

1                   **From data on gross activity to the characterization of animal behaviour: which**  
2                   **metrics for which purposes?**

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15 **Key words:** sensors, time budget, animal welfare, health, activity metrics, cow

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18                   **Abstract**

19 The behaviour of an animal is closely linked to its internal state. Various metrics can be calculated from  
20 activity data. Complex patterns of activity within or between individuals, such as cyclic patterns and  
21 synchrony, can inform on the biological functioning, the health status, or the welfare of an animal. These  
22 patterns are now available thanks to sensors that continuously monitor the activity of individual animals  
23 over long periods. Data processing and calculations, however, should be clarified and harmonised across  
24 studies for the results to be comparable. We present metrics describing activity patterns, we discuss their  
25 significance, relevance and limitations for behavioural and welfare studies, and we detail how they can be  
26 calculated. Four groups of metrics are distinguished: metrics related to overall activity (e.g., time spent in  
27 each activity per unit of time), metrics related to fluctuations around mean activity, metrics related to the  
28 cyclicity of activity, and metrics related to the synchrony between animals. Metrics may take statistical  
29 approaches (e.g., average and variance) or modelling approaches (e.g., Fourier Transform). Examples are  
30 taken essentially from cattle for who individual activity sensors are easily available at present. The  
31 calculations, however, can be applied to other species and can be performed on data obtained from  
32 sensors as well as visual observations. The present methodological article will help researchers to obtain  
33 the most benefit from activity data and will support the decision of which metric can be used to address a  
34 given purpose.

36 The behaviour of an animal can inform about the internal state of that animal, in relation to biological  
37 functioning, health and welfare. In farm animals, activity measurements have long been used to identify  
38 differences in walking behaviour to detect lameness (Pastell et al., 2009) or differences in the amount of  
39 activity to detect oestrus (Saint-Dizier & Chastant-Maillard, 2012) or periparturient disorders (Rutten et al.,  
40 2017; Rutten et al., 2013; Weary et al., 2009). Additionally, comparing the activity of a focus animal to its  
41 baseline or to pen-mates allows identification of deviations that potentially indicate a change in internal  
42 state, e.g., an animal becoming ill (Kok et al., 2023). The continuous measurements of activity allow for  
43 complex patterns to be highlighted, such as circadian components and regularity, and these patterns can  
44 be used to identify animals at risk of diseases (van Dixhoorn et al., 2023; Van Dixhoorn et al., 2018; Wagner  
45 et al., 2021).

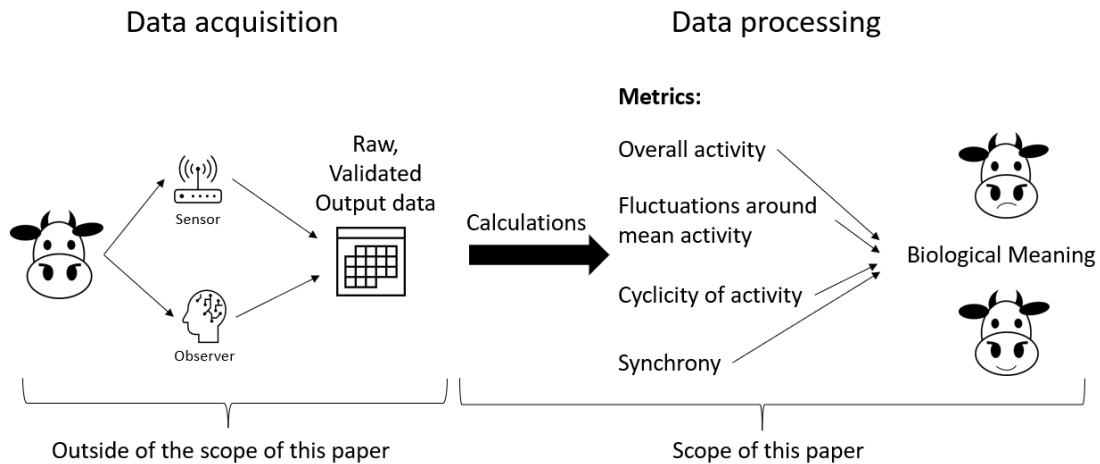
46 Ethologists, and other researchers usually calculate several metrics from activity data to characterise an  
47 animal's behaviour, e.g., time spent on each activity, fragmentation of activity, 24-h patterns or proportion  
48 of animals engaged in the same activity. However, the way these metrics are calculated vary between  
49 studies. For instance, the synchrony between animals, that reflects the functioning of a group, can be  
50 calculated at individual level as the percentage of animals performing the same activity as the focus animal,  
51 then at group level as a mean of that percentage or using concordance indices such as Kappa coefficients  
52 or overdispersion index (Raussi et al., 2011; Tuomisto et al., 2019; Veissier et al., 1990). The pros and cons  
53 of each metric are rarely explained.

54 The activities can be documented by observers, from direct observation or from video recordings, or  
55 obtained using sensors. Direct observation allows precise activities to be recorded. For instance, lying can  
56 be divided into lying head down versus head up with corresponding arousal levels inferred (Veissier et al.,  
57 2001). Direct observation (both real time or from video recordings) creates a high workload and data at  
58 night are often missing due to difficulties in observing animals in the dark. The last ten years have seen a  
59 boom in the development of sensor technologies, which can provide data along time series more easily  
60 than direct observation. Activities (especially in large domestic animals like cattle) can now be recorded  
61 continuously on individual animals and for very long periods with little workload, using accelerometers,  
62 image analysis from videos, or Real Time Locating System (RTLS) (Buller et al., 2020). Most of the  
63 commercially available sensors that monitor cattle activity show excellent performance in validation studies  
64 (Lee & Seo, 2021). They usually provide information on gross activities such as lying, standing, moving,  
65 feeding, and ruminating or the position of animals in the barn. From the organisation of these activities,  
66 specific patterns can be detected, especially those indicative of animal malaise due to illness or stress  
67 (Wagner et al., 2021) or related to the social organization of animal groups (Rocha et al., 2020), allowing  
68 new insight into animal behaviour. However, to date the flood of data obtained from sensors seem under-  
69 utilised (Koltes et al., 2019).

70 Access to data on activity is not only facilitated for ethologists, but also for researchers from other  
71 discipline, e.g., animal health and animal production and for non-scientists like users of precision farming  
72 systems that are not necessarily used to process data on behaviour (Borchers et al., 2016). It is thus crucial  
73 to provide harmonised metrics to analyse behaviour and to discuss what they are supposed to measure and  
74 their limits. This would allow comparisons between studies, help the interpretation of results, extend the  
75 use of activity data beyond ethologists, and ease the re-use of datasets.

76 In the present paper, we consider the metrics that describe different aspects of behaviour from data  
77 collected by sensors or by direct observations (Figure 1). We consider metrics describing 1- overall activity,  
78 2- fluctuations around mean activity, 3- cyclicity of activity, and 4- synchrony between animals. For each of  
79 these four groups of metrics, we identify the main metrics in use, the calculation methods, the limitations  
80 or the difficulties that can be encountered to calculate them, and their biological meaning (i.e. what it  
81 implies for animal welfare or health or the functioning of social groups). Examples are taken essentially  
82 from cattle, for who individual activity sensors are easily available at present. The calculations, however,  
83 can apply to datasets from other species (including other animal-specific activities) and can be performed  
84 on data coming from sensors as well as from observation. This paper does not focus on the validation of  
85 the sensors or the observers (to assess inter or intra observer variation) but on the processing of the data  
86 acquired by the sensors or observers.

87 A methodological exploration is pivotal and timely given the boom of activity data obtained by sensors.  
 88 **The review** will hopefully support researchers by improving the use of activity data to answer their research  
 89 questions. In addition, it should facilitate the consideration of animal behaviour by non-ethologists  
 90 especially in Precision Livestock Farming (**PLF**), with a view to help phenotyping animals for selection,  
 91 monitoring them for the detection of changes due to specific states such as oestrus, disease, or stress, or  
 92 evaluating housing conditions and management aspects.



93

94 **Figure 1** - Visualisation of the data acquisition and processing. The scope of this paper focusses on the  
 95 possible calculations of the data that describe the four metrics: overall activity, fluctuations around  
 96 the mean activity, cyclicity of activity and synchrony. The calculations can be done on data that is  
 97 acquired by observations and/or with sensors.

98

99

### The data

100 In the present paper, we focus on gross activities such as feeding behaviour (including eating and  
 101 drinking), active behaviour (apart from eating or drinking) including walking, running or other movements,  
 102 or inactive behaviour including standing still and lying. More specific activities include grazing and  
 103 ruminating in ruminants (e.g., cattle, sheep, goats), rooting in pigs, and foraging behaviour in poultry. All  
 104 these activities are characterised by lasting for some time. They are sometimes referred to as 'states', as  
 105 opposed to brief behaviours (e.g., interactions between animals) that are referred to as 'events'.

106 Observers can perform different types of sampling methods i.e., continuous, meaning they note  
 107 changes in activity over a certain period of time and record the time the change occurred. Alternatively,  
 108 observers can perform scan sampling i.e. they note the animal's activity as detected at first glance at regular  
 109 intervals (Bateson, 2021). Examples of the calculations with continuous and scan sampling data are shown  
 110 in the supplementary materials. A mix of the two is also possible: the activity is recorded continuously and  
 111 at the end of each interval (e.g. 5 min) the observer notes the predominant activity; the format of data will  
 112 then be similar to that of scan sampling. Sensors generally produce a signal that is nearly continuous; the  
 113 data on gross activity are usually delivered as time spent in each activity per time intervals (e.g. minutes  
 114 per hour or per 15 min) or as predominant behaviour per time interval. The metrics that can be calculated,  
 115 depend on the formats of data (see next sections).

116

117

## Metrics to address overall activity

### 118 Definitions

119 The overall activity refers to the time spent performing specific activities during a certain time period.  
 120 Each activity such as feeding, drinking, walking, standing idling or lying, can be characterised by the duration  
 121 it is performed, the number of bouts (where a bout is defined by the continuous expression of an activity),  
 122 and the average duration of bouts. The overall fractioning of activity refers to how many bouts of activity  
 123 are noticed, in other words, how often the animal changes between activities. The level of activity reflects  
 124 how much an animal is active, that is walking, running, or feeding rather than lying or standing immobile.  
 125 The time period on which these metrics are calculated varies between studies, e.g. an hour or a day. The  
 126 term 'time budget' is specifically used to describe how an animal divides its day (or shorter period) into the  
 127 various activities.

