Unravelling domestic cat behaviour using accelerometers and machine learning

A thesis presented in partial fulfilment of the requirements for the degree of

Doctor of Philosophy

In

Animal Science

At Massey University, Palmerston North,

New Zealand

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2025

Abstract

It is estimated that there are at least 445 million companion cats worldwide. Despite this large number, little is known about how environmental factors (e.g., weather, presence of children, dogs or other cats) are associated with domestic feline behaviour and welfare. Traditional behavioural observation methods are limited by short observational windows, high labour demands, and subjective nature of observations, making them unsuitable for in-depth, longitudinal studies. This thesis leverages recent advances in accelerometer technology and machine learning to overcome these limitations to quantitatively analyse continuous domestic cat behaviour, providing new insights into the influence of environmental factors on their behaviour.

In the first phase of the thesis (Chapter 3), machine learning models were trained to classify cat behaviours from acceleration data. The models achieved a minimum accuracy of 70%, which improved as the number of behavioural classes was reduced, and with random forest models generalising better to new data than self-organising maps. Models for harness-mounted devices (accuracies 77% - 83%) performed slightly better than those for collar-mounted devices. The model for the collar-mounted device that classified eight different behaviours (active, eating, grooming, littering, lying, scratching, sitting, standing), performed adequately (accuracy 73%), and was considered the most practical due to cats being more likely to wear a collar than a harness.

The second and third phases of this thesis investigated how environmental factors influenced cat behaviour, both in semi-outdoor research cats (Chapter 4) and in pet cats within a home environment (Chapter 5). Weather variables, particularly daylength and the temperature humidity wind index, were significantly associated with domestic cat behaviour. Seasonal changes in grooming and scratching were closely linked to the natural hair growth cycle. Behaviours were influenced by individual differences and disruptions, such as the return of a cat to the group after an absence, affecting their behaviour. Among pet cats, those with outdoor access showed behavioural adaptations to seasonal weather changes, seemingly prioritising thermal comfort. Multi-cat households and those with at least one child present were associated with an increase in alertness-related behaviours of increasing sitting with decreasing lying.

By leveraging machine learning and accelerometer data, this research advances current methodologies in animal behaviour studies, providing an approach for continuous, minimally invasive animal behaviour and welfare assessment. This thesis contributed to bridging the gap in our understanding of how environmental factors can shape animal behaviour and welfare and highlighted the importance of taking interindividual differences and environmental factors into account when assessing domestic cat behaviour.

Acknowledgements

Firstly, I would like to thank my supervisors, Associate Professor David Thomas, Associate Professor Rene Corner-Thomas, Dr. Ina Draganova and Dr. Chris Andrews, for their continued support and guidance throughout this journey. Their expertise, insightful feedback and encouragement have been invaluable in shaping this thesis. I am especially grateful for their belief in me and my capabilities as a researcher throughout this journey. I would also like to thank you all for your trust in me to look after your pet, who provided much needed cuddles throughout my PhD. Dave and Rene, thank you for not only putting up with me as my supervisors, but also with me as a tenant of the sleepout in the garden. A special thanks to Dave for offering this amazing PhD opportunity.

I would also like to thank the staff of the Massey University Centre for Feline Nutrition, Karin, Margreet and Rachael, for all their support during my trials. A special thanks for conducting one of my research trials for me, while I was stuck in The Netherlands behind the kitchen table due to border closures. Thank you to everyone who organises and attends the monthly Palmerston North Bioinformatics Meeting. Your advice and insights regarding machine learning have been incredibly helpful and greatly appreciated.

I would like to thank Seer Ikurior for all his help and patience in teaching me how to code in R.

I would like to extend my gratitude to all the cat owners and their cats who volunteered to participate in my research trial. Your willingness to contribute your time and effort has been vital to the success of this study.

Thank you, Becks, Karing, Keely, Margreet and Nina, for the weekly coffee meetings, which provided a safe space for me to share my frustrations, setbacks, and doubts. Your support and advice during these moments were invaluable, and I am grateful for your understanding and encouragement throughout this journey.

Lastly, thank you to my family and friends for their unwavering support throughout my PhD journey at Massey, despite being on the other side of the world. A special thanks to my father, who made sure I got to New Zealand. To my sister, thank you for letting me stay in your apartment during the COVID lockdown. Not having to worry about finding a place and having a space to work on my PhD during such a challenging time was invaluable, and

I am grateful for your support. Thank you, Anne and Thirza, for our calls, which provided much-needed moments of relaxation during times of stress.

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Abbreviations

AUC	Area under the curve
ANN	Artificial neural network
BCS	Body condition score
BW	Bodyweight
CNN	Convolutional neural network
CRF	Random forest model for collar-mounted accelerometer data
CSOM	Self-organising maps model for collar-mounted accelerometer data
CT	Classification tree
DBA	Dynamic body acceleration
DoF	Degrees of freedom
EE	Energy expenditure
FP	False positive
FPR	False positive rate
FN	False negative
GLMM	Generalised linear mixed model
GPS	Global Positioning System
HRF	Random forest model for harness-mounted accelerometer data
HSOM	Self-organising maps model for harness-mounted accelerometer data
KNN	k-Nearest neighbour
LDA	Linear discriminant analysis
LSTM	Long short-term memory
ML	Machine learning
ODBA	Overall dynamic body acceleration
PA	Physical activity
QDA	Quadratic discriminant analysis
RF	Random forest
ROC	Receiver operating characteristic
SOM	Self-organising maps
SVM	Support vector machine
THW	Temperature humidity windchill
TN	True negative
TP	True positive
UWB	Ultrawide band
VeDBA	Vectorial dynamic body acceleration
VHF	Very high frequency
VM	Vector magnitude

Chapter 1 Introduction

The domestic cat (*Felis catus*) is one of the most popular companion animals worldwide, with an estimated population of at least 445 million worldwide (Euromonitor International, 2024). Despite their prevalence in human households, a comprehensive understanding of how their environment influences their behaviour and welfare remains surprisingly limited. Monitoring behaviour is an important, non-invasive tool to assess animal health and welfare, as changes in behaviour can be early indicators of illness, pain or stress (Horwitz & Rodan, 2018). A deeper knowledge of the factors that shape cat behaviour is therefore essential to improve and monitor their welfare.

Traditionally, behavioural research has relied mainly on direct observation methods, which is constrained by short observational windows, high labour demands and subjectivity (Altmann, 1974; Dawkins, 2007). These limitations make in-depth, longitudinal studies challenging, creating a gap in our understanding of how domestic cats adapt to their surroundings. Currently, our knowledge of how cats respond to environmental variables, such as seasonal shifts, daily weather patterns, and the complexities of the home environment, is scarce.

Recent advances in technology offer a powerful solution to overcome some of the methodological hurdles that come with the traditional methods. The integration of triaxial accelerometers and machine learning presents an opportunity to quantitatively and continuously analyse animal behaviour without the need for direct human observation. Once a machine learning model is trained on labelled data, it can be deployed to classify behaviours from new accelerometer data, significantly reducing the labour intensiveness of behavioural studies and enabling continuous monitoring. This approach provides a major advancement in behavioural research, providing objective, high-resolution data on behaviour patterns. While this technology has been applied to other species (Brown et al., 2013; Wilson et al., 2008), its validation and application in domestic cats remains underexplored.

This thesis aims to bridge this knowledge gap by developing, validating and applying an accelerometer-based machine learning model to study the behaviour of domestic cats and gain novel insights into how environmental factors shape their behaviour. To achieve this, the following scientific aims were defined:

1. Develop and validate a machine learning model to classify cat behaviours using accelerometer data (Chapter 3).
2. Apply the validated model to investigate how daylength, seasons and meteorological conditions are associated with changes in the behaviour of domestic cats living in a semi-outdoor research environment (Chapter 4).
3. Apply the validated model to understand the influence of different home environments, including factors like outdoor access and the presence of other animals or children, on the behaviour of privately owned companion cats (Chapter 5).
4. Compare the behaviour of domestic cats living in a semi-outdoor research environment to those of privately owned cats living indoors only or having outdoor access (Chapter 5).

This thesis is structured into five chapters. Chapter 2 provides a comprehensive review of the relevant literature on domestic cat behaviour, accelerometry and machine learning applications in animal behaviour science. Chapter 3 addresses the first scientific aim by detailing the development and validation of machine learning methods for the classification of domestic cat behaviours, comparing different techniques and accelerometer attachment sites. Chapter 4 utilizes the most effective model from the previous chapter to explore the impact of daylength, seasonality and weather on the behaviour of research cats. Chapter 5 extends this research to pet cats, examining how specific factors within the home environment influence their behaviour. Finally, Chapter 6 provides a general discussion that summarises and connects the key findings from all chapters, considers the theoretical and practical implications of the work, acknowledges methodological limitations, and proposes directions for future research.

Through this work, this thesis provides a methodological advancement for studying animal behaviour and provides new insights into how domestic cats adapt to their environment. The findings have important implications for domestic cat welfare, supporting evidence-based recommendations for owners and veterinarians and offering a framework for future studies into the complex lives of companion animals.

