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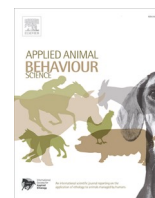
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# Accelerometers contribution to the knowledge of domestic cats' (*Felis catus*) behavior: A comprehensive review

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## ABSTRACT

Even though cats inhabit a large number of our homes, their activity patterns, biological rhythm and behavior are still under-described and, therefore, poorly understood. This lack of knowledge is partly explained by the limited number of tools available for observing cats with limited effort and minimal disturbances to their routines. To this day, we still lack a faithful description of what constitutes a “normal behavior” of a domestic cat. Bio-loggers have been proven to help researchers decipher the individual and group behaviors of wild animals, and are starting to emerge as a tool for monitoring pets' health as well. These tools have been used not only to analyze cats' activity patterns but also examine their detailed activities, such as eating and walking. Bio-logging coupled with data analysis and Artificial Intelligence tools give hopeful perspectives on more complex activities such as grooming, jumping, social interaction, etc. In this review, our aim is to offer an overview of the contribution of bio-logging devices to the current knowledge and understanding regarding the cat's behavior, and their detailed activities. We specifically focus on the knowledge brought to the understanding of cats' biological rhythm and behavior by accelerometry. This review will provide insight into the major advances facilitated by this tool, its limitations, as well as the possible future development in this field of study.

## 1. Introduction

Cats are one of the most popular pets, all over the world. They share our homes as well as our cities and countryside. In Western countries, the population of pets has been on the rise over the last decades (Larkin, 2021; Murray et al., 2015; Shahbandeh, 2024a, 2024b; Statista Research Department, 2024). An increasing number of owners are also expressing a willingness to invest in their pets' well-being, aiming to provide longer and healthier lives for them, as full members of the household (Finka et al., 2019).

Yet, owners need to better understand their cat to provide better care. Owners might expect their cats to follow the same daily routine as themselves or their dogs, often overlooking the unique behavioral differences of cats. For example, a cat running around in the evening or at night, disrupting the owner's rest, might be wrongly considered as abnormal behavior (Ravenscroft et al., 2021). Moreover, confusion may arise when well-behaved cats exhibit sudden behavioral changes. But is this change that sudden, or are owners missing subtle signs that could have warned them of a potential issue with their cats? (Bradshaw, 2018; Heath, 2018) This failure in understanding cats' behavior could bring

frustration to owners when their cats turn aggressive or start to eliminate inappropriately. This frustration can even lead in some cases to the animal being relinquished to a shelter (Coe et al., 2014). Part of this frustration may stem from a lack of understanding about what constitutes cats' "normal behavior". This could be avoided if owners could better understand their animals, and this can only be achieved by making education, advice and tools more easily accessible to everyone (Gazzano et al., 2015). A good knowledge of cats' biological rhythm –which is defined as the ensemble of repetitive bodily functions displayed by an organism, at any time scale (Refinetti, 2008)– is key in this education. Moreover, even with the best education, cats are animals that often conceal their pain and illnesses (Gowan and Iff, 2016) to such an extent that numerous diseases are only identified at an advanced stage. This is because owners may fail to recognize the need to bring their cat to their veterinarian until the illness displays strong external signs. This delay in medical care can lead to prolonged and challenging recovery processes.

Numerous location and activity trackers are readily available on the market for monitoring the activities of both dogs and cats. These tools are primarily designed and used for tracking pets when they are outside

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their home, with the primary goal of preventing the loss of animals. Nevertheless, the amount of literature on the use of animal-borne bi-loggers, which are devices designed to record the activity of animals by being attached to items like collars or harnesses, is growing. This technology has become increasingly accurate in reporting the daily activity patterns of various animals, humans included. Accelerometry, specifically, has emerged as a cost-effective and user-friendly tool for monitoring animal physical activity. With the advent of Artificial Intelligence (AI), the data generated by these sensors could become even more valuable, offering a more nuanced and comprehensive understanding of the daily lives of our pets, including cats. If used on a daily basis, this could be a powerful tool to diagnose illnesses that impact cats' activity level and/or behavior at early stages and alert owners and veterinarians of the observed behavioral changes as soon as they emerge.

The first objective of the present review is, in [Section 3](#), to provide a detailed description of the biological rhythm of the cat, with a specific focus on insights derived from bio-logging devices. After establishing the current understanding of cats' biological rhythms based on existing literature, we will focus, in [Section 4](#), on the possibilities of describing cats' activities in detail. The literature regarding the application of AI on accelerometers to predict cats' activities is currently limited. Therefore, in the subsections 4.3 and 4.4, we will offer a concise overview of existing studies on both cats and dogs. This analysis aims to outline the current state of research and provide insights to guide future studies in this field. [Section 5](#) serves as a conclusion of the review and presents future directions.

## 2. Method

Literature for this review has been searched in December 2023, through Google Scholar and PubMed. The search was made through the association of the keywords "cat" or "Felis catus" and the keywords "activity monitor", "activity tracker", "physical activity", "accelerometer". The additional keywords "Actical", "Actiwatch" and "Fitbark" were added as they retrieved additional publications by being the most common commercially available devices. A few articles were also added by snowball effect.

Inclusion criteria:

- Publications where the domestic cat is the animal whose activity is measured by the bio-logger were included. We also included publications where cats are studied among other species. We retained all publications where the cats are referred to as "feral", "stray", "un-owned", "owned", "domestic", but rejected publications about wild cats or other species.
- Publications where the bio-logging device is an accelerometer or an accelerometer associated with another sensor were included. We included publications with other methods, strictly only in case of lack of accelerometry studies, in order to form a comparison base. For studies not using accelerometers, we limit the date of publication to the ones published after 1980.
- Only peer-reviewed research papers were included.
- Publications written in English or French were included, both languages spoken by the authors.

Selection of articles was primarily based on the title and abstract, in case of doubt, the method section was also used. Selected articles details are presented in Appendix 1.

We separated results from this search into three categories: studies of biological rhythm where activity level is considered as a whole, studies of cats' detailed activities and studies using bio-logger on cats to advance medical knowledge. For the detailed section on cats' detailed activities, the literature being the smallest, we searched for comparison in papers using similar sensors on dogs to predict their behavior. The choice of the dog as comparison was done based on the available literature (number of publications high enough on the species to be able to

analyze the results), the fact that dogs are the other most common pets in human households, and that a portion of the activities performed by dogs are similar in display to cats (walking, eating, sitting, etc).

## 3. Cat's biological rhythm

The biological rhythm of an animal is defined as the ensemble of repetitive bodily functions displayed at any time scale (second, hour, day, month, year, etc) ([Refinetti, 2008](#)).

In this section, the biological rhythm of cats over a 24-hour cycle is discussed, exploring factors such as circadian rhythm, sleep-wake cycles, and the influence of light-dark cycles on a cat's activity pattern. It also delves into how external factors like human presence, seasons, climate, sex, reproductive status, and age can impact the observed biological rhythm in domestic and feral cats. In order to better understand the cat's biological rhythm, we will review studies interested in feral cats as well as domestic ones. Indeed, feral cats are more exposed to environmental synchronization and ecological pressure and will give us a good insight on cats' natural rhythm. However, a portion of domestic cats nowadays are fully indoor animals and might therefore have a different biological rhythm, being exposed to new synchronizers and deprived of others. In this section, we will present findings on both populations and aim at giving an overview of cats' biological rhythm given its different circumstances.