### 128 Calculations

129 *Proportion of time spent in an activity.*

130 The proportion of time spent in a given activity  $a$  in a collection of activity bouts  $B$  (whatever the  
 131 activity) is calculated as follows:

$$132 \quad \text{Proportion Of Activity}_a^B = \left( \sum_{b \in B, A_b=a} D_b \right) / \sum_{b \in B} D_b \quad (1)$$

133 where  $D_b$  is the duration of the bout  $b$  and  $A_b$  is the activity in bout  $b$ .

134 In case of scan sampling, the time spent in an activity is estimated from the number of scans per  
 135 activity, multiplied by the interval between scans - although what the animal has done between scans  
 136 remains unknown. The proportion of time spent in an activity  $a$  in a period  $P$  can be calculated as follows:

$$137 \quad \text{Proportion Of Activity}_a^P = \left( \sum_{p \in P, A_p=a} L_p \right) / \sum_{p \in P} L_p \quad (2)$$

138 where  $p$  is a subperiod of  $P$ ,  $L_p$  is the length of the subperiod  $p$ , and  $A_p$  is the activity in the subperiod  
 139  $p$ .

140 Duration of activities (or proportion of time spent in activities) can be calculated for each activity  
 141 separately and whatever the time period. If the experimenter decides to group two activities (e.g., lying  
 142 ruminating and standing ruminating), the duration/proportion of the new activity (here ruminating) is  
 143 obtained by summing up those of the individual activities.  
 144

### 145 *Number and duration of activity bouts.*

146 Continuous and scan sampling also allow detecting when the activity changes, so that the number  
 147 of activity bouts can be obtained, and the mean duration of bouts can be calculated. The average bout  
 148 duration of activity  $a$  in bouts collection  $B$  is calculated as:

$$149 \quad \text{AvgBoutDuration}_a^B = \left( \sum_{b \in B, A_b=a} D_b \right) / N_B(a) \quad (3)$$

150 where  $D_b$  is the duration of the bout  $b$  and  $N_B(a)$  the number of bouts of the collection  $B$  where the  
 151 activity equals  $a$ .

152 Sensor-based systems, however, sometimes provide the time spent in each activity per time period  
 153 and not the exact timing of a change if any; in this case, the number and the duration of bouts of activity  
 154 remain unknown.  
 155

156 Calculation of the number of bouts of an activity and of the mean duration of the bouts requires  
 157 that the recording is done on long periods to avoid edge effects (changes in behaviour that occur at the

158 boundaries of the observed time period). Indeed, when the monitoring starts, the animal is observed in a  
 159 given activity, but one does not know for how long the animal has been performing the activity. It is  
 160 common practice to remove the first and the last activity bout observed during the time period studied.  
 161 The time period must thus be long enough so that several entire bouts of activity can be recorded. In  
 162 practice, the number of bouts and their mean duration are often calculated per day (see for instance  
 163 Veissier et al., (2004)).

164 Assessing the total number of activity bouts in a day, thus, the number of times an animal changes  
 165 between activities, requires that the ethogram consists of activities described with the same level of details,  
 166 so that the number of bouts does not depend on which activity an animal performs most during the day. In  
 167 case of direct observations to answer a specific question, an experimenter may want to sort activities into  
 168 lying, standing inactive, feeding (all these lasting for minutes or hours) and other activities, that can consist  
 169 of walking, running, exploring the environment, interacting with other animals or self-directed activities (all  
 170 of them lasting for a few seconds or minutes). In that case, the number of times an animal changes between  
 171 activities will largely depend on whether the animal performs the short-lasting activities frequently. The  
 172 grouping of activities into gross activities should be done before the total number of activity bouts is  
 173 calculated. Indeed, in the example given above on ruminating while lying or standing, the number of  
 174 ruminating bouts during a day cannot be calculated by adding the number of lying-ruminating bouts and  
 175 that of standing-ruminating bouts, because the two activities can be performed in the same bout (i.e., the  
 176 animal continues to ruminate whilst getting up or lying down).

177 Duration and number of bouts also largely depend on how bouts are defined. The most common  
 178 practice is to consider each change of activity as the beginning of a new bout. For example, with continuous  
 179 observations the number of lying bouts of a cow can be assessed by the number of times the animal lies  
 180 down; with scan sampling, an eating bout can be defined when eating is observed on at least one scan  
 181 (Tucker et al., 2009). When scan sampling is used, the interval between scans should be smaller than the  
 182 duration of activities to not miss bouts. An animal switching from an activity to another can still be  
 183 considered in the same bout if it returns quickly to the initial activity. One needs to define how long the  
 184 animal must stop an activity between two instances of that activity so that separate bouts are identified  
 185 (Yeates et al., 2001).

186 For instance, eating bouts are usually combined into meals if the interval between successive eating  
 187 bouts is less than the meal criterion. The minimum interval between bouts can be determined by different  
 188 methods (Tolkamp et al., 1998, Yeates et al., 2001, Dado & Allen, 1993), for example, using log-survivorship  
 189 and log-frequency analysis (see Tolkamp et al., (1998), for a description of these methods).  
 190

191 *Activity level.*

192 The overall activity in farm animals is usually summarised into an activity level by assigning a weight  
 193 to each activity, the weight expressing the contribution of the activity to the arousal of the animal (Veissier  
 194 et al., 2001). The level of activity of the period  $P$  is calculated by the sum of the time spent in each activity  
 195 multiplied by the weight of the activity:

196 
$$ActivityLevel_a^P = \left( \sum_{\substack{p \in P \\ a \in A}} T_{ap} \cdot W_a \right) \quad (4)$$

197 where  $T_{ap}$  is the time spent on activity  $a$  in period  $p$ ,  $W_a$  is the weight of activity  $a$ , the summations  
 198 are over subperiods  $p$  in period  $P$  (and over all activities in  $A$ ).

199 The weights can be assigned *a priori* by the experimenter or elicited from observations. Veissier et al. (2001)  
 200 observed calves to investigate their responses to repeated social regrouping and relocation. In that study,  
 201 researchers performed a Factorial Analysis of Correspondence (**FAC**) on the number of instances (scans x  
 202 calves) of each of five activities per hour; the grouping of factors - that summarises most of the variations  
 203 between the 24 hours of the day - brought decreasing weights to feeding (1.438), walking (0.763), standing  
 204 immobile (- 0.085), lying head up (- 0.261), then lying head down (- 0.541), ordering the activities as one  
 205 would intuitively do to express the decreasing arousal. The FAC is based on associations between activities  
 206 and therefore, the outcome of the FAC strongly depends on the level of detail of the activities that are

207 included. Experience told us that the ethogram should not be split in too many (short lasting) activities to  
208 elicit meaningful weights.

### 209 **Biological meaning**

210 The time budget of animals depends on their living conditions and the farm management. Cows  
211 spend about half of the day lying, but this can vary from 8 h to 13 h (reviewed by Tucker et al., 2021). Lying  
212 time is reduced when lying areas are uncomfortable (poorly designed or too hard, wet, small, hot) or not  
213 enough resting places are available for the size of the herd (Tucker et al., 2021). Cows may, nevertheless,  
214 spend more time lying in case of short cubicles preventing them to stand properly in a cubicle and thus  
215 forcing them to lie down as soon as they enter a cubicle (Veissier et al., 2004). The time spent feeding and  
216 walking also largely depends on housing and management conditions: cows grazing at pasture spend much  
217 more time eating and walking than cows kept indoors and fed herbage harvested from the same pasture  
218 (527 min/d eating and 311 min/d walking at pasture vs. 398 min/d and 133 min/d indoor (Dohme-Meier et  
219 al., 2014)); bulls and sheep spend less time eating when the diets contain a large proportion of fibre than  
220 when the diets contain a large proportion of starch (- 67% in bull fed a 45% starch diet and - 18% in sheep  
221 fed a 38% starch diet, compared to animals fed diets with less than 20% starch (Commun et al., 2012; Mialon  
222 et al., 2008)). The effects described in the above paragraph are typically observed in all animals from a herd.

223 Variability is also observed between individuals in a herd. The overall activity of an animal varies  
224 over time due to its physiological state. Young cows are often more active and change more often of activity  
225 than adult ones (Solano et al., 2016). At the time of oestrus, cows are agitated, spending less time eating  
226 but more time active in other ways (more walking, less lying) (Reith & Hoy, 2018). Changes are also observed  
227 due to gestation and parturition: the time spent lying by cows decreases during the weeks before and after  
228 calving and slowly increases thereafter up to end of lactation, with 2 h of amplitude of variation in  
229 multiparous cows (Hut et al., 2022). The changes in activity are generally well marked and short lasting  
230 around oestrus but less marked and gradual around calving, making calving detection from gross activity  
231 more difficult than that of oestrus (Benaissa et al., 2020).

232 The overall activity of an animal can also change due to a pathological state (e.g. due to  
233 inflammation (Dittrich et al., 2019). These modifications are called sickness behaviour, characterised –  
234 among others – by a low activity of the animal (Weary et al., 2009). Metabolic disorders (e.g., hypocalcemia,  
235 ketosis, acidosis) are generally accompanied by an increase in the time spent lying and a corresponding  
236 decrease in the time spent active and feeding (Weary et al., 2009; Belaid et al. 2021). These changes are  
237 more marked in hypocalcemia than in other metabolic diseases, hence the name ‘downer cow’ syndrome  
238 for hypocalcemia (Wadhwa & Prasad, 2002). Acidosis can be accompanied by a higher fractioning of activity:  
239 sheep suffering from acidosis often change their posture from lying to standing (Commun et al., 2012), as  
240 if they do not feel comfortable in either of these postures. Infectious diseases are also associated with an  
241 increase in time spent lying down and a decrease in time spent feeding (Weary et al., 2009). Mastitis  
242 however may result in a decreased time spent lying down, compensated by an increased time spent  
243 standing (Fogsgaard et al., 2015; Medrano-Galarza et al., 2012), presumably due to pain on the udder which  
244 is increased by the pressure on it when the animal is lying. Lameness is also accompanied by sickness  
245 behaviour and a specific pattern of lying behaviour with less lying bouts, but of longer duration (Solano et  
246 al., 2016, de Mol et al., 2013). Sick cows, whatever the origin of the disorders, usually spend less time  
247 ruminating (Calamari et al., 2014).