Chapter 2
Literature review

Image generated with Meta AI

Chapter 2 Literature review

2.1 The domestic cat

To understand the context and significance of the research presented in this thesis, it is important to establish a foundational understanding of the domestic cat (*Felis catus*). The domestic cat is the only domestic species within the Felidae family (O'Brien & Johnson, 2007). It is unclear when domestication of the domestic cat began, but currently, the earliest evidence suggests an intentional relationship between humans and cats 9,500 years ago (Vigne et al., 2004). Nowadays, domestic cats can be found almost everywhere in the world and are one of the most popular companion animal species, with a recent estimate of almost 445 million companion cats around the world (Euromonitor International, 2024). Despite this close relationship, many aspects of their behaviour and the environmental factors that influence it remain poorly understood. This section provides ethological and ecological background required to interpret the findings of this thesis. It will begin by outlining the specific status of domestic cats in New Zealand and positioning this research within its geographical context. Following this, key components of domestic cat behaviour are defined, and the current literature on how seasonal changes, weather and the home environment influence these behaviours is reviewed. Finally, this section will evaluate methods for observing and recording animal behaviour, highlighting the specific limitations that the approach adopted in this thesis aims to overcome.

2.1.1 The domestic cat in New Zealand

According to a 2020 report, New Zealand has an estimated 1.2 million pet cats, with 41% of households owning at least one animal (Companion Animals New Zealand, 2020). Pet cats, however, are not the only category of domestic cat recognised in New Zealand. Within New Zealand, three categories of domestic cats are recognised, which are outlined in the Companion Cats Code of Welfare 2018 (Companion Cats Code of Welfare, 2018):

- **Companion/owned cats:** Companion cats live with humans as companions and are dependent on humans for their welfare. Companion cats include cats in homes, breeding establishments, boarding catteries, animal welfare shelters and pet shops. Companion cats can also be referred to as owned cats.

- **Stray cats:** Stray cats are unowned companion cats which are lost or abandoned, and which are living individually or in a group (colony). Stray cats live around centres of human habituation and have many of their needs indirectly supplied by humans.
- **Feral cats:** Feral cats are also unowned and have none of their needs provided for by humans, exist fully independently of humans and are entirely self-sustaining. Generally, feral cats do not live around centres of human habitation and are identified as a pest in New Zealand.

The definitions outlined above can differ to those outlined in scientific literature (Farnworth et al., 2010). Based on scientific literature, and for the purpose of this thesis, the category 'companion cats' is further subdivided into:

- **Pet cats:** Companion cats that are (privately) owned by, and live closely with, humans. They are dependent on humans for their welfare and can be housed indoors, outdoors, or have both indoor and outdoor access.
- **Farm cats:** Cats that live rurally on a farm in close proximity to humans. They are partially dependent on humans for food and shelter (Macdonald et al., 1987).
- **Shelter cats:** Cats that are (temporarily) housed in an animal welfare shelter (e.g., SPCA) and are dependent on humans for their welfare. They can be pet cats that have been relinquished, or stray cats that have been caught. Shelter cats do not roam outside the shelter facility and can be housed individually or in groups (colony).

Other terms encountered in literature are research cats and free-roaming, or free-ranging, cats:

- **Research cats:** Cats used for research, testing, and/or teaching and do not live in a home, but rather in a research facility, often under controlled circumstances. They are dependent on humans for their welfare and can live individually or in a group and do not roam outside the research facility.
- **Free-roaming/free-ranging cats:** Cats that (can) freely roam outside. The term can refer to pet cats that are allowed to freely roam outside or stray and feral cats.

As living conditions play a central role win this thesis, it is important to easily distinguish between them. Therefore, the categories of stray, feral, farm, shelter, pet, and research cats are used as described above. When used as a stand-alone category, 'free-roaming' may refer to stray, feral, farm or pet cats with outdoor access. This usage only applies when no distinction could be made between these subgroups.

2.1.2 Normal cat behaviour

According to the Animal Welfare Act 1999 (2023) owners, and persons in charge of animals, are required by law to ensure good welfare of the animal under their charge Understanding the behaviour of an animal is essential for monitoring and ensuring its welfare. An understanding of what constitutes 'normal' behaviour is required to identify what is 'abnormal' (Stelow, 2020). Behaviour is defined as "the internally coordinated response (actions or inactions) of whole organisms (individuals or groups) to internal and/or external stimuli" (Levitis et al., 2009).

To systemically study behaviour and establish wat is 'normal', researchers rely on a foundational tool: the ethogram. An ethogram is a comprehensive inventory or catalogue of the species-specific behaviours with corresponding definitions using descriptive terms (Martin & Bateson, 1993). There can be high degree of variation in behavioural definitions across studies, making comparisons difficult. Stanton et al. (2015), and more recently, Kappel et al. (2024) aimed to provide a full overview of the full behavioural repertoire of felines and aimed to standardise the feline ethogram. However, merely describing behaviour is only the first step.

Nikolaas Tinbergen formulated four questions that need to be answered to fully understand why an animal behaves as it does (Tinbergen, 1963):

1. Causation (mechanism): What are the immediate internal and external stimuli that causes the behaviour?
2. Development (ontogeny): How does the behaviour develop and change of the animal's lifetime?
3. Function (survival value): How does the behaviour contribute to the animal's survival and reproduction?
4. Evolution (phylogeny): How did the behaviour evolve over the history of the species?

This thesis primarily focuses on causation and function, examining how external environmental factors such as season and housing conditions influence behavioural changes, and how these adaptations may serve to optimise the cat's welfare.

To investigate these questions quantitatively, an understanding of activity budgets and biological rhythms is required. An activity budget quantifies how much time an animal spends displaying different behaviours. Biological rhythms involve repetitive bodily functions, affecting the regulation of one or more physiological or behavioural variable(s) in living organisms, occurring at any time scale (Refinetti, 2008). Biological rhythms can be (I) a response to environmental cues, (II) endogenously generated (endogenesis), or (III) an endogenous rhythm which can be modulated by environmental cues (entrainment; Refinetti, 2008). The adaptation of biological rhythms to the environment increases the chance of reproduction and survival by optimising the physiological processes and behaviours of animals to best fit their environment (Refinetti, 2016).

2.1.2.1 Circadian rhythms

One of the best known and researched rhythms is the circadian rhythm, which has a period length of 24 hours or one day. Many animals regulate their behaviour over a 24-hour period according to a sleep-wake cycle, aligning their peak activity with periods of daylight (diurnal), darkness (nocturnal), or twilight (crepuscular; Nelson, 2005). A well-known and naturally occurring circadian rhythm, is the light-dark cycle, which is the natural alternation between periods of daylight and darkness within a 24-hour period (Refinetti, 2008). The light-dark cycle plays a key role in the entrainment of the sleep-wake cycle of organisms (Refinetti, 2008, 2016). A polyphasic sleep-wake cycle, with multiple short sleep periods throughout a 24-hour period, has been reported in research cats (Kuwabara et al., 1986). Other research studies, conducted by the same research group, reported the presence of circadian rhythms in activity, feeding, drinking and body temperature fluctuation in research cats that are entrained to the light-dark cycle (Johnson et al., 1983; Randall et al., 1985, 1987).

A bimodal and nocturnal/crepuscular behavioural pattern has been reported in both feral (e.g., Konecny, 1987; Lavery et al., 2020). and research cats (Johnson et al., 1983; Randall et al., 1985, 1987). However, a change in feeding and activity patterns was reported for the research cats when they were not isolated from humans. Johnson et al. (1983) and Randall et al. (1985)

reported an increase in food intake when humans were present, while Randall et al. (1987) reported a third, diurnal, peak in activity coinciding with human presence. It should be noted that cats were not exposed to a natural light-dark cycle in these studies. Indoor-housed research cats exposed to a natural light-dark cycle and humans were reported to be diurnal and crepuscular, with peaks aligned with human activity, but also with sunset (Parker et al., 2017, 2019). A study with outdoor-housed research cats reported similar results, with cats being more diurnal and crepuscular, aligning their peak activity with human presence and sunset (Smit et al., 2022).

Feral cats live exclusively outdoors, whereas research cats often have limited space and the access, or lack thereof, of pet cats to the outdoors is controlled by their owner. There are few studies of the activity patterns of pet cats and their results differ. A study with free-roaming pet cats reported a bimodal crepuscular activity pattern (Dunford et al., 2024). Similarly, Horn et al. (2011) reported a bimodal activity pattern for free-roaming pet cats, though this pattern was hypothesised to be driven by owner activity in the morning and evening, rather than sunrise and sunset. Another study reported that pet cats with extensive outdoor access were nocturnal, whereas pet cats with very limited outdoor access (only one hour per day) were highly synchronised with their owners and were more diurnal in their activity (Piccione et al., 2013). Statistical analyses, however, showed no rhythmicity in activity of the cats with limited outdoor access (Piccione et al., 2013, 2014). This absence of rhythmicity was attributed to the adaptation of the cat to the lifestyle of their owners, where human presence becomes a more dominant cue than the natural light-dark cycle. The activity of the cats with limited outdoor access was driven by the presence or absence of their owners rather than an endogenous clock. This resulted in a fragmented and irregular activity pattern.