### 3.1. Biological rhythm over 24 hours, day and night

#### 3.1.1. Laboratory experiments

Early in the cat rhythm study, evidence of circadian rhythm has been shown in laboratory cats. This rhythm has been measured through body temperature by implanted radiocapsules and monitoring of activities like eating, drinking and other activities ([Johnson et al., 1983](#); [Johnson and Randall, 1985](#); [Randall et al., 1987](#)). The study conducted by [Johnson et al. \(1983\)](#) showed that the activity pattern of the cat is dependent on the light-dark cycles, and disruption by constant exposure to light or darkness varies from one cat to another. It also showed that the five studied cats have greater activity during the dark phase of the day. Additionally, [Kuwabara et al. \(1986\)](#) showed that the sleep-wake cycle of the cat is different from its activity system and is polyphasic. The main limitation of these studies and similar studies conducted in the controlled environment of a laboratory is that cats are easily disturbed by human presence during the cage cleaning, feeding or any other activity close by. However, [Randall et al. \(1987\)](#) isolated cats from humans and other cats, and were able to show the persistence of the circadian rhythm in body temperature and a two-peak cycle of daily activity (around 05:00 h and 18:00 h respectively), even in constant light exposure. [Hilmer et al. \(2010a\)](#) gave evidence that the distinct day-night rhythm of feral cats was modified when those feral cats were held in captivity. The amplitude in body temperature of the captive cats decreased and the cats shifted to a diurnal active phase, whereas their free-ranging counterparts showed a robust circadian rhythm with a body temperature mostly influenced by the time of the day and not only the activity levels. The authors suggested that a combination of decrease in stresses associated with hunting, hiding from predators and strategies related to water conservation may be at play in the change of biological rhythm in these feral cats. The controlled conditions of a laboratory lack the variability in temperature, weather, predator-prey interaction, and social interaction expected for any cat, whether domestic or feral. These biased conditions give a poor understanding of the natural biological rhythm and, additionally, limit the studies to 24-hour cycles. Besides, this type of laboratory experiment is extremely invasive since the monitoring of cats' body temperature was made by implanting the radiocapsule in the peritoneal cavity ([Hilmer et al., 2010a](#); [Johnson and Randall, 1985](#)) and their cerebral temperature was measured by inserting a thermistor between their right and left neocortex ([Kuwabara et al., 1986](#)).

### 3.1.2. Direct observations of free-ranging cats

In order to better understand cats' natural biological rhythm, other studies monitored free-ranging animals. Panaman (1981) observed a colony of 10 female farm cats for over 360 hours. The observations were made by following cats from some distance, in order to disturb them as little as possible, and systematically noting the cat behavior at any time during the observation period. These animals obtained their food through hunting or by consuming food provided by farm owners. The authors reported that the activity intensity pattern of most cats' was bimodal, with peaks at dawn and dusk. This study showed that hunting occurred around noon and at dusk, and sleeping occurred mostly at night. The dawn activity was moderate and probably attributed to human activity, according to the authors.

Even with the best protocols, the human presence can be disruptive to cats' behavior. Additionally, this protocol is very limiting by requiring high-attention from the observer for a long period of time. The risk of losing trace of the animal is high as the observation is made from a distance and therefore limiting the observations to animals already familiar with human presence.

### 3.1.3. Remote observations of free-ranging using radio-collars

To address these limitations, new technologies using portable devices attached to the animal started to emerge to monitor cats remotely. The first tool used to locate free-ranging animals was radio-collars. This technology allows the animals to be located thanks to a radio-transmitter attached to the animal's collar. Tracking the transmitter signal is possible by using tracking towers or hand-held antennas and receivers. The position of the animal is calculated periodically by triangulation (Langham and Porter, 1991; Langham, 1992). The animal activity could be inferred from the received signal: the animal is considered inactive if the signal is constant, and active if the signal is erratic (Alterio and Moller, 1997) or if the location of the animal has changed (Konecny, 1987; Langham and Porter, 1991; Langham, 1992).

The result from the study on 17 feral cats wearing radio-collars (Konecny, 1987) showed a peak of activity near sunrise and another peak near sunset, but contrary to Panaman (1981) the activity was at its lowest at midday. Additionally, this study highlights the ecological flexibility of feral cats: the adaptability of their biological rhythm to prey density, habitat complexity, and social interactions resulting in territory changes. Radio-telemetry has been used successfully in several other studies to get a better understanding of feral cat biological rhythm, such as Alterio and Moller (1997), who reported that feral cats (11 individuals) were mostly nocturnal and showed very little activity during the day. Using radio-telemetry, Langham (1992) also reported an increase in activity around dawn and dusk, when no additional food is provided. They also reported that cats relied on hunting and scavenging but were trying to avoid humans, dogs and other predators living nearby. Again, this points to ecological flexibility and it could explain the difference in activity patterns in studies where the habitat and human presence are different. Izawa (1983) also reported two peaks in cats' daily activity, around dawn and dusk, in feral cats wearing radio-collars. Langham and Porter (1991) showed that cats are nocturnal in open habitat and more active during the day when the habitat provides cover. Hiding from predators, in addition to prey availability, would therefore be a modulator of feral cats activity. This is supported by the diurnal activity of cats when coyotes (nocturnal predators) are present in the area and nocturnal when they are absent (Kays et al., 2015). Horn et al. (2011) used radio-collars to determine cats location and an omnidirectional movement detector mounted on the radio-transmitters to record the amount and the duration of cats activity. They showed evidence of a difference in activity patterns between owned and unowned free-roaming cats. The unowned cats were more nocturnal and had higher overall activity than owned cats. This study also highlighted the increase in activity of owned cats in the early morning and evening, likely due to owners getting ready to go to work in the morning and then returning in the evening.

### 3.1.4. Accelerometry and GPS tracking

In more recent studies, new technologies have been used to monitor cats' activity: accelerometry and GPS tracking. Placed on a collar or on a harness, the accelerometer gives information on cats activity intensity by measuring acceleration through one or several axes. The GPS tracker allows the animal movements to be followed and spots spatial patterns in cats' territories. These technologies no longer require the placement of tracking towers or human observers to follow radio-collared cats, typically done on foot. They allow for longer tracking that can last from a few hours to several days, after which the locally stored data on the collars can be retrieved and analyzed.