248 Stress is another factor affecting the activity of animals. Stressed animals usually spend less time  
249 lying down and change more often between activities, while distressed animals due to a disease may change  
250 between activities less often. For instance, suckling calves separated from their dam and moved from  
251 pasture to a barn respond to these changes by spending less time lying down, more time standing still or  
252 walking, and by fractionating their activities to a larger extent (Veissier et al., 1989). These modifications  
253 fade within days or weeks, indicating habituation to the new environment. Similar changes are observed  
254 when primiparous cows join the lactating herd. Around calving, primiparous cows decrease their time spent  
255 lying to a larger extent than multiparous cows (Hut et al., 2022) and we suspect that this is due to the many  
256 changes undergone by them around calving: they are milked for the first time and they are introduced to  
257 the lactating herd and so exposed to social partners and a pen, both novel to them.

258 Monitoring the overall activity can thus help to check if the animals are managed adequately and  
259 to detect physiological states (especially oestrus), pathological states, or stress. Feeding, ruminating and

260 lying seem especially sensitive to variations in the animal or its environment. Lying is also reduced in case  
261 of an uncomfortable lying area, so it is often considered that a prolonged time spent lying indicates good  
262 welfare (Piñeiro et al., 2019a, 2019b). However, lying time is often increased in case of disease too. In any  
263 case, the value obtained for duration and frequency of activities should be interpreted considering the  
264 context in which these metrics are obtained, for instance the type and management of feeding, the housing  
265 or grazing conditions, and the timing in relation to calving.

## 266 Metrics to address fluctuations around the mean activity

### 267 Definition

268 The activity of an animal varies within and between days (Hut et al., 2022). The variation is  
269 described by metrics calculating how far values, obtained on a given time frame, are spread around the  
270 mean value across several time periods within the time frame. The calculations are generally applied to the  
271 duration of activities or the level of activity, less often to the number of bouts or their duration, with all  
272 values obtained of individual animals. The time period is often the hour within the day (Mialon et al 2008  
273 (eating duration in bulls), Lardy et al., 2023 (level of activity in cows)) or the day within a period for the  
274 actual number of days (Hut et al., 2022 (duration of each activity); Solano et al., 2016 (number of bouts)).

### 275 Calculations

276 The metrics used to describe variations in an animal's activity across time periods (e.g., hours within  
277 a day) are similar to those traditionally used in descriptive statistics except that they are applied at  
278 individual level (to characterise the variability of the activity of a given animal and not the variability  
279 between animals):

280 *Minimum* (**Min**) refers to the minimum value observed/recorded

281 *Maximum* (**Max**) refers to the maximum value observed/recorded

282 *Range* corresponds to the difference between Min and Max

283

### 284 Quantiles

285 Quantiles are cut points dividing the dataset into continuous intervals with equal probabilities. The  
286 most commonly used quantiles are quartiles, which divide the number of data points into four parts, where  
287 the first quartile (Q1, 25<sup>th</sup> percentile) is the maximum value in the 25% of the lowest values in the dataset,  
288 the second quartile (Q2) corresponds to the median, and the third quartile (Q3, 75<sup>th</sup> percentile) is the  
289 minimum value in the 25% of the highest values in the dataset.

290

### 291 Variance and Standard deviation

292 The variance is the sum of the squares of the differences between each value and the mean (see  
293 formula below); and *Standard deviation* (**SD**) is the square root of the variance.

294 
$$\text{Variance}(x) = \frac{1}{N-1} \sum_{i=1}^N (x_i - \mu)^2 \quad (5)$$

295 where  $x$  is the activity (expressed for examples as the level of activity or the proportion of time  
296 spent in a given activity) composed of  $N$  observations,  $x_i$  is the  $i^{\text{th}}$  observation, and  $\mu$  the mean of the activity.

297

298 *Root Mean Square of the Successive Differences (RMSSD):*  
299 RMSSD measures the variations from one interval to the next one. RMSSD is calculated as follows:

300

$$301 \quad RMSSD(x) = \sqrt{\frac{1}{N-1} \sum_{i=1}^{N-1} (x_i - x_{i+1})^2} \quad (6)$$

302 where  $x$  is the sequence of activities (expressed for example as the level of activity) composed of  
303  $N$  observations,  $x_i$  is the  $i^{th}$  observation.

#### 304 *Irregularity*

305 An index of irregularity of behaviour can be calculated as proposed for feed intake (Salgado et al.,  
306 2021a, 2021b). First, a regression line of cumulative data (e.g., cumulative time spent in a given activity) is  
307 drawn, then the differences between observed values and the regression line are calculated. The sum of  
308 these differences brings the irregularity index.

#### 309 **Biological meaning**

310 Maximum activity during the day can be relevant to identify cow states: in a study where many  
311 metrics were used for a random forest classification (i.e., multiple decision trees created using different  
312 random subsets of the data), Lardy et al. (2023) found that the maximum activity during the day and  
313 Quantile 90 (two metrics closely linked) were the most important features to discriminate pathological and  
314 physiological states of cows.

315 Within-day variations of activity are well marked in healthy and non-stressed animals. For instance,  
316 lying is predominant at some time points throughout the day whereas eating and other activities are  
317 predominant at other times. Therefore, the activity level is not constant from hour to hour during the day.  
318 Within-day variations (measured by SD and RMSSD) are less marked in sick animals than in healthy ones;  
319 this is the case for cows affected by mastitis and to a lesser extent by lameness (Veissier et al., 2017). Within-  
320 day variations are also affected by oestrus: variations rise above baseline at the beginning of oestrus then  
321 decrease below baseline for at least two days (Veissier et al., 2017). RMSSD slightly differs from SD. With  
322 the same amount of variation during the day (same SD), an activity that varies smoothly between successive  
323 hours results in a low RMSSD while an activity that fluctuates between successive hours results in a high  
324 RMSSD. In Veissier et al. (2017) the decrease in the within-day variation in the activity of cows affected by  
325 mastitis, lameness and oestrus was more marked when assessed by RMSSD than by SD, suggesting that  
326 cows change of activity more often when diseased or in oestrus. Stress may also be associated with a  
327 reduction in within-day variation in activity, as observed in cattle moved from pasture to indoor housing  
328 (Veissier et al., 1989; using the difference between night and early morning). Spreading activities  
329 throughout the day can also be a way to adapt to specific conditions. Bulls fed fibrous diets eat in few meals  
330 during the day whereas bulls fed high starch diets spread their eating activity over the entire day, which  
331 results in a low SD of eating duration (Mialon et al., 2008). Dispersing small meals over the day is likely to  
332 be a strategy to avoid ruminal acidosis due to high amounts of starch in a diet.

333 Between-day variation in activity can increase when animals are disturbed as a result of disease or  
334 in case their activity pattern is interrupted by sudden events. For instance, cattle and sheep affected by  
335 acidosis or ketosis have more variable activities across days than healthy animals (Commun et al., 2012;  
336 González et al., 2008). At least in case of ketosis, an effective treatment eliminates the effect (Goldhawk et  
337 al., 2009). Lame cows can also display high between-days variation in the duration of lying bouts (Ito et al.,  
338 2010; Solano et al., 2016). A quick return to normal or baseline values after small disturbances (micro-  
339 recoveries) results in low variance, and is considered as a sign of good resilience (Scheffer et al., 2018).  
340 Animals that spontaneously (i.e., apart from diseases or other challenges) have a variable activity are less  
341 prone to further diseases (Van Dixhoorn et al., 2018).

342



343

## Metrics to address the cyclicity of activity

### 344 Definition

345 Cyclicity indicates fluctuations at regular intervals around activity trends. The most common cycle  
346 is the circadian cycle, which is the 24-h rhythm due to the alternance of day and night.

### 347 Calculations

348 Several metrics can be used for addressing the cyclicity of activity (Kok et al., 2023). Autocorrelation  
349 and Fourier transform are basic calculations. Other indices are derived from these two metrics such as non-  
350 periodicity index (Van Dixhoorn et al., 2023; Van Dixhoorn et al., 2018) and degree of functional coupling  
351 (Berger et al., 2003; Scheibe et al., 1999).

#### 352 *Autocorrelation.*

353 Autocorrelation measures the correlation between successive values of a signal. The  
354 autocorrelation depends on the chosen delay, e.g., for hourly data the lag-1 corresponds to the correlation  
355 between successive hours and lag-24 corresponds to the correlation between an hour of the day and the  
356 same hour of the next day, therefore reflecting the circadian cycle. Let  $x$  be the number of measured  
357 behaviour events (e.g. duration, frequency, etc), and " $l$ " the amount of time that has passed (lag  $l$ ). For a  
358 sequence  $x$  of size  $N$ , the autocorrelation function (ACF) with a lag  $l$  is calculated as following:  
359

$$360 \quad ACF(x, l) = \frac{1}{(N-l)\sigma^2} \sum_{i=1}^{N-l} (x_i - \mu)(x_{i+l} - \mu) \quad (7)$$

361 Where  $\sigma$  is the variance of the sequence  $x$ ,  $\mu$  is the average value of the sequence  $x$  and  $x_i$  the  $i^{th}$   
362 element of the sequence  $x$ .  
363

#### 364 *Non-periodicity.*

365 Non-periodicity is calculated by plotting the correlogram of the raw data (which is a graphical  
366 display of a correlation matrix of the data) over a sinusoid with an amplitude of 0.25 and a 24-hour cycle  
367 and assessing the difference between the correlogram and the sinusoid by calculating the mean squared  
368 error (Figure 2) (Van Dixhoorn et al., 2023; Van Dixhoorn et al., 2018). The value of an amplitude of 0.25 is  
369 chosen as it gave the best fit and might be adjusted in other situations where the autocorrelation shows a  
370 circadian rhythm.

$$371 \quad Nonperiodicity(x) = \frac{(\sum_{l=1...100} (ACF(x, l) - 0.25 \cdot \cos(2\pi \cdot l/24))^2)}{100} \quad (8)$$