2.1.2.2 Activity budgets of domestic cats

Understanding how much time an animal commonly spends displaying certain behaviours is required to identify when deviations occur. A small number of studies have reported the activity budgets of domestic cats (Table 2.1). Activity budgets collectively provide a general indication of which behaviours are most commonly displayed. The most common behaviours domestic cats display are sleeping and resting, which together account for more than half of their time (Table 2.1). Sleeping and resting are often grouped together, as they can be hard to distinguish from one another, and can be referred to as recumbent. When the sleep-wake cycle of research cats was monitored using brain activity, cats were found to be asleep and drowsy for more than 12 hours a day (Kuwabara et al., 1986). Other commonly observed, but less frequent, behaviours include grooming, locomotion, and eating and drinking (Table 2.1).

Table 2.1. Overview of studies on activity budgets of domestic cats.

Paper	Country	Sample size	Cat class	Method	Behaviour*				
					Recumbent	Grooming	Locomotion	Eating/ drinking	Hunting
Berteselli et al., 2017	Italy	10	Pet (indoor)	Continuous focal sampling	44.5%	9.7%	6.1%	Grouped[1]	n.i.
Eckstein & Hart, 2000b	United States of America	11	Research (indoor)	Continuous from videorecording	50.0%	4.0%	Grouped[2]	3.0%	n.i.
Hernandez et al., 2018	United States of America	26	Stray	Continuous from videorecording (attached to cat collar)	89.5%	Grouped[3]	9.0%	0.6%	0.9%
Kim et al., 2019	Republic of Korea	10	Research (indoor)	Videorecording	70.0%	2.3%	Grouped[4]	1.37%	n.i.
Panaman, 1981	England		Farm	Instantaneous focal sampling	61.9%	14.5%	2.7%	2.3%	14.8%

* n.i. = not included in study

[1] Eating and drinking were included in 'maintenance', defined as "Eating, stretching, defecating, urinating, sneezing etc.'

[2] Locomotion was included in 'general activity', defined as "Sitting (usually attending to environmental stimuli) or mobile (exploring, playing), while not engaged in another specific behaviour."

[3] Grooming was included in 'inactive states', which included sleeping, grooming and resting. Though a % of total time was reported for sleeping/resting (recumbent), this was not done for grooming.

[4] Locomotory behaviours were included in 'general activity', which included "…moving about the cage and sitting where grooming could easily occur."

Studies indicate that there are variations in the time domestic cats spend on specific behaviours (Table 2.1). Berteselli et al. (2017) reported that indoor pet cats spent about 45% of their time recumbent, whereas Hernandez et al. (2018) reported that number to be almost 90% in stray cats. Pet cats, however, were observed for only two 10-minute sessions per individual, over six days while the owners were present. As previously discussed, human presence can increase the activity of cats (Parker et al., 2017, 2019; Smit et al., 2022), so it is likely that the 45% is an underestimation of the total time cats spent recumbent. Eating and drinking behaviour ranged from 0.6% Hernandez et al. (2018) to 3.0% (Eckstein & Hart, 2000b). However, it should be noted that in the study by (Hernandez et al., 2018), eating behaviour was only recorded when stray cats were eating from the food provided at the feeding station, and thus may be an underestimation.

It is not uncommon for behaviours to be grouped together in studies. Hernandez et al. (2018), for example, grouped grooming with resting and sleeping, and Eckstein and Hart (2000b), and Kim et al. (2019) both grouped locomotion with sitting into an active category. Grouping behaviours can be a practical way to simplify complex data for analysis, allowing researchers to focus on certain behaviours of interest or broader patterns. However, this approach has significant drawbacks, the most important one being a loss of nuance. Oversimplification can lead to misinterpretation. For example, grouping sitting, a generally low-energy state, as 'active' alongside locomotion masks important differences in both energy expenditure and behavioural intent. No clear ethological justification for the grouping of behaviours was given in any of these studies. The studies also differed in methods and duration over which the behaviours were assessed, with some using direct observation (Berteselli et al., 2017; Panaman, 1981), some scoring behaviours from video recordings (Eckstein & Hart, 2000b; Kim et al., 2019), and others classifying behaviour from a collar-mounted camera (Hernandez et al., 2018). These differences in methodology are another factor that contributes to the often highly variable and not directly comparable results from different behavioural studies in cats.

2.1.2.3 Interindividual variation

Many animal studies require multiple animals to be included to ensure sufficient statistical power. If a behaviour is of importance in a study, careful selection of group size is needed to account for individual variability. In domestic cats, several studies have identified considerable interindividual variation in activity. For example, Andrews et al. (2015) reported a high interindividual variation in physical activity (PA) when measured using an accelerometer. Another two studies found a high degree of variability between individuals in the distances covered throughout the day, despite those individuals being housed under the same conditions (,et al., 2017; 2019). Furthermore, research suggests that there is variation among behavioural rhythms of cats throughout the day (Johnson et al., 1983; Randall et al., 1985; Refinetti et al., 2016).

Refinetti et al. (2016) studied the chronotype (diurnal, nocturnal, etc.) of different mammalian species and identified that the interindividual variation in both onset of activity and activity patterns was high for domestic cats. Despite reporting that most research cats were nocturnal under strictly controlled conditions, both Johnson et al. (1983) and Randall et al. (1985) observed that some cats were diurnal and some even arrhythmic. Thus, caution is needed when analysing activity or behavioural data from groups of cats. Therefore, a more appropriate approach to researching cat behaviour may be an individualised approach, with each cat serving as its own control.

2.1.3 Seasonal and meteorological associations

As previously established, the naturally occurring light-dark cycle is an important cue to which a domestic cat entrains its behavioural rhythms. However, the pattern of the light-dark cycle can fluctuate significantly throughout the year, depending on the latitude of the location. In equatorial regions, the fluctuation is minimal, but as one travels further away from the equator, this fluctuation becomes more noticeable and extreme. This fluctuation in the light-dark cycle is an important driver of the seasons, so in equatorial regions there are often simply wet and dry seasons, while spring, summer, autumn and winter become more apparent with increasing latitude (Bikos & Kher, n.d.).

A study conducted with indoor research cats under natural light conditions with constant temperature and relative humidity, reported that season was associated with the daily distance covered by cats (Parker et al., 2022a). Maximum distances were covered in both spring and autumn, while the cats covered the lowest distance in winter. Since temperature and relative humidity were constant, the most likely trigger for changes in activity, as measured by distance covered, was daylength. Similar results were reported for free-roaming pet cat activity measured using radio-tracking and a movement sensor: PA was highest in spring and autumn, and lowest levels in winter (Horn et al., 2011). They also studied the PA of free-roaming unowned (stray) cats and reported the highest PA in autumn and winter, while it was lowest in spring and summer. They argued that the higher PA of the stray cats in the colder months was due to an increase in energy demands, resulting in increased foraging behaviour, whereas the lower PA of free-roaming pet cats was the result of the provision of food and shelter. Other studies, however, have reported fewer sightings of free-roaming cats in autumn and winter than in spring and summer (Goszczyński et al., 2009; Merčnik et al., 2023). The differences in results between studies, could be due to differences in the methods used, but also other factors, such as the exposure to weather or meteorological conditions, and these should be considered.

Seasons are often characterised by different meteorological conditions, such as changes in amount of precipitation and temperature. Ferreira et al. (2016) reported that free-roaming pet cats in Brazil were more active during the dry season than they were during the wet season. Several other studies reported a negative correlation between rain and activity in domestic cats (Goszczyński et al., 2009; Harper, 2007; Haspel & Calhoon, 1993; Izawa, 1983). For temperature, some studies reported a positive correlation with PA (Goszczyński et al., 2009; Haspel & Calhoon, 1993), while others reported a negative correlation (Smit et al., 2022). It is important to note that these studies were conducted in different countries, with different climates and temperature ranges, which could have led to different results.

2.1.3.1 Seasonal moulting and hair replacement

Moulting in domestic cats is a continuous, cyclical process of hair replacement regulated primarily by photoperiod (Baker, 1974; Hendriks et al., 1997; Ryder, 1976). Cats show a mosaic pattern in which follicles act independently, resulting in gradual shedding rather than a single obvious moult, ensuring the cat maintains a functional coat year-round (Baker, 1974; Ryder, 1976). The physiological mechanism driving this process is a single, annual sinusoidal cycle of follicle activity, with growth peaking in summer and reaching a minimum in winter (Hendriks et al., 1997; Ryder, 1976). Follicle activity rises with increasing daylength, but is never fully synchronized, as many follicles remain dormant even during peak growth (Ryder, 1976). This incomplete synchrony produces the gradual nature of moulting in domestic cats. While the physiological process is a single, continuous annual cycle, this cycle results in two distinct periods of increased shedding, which can be described as a biannual moult. These periods correspond to the shedding of the denser winter coat in spring and summer, and the replacement of the lighter summer coat in autumn and winter (Baker, 1974; Hendriks et al., 1998; Ryder, 1976). A large portion of the shed hair, about two-thirds, is ingested during self-grooming and is later passed in the faeces (Hendriks et al., 1998). Periods of increased hair loss during the two peak moulting phases are therefore expected to drive a corresponding rise in grooming behaviour, allowing cats to remove loose hair and maintain coat condition.

