.

Although active behavior was numerically higher under heat stress across time periods, no significant treatment effect was detected, indicating that elevated temperature did not measurably increase locomotor activity. Nevertheless, heat exposure may still influence how activity is distributed across the day, as part of thermoregulatory adaptation (Wang et al., 2018). Such adjustments may reflect coping responses (Quinteiro-Filho et al., 2010), but they can also indicate compromised welfare if they increase energetic costs and disrupt rest. Patterns reported in the literature are mixed:Li et al. (2015) observed increased

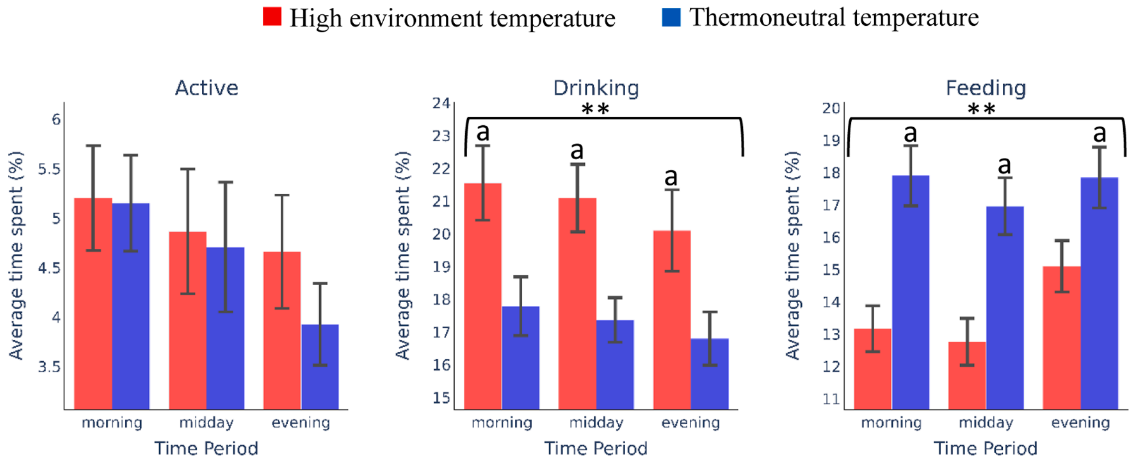

Fig. 8. Average behavioral values (active time, time spent at drinker and feeder zones) pooled across days 8–40 of broiler chickens across three different times of day (morning, midday, and evening) under two environmental conditions: heat stress (HS) and thermoneutral (TN). Mean environmental temperatures (HS vs. TN) were 29.1 ± 1.0°C vs. 21.6 ± 1.7°C (morning), 29.4 ± 1.1°C vs. 21.9 ± 2.0°C (midday), and 21.6 ± 0.9°C vs. 20.7 ± 1.1°C (evening). Different letters indicate significant differences among time periods within behaviors ($p < 0.05$); asterisks indicate significant main effects of temperature.

walking in heat-stressed broilers compared with controls, whereas Oso et al. (2025) reported reductions in high-intensity movement under high environmental temperature, consistent with the progressive decline in high-intensity activity observed in our data. Importantly, their single-camera approach captured short-term responses, whereas our multi-camera tracking followed trajectories over an extended period (8–40 days), allowing activity dynamics to be interpreted alongside age-related changes and diurnal variation, in addition to environmental conditions.

Behaviors followed a clear diurnal rhythm, with activity peaking in the morning and midday before declining in the evening. This pattern aligns with previous work showing that broiler behavior is strongly regulated by the light–dark cycle and exhibits pronounced morning activity peaks (Olanrewaju et al., 2006; Liu et al., 2015; Cangar et al., 2008; Estevez et al., 2007; Deep and McGreevy, 2012). Under high environmental temperature, these rhythms were disrupted: times spent at feeder zone decreased and times spent at drinker zone increased during the morning and midday challenge periods, indicating that thermal load interacts with and amplifies the birds' inherent chronobiological patterns.

Time spent at feeder and drinker zones also shifted with age and thermal conditions. As metabolic heat production increases with growth, so do water requirements for thermoregulation (Lara and Rostagno, 2013). This was reflected in a progressive rise in time spent at drinker zone, with midday and evening peaks. Holik (2010) reported a rise in the water-to-feed intake ratio, from 1.82:1 at 15°C to 4.9:1 at 30–35°C, under high environmental temperature. Interestingly, time spent at feeder zone increased at night in the high environmental temperature group, when temperature returned to thermoneutral levels, suggesting compensatory intake. Time spent at drinker zone also remained elevated at night, likely in response to higher feed intake, as water is essential for swallowing and digestion (Rodrigues and Choct, 2018).