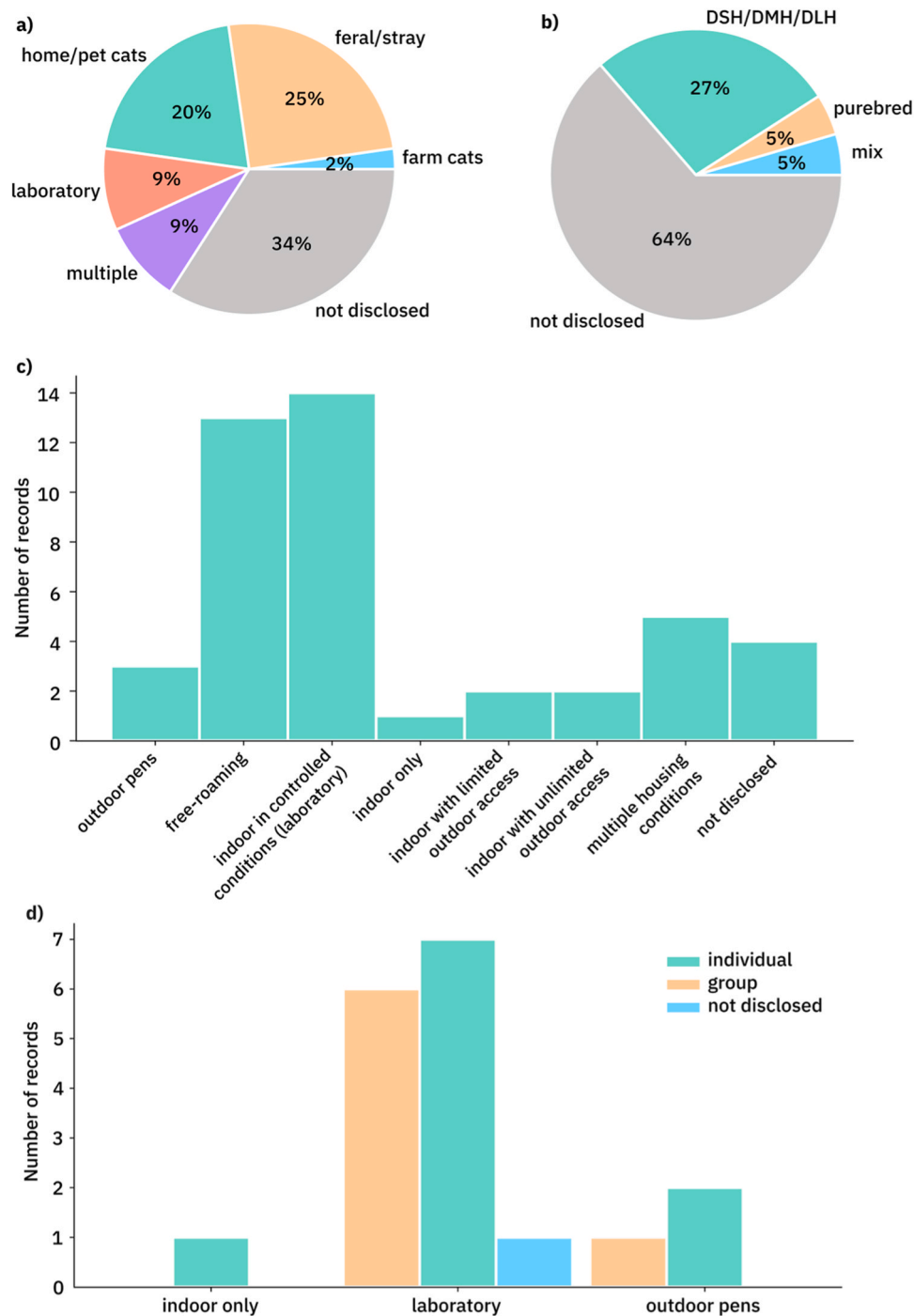
Even though accelerometers allow tracking of free-ranging animals, early studies of this new technology were conducted on cats held in laboratory conditions or in strict captivity. These studies have confirmed the cats' ability to adapt their activity to changes in light and dark phases, supporting an endogenous circadian oscillator (Cerutti et al., 2022, 2018). A two-peak daily activity pattern was observed in these controlled conditions (Cerutti et al., 2018), but depending on the study, captive cats had a tendency toward diurnality (Sciabarrasi et al., 2017) or nocturnality (Cerutti et al., 2018). Cats held in outdoor colony cages showed a two-peak daily activity, one in the morning (between 07:00 h and 13:00 h, probably associated with human activity) and another in the evening (not associated with any human intervention, between 17:00 h and 22:00 h) (Smit et al., 2022). Hilmer et al. (2010b) used the GPS tracker to confirm the evidence that the circadian rhythm of feral cats seen in their body temperature is strongly dependent on time of day (generated by an unknown endogenous oscillator) and not only on locomotor activity. They also supported the idea that diurnal peaks in body temperature for feral cats during the day are associated with hunting, territory fights or long-distance movements.

Using an accelerometer, studies showed that cats with limited access to the outside are highly synchronized with their owners and show a diurnal activity (Piccione et al., 2014, 2013), whereas cats with great outside space access are mostly nocturnal (Piccione et al., 2013). However, cats with limited access to the outside did not show any daily rhythmicity in the amount of total locomotor activity (Piccione et al., 2014).

### 3.1.5. Overview of cats' daily biological rhythm

These studies support the difference in biological rhythm for domestic cats (depending on humans to access food) and feral (or unowned) cats. It is therefore crucial to further study all these different populations, separately and comparatively, to better understand the cat's biological rhythm. Fig. 1a shows the distribution of the cat's breeding origin. Among the 38 studies included in this review section, 34% did not disclose the breeding origin of the cats. The remaining studies used cats from various backgrounds, including feral, laboratory, owned, or farm cats, or a combination of different breeding origins. The majority of the experiments (Fig. 1c) were conducted either in the controlled conditions of a laboratory (14 studies) or by tracking free-roaming cats (13 studies). In addition, the cats studied in the experiments with restrictive housing conditions (laboratory, outdoor pens, or owners home) are either housed individually or in groups (Fig. 1d). Cats' behavior, well-being, and activity levels are likely influenced by the presence of intraspecific social interaction. Therefore it is crucial to accurately document such interactions in the method section of studies and to take them into consideration when interpreting results.

The unowned cats depend on hunting and scavenging to eat and have to modulate their rhythm with survival constraints such as water and prey availability and predator presence. Domestic cats will synchronize their biological rhythm with food and care distribution by the human(s) they depend on. Humans being highly diurnal, indoor cats will shift their biological rhythm to match that of their owner. With greater access to the outside, cats may rely less on humans for food and get preys to supplement their diet, and therefore turn to a less diurnal rhythm. When available, cats will integrate food provided by humans in addition to



**Fig. 1.** Cats profiles and housing conditions during experiments in the 38 biological rhythm studies described in this review. (a) Breeding origin, feral/stray: cats that do not solely rely on humans for food and shelter, laboratory: cats purposely bred for experimentation, home/pet cats: cats that strictly rely on humans for food and shelter, multiple: mix of owned and unowned (feral/stray) cats, farm cats: cats that live in farms, outdoors but depend partly on humans for food. (b) Cats breed, domestic: domestic short-, medium- and longhair (DSH, DMH and DLH), purebred: purebred cats, mix: DSH/DMH/DLH and purebreds and/or cats of mixed breeds. (c) Cats' housing during the experiment (d) Housing details for cats in restrictive housing conditions, in green: cats were housed individually, in orange: cats were group-housed, blue: unknown conditions regarding if individually or group-housed.

prey on wildlife and this reflects on their daily activity pattern (Cove et al., 2017), hunting to feed occurring rather at night than during the day.