2.1.4 The home environment

The home environment is complex, consisting of a multitude of stimuli that can potentially affect the behaviour of a domestic cat. In New Zealand, for example, 83% of pet cats have both indoor and outdoor access, with only 11% living exclusive indoors (Companion Animals New Zealand, 2020). It is generally assumed that cats with outdoor access are more active than indoor-only cats (Rochlitz, 2005), although to date, there is only one study of pet cats that provides quantitative data to support this. Piccione et al. (2013) compared the PA, measured objectively with an accelerometer, of pet cats under two different housing conditions: one group were mainly housed indoors with one hour of access to a garden per day, while the other group had free access to the garden during the day and were kept outside during the night. The cats with the greater outdoor access had higher total PA than the cats kept mainly indoors. However, PA is a general measure and does not give information about specific behaviours, and to date, it is unknown how these different housing situations are associated to the activity budgets of pet cats.

Another important aspect in the life of pet cats is their social environment. The social environment can consist of humans, other cats, and/or other pet animals (e.g., dogs). Some research has been conducted on cat-cat relationships, comparing the wellbeing of cats in single- and multi-cat households, although results are inconsistent and sometimes even contradictory, with high interindividual diversity (Finka & Foreman-Worsley, 2022; Foreman-Worsley & Farnworth, 2019). The degree of socialisation of kittens during the sensitive developmental period, between three and seven weeks of age (Karsh & Turner, 1988), and previous experience appears to play an important role in how individual cats respond to other cats and humans (Finka & Foreman-Worsley, 2022). Familiarity also plays a role in the relationship between cats, with related cats being more friendly to one another (Bradshaw &

Hall, 1999), and interacting more with one another than with unrelated cats (Parker et al., 2017). Another study found that related pet cats living in the same home had completely overlapping home ranges, both indoors and outdoors (Barratt, 1997). The same study found that unrelated cats in the same home had overlapping core areas (house and yard) and were amicable to one another within them but tended to have non-overlapping areas outside of the core areas (Barratt, 1997). A study conducted in a home with 14 unrelated pet cats found that unrelated cats time-share resources, such as favoured resting spots, thereby avoiding conflict (Bernstein & Strack, 1996). In this home study, there were one or two dominant cats with no clear hierarchy below these evident to the observers (Bernstein & Strack, 1996). No fighting between the cats was observed and it was hypothesised that the hierarchy was likely developed and maintained in subtle ways, which were not easily distinguished by the human observers.

While the dynamics of relationships between cohabitating cats have been a focus of behavioural research, research into the relationship between with other household members, particularly companion dogs and children remain sparse. One of the few published studies that directly observed the interaction between cohabitating companion cats and dogs found that cats were more likely to be amicable towards dogs if the first encounter took place when the cat was less than six months of age (Feuerstein & Terkel, 2008). The study also reported that both cats and dogs were able to understand the body language of the other species, despite some of the postures having an opposite meaning.

Turning to cat-human interactions, much of the existing research focuses on how companion animals contribute to the child's development and welfare (Groenewoud et al., 2023; Melson, 1990), while studies from the perspective of the cat are scarce. One of the few studies to address this, is a survey-based study by Hart et al. (2018), which found that relationships between children and cats are often looking at the relationship between cats and their owners found that a cat-child relationship was perceived as less affectionate than those between cats and adults. The study suggested that the behaviour of the cat is often the limiting factor, with parents reporting that cats were less affectionate toward children aged between three and five than toward adults. Such situations can create conflict, as children seek affection while cats may perceive their advances as threatening and respond by withdrawing or becoming defensive. This dynamic can be negative for both child and cat, with the child facing rejection and the cat experiencing stress. The study identified several risk factors for these outcomes, including the cat being older or the only cat in the home, which was associated with increased aggression. Given these findings, it is clear that both cat-dog and cat-child relationships are complex and can significantly impact the welfare of companion cats. Currently, no other studies have been published in this area, and more in-depth studies are needed on both cat-dog and cat-child relationships and how they affect the domestic cat.

To date, studies of how a complex home environment can affect the behaviour of pet cats have not been carried out. Most studies regarding the effect or association of an environmental factor have been conducted in shelters, catteries or laboratories (Foreman-Worsley & Farnworth, 2019). Since both research cats and shelter cats live under different conditions to the home, results from these studies are not necessarily transferable to pet cats. Specifically, the controlled and often simplified environment of research settings cannot replicate the dynamic social and physical complexity of a home environment. Research cats, for instance, often have limited space and scheduled human interaction, which can alter natural circadian rhythms and activity budgets compared to free-roaming pet cats with constant access to varied stimuli. Furthermore, social dynamics, such as the formation of relationships with children or dogs, create behavioural challenges and responses, such as heightened alertness (Hart et al., 2018), that are absent in research colonies. However, it is not surprising that few studies regarding the behaviour of pet cats in a home environment have been conducted. The multi-factorial character of the home environment, the uniqueness of each home, and the individuality of each cat makes these types of studies very complex. In addition, behavioural studies inside a private home can raise privacy concerns, particularly when they involve direct or indirect observation methods, such as video recording.

2.1.5 Methods for physical activity and behavioural observations

Methods used in animal behaviour studies have evolved significantly over time, partly driven by advances in technology. Traditionally, researchers relied on direct observation of the animal(s) and manual recording of behaviours, using an ethogram (Altmann, 1974; Dawkins, 2007). Though effective, the direct observation method is labour intensive, limited by the ability of the observer to continuously monitor animals, especially for long periods or in challenging environments, and subjective (Altmann, 1974; Dawkins, 2007). The emergence of video recording allowed more detailed capture and analysis of behaviours to occur, with the ability to pause and review footage multiple times, thereby limiting the effect of observer fatigue (Dawkins, 2007). Video recording, when operated from a distance or remotely, can also limit or eliminate the potential effect the presence of the observer can have on animal behaviour (Dawkins, 2007). More recently, animal-mounted cameras have been used to capture behaviour (Hernandez et al., 2018; Huck & Watson, 2019). Although video recording can limit the effects of observer fatigue, it is still labour intensive, as the behaviour must still be scored manually. The integration of automated tracking technologies into animal behaviour research enables continuous monitoring of animals in their natural habitats, providing high-resolution data on movement, activity patterns, behaviour and physiological states, without the need for a human to be present (Wilson et al., 2008).

Radio telemetry is a widely used tracking technology, which includes techniques such as radio-tracking, very high frequency (VHF) transmitters, and Global Positioning System (GPS) tracking. These techniques can be used to determine the location of an animal and have been frequently used in domestic cat studies to determine, for example, home ranges (Hall et al., 2016). Several studies, however, have reported the blocking of signals when cats were inside buildings (Horn et al., 2011; Langham, 1992; Thomas et al., 2014). Parker et al. (2017) validated the use of ultrawide band (UWB) tags – a form of radio telemetry – in an indoor research environment to monitor the location of cats and the distance they travelled, thereby overcoming these limitations. However, while radio telemetry techniques can provide valuable information on when and where animals are most active, they do not give detailed information about specific behaviours.

Accelerometers have emerged as a highly effective tool to measure PA and behaviour in a range of animal species (Brown et al., 2013; Wilson et al., 2008). Accelerometers can detect and record changes in movement and acceleration in one or multiple axes, enabling the capture of intensity, frequency and duration of the activities of an animal (Santos-Lozano et al., 2011; Watanabe et al., 2005). A more detailed description of how accelerometry works, and how it can be used to quantify PA and behaviour, is given in section 1.2. As early as 2005, Watanabe et al. (2005) used accelerometer data to successfully differentiate behaviours of a single cat. Since then, in domestic cat research, accelerometers have predominantly been used to quantify PA, but few further advances were made in behavioural classification (Garcia &

Chebly, 2024). The most commonly used device has been the Actical® (Mini Mitter, Bend, OR, USA) accelerometer, which has been validated to quantify PA of domestic cats (Andrews et al., 2015; Lascelles et al., 2008). The Actical® quantifies PA by processing raw acceleration data to generate a metric known as 'activity counts'. However, the specific algorithm used for this conversion is proprietary, meaning the resulting counts are device-specific that does not allow for direct comparison across different accelerometers (Chen & Bassett, 2005). Activity counts are a relatively simple measure to analyse and can easily be summed to generate hourly, daily or weekly values, so do not necessarily require the data to be collected at a high frequency. However, several studies have highlighted the importance of sampling frequency relative to body movement for the classification of animal behaviour, often referring to the Nyquist-Shannon sampling theorem to determine minimal sampling frequency (Brown et al., 2013; Chen & Bassett, 2005; Nathan et al., 2012; Tatler et al., 2018). This theorem states that the sampling frequency should be at least twice the frequency of the fastest body movement (Shannon, 1949). In domestic cats, jumping, for example, can have a duration of only 0.188 seconds (Sharon et al., 2020), requiring a minimum sampling frequency of 11 Hz (i.e., 11 datapoints per second) to be able to correctly classify it in a dataset. This high sampling frequency can easily lead to very large datasets that can be complex to analyse. However, with the increased availability of machine learning (ML) to process such large datasets, the classification of cat behaviour using accelerometer data has received renewed attention (Garcia & Chebly, 2024). Although the pre-processing of data for a ML model can be labour intensive (Brown et al., 2013), once a good model has been created, it can be deployed on previously unseen data and without any direct or indirect observation of the animal. A more detailed explanation on the use of ML in animal behaviour research is given in section 2.3.

