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Research article

A tri-axial acceleration-based behaviour template for translocated birds: the case of the Asian houbara bustard

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Understanding the behaviours and time budgets of translocated animals post-release has the potential to improve rearing and release protocols, and therefore survival rate. *Otididae* (bustards) inhabit open landscapes across the Middle East and Asia, are highly mobile on the ground and have similar lifestyles and body plans. The Asian houbara *Chlamydotis macqueenii* is a bustard of conservation concern inhabiting the Middle East to Central Asia and is frequently reared in captivity for population management. We deployed tri-axial accelerometers on 20 captive Asian houbaras in two seasons to catalogue basic behaviours, provide a template applicable to other bustard species and examine seasonal differences in behaviour. We created Boolean algorithms to define the following behaviours using raw acceleration data and derived metrics: stationary, eating/drinking and locomotion. We used video recordings to cross-validate the algorithms, yielding recalls from 95 to 97%, and precisions between 97 and 98%. Houbaras spent significantly more time 'stationary' and less time on 'locomotion' in summer (June) compared to spring (March). Simple Boolean algorithms proved useful in identifying several behaviours and have the potential to be applicable to other bustard species, in captivity and in the wild post-release.

Keywords: accelerometer, animal behaviour, Asian houbara bustard, captive breeding, conservation translocation

Introduction

Translocation of captive-bred animals is an increasingly popular approach for augmenting populations of endangered species and boosting populations for commercial and recreational purposes (Armstrong and Seddon 2008, Ewen et al. 2012). Over 3000 vertebrate species were being bred in captivity in 2009 (Razzetti and Scali 2009). Monitoring individual behaviour in captivity and post-release could help improve conservation and management efforts (Heezik et al. 2009, West et al. 2019).



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Post-release monitoring of behaviour is necessary for evaluating factors affecting translocation success (IUCN/SSC 2013), yet it is challenging due to difficulties in locating and directly following released individuals for extended periods of time. Technological advancements are now enabling the remote monitoring of animals in the wild, providing high-resolution location and behavioural data, mostly attributed to animal-attached accelerometers (Shepard et al. 2008, Sur et al. 2017, Gudka et al. 2019). However, the use of accelerometers is still limited within the conservation community, with few studies employing accelerometers on translocated birds (Armenteros et al. 2015, Forbey et al. 2017, Wann et al. 2019).

The Asian houbara *Chlamydotis macqueenii* is a sexually dimorphic bird, inhabiting semi-deserts across the Middle East and Central Asia. The species is classified as vulnerable in the wild, declining relative to historic records, primarily due to unregulated hunting, illegal trade and habitat degradation (Riou et al. 2011, Riou and Combreau 2014, BirdLife International 2024). The International Fund for Houbara Conservation (IFHC; www.houbarafund.org) has been breeding houbaras in captivity for release, both for long-term conservation and sustainable hunting.

Post-release survival is critical for the success of houbara translocations, which is affected by environmental conditions (Monnier-Corbel et al. 2022), intrinsic factors (Harris et al. 2023) and rearing and release methods (Hardouin et al. 2014, 2015, Bacon et al. 2018). Identifying the underlying causes that influence survival, including behaviour, is therefore crucial to optimise fitness and ultimately translocation success (Sarrazin and Barbault 1996, Dolman et al. 2021). Captive conditions may affect several houbara traits, including physiology, anatomy and personality development, with cascading effects on post-release performance. For instance, if juveniles are not exposed to wild adult behaviours they may show delayed learning, weakening important survival skills critical in their natural habitat (Hardouin et al. 2014, Azar et al. 2018). Understanding individual behavioural variation can improve rearing and release protocols and reduce post-release mortality (Smith and Blumstein 2008, Azar et al. 2016). Tracking technology provides direct data on behaviour and has the potential to identify maladaptive behaviours and less optimal time budgets that may result from captivity.

Behaviours that result from captivity and lower the survival probability of an individual may include: lower foraging activity compared to wild counterparts (Hess et al. 2005, Rose et al. 2022), preferences for low-nutritional foods (Jayson et al. 2018), reduced flight endurance and an inability to respond to threat cues (Hess et al. 2005). In the context of houbaras, most previous studies on behaviour in the wild have focused on traditional tracking technologies, such as very high frequency (VHF) and global positioning system (GPS) sensors, which provide only sporadic positional data and, in the case of mortality, the final location of a bird. Consequently, such research is restricted to investigating factors such as survival rates, breeding events and broad-scale

movements (Azar et al. 2016, 2018, Bacon et al. 2018). However, for a comprehensive understanding of behaviour and for identifying potential issues pre- and post-release there is a need to obtain accurate behavioural data through technology such as accelerometers. Pairing accelerometry data with observations has the potential to generate detectable signatures for behaviours, as demonstrated with the tracking of migratory birds (Bäckman et al. 2017).

