

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



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Abstract

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



36

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

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

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

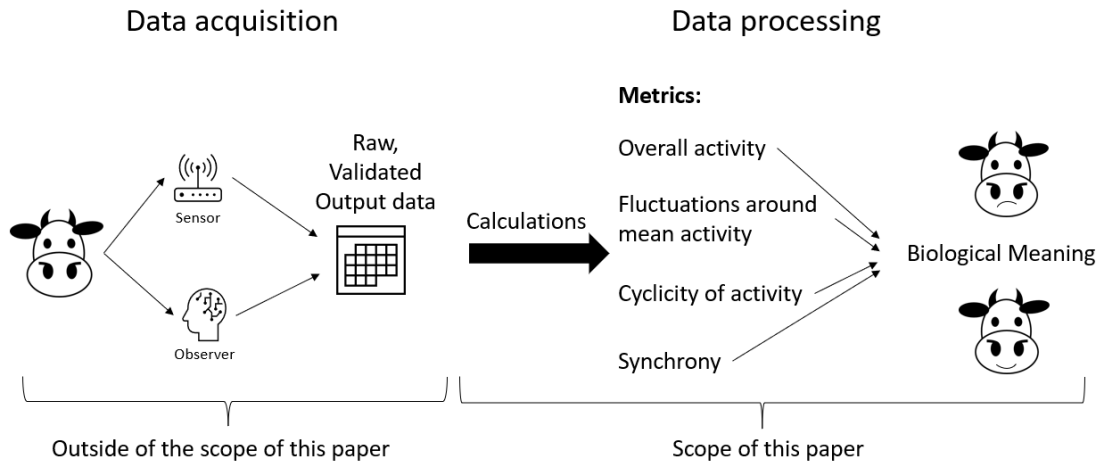
71 Access to data on activity is not only facilitated for ethologists, but also for researchers from other
72 discipline, e.g., animal health and animal production and for non-scientists like users of precision farming
73 systems that are not necessarily used to process data on behaviour (Borchers et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

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

88 We believe such a methodological review is pivotal and timely given the boom of activity data obtained
89 by sensors. The review will hopefully support researchers by improving the use of activity data to answer



90 their research questions. In addition, it should facilitate the consideration of animal behaviour by non-
 91 ethologists especially in Precision Livestock Farming (PLF), with a view to help phenotyping animals for
 92 selection, monitoring them for the detection of changes due to specific states such as oestrus, disease, or
 93 stress, or evaluating housing conditions and management aspects.



94

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



99

100 The data

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



107 Observers can perform focal (and continuous) sampling i.e., they note changes in activity with reference
 108 to the time of the change occurrence. Alternatively, observers can perform scan sampling i.e. they note the
 109 animal's activity as detected at first glance at regular intervals (Bateson, 2021). Examples of the continuous
 110 and scan sampling data are shown in the supplementary materials. A mix of the two is also possible: the
 111 activity is recorded continuously and at the end of each interval (e.g. 5 min) the observer notes the
 112 predominant activity; the format of data will then be similar to that of scan sampling. Sensors generally
 113 produce a signal that is nearly continuous; the data on gross activity [is](#) usually delivered as time spent in
 114 each activity per time intervals (e.g. minutes per hour or per 15 min) or as predominant behaviour per time
 115 interval. The metrics that can be calculated, 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 of activity. The level of activity reflects how much
 124 an animal is active, that is walking, running, or feeding rather than lying or standing immobile. The time
 125 period on which these metrics are calculated varies between studies, e.g. an hour or a day. The term 'time
 126 budget' is specifically used to describe how an animal divides its day (or shorter period) into the various
 127 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
$$\text{Proportion Of Activity}_a^B = \left(\sum_{b \in B, A_b=a} D_b \right) / \sum_{b \in B} D_b \quad (1)$$

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
$$\text{Proportion Of Activity}_a^P = \left(\sum_{p \in P, A_p=a} L_p \right) / \sum_{p \in P} L_p \quad (1)$$