Overall, time spent at feeder zone declined with age and was consistently lower in birds exposed to high environmental temperatures during the periods when elevated temperatures were applied. Liu et al. (2015) similarly reported increased time at the drinker zone and reduced time at the feeder zone under high temperatures, supporting existing evidence that birds decrease feed intake under heat to limit metabolic heat production (Yahav et al., 2000; Quinteiro-Filho et al., 2010). Additionally, increasing body mass may restrict access and willingness to reach the feeders and drinkers (Reiter and Bessei, 1997; Santos et al., 2024). However, under thermal stress, drinkers likely become a prioritized resource as birds increase water-seeking behavior to support evaporative cooling and hydration.. The peak in time spent around the feeder time spent at feeder zone at approximately day 20 may be related to the transition between diets, as feed changes are known to transiently modify feed intake and feeding behavior in broilers (Bizeray et al., 2002; Mendes et al., 2004; Nascimento et al., 2017).

By continuously tracking behavior throughout the production cycle, this study demonstrated the value of automated, non-invasive systems for real-time flock monitoring. Such tools could enable early detection of health and welfare concerns, such as leg disorders (in case of reduced activity, mainly when in early life), high environmental temperature (reflected by increased time spent at drinker zone and reduced time spent at feeder zone), or acute stressors like predators or equipment failures (evidenced by sudden spikes in movement). This approach also lays the groundwork for future research on responses to cold stress, enrichment, or disease, based on deviations from expected behavior patterns.

Despite its strengths, the study has limitations. First, behavior classification was limited to three categories. However, more specific behaviors (such as panting, wing flapping, exploring, dustbathing and preening) offer additional welfare-relevant insights, that would help distinguish more precisely health / welfare issues that may appear similar at the first sight (e.g., heat stress vs. respiratory disease). Future work should therefore extend behavior classification to a richer ethogram, incorporating also specific postures, such as sitting, standing and laying, to allow more precise and detailed behavior assessment. Additionally, time spent at feeder and drinker zones were inferred based on proximity, which may have under or upper estimated actual engagement in those behaviors. A further limitation concerns external validity. The stocking density used here (14 kg/m^2) is substantially lower than commercial practice, where larger flocks show different social dynamics, greater competition for space, and altered movement and resource-use patterns (Buijs et al., 2009). Higher densities may constrain locomotion, reduce activity, and modify access to feeders and drinkers, which could affect both behavioral expression and tracking performance. Nevertheless, the multi-camera design and ground-plane tracklet fusion were implemented to mitigate occlusion and identity loss, two challenges expected to intensify at commercial densities. This supports the potential transfer of the framework to industry settings, although validation under standard commercial stocking densities remains necessary.

Conclusion

Our automated system captured long-term behavioral dynamics. Our results document age-related and time of day trends in activity and time spent at feeder and drinker zones under both thermoneutral and high environmental temperature conditions. The study demonstrated that age, high environmental temperature, and time of day influence broiler behavior, with a progressive decline in activity and time spent at feeder zone over the production cycle. Under high environmental temperature conditions, broilers spent more time at the drinker zone and less time at the feeder zone.

The automated tracking system enabled the identification of relevant behavioral patterns over production cycle. While this approach offers valuable insights for broilers monitoring, it is also important to recognize its limitations. Behavior classification was restricted to three categories, and feeding/drinking were inferred by proximity, which may not reflect true engagement. While it provides a suitable model for research purposes, the low stocking density limits external validity to experimental settings; commercial flocks experience different social dynamics, space competition, and movement constraints that can alter both behavior and tracking performance. Validation under commercial conditions is therefore needed to confirm practical applicability.

CRediT authorship contribution statement

Patricia Soster: Writing – original draft, Visualization, Methodology, Investigation, Conceptualization. **Thorsten Cardoen:** Writing – original draft, Visualization, Validation, Software, Investigation, Formal analysis, Data curation, Conceptualization. **Camila Lopes Carvalho:** Methodology, Investigation, Conceptualization. **Imad Khan:** Methodology, Investigation. **Bassem Khalfi:** Methodology, Investigation. **Ana Martos Martinez-Caja:** Writing – review & editing, Investigation. **Frank Tuyttens:** Writing – review & editing, Visualization, Supervision, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization. **Maarten De Gussem:** Writing – review & editing, Project administration, Investigation, Funding acquisition. **Sam Leroux:** Writing – review & editing, Formal analysis. **Pieter Simoens:** Writing – review & editing, Formal analysis, Data curation, Conceptualization. **Gunther Antonissen:** Writing – review & editing, Visualization, Supervision, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization.

Disclosures

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.psj.2026.106759.

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