372 where  $x$  is a variable measured at hourly (or other chosen time interval) time intervals,  $ACF(x, l)$  is  
373 the autocorrelation function for variable  $x$  at lag  $l$  (ranging from 1 to 100),  $0.25 \cdot \cos(2\pi \cdot l/24)$  is the cosine  
374 function with a 24-h cycle and an amplitude of 0.25 that is used as a fit function.  
375

#### 376 *Fourier transform.*

377 Fourier transform represents the sinusoids that compose the original variation. Each sinusoid is  
378 defined by a frequency and an amplitude. The contribution of each sinusoid to explain the original variation  
379 is expressed in absolute or relative power, usually referring to the frequency of the sinusoid or to frequency  
380 bands. For instance, the contribution of the circadian cycle and of ultradian cycles can be calculated. When  
381 variations within 24 h time series are analysed by Fourier transform, the fundamental (h0) refers to the  
382 average activity during 24 h, harmonic 1 (h1) refers to variations following a 24 h cycle (once per day); h2,  
383 to a 12 h cycle (twice per day); h3, to an 8 h cycle (3 times per day); h4 to a 6 h cycle (4 times per day), etc.  
384 The main cycle is the circadian one; the activity of an animal can therefore be modelled by its overall activity  
385 (mean during 24 h) and the variations around overall activity following a 24 h cycle, in other words into h0  
386 and h1. The Fourier-based approximation with thresholding (**FBAT**) method was developed to compare  
387 such models obtained on successive time series (Wagner et al., 2021). An alternative to the Fourier  
388 transform is the Cosinor method. Cosinor and Fourier are analogous in formulation, but differ in operation

389 (see (Chkeir et al., 2019), for a comparison of the two modelling approaches). An example of Fourier  
390 transform is visualised in Figure 2.

### 391 *Degree of functional coupling (DFC).*

392 The degree of functional coupling is obtained by calculating autocorrelations, then applying Fourier  
393 transform to the correlogram, extracting the significant harmonics and calculating the power of each  
394 significant harmonics out of the power of all significant harmonics (DFC). More specifically, the relative  
395 power of the harmonic corresponding to a 24 h cycle expresses how much the variations are due to the  
396 circadian cycle: when DFC equals 100%, the variation in activity follows strictly a circadian cycle vs. when  
397 DFC equals 0%, the activity does not at all depend on the 24 h cycle (Berger et al., 2003).

398 In theory, data during 24 h only can be used to identify a circadian cycle. In practice, activity data  
399 usually contains noise, i.e., erratic fluctuations so that more than one day is necessary to identify correctly  
400 cyclic components. The number of days required depends on the amount of noise vs. cyclic components.

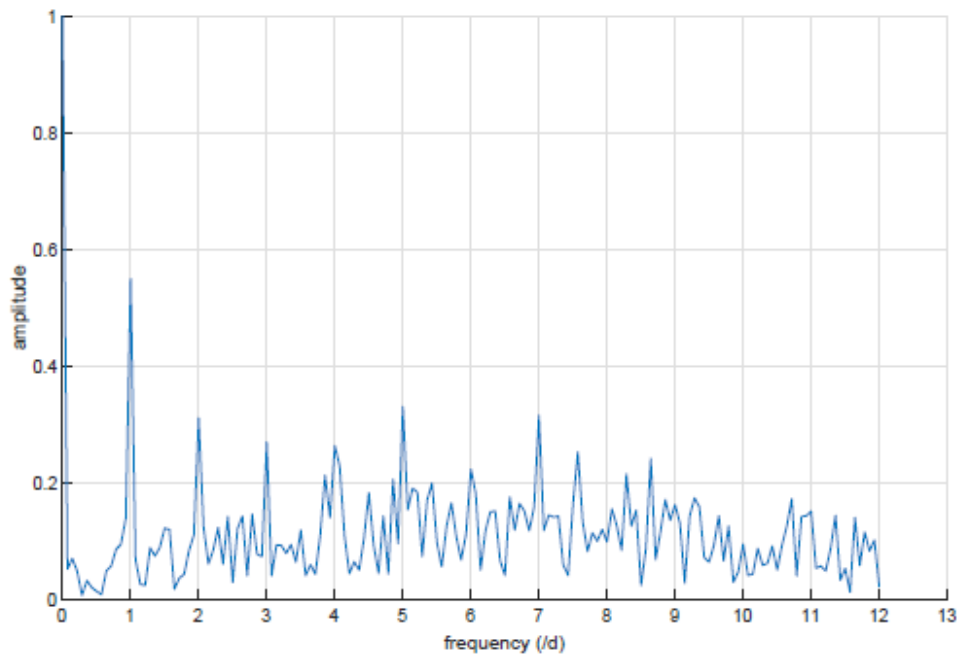
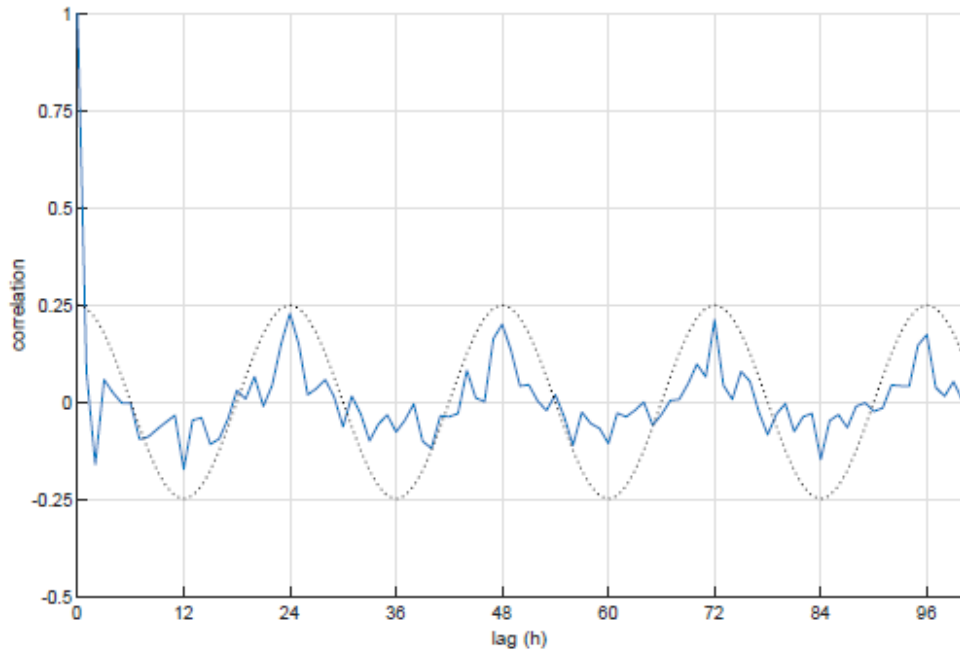
401 In general, the activity of an animal peaks several times during the day, e.g., depending on the  
402 timing of feeding or milking, whereas the activity stays low at night. Autocorrelations and Fourier transform  
403 hardly take the dissymmetry between day and night activity into account. Wavelet methods could be used  
404 to overcome this problem (discussed in Wagner et al., 2021).

### 405 **Biological meaning**

406 Daily periodicities are influenced by internal clocks (endogenous driven biological cycles) and  
407 external factors such as temperature, light, humidity, feeding time (exogenously driven biological cycles)  
408 (Saper et al., 2005). Internal clocks generate a rhythm of about 24 h period. In mammals, the central internal  
409 clock situated in the brain (suprachiasmatic nuclei) coordinates peripheral clocks in the body (Honma,  
410 2018). Among external cues (or “Zeitgebers), light is known to be the most powerful one, impacting both  
411 on behaviour and physiological functions (Honma, 2018). For instance, cows are typically diurnal animals:  
412 they eat essentially between dawn and dusk and they predominantly rest at night (DeVries et al., 2003;  
413 Hafez et al., 1969). Variations can nevertheless be observed between cows in the cyclicity of their  
414 behaviour. Competition for resources (e.g. feed, lying area), due to overstocking or ambiguity in the ranking  
415 order because of frequent change in group composition, can cause a misalignment with the circadian  
416 rhythm (McCabe et al., 2021; Van Dixhoorn et al., 2023; Van Dixhoorn et al., 2018; Van Erp et al., 2020).

417 Cows with more marked circadian patterns of activity seem more resistant to health disorders. For  
418 instance, cows with marked cyclicity of eating, walking or lying before calving are less affected by post-  
419 partum health disorders (including inflammatory and metabolic problems (Van Dixhoorn et al., 2023; Van  
420 Dixhoorn et al., 2018)). Indeed, dairy cows need to have their physiological mechanisms fine-tuned to be  
421 able to produce large quantities of milk while avoiding nutritional and metabolic deficiencies (negative  
422 energy balance or mineral deficiencies such as hypocalcemia). We hypothesise that good cyclicity, aligned  
423 with circadian rhythm can help to avoid such dysfunctions, especially in the demanding postpartum period.

424 Any change of the internal state of an animal - due to stress, disease or some specific reproductive  
425 status (parturition, oestrus) – can in turn affect the cyclicity of activities. For instance, the difference  
426 between activity during the day and at night is less marked in heifers experiencing a large change in their  
427 environment – weaning and turning from pasture to indoors – and in cows affected by mastitis or lameness  
428 (Veissier et al., 1989; Veissier et al., 2017). Variations during the day can be modelled, e.g., thanks to Fourier  
429 transform in the FBAT method. The distance between models obtained on successive 24 h series increases  
430 when cows are stressed, diseased, in oestrus or about to calve, expressing a change in daily patterns  
431 (Wagner et al., 2021). These effects may be due to the release of glucocorticoids during stress, disease or  
432 even calving. Indeed, glucocorticoids, the secretion of which follows a circadian pattern, help to coordinate  
433 peripheral clocks with the brain pacemaker (Dumbell et al., 2016).



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**Figure 2** - Examples of non-periodicity of eating behaviour visualised through correlograms (top), and Fourier transform pattern (bottom) (frequency of activity performed per day). In the correlograms, dotted lines represent the expected cyclicity of the specific behaviour, while the solid lines indicate the observed behaviours. Non-periodicity is assessed by calculating the Root Mean Squared Error (RMSE) of the correlogram as compared to the sinusoid. In the Fourier transform pattern the amplitude is given per frequency, expressing the strength of the cycles in activity for that frequency. The peak at frequency 1 shows that this cow has a strong circadian pattern. The sum of the amplitudes at frequency 1, 2, 3 and 4 represents the strength of the cycles in activities with a 24, 12, 8, and 6 h cycles and is used as a measure of the cyclicity of the cow.