The effect of the cat's breed on biological rhythm is still to be investigated (Fig. 1b). Of the studies included in this review, 64% did not evaluate the cat's breed or disclaim the information. A large portion of studies used domestic short-, medium- or longhair cats, with the dominance of domestic shorthair cats. Studies including purebred cats

often neglected the variations in activity patterns or specific behaviors across different cats' breeds, such as playfulness, hunting behavior or sleep patterns that may vary among breeds. Only 5% of the studies used cats from different breeds.

### 3.2. Biological rhythm over a week

Differences in activity based on human presence has also been

highlighted by studies comparing cats' activity levels on weekends and weekdays. Cats held in laboratory conditions and monitored by an omnidirectional accelerometer were less active during weekends compared to weekdays, probably because caregivers' activity in the facility is reduced on weekends (Lascelles et al., 2008). This higher level of activity during weekdays compared to weekends has been reported regardless if the cat was lean or overweight (De Godoy and Shoveller, 2017). Domestic cats were showing a different pattern in their bimodal activity: the peak in the evening was equivalent during the whole week, whereas the morning peak was a bit later during weekends compared to weekdays (Gruen et al., 2017). This shift is probably due to the change in the schedule of the cats' owners and suggests the ability of the cats to adapt to such changes from one day to another. This is also supported by the sharp activity peak in the morning throughout the week, when owners are more likely to be on a more strict schedule and feeding and caring are more likely to always occur at the same time. The evening activity peak during weekdays is broader and can be explained by the fact that owners return home at less consistent hours (Gruen et al., 2017).

### 3.3. Effect of the seasons on the biological rhythm

Environmental rhythm modulators can be particularly hard to study, and isolating a single modulator might be impossible. One of the most studied environmental effects on cats' biological rhythm is the seasons. In particular, cats living (at least partly) outside are particularly exposed to change in temperature, rain and prey availability. The effect of the season has been studied with a variety of bio-logging devices such as radio-collars (Alterio and Moller, 1997; Ferreira et al., 2016; Horn et al., 2011; Izawa, 1983), cameras placed on collars (Hernandez et al., 2018), Ultra WideBand (Parker et al., 2022a), and accelerometers either implanted (Kovalzon et al., 2022) or on collars (Smit et al., 2022). These cats display their highest activity in spring and autumn (Hernandez et al., 2018; Parker et al., 2022a), but it is unclear if cats are more active in the fall (Hernandez et al., 2018) compared to the spring or if the activity is equivalent during these two seasons (Alterio and Moller, 1997; Parker et al., 2022a). Activity has been reported to be lower in summer compared to spring (Hernandez et al., 2018; Parker et al., 2022a; Smit et al., 2022). As of winter, the analysis of activity during this season has yielded conflicting results: in some studies cats displayed high (even their highest) level of activity during winter (Ferreira et al., 2016), while other cats displayed lower levels of activity in this season (Kovalzon et al., 2022; Parker et al., 2022a). Horn et al. (2011) has shown a difference in this case between owned and unowned cats. The unowned cats had an increase in their activity level in the colder month of the study, whereas owned cats showed reduced activity during the hottest months of summer and during the coldest months of winter. Izawa (1983) also studied unowned cats and was not able to measure a change in overall activity level, but observed a shift to nocturnality in summer, and a diurnal activity during winter.

The change in temperature associated with the change of the season might be a key element to explain the variation in activity patterns. Some researchers have suggested that during winter, outdoor cats might need to increase their activity level to maintain body temperature, while cats cared for by humans might naturally be more active in a temperature range associated with comfort (Horn et al., 2011). Additionally, temperature might also have a direct effect on the circadian rhythm of the cat. Kovalzon et al. (2022) showed that the rhythmicity in body temperature in domestic cats is stronger in winter than in autumn, when the temperatures are lower.

Studies conducted in different world locations may lead to different results, since the climate might be completely different from one study to another. The reported effect of the temperature on cats may not be visible in studies where the change in seasons is not necessarily defined by a change in temperature and day length. This is the case, for example, in Brazil (Ferreira et al., 2016) where the temperature is constant

throughout the year and seasonal changes are defined by the level of rainfall. However, it remains unclear if these types of seasonal changes have an effect on cats' daily activity. Konecny (1987) did not observe any significant change between the wet and the dry seasons in the Galápagos Islands, whereas Ferreira et al. (2016) reported higher activity during the dry season (winter) compared to the wet season (summer) in Brazil. It is worth noting that rain has been identified as a factor reducing the density and activity of cats in a given area, as reported by Goszczyński et al. (2009) in Poland and Harper (2007) in New Zealand.

The climate also has an impact on the local fauna, affecting the availability of different prey for cats to hunt. The adaptation to the biological rhythm of these prey species might have an impact on cats' biological rhythm. This hypothesis is supported by the observed variation in cats diet across seasons, depending on the availability of prey, confirming the cat's role as a generalist predator (Hervías et al., 2014). This dietary variation is more pronounced in countries with more significant seasonal changes, such as Spain (Millan, 2010), compared to countries with softer seasonal changes, such as Brazil (Ferreira et al., 2014). In regions with drastic seasonal changes, studies suggest that the niche amplitude is higher in dry seasons compared to wet seasons (Ferreira et al., 2014; Millan, 2010). Overall, these findings indicate that the opportunistic nature of cats as predators strongly influences their activity patterns.

### 3.4. Effect of the sex, reproductive status and age on the biological rhythm

Langham (1992) reported that the studied female cats were mostly nocturnal, whereas male cats were active during 24 h, pointing toward a difference between males and females, but this study is based on a limited number of feral individuals: nine females and four males. Parker et al. (2019) observed seven males and seven females living mostly indoors in a cattery and reported that females were globally diurnal and males were globally nocturnal. The authors also reported higher rhythmicity in the locomotor behavior in males. Ferreira et al. (2016), studying 15 males wearing radio-collars, suggested that male cats show higher nocturnal activity when no females shared their territory. Other studies have found no differences between males and females (Hernandez et al., 2018; Horn et al., 2011). Smit et al. (2022) did not show any difference in overall mean activity level between entire males and entire females.

An important parameter that might be overlooked in those studies is the reproductive cycle that may vary between female cats and therefore induce differences in their biological rhythm. This is supported by the study of Andrews et al. (2022), where female cats experienced a controlled reproductive cycle while wearing accelerometers. The cats' reproductive cycle was blocked to measure the baseline activity and then the follicular growth was induced until ovulation could be measured. They showed a significant increase in activity level during follicular growth compared to the baseline activity, with a significant peak three days after the onset of this phase. Further investigation of the cat's natural reproductive cycle is warranted to confirm these findings, especially with a large portion of the domestic cat population being neutered. Six cats were monitored using radio-collars before and after castration, and the results showed that the overall activity was reduced in males, but the activity patterns were identical to the ones observed before the surgical intervention: the cats were mostly nocturnal and crepuscular (Ferreira et al., 2020). For female cats, neutering has been reported to decrease activity levels dramatically, especially during the dark period (three to five times less activity counts in the weeks following spaying) (Belsito et al., 2009; Vester et al., 2009). Yet, these results are contradictory to the ones of Smit et al. (2022), which showed that activity levels are decreased in neutered males but not in neutered females, compared to their intact counterparts. Iwazaki et al. (2022) also did not report any significant difference in activity levels in female cats after neutering.