The behavioural repertoire of the houbara has been quantified in captivity, encompassing activities such as parental care, resting, eating, locomotion and sexual and social interaction (Launay and Paillat 1990, Warren 1996). Our research aims to assess the extent to which accelerometry can be used to detect behaviours, with a view to tag released and wild houbaras in future studies. For this, we identify the main behaviours of captive juvenile houbaras (stationary, feeding and locomotive movements) using bird-attached accelerometers and simple threshold-based Boolean algorithms. We evaluate the performance of this methodology and assess potential variation in behavioural durations between two different periods of the year (spring and summer). These comparisons demonstrate the potential to understand how behavioural time budgets may vary between individuals and over time, which may help fine-tune management and release protocols e.g. in future studies comparing budgets between released and wild houbaras at different periods of the year. We then discuss the potential of our methodology for post-release monitoring, which could also be employed on other bustard species, in the wild or in captivity.

Material and methods

This study was conducted at the National Avian Research Centre (NARC), Abu Dhabi, in the United Arab Emirates (UAE), one of the research and conservation facilities of the IFHC. Birds are bred through artificial insemination and reared by keepers following established protocols (IFHC 2019). Prior to being released into the wild, houbaras are maintained in large outdoor aviaries (30 × 9 × 1.8 m; length, width, height) housing mixed-sex groups of 12–20 individuals. Captive houbaras are fed dry pellets and fresh alfalfa and have free access to water.

We studied a total of 20 juveniles (8 males, 12 females; n = 20 in March and n = 13 of the same individuals in June), aged 9 to 13 months (298 days to 382 days) at the start of recording in March, as houbaras are released at the research centre before they reach adulthood. Our sample size of individuals was lower in June than March due to unexpected practical constraints (i.e. soldering of tags to batteries loosened during transport). We temporarily housed the houbaras individually inside aviary partitions (10 × 9 × 1.8 m; length, width, height), allowing continuous monitoring of individual behaviour through video recording, while minimizing the confounding effects of inter-individual interactions. To prevent visual interaction between neighbouring houbaras, we shaded partitions.

Logger preparation and tag deployment

We tagged birds with ‘daily diary’ (DD) units provided by Wildbyte Technologies (<http://www.wildbytetechologies.com>) which log inter alia tri-axial (orthogonal) acceleration with 12-bit resolution (range of -16 to 16 g) and were set to record continuously at 40 Hz (40 samples per second). This unit was powered by a 3.6 V Lithium Thionyl Chloride battery (EVE EF651625 battery, LTC-7PN, 750 mAh, mass 8 g; battery life of approximately seven days at 40 Hz), with both the circuit board and battery enclosed in a plastic case ($3.6 \times 1.9 \times 1.5$ cm), lined with 3 mm thick foam to ensure the logger remained stable inside. The complete mass of the operating unit was 15 g, which represented a maximum of 0.46% of a bird’s body mass.

We modified the tag housing to fit to a harness (Fig. 1A; see Supporting information for details). Individuals were thus tagged and released into their individual aviaries (Fig. 1B). The DDs were deployed on individuals for six days in March 2019 (plus one day prior to the six days for acclimatisation) and for six days in June 2019 (plus one day prior for acclimatisation). We placed the units so that the three acceleration axes aligned with the birds’ main body axes: longitudinal

(z), lateral (x) and dorso-ventral (y) (Fig. 1A). The associated linear motions were identified as sway, surge and heave, respectively, in relation to the tags’ position on the houbaras (Fig. 1A). Figure 1A shows the rotations associated with each axis: pitch, roll and yaw, respectively.

We regularly monitored the health of all tagged individuals, taking weight measurements before and after tag deployment. No changes in individual behaviour in relation to the logger were observed.

Ground truthing of accelerometer signals with behaviours

We used video recordings to match the accelerometry data to behaviours (see Table 1 for a list of behaviours identifiable using accelerometry). For this, we mounted cameras onto plastic feeders (to reduce the potential influence of a novel object on individual behaviour) and placed these within the aviaries. Each camera was positioned in a corner of the partitioned aviary, to allow full coverage of the field of view. A total of four cameras were employed and repositioned between aviaries to obtain videos of all the experimental birds ($n = 20$ birds with $n = 15$ for training and $n = 5$ for testing