444

## Metrics to address the synchrony between animals

### 445 Definition

446 Synchrony measures the extent to which animals of a given group perform the same activity at the  
447 same time. The synchrony can be assessed between two animals, between an animal and the group it  
448 belongs to, or at the group level.

### 449 Calculations

450 Synchrony is to be assessed based on what animals do at certain points in time spaced at regular  
451 intervals. Collecting data using scan sampling is therefore appropriate for calculations of synchrony metrics.  
452 In case of continuous observations, where changes in behaviour are noted for each animal exactly when  
453 they occur, a pre-processing of data is necessary: at each time interval the instantaneous activity of each  
454 animal of the group need to be extracted (resampling procedure). When data are expressed as main activity  
455 of each animal during a certain interval, as often done with sensors, synchrony can only be approximated:  
456 if the intervals at which the activity is noted are short enough (e.g. 5 min) then it may be considered that  
457 the animal kept the same activity during the whole interval, and the data can then be processed as scan  
458 sampling.

459 Several metrics can be found in the literature to calculate synchrony. We cite here the most  
460 common ones.

461 (a) The synchrony between two animals is calculated as the proportion of the scans during  
462 which they are engaged in the same activity (see example in Veissier et al., 1989):

463 
$$\text{synchrony} = \frac{1}{n} \sum_{i=1}^n S_i \quad (9)$$

464 where  $n$  is the number of scans,  $S_i$  equals 1 if the two animals have the same activity at scan  $i$  and  
465 0 if they do not.

466 The synchrony of a focal animal (i.e., the animal observed) with the rest of the group or a certain  
467 sub-group of animals in the group can be calculated as:

469 (b) the average of the proportion of animals from the group or the sub-group performing the  
470 same activity as the focal animal across scans. This also corresponds to the average of synchrony indices (a)  
471 obtained for a focal animal and any other animal from the herd or the sub-group (Veissier et al., 1989):

472 
$$\text{synchrony} = \frac{1}{n(m-1)} \sum_{j=1}^{m-1} \sum_{i=1}^n S_{ij} \quad (10)$$

473 where  $n$  is the number of scans,  $m$  is the number of animals in the group,  $S_{ij}$  equals 1 if the focal  
474 animal and the other animal  $j$  have the same activity at scan  $i$  and 0 if they do not.

475 (c) the proportion of scans during which the focal individual performs the same activity as  
476 most individuals of the rest of the group (Ruckstuhl, 1999). The calculation is similar to that for the  
477 synchrony between two animals given in (a) above but with  $S_i$  equals 1 when the focal animal has the same  
478 activity as most of the group and 0 when it does not.

479 At group level, the synchrony can be calculated with several indices:

480 (d) The proportion of scans where all animals of the group perform the same activity; Again,  
481 similar calculations as for (a) are used with  $S_i$  equals 1 if all animals perform the same activity and 0 if not.

482 (e) **The average of metrics (b) (Veissier et al., 1989) or (c) (Asher & Collins, 2012).**

483 The metrics presented above depend largely on the number of activity categories and the number  
484 of animals in the group (especially metrics (d)): when the group is large and the number of activity  
485 categories is high, there is little chance that animals perform the same activity at the same time. Asher and

486 Collins (2012) thus recommend comparing the distribution of activity observed with the one obtained at  
487 random. This can be done with:

488 (f) Kappa coefficient of agreement. For instance, the proportion of pairs of animals observed  
489 with the same activity is calculated (Rook & Penning, 1991):

$$490 \quad P(O) = \frac{1}{np} \sum_{i=1}^n S_i \quad (11)$$

491 Where capital P refers to proportion,  $n$  is the number of scans,  $p$  is the total number of pairs of  
492 animals in the groups, and  $S_i$  the number of pairs of animals performing the same activity at scan  $i$ .

493 The expected proportion of pairs that would perform the same activity by chance is then  
494 calculated:

$$495 \quad P(E) = \frac{1}{(nm)^2} \sum_{k=1}^l C_k^2 \quad (12)$$

496 where  $n$  is the number of scans,  $m$  is the group size,  $l$  is the number of activity categories, and  $C_k$   
497 the frequency of observation of activity category  $k$  (i.e., total number of scan x animals occurrence of the  
498 activity).

499 Then

$$500 \quad \text{Kappa coefficient} = \frac{P(O) - P(E)}{1 - P(E)} \quad (13)$$

501 The Kappa coefficient equals 1 if all animals always perform the same activity at the same time (full  
502 synchronization). It equals 0 when animals are not synchronised more than at random.

503 (g) Other methods can be found in the literature to compare the synchrony observed to that  
504 expected on a randomised dataset: calculating a dispersion index (Raussi et al., 2011) or applying Monte-  
505 Carlo methods (Whitehead, 1999). These two options are rarely used in the literature on behaviour (e.g.,  
506 we did not find studies using the dispersion index apart from that of Raussi et al. (2011)). In most cases,  
507 these methods may not have added value compared to the Kappa coefficient of agreement.

508 The activity categories should be carefully chosen. If there are too many categories (e.g., detailing  
509 precisely what the animals do when standing active: walking, scratching, interacting with each other), the  
510 animals will seem little synchronised whereas if there are too few categories (e.g., active vs. inactive) they  
511 will seem very synchronised. Asher and Collins (2012) recommend using 5 activity categories in laying hens.  
512 It must be considered whether or not we expect social facilitation of an activity to occur (that is one animal  
513 engaging in an activity leads to other animals engaging in the same activity). In ruminants, ruminating  
514 appears as a reflex activity, ruminating thus should not be used as a separate activity but rather included in  
515 lying and standing idling (i.e., postures when ruminating can occur) because we do not expect social  
516 facilitation of ruminating.

517 To be interpreted in terms of a positive relationship between two animals, the synchrony needs to  
518 be estimated between animals that have about the same time budget (i.e., same amount of time spent in  
519 each activity per day). For instance, although a cow has a strong bond to its new-born calf, the apparent  
520 synchrony between them may be low because the cow spends lot of the time foraging whereas the calf  
521 spends more time lying (Veissier et al., 1990).

## 522 **Biological meaning**

523 Animals may be synchronised because the activity of an animal is influenced by that of other  
524 animals. Social facilitation has been described in many species and contexts (Clayton, 1978). Animals may  
525 be synchronised also because they adopt a similar rhythm of activity: activities follow a circadian rhythm  
526 triggered at least in part by external cues such as light or timing of food distribution (or milking in dairy

527 cows) so if animals are subjected to the same cues, their activity will tend to be similar (Flury & Gyga,  
528 2016).

529 The synchrony between two animals (fighting excluded) gives us an estimate of how closely (and  
530 positively) they are related to each other. Two animals bond by a positive social relationship have more  
531 chances than unrelated animals to express the same activity at the same time. For instance, when calves  
532 stay with their dam after weaning they keep preferential relations that are shown by proximity, exchanges  
533 of positive interactions, and also synchrony (Veissier et al., 1990).

534 Synchrony at the group level reflects social cohesion, i.e. the strength of the bonds between the  
535 animals in the group (Clayton, 1978). Groups newly formed are usually less cohesive, with animals  
536 exchanging aggressive interactions and being less synchronised (Mounier et al., 2005). The synchrony can  
537 also decrease if there is competition for access to a resource, e.g., food and lying places. For instance, in  
538 cows and sheep, synchrony of lying decreases when lying space is limited (Bøe et al., 2006; Winckler et al.,  
539 2015). The synchrony between an animal and the rest of the group reflects the familiarity of that animal  
540 with the group: synchrony may be low in case of a newly introduced animals until the organization of the  
541 group is stabilised (Arey, 1999; Boyle et al., 2013). A variation in synchrony can also be caused by a health  
542 disorder: the activity of an animal is modified in case of disease (Dantzer et al., 2008), so that the diseased  
543 animal can depart from the rest of the group (e.g., a cow isolates and stay standing idling or lying for longer  
544 when ill (Proudfoot & Habing, 2015; Proudfoot et al., 2012).

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**Table 1** - Summary of metrics to describe the activity of animals with their condition of use

Category	Metrics	Raw data	Purpose	Limitations	Reference
<b>Overall activity</b>	Proportion of time spent in an activity	Collection of activity bouts with duration	Detection of physiological states (e.g., oestrus), pathological states (lameness), or stress	Depends on their living conditions and the farm management Modifications are also observed between individuals	Veissier 2004
	Number and duration of activity bouts	Collection of activity bouts with duration		There is a need to : - record for long periods to avoid edge effects. - describe activity with similar details - have a clear delineation of when a new activity starts Weights of each activity to be elicited.	Tucker et al., 2009. Ledgerwood et al., 2010. Yeates et al., 2001
	Activity level	Time spent on activities			
<b>Fluctuations around the mean</b>	Min/max/range/quantiles/variance/RMSSD	Timeseries	To identify pathological or physiological states of cows		Hut et al., 2022; Lardy et al., 2023; Mialon et al. 2008.
<b>Cyclicity</b>	Irregularity Autocorrelation Non-periodicity Cosinor method Fourier transform Degree of functional coupling (DFC)	Continuous sampling Continuous sampling Continuous sampling Continuous sampling Continuous sampling	Detection of physiological states (e.g., oestrus), pathological states (lameness), or stress. To predict resilience.	Recording for long periods (longer than the cycle to be detected)	Salgado et al. 2021a&b Dixhoorn et al., 2023, 2018; Chkeir et al., 2019  Berger et al., 2003; Scheibe et al., 1999 Veissier et al., 1989
<b>Synchrony between individuals</b>	Proportion of animals from the group or the sub-group performing the same activity as a focal individual.	Scan sampling	Bonds between animals and / or availability of resources	Depends on the number of animals and number of activity categories	
<b>Synchrony at herd level</b>	Proportion of scans during which a focal individual performs the same activity as most individuals of the rest of the group	Scan sampling	Inclusion of an animal in a group. Detection of health disorder		Ruckstuhl, 1999 Asher & Collins 2012
	The average of metrics taken at individual level.	Scan sampling and continuous sampling	Social cohesion Competition for resources		Veissier et al., 1989; Stoye et al. 2012 Arsher and Collins, 2012
	The proportion of scans where all animals of the group perform the same activity Kappa coefficient of agreement				Stoye et al., 2012 Rook and Penning, 1991

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552 In this **review** we present metrics that can be calculated from data on gross activity and identify  
553 their conditions for use (summarised in Table 1). We divided the metrics into four groups that represent  
554 different aspects of animal behaviour: the overall activity, the fluctuations around the mean activity, the  
555 cyclicity, and the synchrony between animals.

