

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

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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).

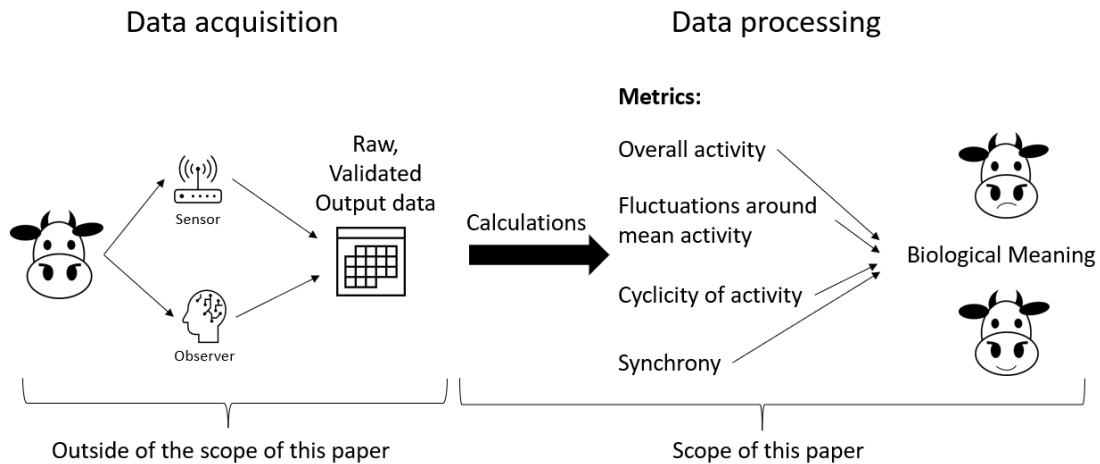
46 Ethologists, and other researchers usually calculate several metrics from activity data to characterise an
47 animal's behaviour, e.g., time spent on each activity, fragmentation of activity, 24-h patterns or proportion
48 of animals engaged in the same activity. However, the way these metrics are 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 Our paper 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, 25th 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, 75th 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^{th} observation, and μ 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 σ is the variance of the sequence x , μ 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.*

392 The degree of functional coupling (DFC) is obtained by calculating autocorrelations, then applying
393 Fourier transform to the correlogram, extracting the significant harmonics and calculating the power of
394 each significant harmonics out of the power of all significant harmonics. 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.

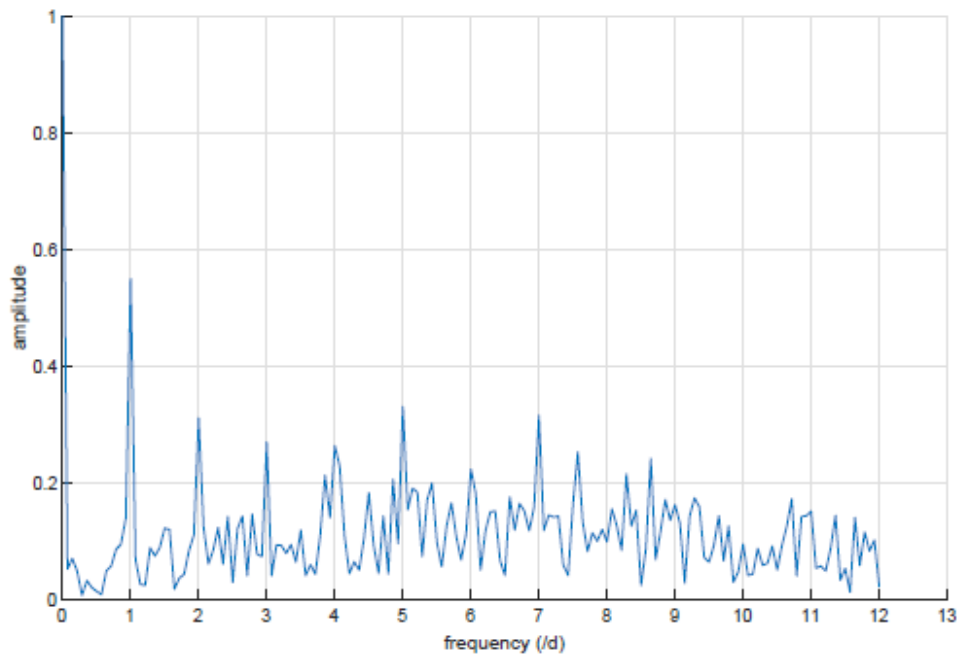
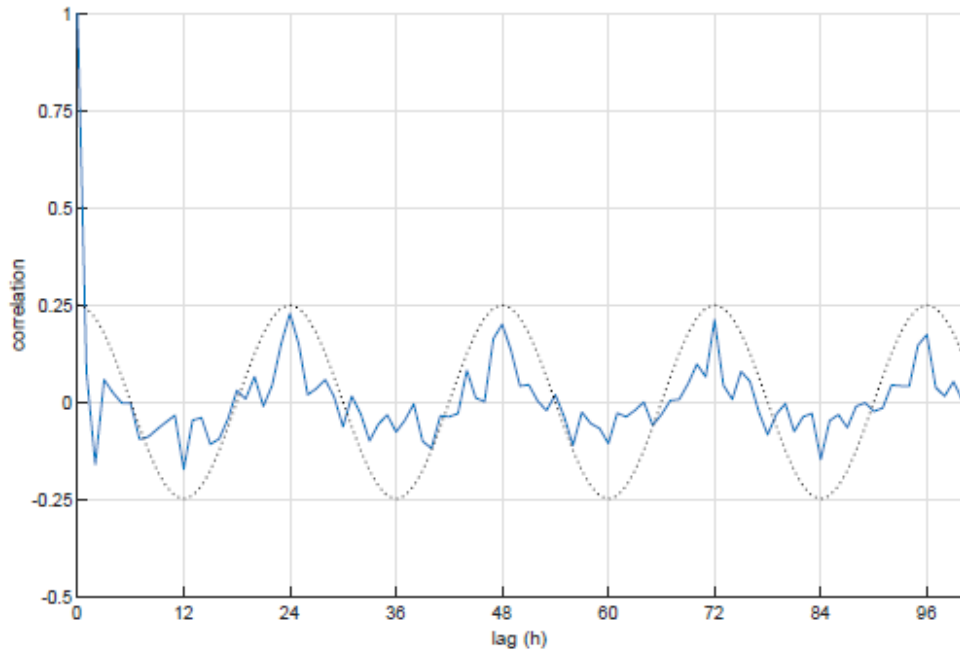
401 In general, the activity of an animal peaks several times during the day, e.g., depending on the
402 timing of feeding or milking, whereas the activity stays low at night. Autocorrelations and Fourier transform
403 hardly take the dissymmetry between day and night activity into account. Wavelet methods 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 cyclicality 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 cyclicality 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) that
483 represent the average synchrony calculated across all animals in a group. If all animals perform always the
484 same activity, the result will be 1 with metrics (d) and (e). If not, metrics (e) will provide higher and values