It is interesting to note that the age of neutering does not seem to have an influence on the decrease in activity levels, which was found to be around 25% for cats aging between 19 and 52 weeks, and thus for both male and female cats (Allaway et al., 2017, 2016).

To study the impact of age on the activity level in cats, other studies have focused on measuring activity levels throughout the cat's life. A decrease in activity levels has been reported to occur once the cat reaches adulthood, but the results are conflicted as if the decline is continuous throughout the cat's life (Naik et al., 2018; Yamazaki et al., 2020) or if the activity level plateaus after three years (Smit et al., 2022). Yamazaki et al. (2020) reported that the total activity level and the number of jumps significantly decreases with age, regardless of the cat's sex. The daily average of total resting and sleeping time is significantly increased with age, especially in the daytime.

The primary obstacle in studying the effects of sex, age and neutering on cats' activity levels and patterns lies in the limited number of individuals used in most biological rhythm studies (Fig. 2c), due to logistical challenges and difficulties in recruiting both cats and owners for the entire study duration. This limitation impedes the ability to analyze these factors comprehensively. Given the likelihood of future studies encountering similar recruitment challenges, drawing conclusions on these aspects may necessitate a multitude of medium-sized studies. New studies should also take into consideration the cats' profiles when interpreting their results. Indeed, 27% of the studies included in this review used only male cats, while 20% used only female cats, and only 36% of the studies used cats from both sex (Fig. 2a). On the other hand, only 9% of the studies used both neutered and intact cats (Fig. 2b). Studies using only adult cats, or cats from the same sex, or only neutered animals should be careful when extending their conclusion to all cats, and at least always carefully report these details in their method. As shown in Fig. 2a-b and d, a significant number of studies did not disclose sex, reproductive status and age of the cats participating in the study.

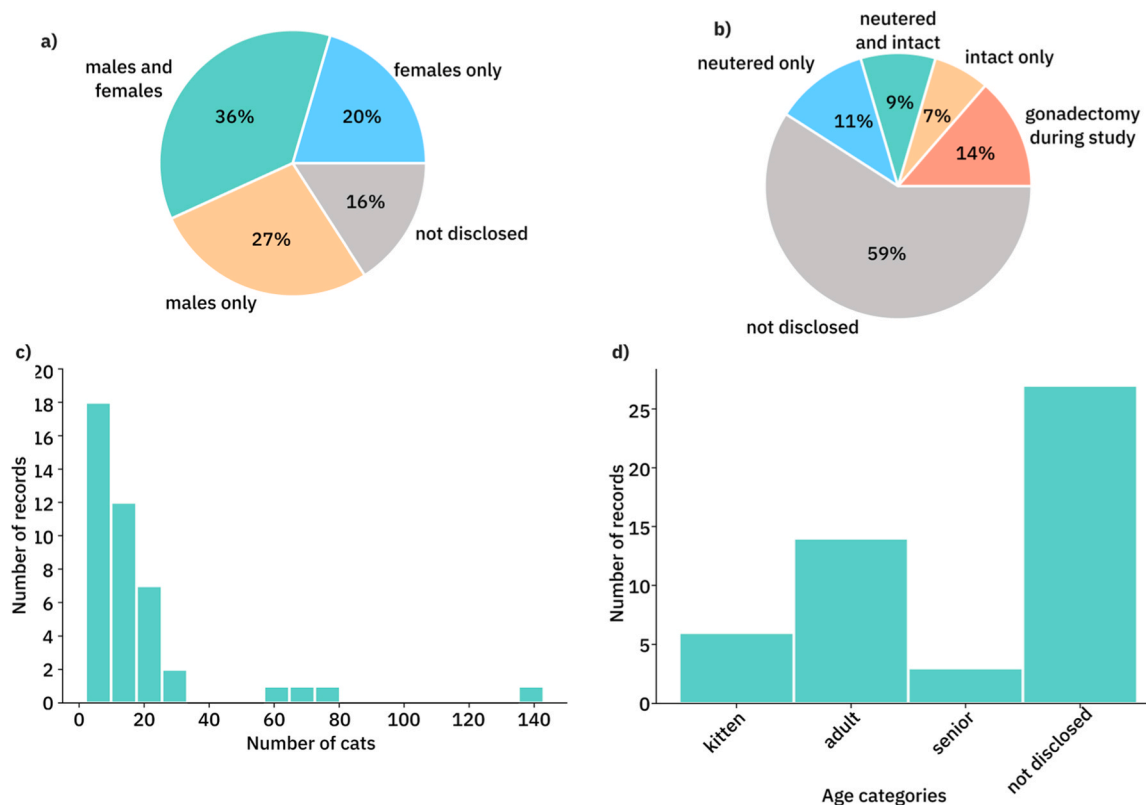
Additionally, body weight, influenced by age, sex and reproductive status, is another crucial factor. This parameter is associated with changes in activity levels, and this further complicates the task of disentangling the impact of each factor on activity levels.

### 3.5. Overview on cats' biological rhythm

In conclusion, current studies have demonstrated a circadian rhythm in cats, responding to an undefined endogenous cue. They tend to display a two-peak activity pattern, one in the morning and one in the evening. But cats are also highly adaptive: their rhythm can rapidly change to adapt to environmental synchronizers. When not dependent on humans for food and shelter, cats are opportunistic and adapt to prey and water availability and to predator presence, according to the climate of their location, the local fauna and the seasons. Domestic cats, in particular ones with limited access to the outside, have synchronized to human activities. The activity pattern is maintained throughout the cat's life, but the overall activity level is higher in younger cats than in older ones.

However, conclusions should be made taking into account the effect of human presence on the studied cats. Hooper et al. (2017) have suggested that activity levels measured during interactions with humans might not accurately reflect variations in activity levels, as cats with a social personality seek interactions with the caregivers and shy cats avoid them. They also showed, using accelerometers placed on collars, a difference in results when the activity counts recorded during periods of human interactions were omitted from the analysis. A significant increase in activity was observed when discarding human interaction periods, compared to negligible change in activity when included.

Importantly, cats have been demonstrated, by studies using accelerometers, to be one of the animals showing the most inter-subject variability (variability from an individual to another) in circadian



**Fig. 2.** Distribution of cats' sex, reproductive status and age, and cohort sizes of the 38 studies on biological rhythm described in this review. (a) Cats sex. (b) Cats' reproductive status. (c) Distribution of the cohort sizes. (d) Cats age categories, kitten: cats under the age of one year, adult: cats from one to eleven years old, senior: cats of age over 11 years, unknown: cats of age undisclosed by the studies; studies including several age classes are counted once for each class included.

rhythm for an average intra-subject variability (variability for a single individual from a day to another) (Refinetti et al., 2016). This translates into the daily activity pattern from a cat to another that varies greatly, even when the cats are of comparable size and weight. Thus, the construction of an average cat daily activity pattern might be impossible (Andrews et al., 2022, 2015; Gruen et al., 2017; Refinetti et al., 2016). This finding calls for a more individual analysis of the cats' activities and a high caution when drawing global conclusions that might not describe any existing cat. Each cat should, therefore, probably be considered as its own control when examining changes in activity levels (Andrews et al., 2022, 2015).