556 The overall activity is the most often studied aspect. It represents the total duration and  
557 organisation of the activity in bouts. The fluctuations of activity during the day or across days and the  
558 organisation of these fluctuations according to (circadian) cycles are less often addressed but are gaining  
559 attention in research. Synchrony between animals is generally used to study the social organisation of a  
560 group of animals, but is also more and more used as specific indicators (e.g. likelihood of diseases or  
561 evaluation of the management) and constitutes also a promising indicator of positive welfare (Keeling et  
562 al., 2021; Napolitano et al., 2009).

563 These four groups of metrics can be used to analyse the impact of housing and management  
564 procedures. In that case, the values at herd level are evaluated, all animals within the herd are taken into  
565 account. In most cases, the average herd level values per metric are expected to not vary much in time,  
566 unless management or housing change. However, seasonality may affect some metrics due to photoperiod,  
567 weather, or the reproductive period (e.g. females may be less synchronised with the rest of the group when  
568 they have young).

569 These metrics can also be used to compare animals within a herd individually (with same  
570 management and housing). Animals are usually consistent with time, so that the data can be used to  
571 phenotype them (Bacher et al., 2022; Poppe et al., 2022). In turn the behavioural phenotype can inform  
572 about other traits. For instance, a cow that shows low regularity in activity is likely to be more susceptible  
573 to post-partum diseases, when she has to cope with metabolic constraints (van Dixhoorn et al., 2023).

574 Transient changes in activity can be observed under certain circumstances at animal level,  
575 especially when an animal is sick, in a specific physiological state (oestrus, calving), or stressed. When such  
576 transient changes are observed concurrently in most animals of the herd, it is likely that the herd has been  
577 disturbed by external events (e.g., handling to apply a treatment, hoof trimming, period of heat stress).  
578 When the transient change is observed in only one or few animals, it is more likely an individual case of  
579 disease or a reproductive event.

580 Combining several behavioural metrics is usually necessary to have a comprehensive overview of  
581 the internal state of an animal. For instance, to infer the internal state of a cow (diseased, in oestrus, about  
582 to calve, or stressed), metrics on overall activity, fluctuations and cyclicity are necessary to be able to classify  
583 the cow into the corresponding state (Lardy et al., 2023).

584 In this paper, only metrics describing overall activity, fluctuations around mean activity, cyclicity,  
585 and synchrony between animals are described and discussed. The data can nevertheless be further  
586 processed to extract more information. For instance, a network analysis could be performed with links  
587 between individuals of a group estimated from their synchrony. Such an approach could probably be  
588 applied to study group effects such as social facilitation, leadership, or cooperation among individuals.  
589 Markov chains can be used to analyse sequences of activities to better understand the organisation of  
590 activities (Rugg & Buech, 1990; Schafer et al., 2020). Machine learning applied to metrics describing activity  
591 can also help to classify animals according to their phenotype or to detect changes in activity for specific  
592 animals and days (Lardy et al., 2023; Wagner et al., 2020; Debauche et al., 2021).

593 In conclusion, activity data provide the raw material for the calculation of several metrics that  
594 describe animal behaviour. The choice of which metrics to use, depends on the research question or  
595 potential application. A clear research question is essential for the selection of the most appropriate metrics  
596 that best characterise specific aspects of the behaviour of the animals, suitable for answering question(s)  
597 asked. We believe that clarification of the metrics and on how they should be calculated will help to  
598 standardise these metrics, making them easier to use and allowing comparisons between studies.

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## **Data, scripts, code, and supplementary information availability**

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Supplementary material : Examples of calculations of metrics using R software are available online: Supplementary materials belonging to From data on gross activity to the characterization of animal behaviour: which metrics for which purposes: <https://doi.org/10.6084/m9.figshare.24891252>.

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## **Conflict of interest disclosure**

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The authors declare that they comply with the PCI rule of having no financial conflicts of interest in relation to the content of the article. Isabelle Veissier is recommender of PCI Animal Science.

- 616 Arey, D. S. (1999). Time course for the formation and disruption of social organisation in group-housed sows  
 617 [Article]. *Applied Animal Behaviour Science*, 62(2-3), 199-207. [https://doi.org/10.1016/S0168-](https://doi.org/10.1016/S0168-1591(98)00224-X)  
 618 [1591\(98\)00224-X](https://doi.org/10.1016/S0168-1591(98)00224-X)
- 619 Asher, L., & Collins, L. M. (2012). Assessing synchrony in groups: Are you measuring what you think you are  
 620 measuring? [Article]. *Applied Animal Behaviour Science*, 138(3-4), 162-169.  
 621 <https://doi.org/10.1016/j.applanim.2012.02.004>
- 622 Bacher, L. M., Prieur, V., Veissier, I., & Boivin, X. (2022). Association between breeding bulls' reactivity to  
 623 humans or handling and their daily behaviour and growth. *Animal*, 16(7), 100568.  
 624 <https://doi.org/10.1016/j.animal.2022.100568>
- 625 Bateson, M. M., Paul. (2021). *Measuring Behaviour: An Introductory Guide*. Cambridge University Press.
- 626 Benaissa, S., Tuytens, F. A. M., Plets, D., Trogh, J., Martens, L., Vandaele, L., Joseph, W., & Sonck, B. (2020).  
 627 Calving and estrus detection in dairy cattle using a combination of indoor localization and  
 628 accelerometer sensors. *Computers and Electronics in Agriculture*, 168, 105153.  
 629 <https://doi.org/10.1016/j.compag.2019.105153>
- 630 Berger, A., Scheibe, K. M., Michaelis, S., & Streich, W. J. (2003). Evaluation of living conditions of free-ranging  
 631 animals by automated chronobiological analysis of behavior. *Behavior Research Methods,*  
 632 *Instruments, & Computers*, 35(3), 458-466. <https://doi.org/10.3758/BF03195524>
- 633 Bøe, K. E., Berg, S., & Andersen, I. L. (2006). Resting behaviour and displacements in ewes—effects of  
 634 reduced lying space and pen shape. *Applied Animal Behaviour Science*, 98(3), 249-259.  
 635 <https://doi.org/10.1016/j.applanim.2005.10.001>
- 636 Borchers, M. R., Chang, Y. M., Tsai, I. C., Wadsworth, B. A., & Bewley, J. M. (2016). A validation of  
 637 technologies monitoring dairy cow feeding, ruminating, and lying behaviors [Article]. *Journal of*  
 638 *Dairy Science*, 99(9), 7458-7466. <https://doi.org/10.3168/jds.2015-10843>
- 639 Boyle, A. R., Ferris, C. P., & O'Connell, N. E. (2013). Does housing nulliparous dairy cows with multiparous  
 640 animals prior to calving influence welfare- and production-related parameters after calving?  
 641 [Article]. *Applied Animal Behaviour Science*, 143(1), 1-8.  
 642 <https://doi.org/10.1016/j.applanim.2012.11.004>
- 643 Buller, H., Blokhuis, H., Lokhorst, K., Silberberg, M., & Veissier, I. (2020). Animal welfare management in a  
 644 digital world [Review]. *Animals*, 10(10), 1-12, Article 1779. <https://doi.org/10.3390/ani10101779>
- 645 Calamari, L., Soriani, N., Panella, G., Petrera, F., Minuti, A., & Trevisi, E. (2014). Rumination time around  
 646 calving: An early signal to detect cows at greater risk of disease [Article]. *Journal of Dairy Science*,  
 647 97(6), 3635-3647. <https://doi.org/10.3168/jds.2013-7709>
- 648 Chkeir, A., Abdallah, M., Soubra, R., & Nassereddine, M. (2019, 9-11 April 2019). A mathematical approach  
 649 using a thoracic temperature sensor for detecting human circadian rhythms. 2019 IEEE Jordan  
 650 International Joint Conference on Electrical Engineering and Information Technology (JEEIT),
- 651 Clayton, D. A. (1978). Socially Facilitated Behavior. *The quarterly review of biology*, 53(4), 373-392.  
 652 <http://www.jstor.org.ezproxy.library.wur.nl/stable/2826580>
- 653 Commun, L., Silberberg, M., Mialon, M. M., Martin, C., & Veissier, I. (2012). Behavioural adaptations of  
 654 sheep to repeated acidosis challenges and effect of yeast supplementation [Article]. *Animal*, 6(12),  
 655 2011-2022. <https://doi.org/10.1017/S1751731112001309>
- 656 Dado, R. G., & Allen, M. S. (1993). Continuous Computer Acquisition of Feed and Water Intakes, Chewing,  
 657 Reticular Motility, and Ruminant pH of Cattle. *Journal of Dairy Science*, 76(6), 1589-1600.  
 658 [https://doi.org/10.3168/jds.S0022-0302\(93\)77492-5](https://doi.org/10.3168/jds.S0022-0302(93)77492-5)
- 659 Dantzer, R., O'Connor, J. C., Freund, G. G., Johnson, R. W., & Kelley, K. W. (2008). From inflammation to  
 660 sickness and depression: when the immune system subjugates the brain. *Nat Rev Neurosci*, 9(1),  
 661 46-56. <https://doi.org/10.1038/nrn2297>
- 662 De Mol, R. M., André, G., Bleumer, E. J. B., van der Werf, J. T. N., de Haas, Y., & van Reenen, C. G. (2013).  
 663 Applicability of day-to-day variation in behavior for the automated detection of lameness in dairy  
 664 cows [Article]. *Journal of Dairy Science*, 96(6), 3703-3712. <https://doi.org/10.3168/jds.2012-6305>
- 665 Debauche, O., Elmoulat, M., Mahmoudi, S., Bindelle, J., & Lebeau, F. (2021). Farm animals' behaviors and  
 666 welfare analysis with ia algorithms: A review [Review]. *Revue d'Intelligence Artificielle*, 35(3), 243-  
 667 253. <https://doi.org/10.18280/ria.350308>