2.1.5.1 Commercial companion animal trackers

Nowadays, both pet cats and dogs are often regarded as family members by their owners, which goes hand in hand with owners being more invested in ensuring good health and welfare (Companion Animals New Zealand, 2020; Forrest et al., 2023). It should, therefore, not be surprising that commercial companion animal trackers have been developed to allow owners to monitor their companion animals (Table 2.2). The overview in Table 2.2 has been compiled using a systematic search in PubMed in combination with Connected Papers and google search engine. Trackers were excluded if they were GPS-only, if they were no longer actively sold (as per September 2025), and if they did not have their own company website.

The majority of the trackers listed in Table 2.2 are available and marketed for pet dogs only (n = 13), with only four specifically for pet cats, and three for both species. Garcia and Chebly (2024) stated a few reasons for the greater interest in classifying dog behaviour than cat behaviour. One of these reasons is that dogs are easier to train and therefore easier to instruct to display specific behaviours like sitting, lying or walking, making data collection for these behaviours easier. Secondly, dogs also perform a range of services and duties, such as guiding blind people, police and rescue services and shepherding.

The trackers differ in the information they provide to the owner, with some only giving information about PA and location (e.g., Halo Collar 3), and others giving information about different behaviours and calories burned (e.g., Whistle trackers). Of the commercially available trackers, very few have been validated. The validated trackers are all designed for dogs: the FitBark (Colpoys & DeCock, 2021) and Heyrex (Bolton et al., 2021; Mejia et al., 2019) are both validated for PA, the PetPace has been validated for PA (Belda et al., 2018; Ortmeyer et al., 2018) and heart rate (Görisch, 2020), and the Whistle has been validated for PA (Yashari et al., 2015) and behaviour classification (Chambers et al., 2021). The Heyrex was validated to quantify PA of domestic cats (Andrews, 2021), but currently is not marketed for them.

Table 2.2. Overview of commercially available companion animal trackers (GPS-only trackers not included), the animal they are available for and their data output.

Device	Country of origin	Available for	Output
Actijoy	Czech Republic	Dog	Physical activity, rest/sleep, calories
Animo	United States of America	Dog	Physical activity, rest/sleep, barking, scratching, shaking, calories
Felcana go	United Kingdom	Dog, cat	Physical activity, sleep, calories
Fi	United States of America	Dog	Steps, sleep, location
FitBark 2	United States of America	Dog	Physical activity, sleep, calories
FitBark GPS	United States of America	Dog	Physical activity, sleep, calories, location
Halo Collar 3	United States of America	Dog	Physical activity, location
Heyrex™ 2.0	New Zealand	Dog	Running, walking, awake/moving, sleeping, scratching, location
JAG GPS S2	France	Dog	Physical activity, sleep, calories, location
Kippy CAT	Switzerland	Cat	Steps, running, playing, walking, grooming, sleeping, feeding, jumping, calories, location
Kippy EVO	Switzerland	Dog	Steps, running, play, walking, sleeping, calories, location
LavvieTAG	Republic of Korea	Cat	Physical activity, sleep, walking, running, zoomies, calories
Link	United States of America	Dog	Physical activity, steps, calories, location
Moggie	United Kingdom	Cat	Physical activity, sleep, play, jump
Pawfit 3	United Kingdom	Dog, cat	Physical activity, rest, calories, location
PetPace	United States of America	Dog, cat	Physical activity, sleep, calories, body temperature, respiratory rate, heart rate, location
PitPat Dog Activity Monitor	United Kingdom	Dog	Running, walking, playing, calories
PitPat GPS Tracker	United Kingdom	Dog	Running, walking, playing, calories, location
Tractive CAT Mini	Austria	Cat	Physical activity, sleep, location
Tractive Dog 4	Austria	Dog	Physical activity, sleep, location

2.2 Accelerometry

Accelerometry measures the movement of an object in terms of acceleration and is generally measured in gravitational units (g; 1 g = 9.81 m·s-2; Chen & Bassett, 2005). Accelerometers are devices used to measure movement by converting acceleration into a proportional electrical signal using a sensor. Generally, an accelerometer contains a mass of a known weight (seismic mass) suspended in a casing or housing. When subjected to acceleration, the seismic mass undergoes inertial forces, causing it to move relative to the housing. There are different ways in which the seismic mass can be suspended within the housing, including based on displacement (Figure 2.1a) or a cantilever beam (Figure 2.1b). Modern accelerometers are often micro-electro-mechanical systems (MEMS). Using the MEMS fabrication technology allows for the manufacture of very small devices (Alegria, 2022).

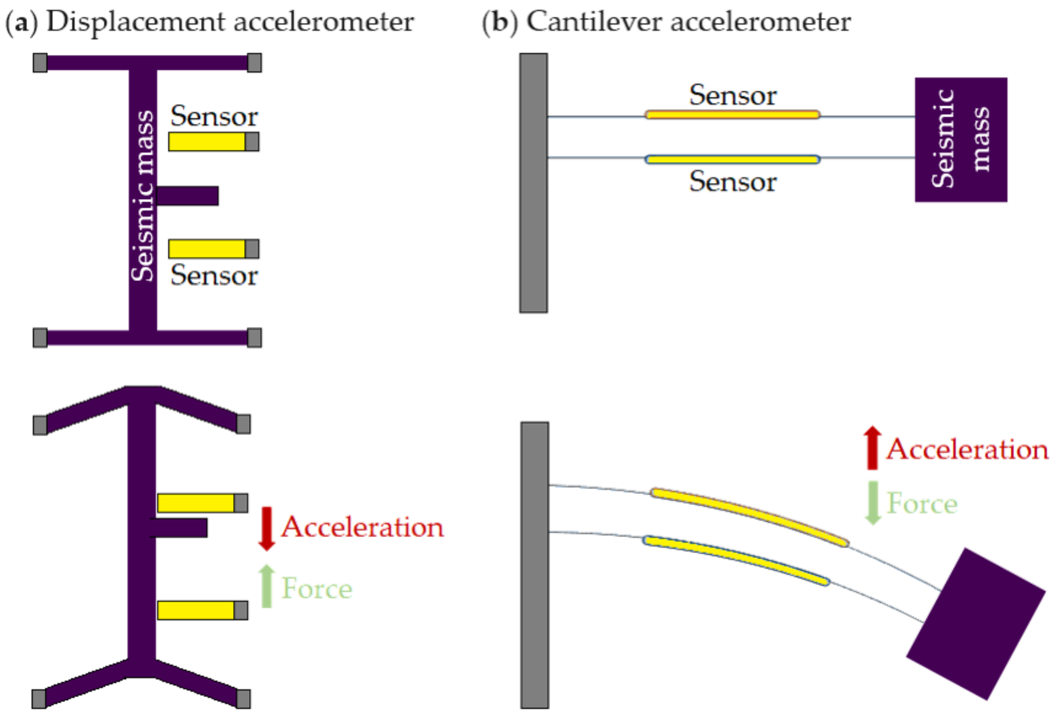

Figure 2.1. Example of a (a) displacement and (b) cantilever accelerometer.

Micro-electro-mechanical systems accelerometers can contain any of the three types of sensors that are generally used in accelerometers: (1) capacitive, (2) piezoelectric, and (3) piezoresistive (Hanly, 2016). Capacitive sensors measure changes in capacitance, which is the ability of a material or component to store an electric charge (Alegria, 2022; da Silva et al., 2006). A capacitive sensor consists of two conductive plates separated by a non-conductive (dielectric) material (Figure 2.2a). When a force acts upon the sensor, the capacitance between the two plates changes, resulting in a change in the voltage. Piezoelectric sensors use the ability of certain crystals (e.g., quartz) to become electrically polarised when mechanical stress is applied (Figure 2.2b; Alegria, 2022; da Silva et al., 2006). While piezoelectric sensors generate an electric charge in response to a force, they do not measure static accelerations (Alegria, 2022). Piezoresistive sensors measure changes in the resistance of flexible materials with piezoresistive materials integrated within them (Figure 2.2c; Alegria, 2022; da Silva et al., 2006). When a force is applied, the material deforms, causing a change in resistance.