138 where p 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
$$\text{AvgBoutDuration}_a^B = \left(\sum_{b \in B, A_b=a} D_b \right) / N_B(a) \quad (2)$$

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. Indeed, when the monitoring starts, the

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

163 Assessing the total number of activity bouts in a day, in other words the number of times an animal
164 changes of activity, requires that the ethogram consists of activities described with the same level of details,
165 so that the number of bouts does not depend on what activity an animal performs most during the day.
166 The gross activities detected by sensors are usually adequate. This is not necessarily the case with direct
167 observations. For instance, to answer a specific question, an experimenter may want to sort activities into
168 lying, standing inactive, feeding (all of these lasting for minutes or hours) and other activities, that can
169 consist of walking, running, exploring the environment, interacting with other animals or self-directed
170 activities (all of them lasting for few seconds or minutes). In that case, the number of times an animal
171 changes of activity will largely depend on whether the animal performs the short-lasting activities
172 frequently. The grouping of activities into gross activities should be done before the total number of activity
173 bouts is calculated. Indeed, in the example given above on ruminating while lying or standing, the number
174 of 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.

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

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

190 *Activity level.*

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

$$195 \quad \text{ActivityLevel}_a^P = \left(\sum_{\substack{p \in P \\ a \in A}} T_{ap} \cdot W_a \right) \quad (3)$$

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

198 The weights can be assigned *a priori* by the experimenter or elicited from observations. Veissier et al. (2001)
199 performed a Factorial Analysis of Correspondence (FAC) on the number of instances (scans x calves) of each
200 of five activities per hour; the first axis - that summarises most of the variations between the 24 hours of
201 the day - brought decreasing weights to feeding (1.438), walking (0.763), standing immobile (- 0.085), lying
202 head up (- 0.261), then lying head down (- 0.541), ordering the activities as one would intuitively do to
203 express the decreasing arousal. The FAC is based on associations between activities and therefore, the
204 outcome of the FAC strongly depends on the level of detail of the activities that are included. Experience
205 told us that the ethogram should not be split in too many (short lasting) activities to elicit meaningful
206 weights.

207 **Biological meaning**

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

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

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

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

255 Monitoring the overall activity can thus help to check if the animals are managed adequately and
256 to detect physiological states (especially oestrus), pathological states, or stress. Feeding, ruminating and
257 lying seem especially sensitive to variations in the animal or its environment. Lying is generally reduced in
258 case of stress or an uncomfortable lying area, so it is often considered that a prolonged time spent lying
259 indicates good welfare (Piñeiro et al., 2019a, 2019b). However, lying time is often increased in case of
260 disease too. In any case, the value obtained for duration and frequency of activities should be interpreted

261 considering the context in which they are obtained, for instance the type and management of feeding, the
262 housing or grazing conditions, and the timing in relation to calving.



263 Metrics to address fluctuations around the mean activity

264 Definition

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



272 Calculations

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



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



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

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

280

281 Quantiles

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



288 Variance

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



291
$$\text{Variance}(x) = \frac{1}{N-1} \sum_{i=1}^N (x_i - \mu)^2 \quad (4)$$

292 where x is the sequence of activities (expressed for example as the level of activity) composed of N
293 observations, x_i is the i^{th} observation, and μ the mean of the activities.
294

295 Root Mean Square of the Successive Differences (RMSSD):

296 RMSSD measures the variations from one interval to the next one. RMSSD is calculated as follows:

297

298
$$\text{RMSSD}(x) = \sqrt{\frac{1}{N-1} \sum_{i=1}^{N-1} (x_i - x_{i+1})^2} \quad (5)$$

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



301 *Irregularity.*
302 An index of irregularity of behaviour can be calculated as proposed for feed intake (Salgado et al.,
303 2021a, 2021b). **Fist** a regression line of cumulative data (e.g., cumulative time spent in a given activity) is
304 drawn, then the differences between observed values and the regression line are calculated. The sum of
305 these differences brings the irregularity index.