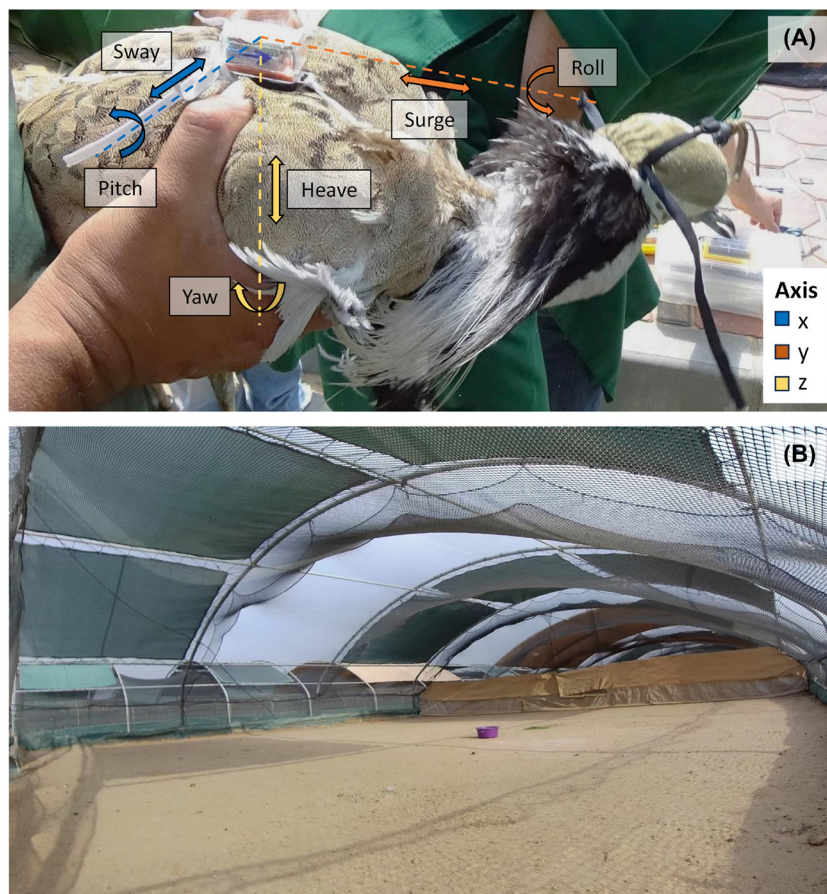


Figure 1. (A) The position of the harness holding the accelerometry daily diary (DD) device in its housing on a male Asian houbara. Arrows show the axes of acceleration and associated translational linear movements and rotations: x (sway and pitch), y (surge and roll) and z (heave and yaw). (B) Tunnel partition within an aviary, approximately $10 \times 9 \times 1.8$ m (length \times width \times height), within which a single houbara was housed.

Table 1. Behaviours of captive houbaras quantified through accelerometry, following definitions in [Launay and Paillat \(1990\)](#).

Behaviour	Definition	Additional information
Stationary	No movement	Individuals may have their ruffles out, tail fanned, and neck stretched when standing or sitting
Eating/drinking	The body is pitched forward, with movement towards the ground (head lowered first with the body following). The body pitch fluctuates slightly, as the bird jerks its head repeatedly towards the ground. The individual then returns to an upright position, progressively decreasing overall body pitch	Without considering the position of food and water, individual movements for eating and drinking appear indistinguishable by eye. Searching for, and chasing, mobile prey were observed infrequently, as alfalfa and dry pellets were placed in the aviary
Locomotion	Individual moves forward. One foot leads, and the other follows before switching. One foot is always on the ground	Individuals may pace and have ruffles out and wing/s extended to some degree

with this allocation determined using a random generator). The total video recording footage we used for each individual houbara was 30 min. A total of 10 h of video recordings were obtained for all 20 birds over two days during the March deployment between 07:00 and 15:00, with one continuous recording per individual. We initially scheduled video recordings for additional time periods, to obtain footage of each individual during both the morning and afternoon, but this was not possible due to weather conditions (i.e. sandstorms and high wind speeds). Video recordings commenced at least 24 h after deploying the tags on the individuals, to allow the birds to acclimatize to the new environment and the tag after handling.

Accelerometry analysis

We identified behaviours in video recordings, where bouts were recorded and defined as behaviours lasting five or more seconds. For eating and drinking behaviour, if the individual raised their head for less than five seconds, we considered this as the same bout of behaviour. Similarly, if individuals paused between locomotion steps for less than five seconds (often between paces along the length of an aviary), we considered this as the same bout of behaviour. We matched the identified behaviours to accelerometry signals using specialized software for visualizing high-frequency accelerometry data (daily diary multiple trace provided by Wildbyte Technologies (DDMT 2019), <http://www.wildbytetechologies.com>; manual available online) (Table 1).

While machine-learning algorithms have shown success in classifying behaviours using accelerometry data, and each approach has its advantages, issues lie with overfitting, subjectivity, computational demands and incorporating temporal aspects within behaviours. In [Wilson et al. \(2018\)](#), a Boolean method detected behaviours within varied datasets comparably or better than nine different machine-learning-based methods. However, the processing speed was much faster, given specialist knowledge was used as a basis rather than entering all raw and derived variables into a process ([Wilson et al. 2018](#)). The Boolean approach identified behaviours including sheep biting and condor thermalling in only 1% of the time the most effective machine-learning algorithm took to run ([Wilson et al. 2018](#)). Success has also been shown

in using a Boolean approach to identify urination events in sheep to an accuracy of 100% ([Marsden et al. 2021](#)), demonstrating the comparable success of simple Boolean methods compared to machine learning algorithms. Thus, we used a Boolean approach to identify behaviours in the data.