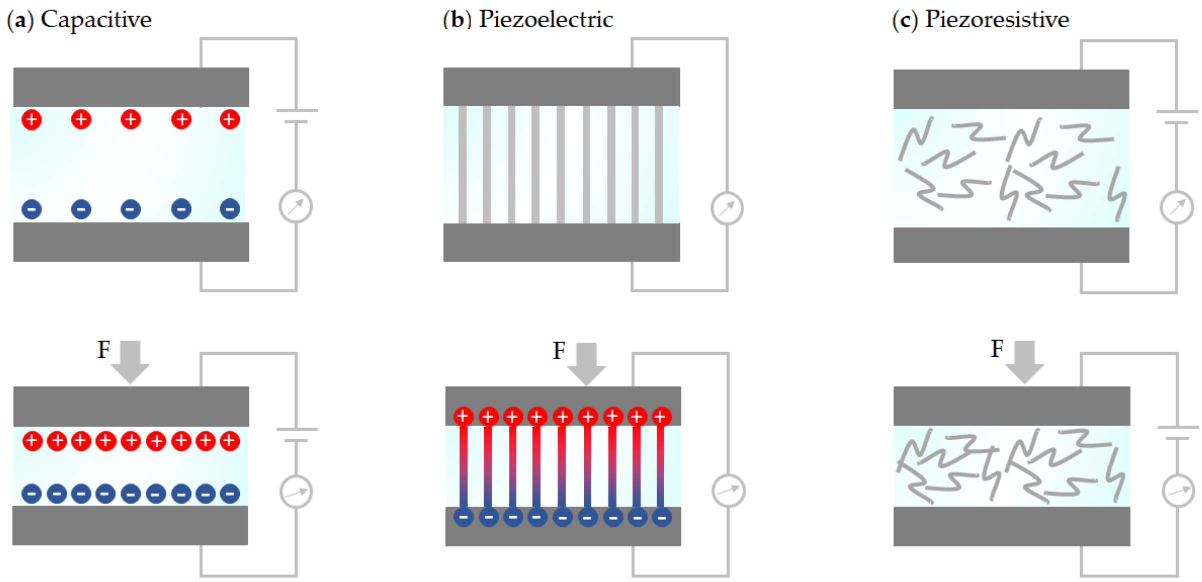

Figure 2.2. Working mechanism of a (a) capacitive, (b) piezoelectric, and (c) piezoresistive sensor. F = force. Figure adapted from Wang et al. (2019).

2.2.1 Newton's laws

Newton's laws of motion describe the relationship between the motion of an object and the external forces acting on it. Acceleration (a) denotes a change in velocity (Δv) of an object over time (Δt; equation 2.1; Gleiss et al., 2011).

2.1) $a = \Delta v / \Delta t$

Velocity (v) is the rate (Δt) at which an object changes its position (Δs) in a particular direction (equation 2.2). Velocity is similar to speed but also includes the direction.

2.2) $v = \Delta s / \Delta t$

Newton's first law of motion, also referred to as the law of inertia, states that an object is at constant velocity, or rest, unless an external force acts upon it to change the motion. To apply a force, energy in the form of work (W) is transferred to or from the object. The work required is denoted by the force (F) required over a given distance (d; equation 2.3).

2.3) $W = F * d$

According to Newton's second law, force can be calculated by multiplying the mass (m) of an object by its acceleration (a; equation 2.4).

2.4) $F = m * a$

Work is the transfer of energy (E) onto an object and both work and energy are expressed in joules (J), and the amount of energy is equal to the work done. Neither work nor energy consider the time it takes a force to cause displacement of the object (Wilson, 2020). The power (P) is defined as the amount of work (W), or energy, transferred to the object per unit time (t; equation 2.5).

2.5) $P = W/t$

Combining the above equations, the equation for power (equation 25) can be substituted (equation 2.6).

2.6) $P = \frac{W}{\Delta t} = \frac{F*d}{t} = F * v = m * a * v$

2.2.2 Six degrees of freedom

There are six basic ways in which a rigid body can move through a three-dimensional space, also referred to as the six degrees of freedom (DoF; Figure 2.3a; Noda et al., 2012). Similarly, the movement of an animal as a whole can be described in terms of six DoF: three translational and three rotational (Fish, 2004). The translational DoF correspond to movement along the X, Y, and Z axis, commonly described as moving forward-backwards (surge), left-right (sway), and up-down (heave), respectively (Figure 2.3b; Brown et al., 2013; Noda et al., 2012). The rotational DoF correspond to movement around the X-, Y-, and Z-axis, commonly referred to as roll, pitch, and yaw, respectively (Figure 2.3a; Noda et al., 2012). The translational DoF correspond to anatomical directions, where surge is craniocaudal movement, sway mediolateral, and heave dorsoventral (Table 2.3; Brown et al., 2012). It should be noted that the orientation of the accelerometers can change the anatomical direction each axis corresponds to. Accelerometers can contain between one and three accelerometer sensors that are aligned orthogonally to one another, so that each sensor measures acceleration in one of three dimensions: surge, sway, and heave (Brown et al., 2013).

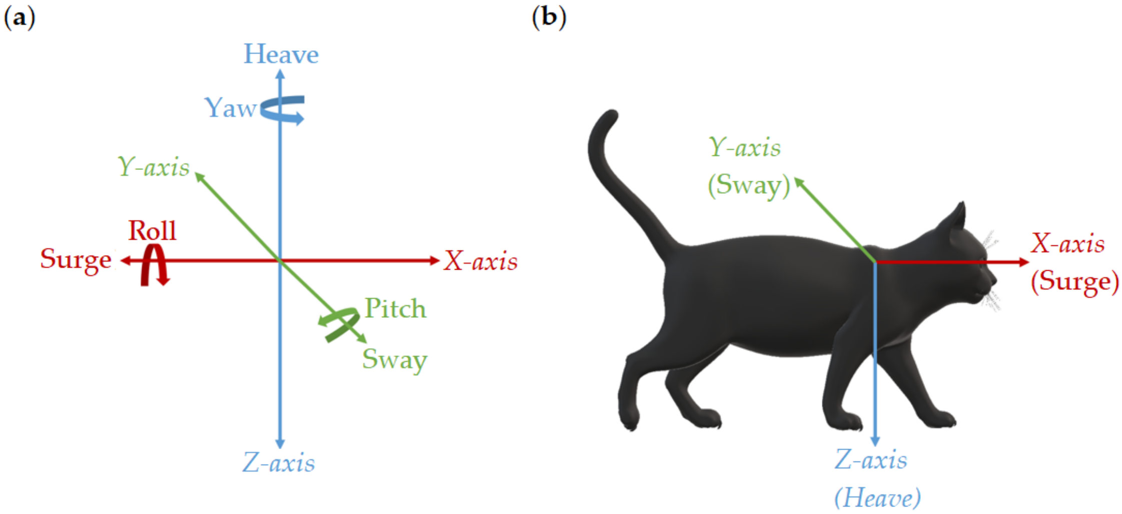

Figure 2.3. Overview of the (a) six degrees of freedom (DoF) and (b) translational DoF applied to a domestic cat as can be measured with an accelerometer.

Table 2.3 Overview of dimensions and corresponding anatomical directions of a quadruped animal as depicted in figure 2.3b.

Axis	Translational DoF	Directional term	Anatomical direction	Direction
X-axis	Surge	Craniocaudal	Cranial/caudal	Forwards/backwards
Y-axis	Sway	Mediolateral	Medial/lateral	Side-to-side, left/right
Z-axis	Heave	Dorsoventral	Dorsal/ventral	Up/down

2.2.3 Possible applications of accelerometers in animals

2.2.3.1 *Energy expenditure of physical activity*

In animals, mechanical work is facilitated by muscles, converting energy into movement by muscular contraction. Following the equations outlined in section 2.2.1, it is evident that acceleration is proportional to (mechanical) work and power; or in the case of energy expenditure, to energy expended through PA. Acceleration is a vectorial quantity, having both direction and magnitude, so the total acceleration (A) can be calculated by the vectorial sum of the acceleration measured in all three axes (equation 2.7; Gleiss et al., 2011):

2.7) $$A_{total} = \left({A_X}^2 + {A_Y}^2 + {A_Z}^2\right)^{0.5}$$

Acceleration measured with an accelerometer consists of both static and dynamic components (Wilson et al., 2008). Of these two, only the dynamic component is the result of animal movement and therefore represents PA. The dynamic component, also referred to as dynamic body acceleration (DBA; Wilson et al., 2006), thus needs to be separated from the static component. The static component can be approximated by smoothing the acceleration for each axis separately (Wilson et al., 2006) or by using proprietary filters (Chen & Bassett, 2005). The smoothed (or filtered) acceleration data are then subtracted from the acceleration for each axis, resulting in a separate DBA value for each axis. Wilson et al. (2006) were the first to formalise DBA. Following the derivation of DBA, they summed the absolute values of the DBA of each axis to calculate the overall dynamic body acceleration (ODBA; equation 2.8; Wilson et al., 2006).

2.8) $$ODBA = |DBA_X| + |DBA_Y| + |DBA_Z|$$

Overall dynamic body acceleration, however, does not consider that acceleration is a vectorial quantity. Following equation 2.7, the total vectorial DBA (VeDBA) is then calculated (equation 2.9).

2.9) $$VeDBA = \left(DBA_X{}^2 + DBA_Y{}^2 + DBA_Z{}^2\right)^{0.5}$$

Accelerometers only detect changes in acceleration as a result of animal movements, and therefore, can only be used to approximate the amount of energy expended (EE) through PA. As the proportion of PA to the EE decreases, so does the power of accelerometry to approximate EE (Wilson et al., 2019). For a more detailed explanation on the use of acceleration as a proxy for energy expenditure, see Gleiss et al. (2011).