306 **Biological meaning**

307 Maximum activity during the day can be relevant to identify cow states: in a study where many
308 metrics were used for **a random forest classification**, Lardy et al. (2023) found that the maximum activity
309 during the day and Quantile 90 (two metrics closely linked) were the most important features to
310 discriminate pathological and physiological states of cows.

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

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

338 **Metrics to address the cyclicity of activity**

339 **Definition**

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

342 **Calculations**

343 Several metrics can be used for addressing the cyclicity of activity (Kok et al., 2023). Autocorrelation
344 and Fourier transform are basic calculations. Other indices are derived from **them** such as non-periodicity
345 index (Van Dixhoorn et al., 2023; Van Dixhoorn et al., 2018) and degree of functional coupling (Berger et
346 al., 2003; Scheibe et al., 1999).

347 *Autocorrelation.*

348 **The autocorrelation measures** the correlation between successive values of a signal. The
349 autocorrelation depends on the chosen delay, e.g., for hourly data the lag-1 corresponds to the correlation

350 between successive hours and lag-24 corresponds to the correlation between an hour of the day and the
351 same hour of the next day, **therefore depending on the circadian cycle**. For a sequence x of size N , the
352 autocorrelation with a lag l is calculated as following:
353

$$354 \quad ACF(x, l) = \frac{1}{(N - l)\sigma^2} \sum_{i=1}^{N-l} (x_i - \mu)(x_{i+l} - \mu) \quad (6)$$

355 Where σ is the variance of the sequence x , μ is the average value of the sequence x and x_i the i^{th}
356 element of the sequence x .
357

358 *Non-periodicity.*

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

$$365 \quad Nonperiodicity(x) = \frac{(\sum_{l=1...100} (ACF(x, l) - 0.25 \cdot \cos(2\pi \cdot l/24))^2)}{100} \quad (9)$$

366 where x is a variable measured at hourly (or other chosen time interval) time intervals, $ACF(x, l)$ is
367 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
368 function with a 24-h cycle and an amplitude of 0.25 that is used as a fit function.
369

370 *Fourier transform.*

371 Fourier transform represents the sinusoids that compose the original **variations**. Each sinusoid is
372 defined by a frequency and an amplitude. The contribution of each sinusoid to explain the original **variations**
373 is expressed in absolute or relative power, usually referring to the frequency of the sinusoid or to frequency
374 bands. For instance, the contribution of the circadian cycle and of ultradian cycles can be calculated. When
375 variations within 24 h time series are analysed by Fourier transform, the fundamental (h0) refers to the
376 average activity during 24 h, harmonic 1 (h1) refers to variations following a 24 h cycle; h2, to a 12 h cycle;
377 h3, to an 8 h cycle; h4 to a 6 h cycle, etc. The main cycle is the circadian one; the activity of an animal can
378 therefore be modelled by its overall activity (mean during 24 h) and the variations around overall activity
379 following a 24 h cycle, in other words into h0 and h1. The Fourier-based approximation with thresholding
380 (**FBAT**) method was developed to compare such models obtained on successive time series (Wagner et al.,
381 2021). An alternative to the Fourier transform is the Cosinor method. Cosinor and Fourier are analogous in
382 formulation, but differ in operation (see (Chkeir et al., 2019), for a comparison of the two modelling
383 approaches). An example of Fourier transform is visualised in Figure 2.