We used a method which recognizes the lowest common denominator (LoCoD) of each behaviour e.g. a single step in locomotion, based on [Wilson et al. \(2018\)](#). The LoCoD is then broken into base elements e.g. an increase followed by a drop in acceleration for locomotion. To identify base elements, we visualised the data to examine details of the movement and identify distinctive patterns, based on body motion (dynamic acceleration component) and body posture (static acceleration component, sensu [Shepard et al. 2008](#)) (equations in Supporting information). We also calculated summary metrics quantifying dynamic body acceleration for consideration as simple measures of overall activity levels in relation to behaviours. Specifically, we calculated vectorial dynamic body acceleration (VeDBA) and the overall dynamic body acceleration (ODBA) according to the formulae given by [Qasem et al. \(2012\)](#) (equations in Supporting information). For each behaviour, the metrics and criteria/criterion we chose to create the algorithm were based on logic from in-person observations and signal clarity, and an understanding of how the acceleration signal value related to animal pitch and roll ([Fig. 1A](#)) ([Shepard et al. 2008](#)). The various acceleration-based metrics we used as candidates for behaviour recognition are shown in [Table 2](#). We considered smoothing the data to enhance pattern recognition, by averaging data over a sliding window of defined durations (specified for each behaviour in [Table 2](#)) ([Shepard et al. 2008](#)). Where noise (random fluctuations) was still apparent in the selected acceleration signal after smoothing, we considered differentials to standardize the output (given accelerometry data are sensitive to the angle of the terrain and the tag placement). Differentials were calculated for each point n as $(x_n - x_{n-y})$ where x is the value at point n and y is the stepping difference or the number of points over which to measure the rate of change.

We constructed algorithms and used the *Behaviour Builder* function within DDMT to find all instances of the considered behaviours. Where the LoCoD for a behaviour was broken into more than one base element, we ordered these base elements. We specified the time over which a base element

Table 2. Algorithms defining behaviours of the houbara created in daily diary multiple trace (DDMT) (Wildbyte Technologies 2019). Algorithms take the form: **IF** (condition 1) **AND/OR** (condition 2) [for condition numbers from 1 to n], **THEN mark as** (behaviour x). Information on the duration or temporal sequence of behavioural elements can be added in further steps, referred to as ‘time elements’. Through time elements, the minimum duration of one or more conditions (expressed as number of events, i.e. sequential data points; the period between adjacent data points here was 0.025 s) can be defined. It is also possible to specify the number of sequential data points to skip before searching for the next condition (‘range’) and the time within which the next condition must occur (‘flexibility’). Finally, if two identical behaviours occurred within a defined period of each other, they can be merged (**merge if × events in proximity**). The columns ‘dt window’ and ‘smoothing window’ refer to the time windows over which differentials were calculated and over which the data were sequentially smoothed via a running mean, respectively.

Behaviour	Algorithm	dt window (events)	Smoothing window (events)
Stationary	Stationary=IF (dVeDBA/dt) < 0.04 g AND (dVeDBA/dt) > -0.04 g THEN mark events Time element (1): Stationary, present for ≥ 200 events Merge if < 1 event in proximity	5	6
Eat/drink	Eat/drink=IF (Ch (Pitch) < -10.353°) THEN mark events Time element (1): Eat/drink, present for ≥ 20 events Merge if < 200 events in proximity	0	0
Locomotion	Locomotion=IF (dAccelZ/dt) > 0.055 g AND (dAccelZ/dt) < 0.576 g) THEN mark events Time element (1): Locomotion, present for 1 event, with next expression starting from range of 15 events, flexibility after of 15 events Time element (2): Locomotion, present for 1 event Merge if < 200 events in proximity	5	6

was maintained for the condition to be true, alongside the ‘range’ which is the time to be skipped before searching for the next base element. We also defined ‘flexibility’, the length of time over which the base element may occur. Note that sensor recordings we considered were taken 24 h after deploying the tags on the individuals.

To assess validity, we used the algorithms to identify behaviours in 30 min of accelerometry data from each of five individuals, which had not been used in the creation of the algorithms. Behaviours we identified were cross validated using corresponding video footage and classed as: true positive (TP), false positive (FP) and false negative (FN). The recall (the ability of the model to find a particular behaviour in the data) and precision (the proportion of the data points that the model classified as a particular behaviour that were observed as the actual behaviour) of each algorithm was calculated as below (Eq. 1–2).

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \times 100 \quad (1)$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \times 100 \quad (2)$$

Note that we did not calculate accuracies, as our method does not consider each data point individually, so quantification of the identification result cannot give a true negative result.

Statistical analysis

Acceleration data from the tags, corresponding to the various behaviours (as identified by the algorithms), were automatically detected by DDMT before we exported the durations of each behaviour per month for each individual.

To understand the differences in time budgets between the months, we created a linear model for each behaviour (stationary, eating/drinking and locomotion). For each model, we set the percentage of time spent on a given behaviour as the dependent variable (D) and month (M) as the fixed effect. We set individual identity as the random intercept (I) if the model was not singular as a result. We checked model assumptions (i.e. normality and homoscedasticity of residuals), and transformed the dependent variable by a square root transformation in one of the three cases where these were breached (Supporting information). We conducted all analyses in R (RStudio Team 2018, www.r-project.org), using the packages ‘lme4’ (*lmer()* and *isSingular()* functions) for fitting mixed linear models and checking their singularity (Bates et al. 2015), ‘performance’ (*check_singularity()* function) to determine the singularity of linear models (Lüdtke et al. 2021), and ‘car’ (*Anova()* function) to calculate ANOVA type III p-values (Fox et al. 2019). For models including individual identity, we calculated individual repeatability (the proportion of observed variance attributable to among-individual differences) using the R package ‘rptR’ (*rpt()* function) (Stoffel et al. 2017).