485 than metric (d). for instance, if animals never perform all the same activity, metric (d) will be 0 whereas
486 metrics (e) can still give an idea of how many animals perform the same activity.

487 The metrics presented above depend largely on the number of activity categories and the number
488 of animals in the group (especially metrics (d)): when the group is large and the number of activity
489 categories is high, there is little chance that animals perform the same activity at the same time. Asher and
490 Collins (2012) thus recommend comparing the distribution of activity observed with the one obtained at
491 random. This can be done with:

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

494
$$P(O) = \frac{1}{np} \sum_{i=1}^n S_i \quad (11)$$

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

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

499
$$P(E) = \frac{1}{(nm)^2} \sum_{k=1}^l C_k^2 \quad (12)$$

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

503 Then

504
$$\text{Kappa coefficient} = \frac{P(O) - P(E)}{1 - P(E)} \quad (13)$$

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

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

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

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

526 **Biological meaning**

527 Animals may be synchronised because the activity of an animal is influenced by that of other
528 animals. Social facilitation has been described in many species and contexts (Clayton, 1978). Animals may
529 be synchronised also because they adopt a similar rhythm of activity: activities follow a circadian rhythm
530 triggered at least in part by external cues such as light or timing of food distribution (or milking in dairy
531 cows) so if animals are subjected to the same cues, their activity will tend to be similar (Flury & Gyga,
532 2016).

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

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

549
550

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

Category	Metrics	Raw data	Purpose	Limitations	Reference
Overall activity	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			
Fluctuations around the mean	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.
Cyclicity	Irregularity	Continuous sampling			Salgado et al. 2021a&b
	Autocorrelation Non-periodicity Cosinor method Fourier transform Degree of functional coupling (DFC)	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)	Dixhoorn et al., 2023, 2018; Chkeir et al., 2019 Berger et al., 2003; Scheibe et al., 1999 Veissier et al., 1989
Synchrony between individuals	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	
	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
Synchrony at herd level	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

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

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

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

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

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

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

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

597 In conclusion, activity data provide the raw material for the calculation of several metrics that
598 describe animal behaviour. The choice of which metrics to use, depends on the research question or
599 potential application. A clear research question is essential for the selection of the most appropriate metrics
600 that best characterise specific aspects of the behaviour of the animals, suitable for answering question(s)
601 asked. We believe that clarification of the metrics and on how they should be calculated will help to
602 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>.

615

Conflict of interest disclosure

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