384 *Degree of functional coupling (DFC).*

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

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

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

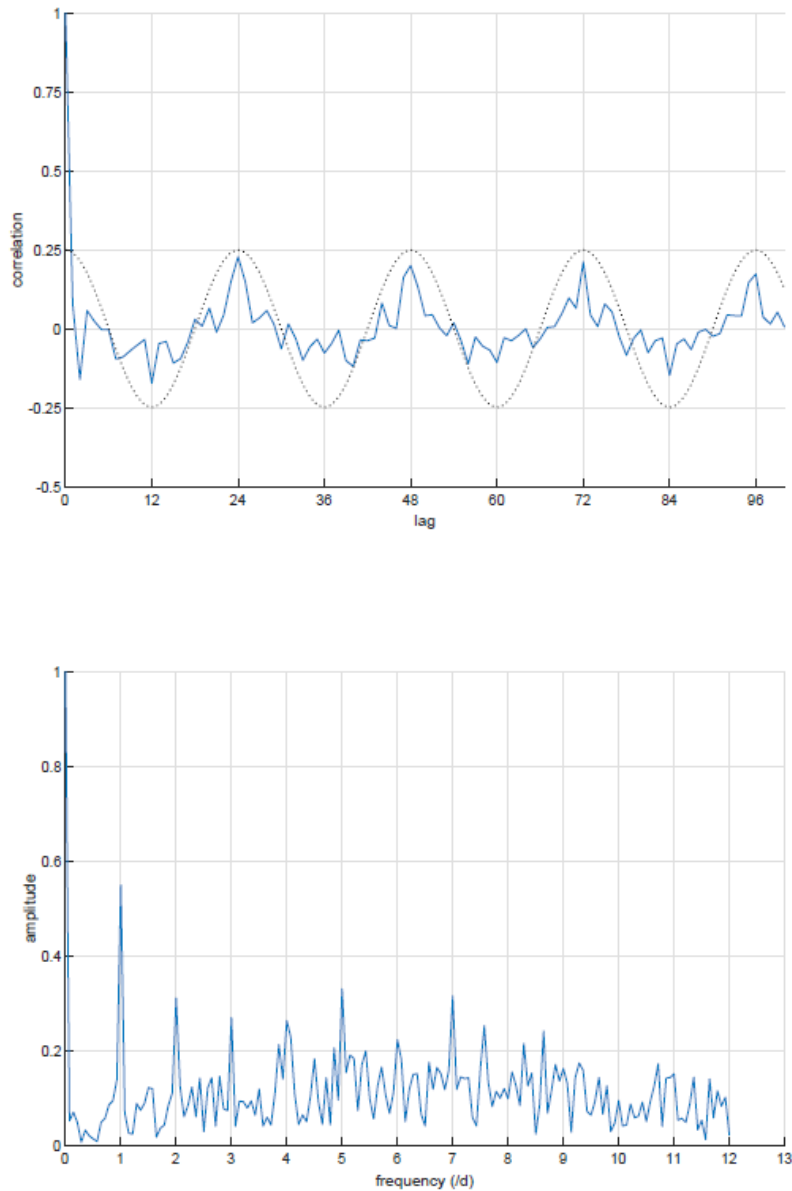
398 **Biological meaning**

399 Daily periodicities are influenced by internal clocks (endogenous driven biological cycles) and
400 external factors such as temperature, light, humidity, feeding time (exogenously driven biological cycles)
401 (Saper et al., 2005). Internal clocks generate a rhythm of about 24 h period. In mammals, the central internal
402 clock situated in the brain (suprachiasmatic nuclei) coordinates peripheral clocks in the body (Honma,
403 2018). Among external cues (or “Zeitgebers), light is known to be the most powerful one, impacting both
404 on behaviour and physiological functions (Honma, 2018). For instance, cows are typically diurnal animals:
405 they eat essentially between dawn and dusk and they predominantly rest at night (DeVries et al., 2003;
406 Hafez et al., 1969). Variations can nevertheless be observed between cows in the cyclicity of their
407 behaviour. Competition for resources (e.g. feed, lying area), due to overstocking or ambiguity in the ranking
408 order because of frequent change in group composition, can cause a misalignment with the circadian
409 rhythm (McCabe et al., 2021; Van Dixhoorn et al., 2023; Van Dixhoorn et al., 2018; Van Erp et al., 2020).

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

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



437

Metrics to address the synchrony between animals

438 Definition

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

442 Calculations

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

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

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

456
$$\text{synchrony} = \frac{1}{n} \sum_{i=1}^n S_i \quad (7)$$

457 where n is the number of scans, S_i equals 1 if the two animals have the same activity at scan i and
458 0 if they do not.