Results

All tags deployed on birds recorded data for the full duration of the deployment period. Hence during the March deployment, where data were collected from twenty individuals over six days, approximately 60 million acceleration data points per individual or 1.2 billion data points for the group were collected. Within the video recordings we used for training (n = 15 individuals), we observed stationary behaviour for a total of 3787 s [henceforth ‘s’] across thirteen individuals (sitting for a total of 176 s for one individual and standing for the remaining time across thirteen individuals), eating behaviour

for a total of 569 s across nine individuals, drinking behaviour for a total of 442 s across six individuals and locomotion for 5098 s across all 15 individuals. See Supporting information for further details on the number of behavioural bouts we observed per individual.

We identified a total of three behaviours which could be defined by specific patterns in acceleration values over time (see Supporting information for video examples).

Stationary

‘Stationary’ behaviour was typified by relatively unchanging raw acceleration values in all three axes, with no value deviating by more than 0.1 g in < 1 s (Fig. 2A). The algorithm we used to define ‘stationary’ behaviour used VeDBA, as this summarizes the stability of all three orthogonal axes within a single measure, allowing the creation of a concise algorithm. Under these conditions, waveforms in the differential VeDBA channel were nevertheless still apparent (partly attributed to breathing). Our final algorithm used the differential (rate of change) of VeDBA (dVeDBA/dt), calculated over a window of five time points [or 0.125 s], followed by a running mean that smoothed the data over eight points [0.2

s], which resulted in dVeDBA/dt values for stationary individuals never exceeding 0.04 g/s or being less than -0.04 g/s (Fig. 2B, Table 2). We added a time element, requiring these conditions to be met for at least 200 consecutive data points [5 s] (Fig. 2B, Table 2).

Eating/drinking

‘Eating’ could not be distinguished from ‘drinking’ based on the accelerometry data due to similar movement patterns. In both behaviours, the raw z acceleration never descended below 0.8 g while the raw y acceleration never descended below 0.9 g, with the greatest deviation occurring in the x acceleration axis, away from 0 g, where values fell to as low as -0.6 g (Fig. 2C). Visual observation of the birds showed that the pitch of the houbara increased as the bird rotated about its central lateral axis to bring its head towards the ground prior to eating and drinking and exactly this was apparent in the data. The pitch in all the training set examples fell below a threshold of -10.353° over a period of at least 20 data points [0.5 s], so we used this criterion to create the algorithm (Fig. 2D, Table 2).

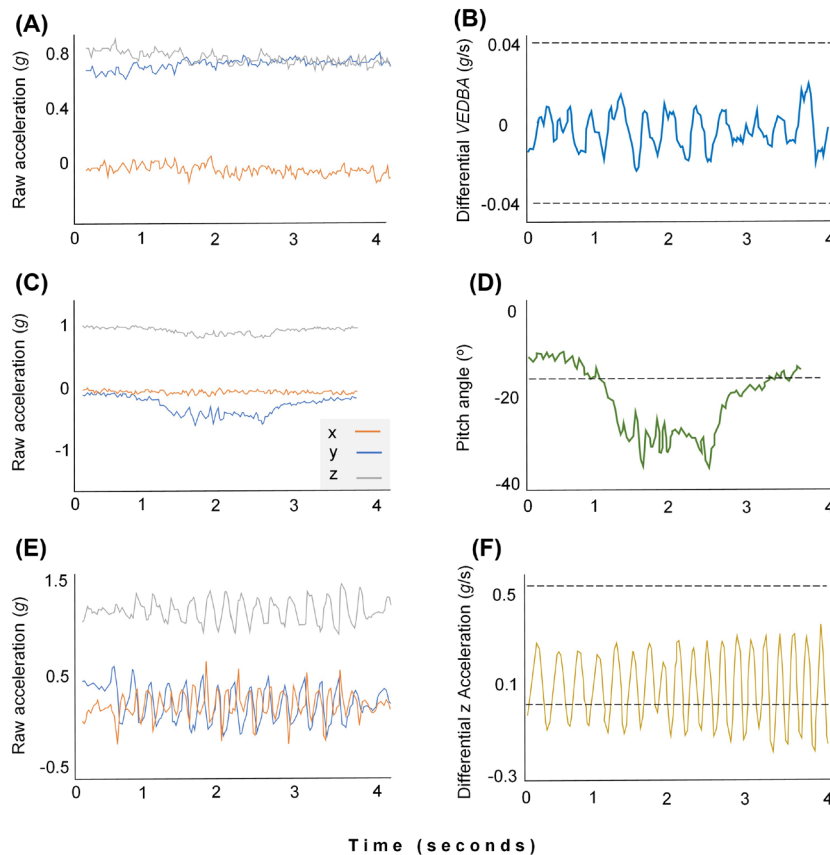


Figure 2. Examples of houbara behaviours identified in daily diary multiple trace (DDMT) (2019): (A–B) ‘stationary’; (C–D) ‘eat/drink’; (E–F) ‘locomotion’. The left-hand panels (A, C, E) show the raw acceleration signals (note the changing scales with behaviour) where channels corresponding to principal body axes are denoted by colours: orange=lateral/sway (x-axis), blue=dorso-ventral/heave (y-axis) and grey=longitudinal/surge (z-axis). The right-hand panels (B, D, F) show the acceleration metrics used to detect the behaviours, where the dashed lines show the ranges (B and F) and thresholds (F) used.