#### 4. Studies on cat's detailed activities

A strong limitation of the studies in the previous section is that they have been analyzing cats' activity as a whole. In some cases, any behavior different from resting and sleeping is considered as "activity" and therefore no difference is made between high energy consuming activities such as roaming, hunting or fighting, and low energy activities such as grooming or eating. In other cases, only the locomotor activity has been taken into account as "activity". Any work attempting to describe cats' biological rhythm without trying to decipher which behavior is at play when the cat is active might therefore overlook simple explanations for discrepancies with previous results. In order to understand this difference, multiple researches have been conducted using different sensors and methods.

##### 4.1. Detailed activities assessed using Ultra WideBand technology

UWB (Ultra WideBand) technology has been used to follow cats in different husbandry conditions to track locomotion behavior (Parker et al., 2017). The UWB technology is based on a radio-emitting tag placed on cats' collar and antennas placed at different locations, recording cats' location and allowing distance calculation within the covered area. This technology makes the recording of cats movement indoors accurate, which is not the case with GPS. A passive-RFID tag on the cat's collar, giving the cat access to the food, and an electronic scale are used to record the daily food consumption (feeding time and food weight) for each animal (Parker et al., 2019).

With this technology, cats held in cattery (indoor area of 22.5 m<sup>2</sup> and an outdoor courtyard of 7 m<sup>2</sup>) showed four peaks of activity: two in the morning (both coinciding with technicians entering the facility for cleaning the areas or feeding the animals), one in the afternoon (also coinciding with technicians being in the facility) and one in the evening around sunset (Parker et al., 2017). The highest peak of activity (the second one) coincided with the feeding time. The only peak not coinciding with human activity was the one in the evening, showing that even when synchronized with human activity, cats retained part of their nocturnal activity. The locomotive behavior was shown to be more rhythmic than the food intake (Parker et al., 2022a, 2019). The feeding behavior had two main peaks, one in the morning before sunrise and one in the evening before sunset, supporting the crepuscular nature of the cat. At midday and midnight, the cats showed their lowest level of activity and food intake. To detect if cats had seasonal modulation of their biological rhythm, Parker et al. (2022a) followed six cats, in the same cattery conditions described previously, for three weeks each season. The season had no effect on the mean daily amount of food ingested by the cats, but a 24-hour cycle was shown. These shelter cats were described as more diurnal than nocturnal in their locomotor rhythm, this is compatible with an activity pattern influenced by the human activity of the shelter technicians. This study showed preservation of the crepuscular behavior throughout the seasons, peaks at sunset and sunrise shifting with change in day length, whereas peaks of locomotion and food consumption triggered by human interaction were not fluctuating seasonally. Parker et al. (2022b), by comparing shelter cats with and without great access to outdoor space, observed that all cats displayed

bimodality in their activity, but outdoor cats showed less rhythmicity in their behavior. Outdoor cats were overall more active than indoor cats, they covered more distance and ate more but displayed less rhythmicity in their behaviors (Parker et al., 2022b). The authors argued that outdoor cats might encounter more environment disruptors that affect their rhythmicity. Finally, similarly to Piccione et al. (2013), the authors showed that outdoor cats are more nocturnal than indoor cats. They suggested that the lack of stimulation at night for indoor cats might inhibit nocturnal activity.

The association between the UWB technology and the RFID-triggered feeders have given more accurate and detailed information on cats' locomotion activity and eating, but they pose several limitations. Some very important activities are overlooked such as drinking –which has been previously suggested to be an environmental modulator for feral and stray cats–, grooming, social interaction and other activities. In addition, the monitoring of cats' locomotion and feeding activities requires the deployment of several detectors and sensors, which need to be placed strategically in order to be efficient, and this seems difficult to deploy at larger scales.

##### 4.2. Detailed activities using cameras

To get details on a larger number of cats' activities, some studies used cameras: either camera traps that will start recording when an animal is detected or animal-borne (wearable) cameras. The camera traps have to be placed in strategic places such as feeding stations (Cove et al., 2017) or known animal trails (Kays et al., 2015) decided by human observers, and will record only a fraction of the animal's day. Animal-borne cameras can be heavy (90 g for Hernandez et al. 2018 but 32 g for Huck and Watson 2019), exceeding for most cats the limit of 2% of the cat's body mass recommended by Coughlin and Van Heezik (2015) for minimal disruption of the animal's behavior. The activity labeling might also be difficult since some activities like resting, walking and running are difficult to distinguish based only on an animal-borne camera (Huck and Watson, 2019).

Other studies have investigated the use of cameras placed in the room to recognize indoor cat's posture -such as sitting, jumping, walking, etc- by using computer vision algorithms (Pons et al., 2017). This field is still emerging and the number of studies using such techniques to analyze cats' activities is still limited. Further development is required to establish models capable of recognizing more complex activities such as grooming, eating, etc.

The use of indoor cameras offers similar limitations to the use of camera traps: they require the deployment of cameras in strategic places in order to be efficient, and give fragmented information on the cat's activity, limited to the moment where the animal is in the camera's field of view.

Additionally, image footage of cats' activities still relies mainly on manual recognition and labeling of the cat's activity with limited possibilities for automatic alternatives yet. As an alternative to manually labeling video footage of cats activities, computer vision techniques could be employed for automatic detection of cat activities. Several studies using computer vision methods have shown encouraging results in recent years, in particular in livestock (García et al., 2020; Tscharke and Banhazi, 2016) and sea animal (Barbedo, 2022) activity recognition. But, these studies employed Machine Learning models that still need a manually labeled dataset, with a good labeling quality, to be trained. The potential of employing computer vision techniques in cat studies, particularly with bio-loggers, remains largely unexplored.

##### 4.3. Artificial Intelligence classification for cats activities using accelerometer

In addition to being lightweight, accelerometer devices have proven to be a useful and a reliable system to distinguish different cat's activities even when a single accelerometer axis is recorded (Watanabe et al.,



2005). Watanabe et al. (2005) recorded the surging acceleration of a single cat, with a device weighing 18 g, representing 0.5% of the animal's body mass. The authors were able to successfully discriminate between drinking, eating, trotting and galloping, but obtained poor results for grooming and walking, with an overall accuracy of 57.3%. This attempt at automatically classifying cats' behaviors based on the accelerometer signal and a Canonical Discriminant Analysis (CDA) paved the way for new possibilities of deciphering the cat's day with a level of detail not achievable before. After this study, only a few others attempted to classify cats' behavior using Machine Learning and Deep Learning methods for classification.

Sharon et al. (2020) placed an omnidirectional accelerometer on a collar, under the neck, of 13 cats in controlled conditions. They recorded five to eight hours of cats' activities and attempted to classify three types of jumps: jump up, jump down, and jump across using a Linear Discriminant Analysis (LDA). They obtained an overall misclassification error of 5.4% per cat, meaning 5.4% of the jumps were classified as a jump of an incorrect kind (for example a jump down classified as a jump up). These good results are encouraging, but classification performance has been assessed by ignoring any other kinds of activities performed by the observed cats (walking, grooming, eating, etc). The performance of such a classifier in cats' daily life is therefore questionable.