668 DeVries, T. J., Von Keyserlingk, M. A. G., & Beauchemin, K. A. (2003). Short communication: Diurnal feeding  
669 pattern of lactating dairy cows [Article]. *Journal of Dairy Science*, 86(12), 4079-4082.  
670 [https://doi.org/10.3168/jds.S0022-0302\(03\)74020-X](https://doi.org/10.3168/jds.S0022-0302(03)74020-X)

671 Dittrich, I., Gertz, M., & Krieter, J. (2019). Alterations in sick dairy cows' daily behavioural patterns [Review].  
672 *Heliyon*, 5(11), Article e02902. <https://doi.org/10.1016/j.heliyon.2019.e02902>

673 Dohme-Meier, F., Kaufmann, L. D., Görs, S., Junghans, P., Metges, C. C., Van Dorland, H. A., Bruckmaier, R.  
674 M., & Münger, A. (2014). Comparison of energy expenditure, eating pattern and physical activity  
675 of grazing and zero-grazing dairy cows at different time points during lactation [Article]. *Livestock*  
676 *Science*, 162(1), 86-96. <https://doi.org/10.1016/j.livsci.2014.01.006>

677 Dumbell, R., Matveeva, O., & Oster, H. (2016). Circadian Clocks, Stress, and Immunity. *Front Endocrinol*  
678 *(Lausanne)*, 7, 37. <https://doi.org/10.3389/fendo.2016.00037>

679 Flury, R., & Gygax, L. (2016). Daily patterns of synchrony in lying and feeding of cows: Quasi-natural state  
680 and (anti-) synchrony factors. *Behavioural Processes*, 133, 56-61.  
681 <https://doi.org/10.1016/j.beproc.2016.11.004>

682 Fogsgaard, K. K., Bennedsgaard, T. W., & Herskin, M. S. (2015). Behavioral changes in freestall-housed dairy  
683 cows with naturally occurring clinical mastitis [Article]. *Journal of Dairy Science*, 98(3), 1730-1738.  
684 <https://doi.org/10.3168/jds.2014-8347>

685 Goldhawk, C., Chapinal, N., Veira, D. M., Weary, D. M., & von Keyserlingk, M. A. G. (2009). Parturition  
686 feeding behavior is an early indicator of subclinical ketosis. *Journal of Dairy Science*, 92(10), 4971-  
687 4977. <https://doi.org/10.3168/jds.2009-2242>

688 González, L. A., Tolkamp, B. J., Coffey, M. P., Ferret, A., & Kyriazakis, I. (2008). Changes in Feeding Behavior  
689 as Possible Indicators for the Automatic Monitoring of Health Disorders in Dairy Cows. *Journal of*  
690 *Dairy Science*, 91(3), 1017-1028. <https://doi.org/10.3168/jds.2007-0530>

691 Hafez, E., Schein, M., & Ewbank, R. (1969). *The behaviour of Domestic Animals*. Baillere, Tindall & Casell.  
692 <https://wellcomecollection.org/works/zvgxb37r>

693 Hut, P. R., Kuiper, S. E. M., Nielen, M., Hulsen, J. H. J. L., Stassen, E. N., & Hostens, M. M. (2022). Sensor  
694 based time budgets in commercial Dutch dairy herds vary over lactation cycles and within 24 hours.  
695 *PLoS One*, 17(2). <https://doi.org/10.1371/journal.pone.0264392>

696 Ito, K., von Keyserlingk, M. A. G., LeBlanc, S. J., & Weary, D. M. (2010). Lying behavior as an indicator of  
697 lameness in dairy cows [Article]. *Journal of Dairy Science*, 93(8), 3553-3560.  
698 <https://doi.org/10.3168/jds.2009-2951>

699 Jud, C., Schmutz, I., Hampp, G., Oster, H., & Albrecht, U. (2005). A guideline for analyzing circadian wheel-  
700 running behavior in rodents under different lighting conditions [Article]. *Biological Procedures*  
701 *Online*, 7(1), 101-116. <https://doi.org/10.1251/bpo109>

702 Koltjes, J. E., Cole, J. B., Clemmens, R., Dilger, R. N., Kramer, L. M., Lunney, J. K., McCue, M. E., McKay, S. D.,  
703 Mateescu, R. G., Murdoch, B. M., Reuter, R., Rexroad, C. E., Rosa, G. J. M., Serão, N. V. L., White, S.  
704 N., Woodward-Greene, M. J., Worku, M., Zhang, H., & Reecy, J. M. (2019). A Vision for Development  
705 and Utilization of High-Throughput Phenotyping and Big Data Analytics in Livestock [Review].  
706 *Frontiers in Genetics*, 10(1197). <https://doi.org/10.3389/fgene.2019.01197>

707 Lardy, R., Ruin, Q., & Veissier, I. (2023). Discriminating pathological, reproductive or stress conditions in  
708 cows using machine learning on sensor-based activity data [Article]. *Computers and Electronics in*  
709 *Agriculture*, 204, Article 107556. <https://doi.org/10.1016/j.compag.2022.107556>

710 Ledgerwood, D. N., Winckler, C., & Tucker, C. B. (2010). Evaluation of data loggers, sampling intervals, and  
711 editing techniques for measuring the lying behavior of dairy cattle [Article]. *Journal of Dairy*  
712 *Science*, 93(11), 5129-5139. <https://doi.org/10.3168/jds.2009-2945>

713 Lee, M., & Seo, S. (2021). Wearable Wireless Biosensor Technology for Monitoring Cattle: A Review.  
714 *Animals*, 11(10), 2779. <https://doi.org/10.3390/ani11102779>

715 McCabe, C. J., Aryal, U. K., Casey, T., & Boerman, J. (2021). Impact of exposure to chronic light–dark phase  
716 shifting circadian rhythm disruption on muscle proteome in periparturient dairy cows. *Proteomes*,  
717 9(3), Article 35. <https://doi.org/10.3390/proteomes9030035>

718 Medrano-Galarza, C., Gibbons, J., Wagner, S., de Passillé, A. M., & Rushen, J. (2012). Behavioral changes in  
719 dairy cows with mastitis [Article]. *Journal of Dairy Science*, 95(12), 6994-7002.  
720 <https://doi.org/10.3168/jds.2011-5247>

- 721 Mialon, M. M., Martin, C., Garcia, F., Menassol, J. B., Dubroeuq, H., Veissier, I., & Micol, D. (2008). Effects  
722 of the forage-to-concentrate ratio of the diet on feeding behaviour in young Blond d'Aquitaine  
723 bulls. *Animal*, 2(11), 1682-1691. <https://doi.org/10.1017/S1751731108002905>
- 724 Mounier, L., Veissier, I., & Boissy, A. (2005). Behavior, physiology, and performance of bulls mixed at the  
725 onset of finishing to form uniform body weight groups. *Journal of Animal Science*, 83(7), 1696-1704.  
726 <https://doi.org/10.2527/2005.8371696x>
- 727 Pastell, M., Tiusanen, J., Hakojärvi, M., & Hänninen, L. (2009). A wireless accelerometer system with wavelet  
728 analysis for assessing lameness in cattle [Article]. *Biosystems Engineering*, 104(4), 545-551.  
729 <https://doi.org/10.1016/j.biosystemseng.2009.09.007>
- 730 Poppe, M., Mulder, H. A., van Pelt, M. L., Mullaart, E., Hogeveen, H., & Veerkamp, R. F. (2022). Development  
731 of resilience indicator traits based on daily step count data for dairy cattle breeding [Article].  
732 *Genetics Selection Evolution*, 54(1), Article 21. <https://doi.org/10.1186/s12711-022-00713-x>
- 733 Proudfoot, K., & Habing, G. (2015). Social stress as a cause of diseases in farm animals: Current knowledge  
734 and future directions. *Veterinary Journal*, 206(1), 15-21. <https://doi.org/10.1016/j.tvjl.2015.05.024>
- 735 Proudfoot, K. L., Weary, D. M., & von Keyserlingk, M. A. G. (2012). Linking the social environment to illness  
736 in farm animals. *Applied Animal Behaviour Science*, 138(3), 203-215.  
737 <https://doi.org/10.1016/j.applanim.2012.02.008>
- 738 Raussi, S., Jauhainen, L., Saastamoinen, S., Siivonen, J., Hepola, H., & Veissier, I. (2011). A note on  
739 overdispersion as an index of behavioural synchrony: a pilot study in dairy cows. *Animal*, 5(3), 428-  
740 432. <https://doi.org/10.1017/S1751731110001928>
- 741 Reith, S., & Hoy, S. (2018). Review: Behavioral signs of estrus and the potential of fully automated systems  
742 for detection of estrus in dairy cattle. *Animal*, 12(2), 398-407.  
743 <https://doi.org/10.1017/S1751731117001975>
- 744 Rocha, L. E. C., Terenius, O., Veissier, I., Meunier, B., & Nielsen, P. P. (2020). Persistence of sociality in group  
745 dynamics of dairy cattle [Article]. *Applied Animal Behaviour Science*, 223, Article 104921.  
746 <https://doi.org/10.1016/j.applanim.2019.104921>
- 747 Rook, A. J., & Penning, P. D. (1991). Synchronisation of eating, ruminating and idling activity by grazing  
748 sheep. *Applied Animal Behaviour Science*, 32(2), 157-166. [https://doi.org/10.1016/S0168-  
749 1591\(05\)80039-5](https://doi.org/10.1016/S0168-1591(05)80039-5)
- 750 Ruckstuhl, K. E. (1999). To synchronise or not to synchronise: A dilemma for young bighorn males? [Article].  
751 *Behaviour*, 136(6), 805-818. <https://doi.org/10.1163/156853999501577>
- 752 Rugg, D. J., & Buech, R. R. (1990). Analyzing Time Budgets with Markov Chains. *Biometrics*, 46(4), 1123-  
753 1131. <https://doi.org/10.2307/2532453>
- 754 Rutten, C. J., Kamphuis, C., Hogeveen, H., Huijps, K., Nielen, M., & Steeneveld, W. (2017). Sensor data on  
755 cow activity, rumination, and ear temperature improve prediction of the start of calving in dairy  
756 cows [Article]. *Computers and Electronics in Agriculture*, 132, 108-118.  
757 <https://doi.org/10.1016/j.compag.2016.11.009>
- 758 Rutten, C. J., Velthuis, A. G. J., Steeneveld, W., & Hogeveen, H. (2013). Invited review: Sensors to support  
759 health management on dairy farms. *Journal of Dairy Science*, 96(4), 1928-1952.  
760 <https://doi.org/10.3168/jds.2012-6107>
- 761 Saint-Dizier, M., & Chastant-Maillard, S. (2012). Towards an Automated Detection of Oestrus in Dairy Cattle  
762 [Review]. *Reproduction in Domestic Animals*, 47(6), 1056-1061. [https://doi.org/10.1111/j.1439-  
763 0531.2011.01971.x](https://doi.org/10.1111/j.1439-0531.2011.01971.x)
- 764 Salgado, H. H., Méthot, S., Remus, A., Létourneau-Montminy, M. P., & Pomar, C. (2021a). Elucidating the  
765 impact of feeding behaviour on body composition in finishing pigs fed ad libitum using an  
766 integrative feeding behaviour index [Article]. *Livestock Science*, 251, Article 104650.  
767 <https://doi.org/10.1016/j.livsci.2021.104650>
- 768 Salgado, H. H., Méthot, S., Remus, A., Létourneau-Montminy, M. P., & Pomar, C. (2021b). A novel feeding  
769 behavior index integrating several components of the feeding behavior of finishing pigs [Article].  
770 *Animal*, 15(7), Article 100251. <https://doi.org/10.1016/j.animal.2021.100251>
- 771 Saper, C. B., Scammell, T. E., & Lu, J. (2005). Hypothalamic regulation of sleep and circadian rhythms. *Nature*,  
772 437(7063), 1257-1263. <https://doi.org/10.1038/nature04284>
- 773 Schafer, T. L. J., Wikle, C. K., VonBank, J. A., Ballard, B. M., & Weegman, M. D. (2020). A Bayesian Markov  
774 Model with Pólya-Gamma Sampling for Estimating Individual Behavior Transition Probabilities from