Locomotion

As expected during bipedal motion, 'locomotion' behaviour showed a cyclic pattern in all raw acceleration axes (cf. [Byun et al. 2016](#)), deviating no more than 0.7 g from the stationary values, defining one step – left foot or right foot ([Fig. 2E](#)). The highest peak and lowest trough were shown in the raw acceleration of the z (heave) axis, so we used this channel to define this behaviour. The steps became clearer if the differential of the z axis was used over a time interval over five points [0.125 s]. In addition, to reduce noise further, without masking less high activity steps, we smoothed the data by a running mean over six points. The peak value always exceeded 0.055 g/s but never reached 0.576 g/s ([Fig. 2F, Table 2](#)). We specified that at least two consecutive single steps should be detected, with a minimum of 15 data points [0.375 s] and a maximum of 30 data points [0.75 s] between the peaks in the smoothed heave differential ([Fig. 2F, Table 2](#)).

Behaviours excluded from the behavioural catalogue

We observed preening behaviour of the chest, back and tail in the video footage used for training (total of 558 s across five individuals; [Table 3](#)). Higher peaks and troughs of VeDBA were expected for this behaviour in comparison to 'stationary' behaviour, however a large overlap was shown in DDMT due to the inherent variability in preening.

Another behaviour we identified in the training video footage was pecking of the aviary net (365 s across seven individuals) and the base of the feeder which the camera base was attached to (914 s across nine individuals) ([Table 3](#)). We did not catalogue these behaviours as they would not be exhibited in the wild. We observed flapping of the wings for a total of 28 s across three individuals, stretching for a total of 8 s for one individual, scratching for a total of 42 s across two individuals, shaking for a total of 33 s across five individuals and foraging of wild insects for 92 s across two individuals ([Table 3](#)). Defensive and ostensibly 'social' behaviours, identified by the expansion of a houbara's wings upwards or downwards, and a lowering of body pitch, followed by running ([Launay and Paillat 1990](#)), were observed

for a total of 142 s across two individuals. As all these behaviours were not standardised, frequent enough and/or present across at least three individuals, we excluded them from the analysis. The remaining behaviours previously documented in captivity ([Launay and Paillat 1990](#)) were not observed in the video footage. See Supporting information for details on the number of bouts and duration of each of these observed behaviours per individual.

Behaviour identification success

For the testing data (n = 5 individuals), we observed stationary behaviour for a total of 2407 s across all five individuals, eating and drinking behaviour for a total of 402 s across four individuals and locomotion for a total of 4888 s across all five individuals. See Supporting information for details on the behaviours we observed per individual.

The recall of the defined algorithms were calculated as 95.52% for 'stationary' behaviour, 95.00% for 'eating/drinking' behaviour and 100.00% for 'locomotion'. Precisions were calculated as 97.44% for 'stationary' behaviour, 97.59% for 'eating/drinking' and 98.46% for 'locomotion' ([Table 3](#)). Unidentified instances of behaviours (true negatives) included foraging, scratching, preening, shaking, defensive behaviour, pecking of the camera base and aviary net and stretching ([Table 3](#)).

Behavioural expression according to season

Houbaras spent most of their time 'stationary' (mean of 49.67%) in March and in June (mean of 63.73%) (individual ranges from 40.98 to 60.45% in March and 58.04 to 73.82% in June), and their remaining time was primarily found to be spent on 'locomotion' (mean of 22.65% in March and 8.72% in June; individual ranges from 13.10 to 30.56% in March and 0 to 15.20% in June) or 'eating/drinking' (9.70% in March and 20.18% in June; individual ranges from 0.17 to 26.48% in March and 0.73 to 49.58% in June).

Houbaras spent significantly more time stationary in June than in March (mean difference 14.06%; $\chi^2 = 90.03$, $p < 0.001$; individual repeatability = 0.21) and significantly

Table 3. Confusion matrix showing detected behaviours: stationary, eating/drinking and locomotion against observed behaviours (including foraging, scratching, preening, shaking, defensive behaviour, pecking of the camera base and aviary net and stretching). We used 30 min of video footage for each of five individuals for cross-validation of the algorithm created for each behaviour.

		Detected behaviour			
		Stationary	Eating/drinking	Locomotion	True negatives
Actual behaviour	Stationary	64	1	0	3
	Locomotion	0	4	162	0
	Eating/drinking	0	38	1	2
	Foraging	0	1	0	
	Scratching	0	0	1	
	Preening	5	0	0	
	Shaking	0	0	1	
	Defensive	0	2	0	
	Pecking camera base	0	2	0	
	Stretching	0	0	1	
	Pecking aviary net	0	0	2	

more time on locomotion in March than in June (mean difference of 13.93%; $\chi^2 = 68.58$, $p < 0.001$) (Fig. 3). There was no significant difference in the time houbaras spent eating/drinking between the months (mean difference of 10.48%; $\chi^2 = 3.28$, $p = 0.08$) (Fig. 3).