Galea et al. (2021) placed a tri-axial accelerometer on a harness on 10 free-roaming domestic cats, placing the sensors close to the chest of the animals. Using two different classification methods, the Random Forest (RF) and Self-Organizing Maps (SOM), the authors attempted to classify a total of 12 behaviors separated in three categories: sedentary (lying, sitting, grooming, watching), eating and locomotive (eating/drinking, walking, trotting), and hunting (galloping, jumping, pouncing, swatting, biting/holding). The SOM model displayed a higher overall accuracy (~ 99.6% for SOM and 98.9% for RF), precision and specificity, but the RF procedure generally displayed better sensitivity. The SOM performed better than the RF for nine behaviors, RF performed better for two, galloping and pouncing, and both models predicted with equal accuracy the lying behavior. Galea et al. (2021) concluded that the SOM was a model with better performance than the RF model to predict cats' behavior, for half the computation time.

Smit et al. (2023) compared the same classification models, using 12 cats held in semi-outdoor colony cages, wearing two accelerometers each: one on a collar with the sensor on the ventral side, and one on a harness with the sensor sitting on the animal's left shoulder blade. The authors attempted to classify 15 behaviors of four categories: active (climbing, jumping, rubbing, trotting, walking), inactive (lying, sitting, standing), maintenance (digging, eating, grooming, littering, scratching, shaking), and other (allogrooming). Some important behaviors, studied by Galea et al. (2021), were discarded because of lack of data, such as drinking or running/galloping. In this study, results for the four tested models (SOM and RF trained each on the dataset from the collar sensor and the one from the harness) were above 0.7 of overall accuracy. The authors compared the time budget computed using the predictions from each model with the state-of-art time budget defined for domestic cats. The RF models predicted that the cats spent 3–4% of their time eating, whereas SOM models' predictions ranged between 13% and 28% of the time. Literature reports an eating time budget of 0.6% for farm cats (Panaman, 1981), 3% for indoor cats (Eckstein and Hart, 2000) and 2.3% for cats in an outdoor colony (Hernandez et al., 2018), giving more reliability to RF results. Similar conclusions can be drawn for grooming. By giving more consistent predictions and closer to the values already reported by literature, the authors concluded that RF models are more reliable than SOM models with the studied datasets.

Choosing the best model to predict cats activities is still, to this day, an open question. Indeed, Galea et al. (2021) and Smit et al. (2023) have tested the same two models (RF and SOM) and came to opposite conclusions. Even when considering all models already tested to predict cats' behavior, it is difficult to say which one deserves renewed attention in future studies. Discrepancy in results might result from important

differences in experiment protocols, such as:

- placement of accelerometers at different locations: Smit et al. (2023) gave evidence that the placement between collar and harness do not give significantly different results for cats' activities classification, but this parameter requires further investigation as Kumpulainen et al. (2021) showed that sensors placed on the back yielded better model performances than ones placed on the collar for dogs' activities classification.
- precision: 12-bit for Watanabe et al. (2005), 13-bit for Galea et al. (2021), not disclosed for Sharon et al. (2020) and Smit et al. (2023),
- data range:  $\pm 3$  g for Watanabe et al. (2005),  $\pm 8$  g for Galea et al. (2021) and Smit et al. (2023), not disclosed by Sharon et al. (2020),
- sampling rate: 16 Hz for Watanabe et al. (2005), 32 Hz for Sharon et al. (2020), 50 Hz for Galea et al. (2021) and 30 Hz for Smit et al. (2023),
- sequence size for the prediction: 4 or 16 seconds (corresponding to 64 or 256 data points) for Watanabe et al. (2005), 1 second (corresponding to 50 data points) for Galea et al. (2021) and 1 second (corresponding to 30 points) for Smit et al. (2023), the sequence size was variable for Sharon et al. (2020),
- the number and profiles of cats used to create the dataset: only one male cat for Watanabe et al. (2005), 13 cats held in laboratory conditions (six castrated males, four sexually intact females, and three spayed females) for Sharon et al. (2020), ten free-roaming domestic cats (six males, four females) for Galea et al. (2021) and 12 cats held in semi-outdoor colony cages (five desexed males and seven entire females) for Smit et al. (2023),
- the global final size of the dataset, depending on successfully labeled data,
- the dataset size for each behavior or class,
- the overall number of classes: seven classes for Watanabe et al. (2005), three for Sharon et al. (2020), 12 for Galea et al. (2021) and between three and 15 for the various models trained by Smit et al. (2023),
- overall variation in definition of close behaviors: jumping is a behavior that is not defined in the same way in all studies: Galea et al. (2021) classified "pouncing" and "jumping" as two separated behaviors, Smit et al. (2023) distinguished "jump horizontal" and "jump vertical", and Sharon et al. (2020) classified three kinds of jumps ("jump across", "jump up" and "jump down"),
- the features used for predictions: Watanabe et al. (2005) used four features extracted from the sensor signal in the frequency domain, Sharon et al. (2020) used a Functional Data Analysis to extract seven coefficients for each jumping event, Galea et al. (2021) used 26 features and Smit et al. (2023) used 32 features computed from the sensor signal in the time domain.

The limited number of studies does not allow for the evaluation of the impact of every parameter variation from a protocol to another. Additionally, even when comparing results with the exact same protocol parameters, variations may occur between studies, particularly if the number of cats involved is small. This is attributed to the high inter-subject variability among cats, as noted by Andrews et al. (2015), Gruen et al. (2017) and Refinetti et al. (2016). For this reason, a large number of cats is needed to construct a representative group and this might prove complicated in practice. New studies with a limited number of cats may still encounter unpredictable biases. Therefore, the findings of the previously mentioned studies, as well as any future research with the same limitations, should be interpreted with caution until a sufficiently large number of studies have been conducted to thoroughly assess the impact of parameter variations.

#### 4.4. Classification of dogs activities using accelerometers

The activity recognition through Artificial Intelligence (AI)

classification of accelerometer signal has already been applied to different species from human to sea turtles (Brown et al., 2013; Korpela et al., 2019, PREPRINT; Wilmers et al., 2015; Zhang et al., 2018), including the other most common human pet: dogs (*Canis familiaris*). It is interesting to see that a greater work has been made so far in classifying dogs' behavior than cats and several reasons can be cited for that. First, dogs are considered one of the easiest animals to train and, therefore, to prompt for specific behaviors such as sitting, lying or walking to a specific area. Second, dogs are of particular interest for behavioral studies due to their roles as animals of service and not only as pets, such as in shepherding, guiding of the blind, police and rescue services, and more. An overview of the studies aiming at classifying dogs' activities is presented in this section, in order to give an efficient orientation to the future studies on cats' activity recognition.