460 The synchrony of a focus animal with the rest of the group or a certain sub-group of animals in the
461 group can be calculated as:

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

465
$$\text{synchrony} = \frac{1}{n(m-1)} \sum_{j=1}^{m-1} \sum_{i=1}^n S_{ij} \quad (8)$$

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

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

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

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

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

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

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

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

483
$$P(O) = \frac{1}{np} \sum_{i=1}^n S_i \quad (9)$$

484 where n is the number of scans, p is the total number of pairs of animals in the groups, and S_i the
485 number of pairs of animals performing the same activity at scan i .

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

488
$$P(E) = \frac{1}{(nm)^2} \sum_{k=1}^l C_k^2 \quad (10)$$

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

492 Then

493
$$\text{Kappa coefficient} = \frac{P(O) - P(E)}{1 - P(E)} \quad (11)$$

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

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

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

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

514 **Biological meaning**

515 Animals may be synchronised because the activity of an animal is influenced by that of other
516 animals. Social facilitation has been described in many species and contexts (Clayton, 1978). Animals may
517 be synchronised also because they adopt a similar rhythm of activity: activities follow a circadian rhythm
518 triggered at least in part by external cues such as light or timing of food distribution (or milking in dairy
519 cows) so if animals are subjected to the same cues, their activity will tend to be similar (Flury & Gygas,
520 2016).

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





526 Synchrony at the group level reflects social cohesion, i.e. the strength of the bonds between the
527 animals in the group (Clayton, 1978). Groups newly formed are usually less cohesive, animals exchanging
528 aggressive interactions and being less synchronised (Mounier et al., 2005). The synchrony can also decrease
529 if there is competition for the access to a resource, e.g., food and lying places. For instance, in cows and
530 sheep, synchrony of lying decreases when lying space is limited (Bøe et al., 2006; Winckler et al., 2015). The
531 synchrony between an animal and the rest of its group reflects its familiarity with the group: synchrony may
532 be low in case of newly introduced animals until the organization of the group is stabilised (Arey, 1999;
533 Boyle et al., 2013). A variation in synchrony can also be caused by a health disorder: the activity of an animal
534 is modified in case of disease (Dantzer et al., 2008), so that it can depart from the rest of the group (e.g., a
535 cow isolates and stay standing idling or lying for longer when ill (Proudfoot & Habing, 2015; Proudfoot et
536 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
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 on long periods to avoid edge effects. - describe activity with similar details	Tucker et al., 2009. Ledgerwood et al., 2010. Yeates et al., 2001
	Activity level	Time spent on activities		 - have a clear determination of when a new activity starts  Weights of each activity to be elicited.	
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 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.	 cording on long periods (longer than the cycle to be detected)	Salgado et al. 2021a&b Dixhoorn et al., 2023, 2018; Chkeir et al., 2019
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	Berger et al., 2003; Scheibe et al., 1999 Veissier et al., 1989
Synchrony at herd level	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. The proportion of scans where all animals of the group perform the same activity Kappa coefficient of agreement	Scan sampling and continuous sampling	Social cohesion Competition for resources		Veissier et al., 1989; Stoye et al. 2012 Arsher and Collins, 2012 Arsher and Collins, 2012 Stoye et al., 2012 Rook and Penning, 1991

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

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

555 These four groups of metrics can be used to analyse the impact of housing and management
556 procedures. In that case, the values at herd level are evaluated, all animals within the herd are taken into
557 account. In most cases, the average herd level values per metric are expected to not vary much in time,
558 unless management or housing change.

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

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

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

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

583 In conclusion, activity data provide the raw material for the calculation of several metrics that
584 describe animal behaviour. The choice of which metrics to use, depends on the research question or
585 potential application. A clear research question helps to select the metrics that best characterise an animal
586 behaviour in relation to the research or applied question. We believe that clarification of the metrics and
587 on how they should be calculated will help to standardise these metrics, making them easier to use and
588 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>.

601

Conflict of interest disclosure

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