Discussion

Performance of the houbara behavioural algorithms: recall and precision

The primary behaviours we considered could be identified with excellent recall (95–100%) and precision (97–98%). This compares well with other bio-logging studies on birds; for example, Aulsebrook et al. (2024) deployed accelerometers on the ruff *Calidris pugnax* and identified behaviours using random forest and hidden Markov models, achieving an F1-score (a classification performance metric which is the harmonic mean of precision and sensitivity) of 72% for foraging/drinking, 83% for resting and 66% for walking/running. In the case of the houbara, the performance of our algorithms also compares well to other studies using accelerometry data to classify behaviours; display runs of the Canary houbara bustard *Chlamydotis undulata fuertaventurae* were catalogued using random forest models which achieved accuracies of at least over 90% per behaviour (Alonso et al. 2022). Furthermore, ten behaviours of *C. u. fuertaventurae* were catalogued using a radial basis function support vector machine, achieving accuracies of > 90% for ten behaviours including display runs, pre-copulatory movement, vocalization, flying, foraging, laying down, pre-display posture, preening, running and vigilant posture (Abril-Colón et al. 2022). Our

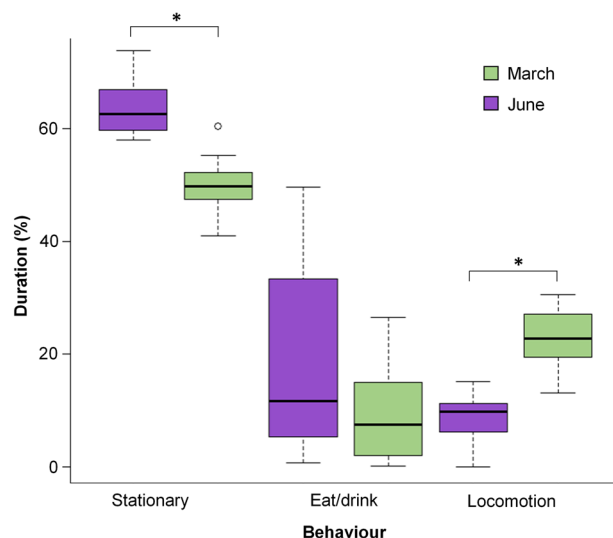


Figure 3. Comparison of the time houbaras spent engaged in the catalogued behaviours 'stationary', 'eat/drink' and 'locomotion' between months: March ($n = 20$ individuals) and June ($n = 13$ individuals). Minimum and maximum values are shown by the whiskers, means are shown as horizontal black lines and outliers are shown as dots. Asterisks mark significant differences.

Boolean threshold-based method is advantageous in that it is simpler and produces similar results to these more complicated approaches.

We could not differentiate between drinking and eating as the birds in this study were provided with food pellets, and reaching down for pellets would have produced a similar postural change to that seen during drinking. Similarly, Aulsebrook et al. (2024) classified drinking and foraging into a single behaviour, identifying instances where *C. pugnax* lowered its head to handle food, drink or search for food. However, in the wild houbaras forage on vegetation and invertebrates (Tigar and Osborne 2000), through search, chase and catch phases (Launay and Paillat 1990). To gain an understanding of the eating habits of released and wild houbara, this would require a more comprehensive approach, considering how they hunt mobile prey. Observing captive birds in aviaries with live prey may provide a useful starting point, e.g. identifying periods of pitching forwards between search and catch phases. Our catalogue would therefore need refining and expanding for wild and released houbara, and the time budgets of wild houbara will differ from captive houbara. Furthermore, future studies could consider social behaviours which would occur in the wild, including playful, defensive and mating behaviours, by grouping captive houbara.

Behaviours with a relatively stable posture but highly variable dynamic component are known to be problematic to identify (Watanabe et al. 2005, Laich et al. 2009, Wang et al. 2015). Preening was not detectable based on accelerometry signals, primarily due to its variability; birds may preen any part of their body (or the tag) which results in correspondingly variable acceleration signals. Furthermore, we did not differentiate running and walking in our study as details of gait (i.e. stride length and speed) were not clearly visible in video recordings, but future work could explore whether stride period could help distinguish these two behaviours, using distance markers and numerous cameras for validation. Similarly, we could not distinguish sitting and standing (within the 'stationary' behaviour category), consistent with previous studies (Ringgenberg et al. 2010), in our case due to a lack of observations of the houbaras sitting.

Our catalogue of behaviours defined using accelerometry data bodes well for using the houbara template for bustards in general, e.g. the great bustard in the UK and the Indian bustard, because these ground birds forage and behave in a similar manner, and are consequently expected to show similar behaviour-linked patterns in acceleration. For example, common behaviours such as locomotion can be split into base elements of a single step (consisting of a cyclical rise and fall in acceleration) across species (Wilson et al. 2018). However, it is important to note that we would expect researchers to modify the details of the algorithms, particularly in terms of parameter thresholds, as these signals are not expected to be identical across species. Factors such as the size of the species affect stride frequency (Claussen et al. 2000), and researchers should be cognizant of the exact position of the tag on the body because heave and surge acceleration signatures

will vary accordingly (Garde et al. 2022). We also stress that researchers should ensure that the tag is placed securely to the birds since this will affect the noise in the behavioural signals (Garde et al. 2022). We hope that our work will provide a useful starting point for those wishing to deploy tri-axial accelerometers to elucidate more about the behavioural budgets of bustards (c.f. Forbey et al. 2017).