2.2.3.2 *Physical activity*

Physical activity has been defined as "any bodily movement produced by skeletal muscles that results in energy expenditure" (Caspersen et al., 1985). To obtain a single value to quantify PA, raw acceleration data is converted into an "activity count" (Chen & Bassett, 2005). To generate these counts, raw acceleration data is pushed through a filter and run through algorithms, which, as explained before, are generally proprietary. Thus, the count from one accelerometer cannot be directly compared to that of another. Physical activity is the direct result of behaviour, and although counts can give information about the intensity and duration of movement, they do not give any information about the behaviour of an individual.

2.2.3.3 *Animal behaviour*

Animal behaviour is characterised by movement of the body or its appendages (Levitis et al., 2009), which can be measured with an accelerometer. Locomotory behaviours, such as walking, running, and jumping, each have their own unique acceleration signature (Brown et al., 2013; Halsey et al., 2011; Shepard et al., 2008). Running, for example, is a more intense behaviour and requires more energy than walking, which is reflected in the acceleration output. Apart from active movement along the three translational DoF, the inclinational angle of the accelerometer axes also affects the accelerometer output (Chen & Bassett, 2005). A triaxial accelerometer that rotates around its own centre, without moving along any of the three translational DoF, will have different acceleration output values depending on the inclination of the axes angle relative to gravity (Figure 2.4). This enables the distinction between static behaviours that differ in posture, such as standing and sitting. Machine learning models can be trained using accelerometer data to classify behaviours based on their unique acceleration signatures (Figure 2.5; Yoda et al., 1999).

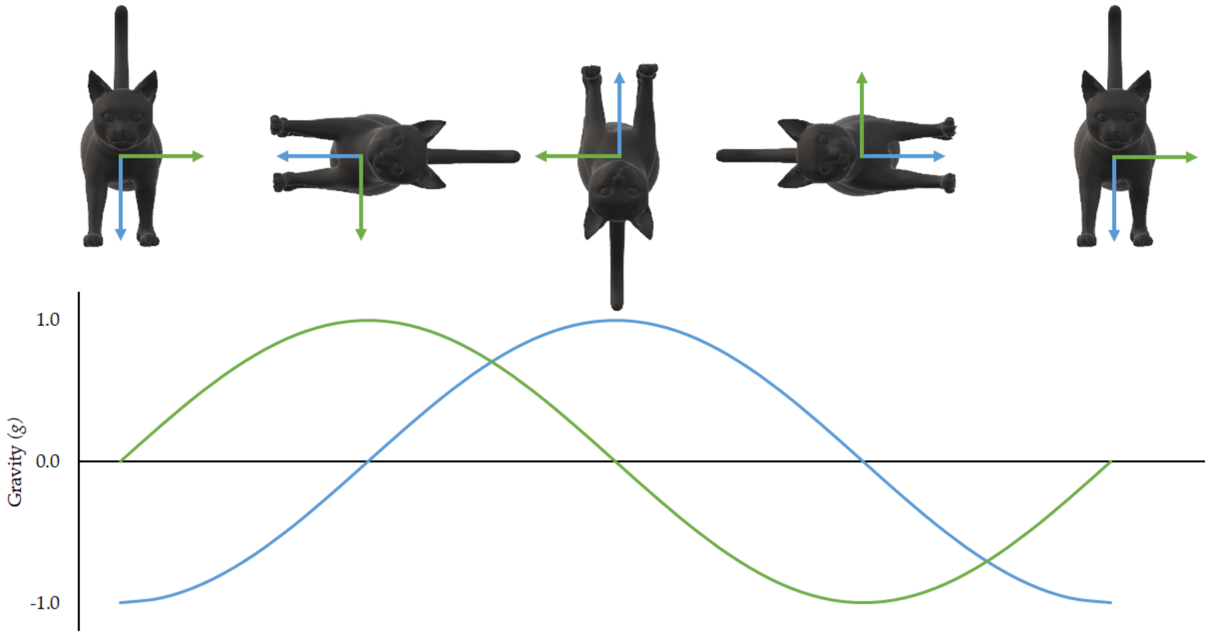

Figure 2.4. Example of acceleration output (*g*) for two axes of a rotating triaxial accelerometer mounted on a rotating domestic cat. Green corresponds to the *Y*-axis and blue corresponds with the *Z*-axis, as defined in Figure 2.3.

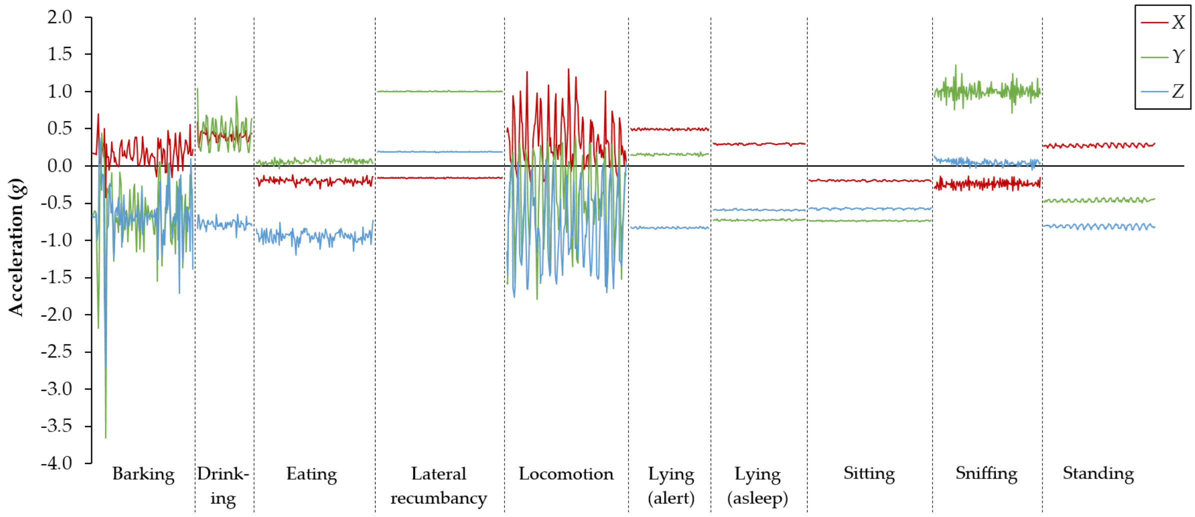

Figure 2.5. Unique acceleration signatures for different behaviours of a single domestic dog (*Canis familiaris*) using raw acceleration data (*g*), collected at 30 Hz. Figure adapted from Redmond et al. (2024).

2.3 Machine Learning in animal behaviour research

Machine learning (ML), a subfield of artificial intelligence, has emerged as a powerful tool for quantitatively analysing animal behaviour. When paired with accelerometer data from wearable sensors like accelerometers, ML algorithms can learn to automatically classify behaviours of an animal from complex movement patterns, offering a powerful method for continuous and monitoring that avoids the limitations and potential biases of human observation (Altmann, 1974; Dawkins, 2007). However, the path from raw accelerometer data to reliable behavioural insights is not straightforward. The application of ML for behavioural classification presents unique methodological challenges, such as naturally unbalanced datasets (e.g., one behaviour is more frequent than others), behavioural variation between individual animals, and the potential for misleading performance metrics require a critical approach. This section will provide an overview of the ML workflow, from data collection with a triaxial accelerometer to model evaluation, while highlighting the specific considerations and trade-offs involved in using these techniques to classify domestic cat behaviour from accelerometer data.

2.3.1 Data acquisition and supervised learning

Data collection is a fundamental part of carrying out research. When using ML, the choice of which ML algorithm(s) will be used, dictate how the data needs to be collected. When the goal is to classify specific, predefined behaviours, the most used ML paradigm is supervised learning (Brown et al., 2013). In supervised learning, a model is trained on labelled examples (Geetha, 2023). For animal behaviour, this means the model must learn what the acceleration pattern of each behaviour looks like, using a dataset where every datapoint is matched with the correct behavioural label. Consequently, the selection of supervised learning requires simultaneous collection of both accelerometer and observational data. Nowadays, it is common to capture animal behaviour via video recording. These video recordings need to be manually annotated, where the correct behavioural labels are assigned to a specific timestamp. An important and often challenging step in this process is aligning the sensor data with the video-based labels to ensure each accelerometer signal is correctly matched to the observed behaviour. Often this requires some manual alignment, matching peak accelerometer signals to high intensity behaviours (Chambers et al., 2021; Galea et al., 2021).

One of the key technical challenges in data acquisition, is choosing an appropriate sampling frequency. Higher frequencies are crucial for capturing details of rapid, short-duration movements, but they can quickly lead to massive datasets that require substantial computational power and limit the deployment period due to memory and battery constraints (Tatler et al., 2018; Yu et al., 2023). Conversely, lower frequencies are more energy-efficient and are computationally manageable but may fail to capture the signature of swift movements, though they can be effective for classifying slower and more static behaviours, such as sitting (Tatler et al., 2018). This creates an important trade-off between data resolution and practical feasibility that researchers must balance according to their specific study aims.