775 Accelerometer Classifications [Article]. *Journal of Agricultural, Biological, and Environmental*  
776 *Statistics*, 25(3), 365-382. <https://doi.org/10.1007/s13253-020-00399-y>

777 Scheffer, M., Bolhuis, J. E., Borsboom, D., Buchman, T. G., Gijzel, S. M. W., Goulson, D., Kammenga, J. E.,  
778 Kemp, B., van de Leemput, I. A., Levin, S., Martin, C. M., Melis, R. J. F., van Nes, E. H., Romero, L.  
779 M., & Olde Rikkert, M. G. M. (2018). Quantifying resilience of humans and other animals.  
780 *Proceedings of the National Academy of Sciences*. <https://doi.org/10.1073/pnas.1810630115>

781 Scheibe, K. M., Berger, A., Langbein, J., Streich, W. J., & Eichhorn, K. (1999). Comparative Analysis of  
782 Ultradian and Circadian Behavioural Rhythms for Diagnosis of Biorhythmic State of Animals.  
783 *Biological Rhythm Research*, 30(2), 216-233. <https://doi.org/10.1076/brhm.30.2.216.1420>

784 Solano, L., Barkema, H. W., Pajor, E. A., Mason, S., LeBlanc, S. J., Nash, C. G. R., Haley, D. B., Pellerin, D.,  
785 Rushen, J., de Passillé, A. M., Vasseur, E., & Orsel, K. (2016). Associations between lying behavior  
786 and lameness in Canadian Holstein-Friesian cows housed in freestall barns. *Journal of Dairy Science*,  
787 99(3), 2086-2101. <https://doi.org/10.3168/jds.2015-10336>

788 Stoye, S., Porter, M. A., & Stamp Dawkins, M. (2012). Synchronized lying in cattle in relation to time of day  
789 [Article]. *Livestock Science*, 149(1-2), 70-73. <https://doi.org/10.1016/j.livsci.2012.06.028>

790 Tolkamp, B. J., Allcroft, D. J., Austin, E. J., Nielsen, B. L., & Kyriazakis, I. (1998). Satiety Splits Feeding  
791 Behaviour into Bouts. *Journal of Theoretical Biology*, 194(2), 235-250.  
792 <https://doi.org/10.1006/jtbi.1998.0759>

793 Tucker, C. B., Cox, N. R., Weary, D. M., & Špinka, M. (2009). Laterality of lying behaviour in dairy cattle.  
794 *Applied Animal Behaviour Science*, 120(3), 125-131.  
795 <https://doi.org/10.1016/j.applanim.2009.05.010>

796 Tucker, C. B., Jensen, M. B., de Passillé, A. M., Hänninen, L., & Rushen, J. (2021). Lying time and the welfare  
797 of dairy cows. *Journal of Dairy Science*, 104(1), 20-46. <https://doi.org/10.3168/jds.2019-18074>

798 Tuomisto, L., Huuskonen, A., Jauhiainen, L., & Mononen, J. (2019). Finishing bulls have more synchronised  
799 behaviour in pastures than in pens [Article]. *Applied Animal Behaviour Science*, 213, 26-32.  
800 <https://doi.org/10.1016/j.applanim.2019.02.007>

801 Van Dixhoorn, I. D. E., de Mol, R. M., Schnabel, S. K., van der Werf, J. T. N., van Mourik, S., Bolhuis, J. E.,  
802 Rebel, J. M. J., & van Reenen, C. G. (2023). Behavioral patterns as indicators of resilience after  
803 parturition in dairy cows. *Journal of Dairy Science*, 106(9), 6444-6463.  
804 <https://doi.org/10.3168/jds.2022-22891>

805 Van Dixhoorn, I. D. E., de Mol, R. M., van der Werf, J. T. N., van Mourik, S., & van Reenen, C. G. (2018).  
806 Indicators of resilience during the transition period in dairy cows: A case study. *J Dairy Sci*, 101(11),  
807 10271-10282. <https://doi.org/10.3168/jds.2018-14779>

808 Van Erp, R. J. J., De Vries, S., Van Kempen, T. A. T. G., Den Hartog, L. A., & Gerrits, W. J. J. (2020). Circadian  
809 misalignment imposed by nocturnal feeding tends to increase fat deposition in pigs [Article]. *British*  
810 *Journal of Nutrition*, 123(5), 529-536. <https://doi.org/10.1017/S0007114519003052>

811 Veissier, I., Boissy, A., dePassillé, A. M., Rushen, J., van Reenen, C. G., Roussel, S., Andanson, S., & Pradel, P.  
812 (2001). Calves' responses to repeated social regrouping and relocation. *J Anim Sci*, 79(10), 2580-  
813 2593. <https://doi.org/10.2527/2001.79102580x>

814 Veissier, I., Capdeville, J., & Delval, E. (2004). Cubicle housing systems for cattle: Comfort of dairy cows  
815 depends on cubicle adjustment [Review]. *Journal of Animal Science*, 82(11), 3321-3337.  
816 <https://doi.org/10.2527/2004.82113321x>

817 Veissier, I., Lamy, D., & Le Neindre, P. (1990). Social behaviour in domestic beef cattle when yearling calves  
818 are left with the cows for the next calving [Article]. *Applied Animal Behaviour Science*, 27(3), 193-  
819 200. [https://doi.org/10.1016/0168-1591\(90\)90056-J](https://doi.org/10.1016/0168-1591(90)90056-J)

820 Veissier, I., & Le Neindre, P. (1989). Weaning in calves: Its effects on social organization [Article]. *Applied*  
821 *Animal Behaviour Science*, 24(1), 43-54. [https://doi.org/10.1016/0168-1591\(89\)90124-X](https://doi.org/10.1016/0168-1591(89)90124-X)

822 Veissier, I., Le Neindre, P., & Trillat, G. (1989). The use of circadian behaviour to measure adaptation of  
823 calves to changes in their environment. *Applied Animal Behaviour Science*, 22(1), 1-12.  
824 [https://doi.org/10.1016/0168-1591\(89\)90075-0](https://doi.org/10.1016/0168-1591(89)90075-0)

825 Veissier, I., Mialon, M. M., & Sloth, K. H. (2017). Short communication: Early modification of the circadian  
826 organization of cow activity in relation to disease or estrus. *J Dairy Sci*, 100(5), 3969-3974.  
827 <https://doi.org/10.3168/jds.2016-11853>

- 828 Wagner, N., Antoine, V., Koko, J., Mialon, M. M., Lardy, R., & Veissier, I. (2020). Comparison of Machine  
829 Learning Methods to Detect Anomalies in the Activity of Dairy Cows. In *Lecture Notes in Computer*  
830 *Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in*  
831 *Bioinformatics)* (Vol. 12117 LNAI, pp. 342-351).
- 832 Wagner, N., Mialon, M. M., Sloth, K. H., Lardy, R., Ledoux, D., Silberberg, M., de Boyer des Roches, A., &  
833 Veissier, I. (2021). Detection of changes in the circadian rhythm of cattle in relation to disease,  
834 stress, and reproductive events [Article]. *Methods*, *186*, 14-21.  
835 <https://doi.org/10.1016/j.ymeth.2020.09.003>
- 836 Weary, D. M., Huzzey, J. M., & Von Keyserlingk, M. A. G. (2009). Board-invited Review: Using behavior to  
837 predict and identify ill health in animals. *Journal of Animal Science*, *87*(2), 770-777.  
838 <https://doi.org/10.2527/jas.2008-1297>
- 839 Whitehead, H. A. L. (1999). Testing association patterns of social animals. *Animal Behaviour*, *57*(6), F26-F29.  
840 <https://doi.org/10.1006/anbe.1999.1099>
- 841 Winckler, C., Tucker, C. B., & Weary, D. M. (2015). Effects of under- and overstocking freestalls on dairy  
842 cattle behaviour. *Applied Animal Behaviour Science*, *170*, 14-19.  
843 <https://doi.org/10.1016/j.applanim.2015.06.003>
- 844 Yeates, M. P., Tolkamp, B. J., Allcroft, D. J., & Kyriazakis, I. (2001). The use of mixed distribution models to  
845 determine bout criteria for analysis of animal behaviour [Article]. *Journal of Theoretical Biology*,  
846 *213*(3), 413-425. <https://doi.org/10.1006/jtbi.2001.2425>

847