Comparison of the houbara behaviour time budget

Our results accord well with observational studies. For instance, Warren (1996) observed captive houbaras ($n=15$) were stationary for a mean of 70% of the day, which is similar to the averages recorded in this study (41–74% depending on the month and individual). However, we would expect the time budgets of grouped captive houbara, released and wild houbara to differ; future studies could monitor released juveniles into adulthood.

In our study, houbaras were found to spend significantly more time 'stationary', and significantly less time on 'locomotion', in the hotter conditions of June (approximately 45°C) than in March (approximately 30°C) (National Center of Meteorology 2019). Activity increases metabolic rate and endogenous heat generation, resulting in homeotherms reducing activity to minimize heat stress in hotter climates (Schmidt-Nielsen 1997, Plessis et al. 2012). Indeed, Jacquet and Launay (1997) used video footage to find houbaras ($n=16$) spent significantly longer periods sitting and reduced locomotor activity at higher temperatures. The shorter day length at the study site in March than in June (approximately two hours difference) should also be considered; Jacquet and Launay (1997) found that houbaras increased their locomotor activity per hour of light when the period of daylight was shorter, so that total activity during the day was not modified by daylength. The differing daylengths between the months were therefore not likely to have contributed to the difference in time budgets found in this study.

We did not find a difference in the time houbaras dedicated to 'eating' or 'drinking' between the months. Individuals are expected to increase their water intake in hotter environmental conditions (Plessis et al. 2012), given heat can be effectively lost through evaporative cooling (Angilletta et al. 2010). Alongside this, as a reduction in activity minimises energy expenditure, decreasing energy requirements, it would be expected that birds spend less time eating in hotter climates (Schmidt-Nielsen 1997). This has been observed in the laying hen *Gallus gallus domesticus*, which showed a reduced appetite as environmental temperatures increased (Song et al. 2012). More relevantly, Jacquet and Launay (1997) observed captive houbara reducing their feeding behaviour in higher temperatures. As we found that the accelerometry signal for 'drinking' was indistinguishable from the signal for 'eating', this may have masked a potential decrease in eating in June compared to March.

We considered the total duration of each behaviour exhibited by an individual within a given month. Relying on overall durations obtained from these data has its limitations as

there may be variability in behavioural time budgets within months. Further studies could export behavioural time budgets for each day, or even hour, to evaluate whether the duration of specific behaviours fluctuates on a finer timescale across individuals. This would enable a more comprehensive understanding of how the time dedicated to behaviours may vary within and between individuals, over time and according to external variables such as temperature.

Demonstration of application and future directions for houbara conservation

Knowledge of the behavioural time budgets of released houbaras has the potential to aid conservation. For instance, Alonso et al. (2021) demonstrated the use of tagging wild North African houbara *Chlamydotis undulata undulata* with accelerometers to understand nocturnal display behaviour, which is associated with mating success, although the performance of the algorithms was not assessed due to the difficulties associated with observing wild houbara. Using a catalogue of validated behaviours, obtained from captive houbara, has the potential to help researchers relate individual behaviour to fitness in the wild. Houbaras that spend much time foraging but are in poor body condition could be considered poor foragers (Pyke 2019) which may have lower survival prospects. Also, some individuals may forage at sub-optimal times of the day, perhaps when less prey is available or more predators are present (Bonter et al. 2013, Houston and McNamara 2014, Pyke 2019). Moreover, simple patterns in ODBA could reveal whether birds are expending excessive energy walking or in flight (Gleiss et al. 2011). Furthermore, pairing accelerometers with location recordings (e.g. VHF or GPS) could provide us with a detailed knowledge of the behaviours and movement linked to survival (Bäckman et al. 2017). Ultimately, understanding causes for maladaptive behaviours and time budgets, that may arise in captivity, could help fine-tune captive-breeding protocols and translocation methods. For instance, through incorporating more wild rearing conditions or softer releases, to improve the survival and breeding success of animals translocated into the wild.

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Author contributions

Kareemah Chopra: Conceptualization (equal); Data curation (equal); Formal analysis (lead); Writing – original draft (lead); Writing – review and editing (equal). **Rory P. Wilson:** Conceptualization (equal); Formal analysis (supporting); Writing – review and editing (equal). **Emily L. C. Shepard:** Conceptualization (equal); Formal analysis (supporting); Writing – review and editing (equal). **Enrico Sorato:** Conceptualization (equal); Data curation (equal); Writing – review and editing (equal). **Yves Hingrat:** Conceptualization (equal); Writing – review and editing (equal).

Data availability statement

Data are available from the Dryad Digital Repository: <https://doi.org/10.5061/dryad.dr7sqvb6d> (Chopra et al. 2024).

Supporting information

The Supporting information associated with this article is available with the online version.

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