Early studies, such as Preston et al. (2012), used data derived from accelerometers placed on the harness to solely estimate the levels of dogs' activity, but later studies have used the sensors' signals to predict dogs' behavior using Artificial Intelligence. The variability in protocols is also seen in these studies and can therefore explain the difference in models' performances. Beyond the previously reported sources of divergence in these studies (placement of the sensors, sampling rate, data range and precision, number of participants, etc), we can add that not all studies used the same type of sensors. All used sensors were tri-axial, but some studies used solely an accelerometer (Chambers et al., 2021; Den Uijl et al., 2017), others accompanied it with a gyroscope (Aich et al., 2019; Gerencsér et al., 2013; Hussain et al., 2022a, 2022b; Kumpulainen et al., 2021; Muminov et al., 2022), while others also added a magnetometer (Marcato et al., 2023). Some studies might also use several sensors of the same kind, placed at different places of the animal's body. For example, Hussain et al. (2022a), (2022b) placed their sensors on the neck and tail, Marcato et al. (2023) placed their sensors on the back, chest and neck and (Kumpulainen et al., 2021) on the neck and back of the dogs. A various number of models have been considered and compared in these studies ranging:

- from simple Machine Learning such as:
  - o LDA and QDA (Linear and Quadratic Discriminant Analysis) (Kumpulainen et al., 2021),
  - o SVM (Support Vector Machine) (Aich et al., 2019; Gerencsér et al., 2013; Kumpulainen et al., 2021; Muminov et al., 2022),
  - o DT (Decision Tree) (Kumpulainen et al., 2021; Muminov et al., 2022),
  - o RF (Aich et al., 2019; Marcato et al., 2023),
  - o NB (Naïve Bayes) (Aich et al., 2019; Muminov et al., 2022),
  - o KNN (K Nearest Neighbors) (Aich et al., 2019; Muminov et al., 2022),
  - o and Isolation Forest (Marcato et al., 2023),
- to Deep Learning models with higher complexity such as:
  - o ANN (Artificial Neural Network) (Aich et al., 2019),
  - o FilterNet (Chambers et al., 2021),
  - o 1-D CNN (1-Dimension Convolutional Neural Network) (Hussain et al., 2022a),
  - o and LSTM (Long Short-Term Memory) (Hussain et al., 2022b).

In these studies classifying dogs' sensor data, the behavior recognition is mostly limited to the posture and the gait of the dog (laying, sitting, standing, walking, trotting, galloping) with a few additional behaviors (eating, drinking, noseworking, jumping, scratching, head or body shaking, etc), classifying from six to ten behaviors per study. The overall accuracy for these models is good with a minimum of 75% for the DT by Kumpulainen et al. (2021) and over 96% for the 1-D CNN used by Hussain et al. (2022a). The lowest accuracy was obtained when several different breeds of dogs were used for the study. Dogs exhibit much greater variation in size and weight than cats, which poses a particular challenge for building a model that can predict the behavior of any dog breed. Some studies have started to work on model transferability but, as

this field is just emerging, the studied number of breeds is still limited: two for Gerencsér et al. (2013) and Marcato et al. (2023) who directly tested for inter-subject accuracy, 20 for Kumpulainen et al. (2021) aiming for a diverse dataset.

These studies dealing with dog behavior show the possibility to classify pets behavior with sensor data and give interesting suggestions on how to improve cats activity recognition. First, the use of an additional sensor to the accelerometer, such as a gyroscope, seems to emerge as a consensus to provide data to the AI model. Second, the type of models used to classify cats' behavior is still very limited (RF, SOM, CDA, LDA) and future research might focus on testing other AI models such as CNN, DT, and others. Third, even though cat breeds do not vary in size and weight as extremely as dog breeds, cats have high inter-subject variability (Andrews et al., 2022, 2015; Gruen et al., 2017; Refinetti et al., 2016) and, therefore, a particular care should be taken in future research to build a model able to describe any cat's behavior, either by providing a large pool of representative cats to train the model or by designing a specific inter-subject validation algorithm. Finally, particularly challenging behaviors to classify (either by their complexity or rarity) such as grooming or gait behaviors should be the center focus of future research as they represent an important portion of the cat's daily life and could be a marker for its health and well-being. Improving cats' behavior recognition with accelerometers in future studies would offer a valuable tool to help monitor cats' health, early diagnose a variety of diseases and better understand cats' behavior changes. This would also facilitate the exploration of the influence of established factors like age, sex, and seasons on cats' specific and daily activities.

## 5. Conclusion and future directions

The examination of the biological rhythms in cats has provided numerous insights into their behavior. When let free outside, cats will adapt to seasonal changes, temperature, human, prey and predator presence, as well as the topography of their habitat. Other parameters impact the level of activity of the cat, such as age, sex, and reproductive status. Despite their ability to adapt, cats retain their circadian rhythm and display the persistence of a two-peak daily activity, around dawn and dusk. For domestic cats, especially indoor ones, they are highly synchronized with their owners' daily and weekly pattern of activity. This underlines the importance for owners to better understand their cats' activity pattern to maintain them as healthy as possible. To do so, the use of bio-loggers such as accelerometers has proven very helpful to decipher cats' lives. Studies using accelerometers have started to provide us information on the effect of different environments on the cat's natural activity/inactivity cycles and has brought new knowledge on the activity patterns of owned and unowned cats.

All these discoveries are facilitated by the raw data provided by accelerometers. However, the full potential of this data remains untapped as studies often confine themselves to examining variations in activity levels or binary classifications of activity and inactivity. With the integration of Artificial Intelligence, there is an opportunity to maximize the utility of this data. A detailed report of cats' activities could be provided by sensor data such as accelerometers, potentially associated with other sensors like gyroscopes, coupled with advanced AI algorithms. This detailed report could pave the way for new investigations into various diseases. For instance, since grooming is a recognized indicator of feline health, a detailed report on the fluctuation in the regularity of such activities could potentially detect emerging health issues before they become apparent to owners.

Future studies should strive to enhance the accuracy of algorithms for recognizing cats' activities, in order to provide owners, veterinarians and scientists with deeper insights into cats' biological rhythms. Accelerometer data has been demonstrated to be a good proxy for cats' activity (Lascelles et al., 2008). With the development of Artificial Intelligence tools, a more detailed account of a cat's daily life could be provided. Questions like when "does my cat wake up?", "how often?", or

“when does it fall back asleep?” could be answered with precision. This detailed level of information could be very helpful in diagnosing illnesses that affect specific cats’ behaviors, and understanding the onset and progression of those illnesses in domestic cats by assessing the effectiveness of treatments and understanding how the environment, including human activity, impacts domestic cat’s behavior. Furthermore, research on cat diseases stands to benefit from such algorithms, providing an objective measure of cats’ behavior across various timescales.

Once these advanced algorithms are developed and accessible, owners could monitor their cat’s daily life by using a bio-logger, gaining insights into fluctuations on a daily basis. This personalized approach is particularly crucial considering the high inter-subject variability among cats, since individualized analysis could be conducted. Finally, the development of such technology could bring forward the research on the cat’s biological rhythm by giving the possibility to study each behavior individually and decipher individual pattern variation according to the cat’s specificity and environment.

### CRedit authorship contribution statement

**Serena Prigent Garcia:** Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation, Conceptualization. **Alia Chebly:** Writing – review & editing, Validation, Supervision, Project administration, Conceptualization.

### Declaration of Competing Interest

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

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### Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at [doi:10.1016/j.applanim.2024.106287](https://doi.org/10.1016/j.applanim.2024.106287).

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