Another key component that needs to be carefully considered, is the physical placement of a sensor. A harness-mounted accelerometer, for example, has been shown to provide clearer signals for static postures compared to a collar-mounted accelerometer, which is prone to rotation and orientation-related noise (Brown et al., 2013; Kumpulainen et al., 2021; Wilson et al., 2008). Conversely, a collar-mounted accelerometer is more likely to pick up on fine-scale head movements involved with eating behaviour (Brown et al., 2013). While sensor placement affects the type and quality of movement signals captured, the behaviours themselves are equally important an equally important biological challenge. The supervised learning process is limited to the behaviours that are observed and labelled during data collection. Animal behaviours vary widely in how frequent and how long they occur, and some may be so rare that they may not occur at all during the limited window of video recording. Even when infrequent behaviours occur, they are greatly outnumbered by frequent behaviours. This leads to unbalanced datasets, a common characteristic of animal behaviour data that poses a major challenge for training unbiased and accurate ML models. There are different ways to handle unbalanced data in the machine learning pipeline, including during the data preparation stage.

2.3.2 Data preparation: translating movement into meaningful data

Real-world data are generally noisy, incomplete, and inconsistent (Geetha, 2023; Han et al., 2012), and raw triaxial accelerometer data may not provide enough information for the model to accurately differentiate between behaviours. Therefore, the raw data must undergo a multi-step preparation process, including cleaning, structuring and transformation to provide a classifier with the features needed to learn behavioural signatures. Before a machine learning model can be trained, this preparatory phase is essential to ensure data quality and consistency (Crabtree, 2022). This process encompasses two main stages: data pre-processing and feature engineering.

2.3.2.1 *Data cleaning and pre-processing*

A critical pre-processing consideration is the handling of outliers. In accelerometry, an outlier is not necessarily an error. It could represent a genuine, biologically significant but brief event, such as a jump, shake, or fight. Automatically removing these outliers risk removing valuable data on rare but important behaviours. Domain expertise is crucial to distinguish between sensor noise and true, high-intensity movements to avoid removal of key behavioural information.

Another step involves cleaning the raw accelerometer signals to remove noise and handle irregularities. Noise can originate from sensor artifacts, environmental interference, or irrelevant, non-behavioural movements that distort the true signal of interest (Brown et al., 2013; Wilson et al., 2008). The most direct approach to noise reduction in accelerometer data is the application of a band pass filter. Band pass filtering keeps only the frequencies within a chosen range and reduces those that fall outside of it (Chen & Bassett, 2005). However, there is a risk that filtering could eliminate behaviourally relevant high-frequency components, such as short bursts of activity like scratching, jumping or body shakes (Chen & Bassett, 2005). Rather than applying a filter to directly handle noise, noise can be handled indirectly with feature engineering.

2.3.2.2 *Feature engineering and selection*

When utilising accelerometers in combination with machine learning for animal behaviour classification, the raw accelerometer data is often segmented into short, fixed-length time windows, or epochs (e.g., 1-2 seconds). From each epoch, a set of descriptive statistic, known as features, is calculated. This process, called feature engineering, transforms the time-series data into a structured feature matrix where each row corresponds to an epoch and each column represents a calculated feature. This step is important because it provides more discriminatory information than the raw signals alone, and it reduces the size of the dataset, making it computationally more manageable when this is a concern. While the specific features vary between studies, they generally fall into several categories (Aguilar-Lazcano et al., 2023):

- **Time-domain statistical features:** These are the most common and calculates summary statistics such as the mean, standard deviation, variance, minimum, maximum, sum, skewness, and kurtosis calculated for each of the three axes (X, Y, Z). This process also averages out and smooths instantaneous, high-frequency noise within the window, acting as a form noise filtering.
- **Derived motion metrics:** These features combine data from the three axes into a single measure of movement of intensity. Overall dynamic body acceleration (ODBA; equation 2.8) and vectorial dynamic body acceleration (VeDBA; equation 2.9) are widely used metrics that provide an estimate of the energy expenditure and activity level of an animal.
- **Frequency-domain features:** Techniques like the Fast-Fourier Transform (FFT) can be used to convert time-series into its frequency components, revealing cyclical patterns such as the rhythmic motion of walking.

With feature engineering, hundreds or even thousands of potential features can be generated for each epoch. This leads to a significant challenge known as the "curse of dimensionality". As the number of features (dimensions) increases, the volume of the data space grows exponentially (Geetha, 2023). This can cause the data to become sparse, making it harder for ML algorithms to find meaningful patterns and increasing the risk of overfitting, where the model learns the noise in the training data rather than the true underlying signal (Jabbar & Khan, 2014). Conversely, a model with only a few features might not contain enough information for the ML algorithms to find meaningful patterns, resulting in underfitting (Jabbar & Khan, 2014). This makes feature selection a critical next step.

Feature selection is the process of selecting a subset of existing features from the original set of features (Geetha, 2023; Ozdemir & Susarla, 2018). Features that are irrelevant or redundant are removed, while features that are the most relevant are selected. Features can be selected based on domain knowledge, where experts select the most important features. Other approaches include filter methods to assess the relevance of features using statistical measures (e.g., ANOVA) or wrapper methods that use the performance of a specific ML algorithm to find the best features (e.g., through forward or backward selection). Some ML algorithms have embedded methods that can help in feature selection. Alternatively, feature dimensionality can be reduced through feature extraction, for which the Principal Component Analysis (PCA) is a prominent method. Unlike feature selection, which generates variables from the original data, PCA transforms the generated features into a smaller set of new, uncorrelated features, called principal components (Ringnér, 2008). An advantage of the PCA is its effectiveness in handling multicollinearity and reducing the feature space while retaining most of the variability in the data.

A key consideration during feature selection and extraction is how to handle correlated features. Some engineered features are inherently correlated (e.g., variance and standard deviation; mean and sum), a statistical property known as multicollinearity. While it is common practice to remove one feature from a highly correlated pair to reduce redundancy, this can risk discarding valuable information. Even when two features are highly correlated, the part of their variation that isn't shared can still hold important information for distinguishing behaviours with similar acceleration patterns. Model-based feature selection methods evaluate the importance of a feature based on its contribution to the predictive performance, thereby accounting for complex interactions and retaining features that are correlated, but still provide unique discriminatory information.

2.3.2.3 Handling imbalanced datasets

A defining characteristic of animal behaviour data is its imbalanced nature. Animals, particularly domestic cats, spend a large proportion of their time in passive states, like resting, lying or sitting (Berteselli et al., 2017; Hernandez et al., 2018; Kim et al., 2019). As a result, these majority behaviours dominate any collected dataset, while infrequent behaviours are severely underrepresented. If a ML model is trained on such an imbalanced dataset, it will become biased and it can easily achieve a high accuracy by simply predicting the majority class while failing to correctly identify minority classes. To address this, several balancing techniques can be used:

- **Undersampling:** This involves randomly removing samples from the majority class(es) to create a more even distribution.

- **Oversampling:** This technique creates synthetic samples for the minority classes to increase their representation. This can be achieved by using algorithms like the synthetic minority oversampling technique (SMOTE) (Chawla et al., 2002).
- **Class weighting:** This method assigns a higher penalty (weight) in the loss function of a model for misclassification of the minority classes (Hussain et al., 2022a).

Recent work in domestic dogs (*Canis familiaris*) has shown that balancing datasets can substantially improve classification accuracy and F1-score for minority behaviours (Abd El-latif et al., 2024). However, improving classification accuracy does not ensure that the derived behavioural proportions are unbiased. (Resheff et al., 2022) showed that when models are trained on balanced datasets, the resulting estimates of behavioural activity budgets were biased, because some behaviours were misclassified more often than others. Therefore, it is important to carefully consider whether the primary goal is to detect every instance of a rare behaviour, or to accurately quantify activity budgets.

2.3.3 Algorithm selection

Once the feature matrix is generated, machine learning can be used to learn the unique patterns in the acceleration signals that characterise different animal behaviours. As mentioned previously, the most common approach for classifying animal behaviour is supervised learning, where models are trained on data labelled with the correct behaviour. This is a classification problem because the goal is to assign observations to specific behaviour categories. Commonly used ML techniques to classify animal behaviour included random forest (RF), support vector machines (SVM), k-nearest neighbours (KNN) and convolutional neural network (CNN) (Aguilar-Lazcano et al., 2023). These methods have frequently been used in domestic dogs (Table 2.4) and other species (Aguilar-Lazcano et al., 2023). Among these, RF, an ensemble method that aggregated the results of many individual decision trees, is particularly prominent (Breiman, 2001). studies comparing the performance of different ML techniques consistently report that RF often performs best for animal behaviour classification. For instance, in a comparative study on griffon vultures (*Gyps fulvus*), RF achieved the highest accuracy (88%) compared to classification and regression trees (CART; 84%), linear discriminant analysis (LDA; 81%), SVM (84%) and artificial neural network (ANN; 85%) (Nathan et al., 2012). Similarly, a study on dingoes (*Canis dingo*) fount that RF models produced superior validation scores compared to SVM, KNN and Naïve Bayes, achieving a mean accuracy of 87% across 14 behaviours (Tatler et al., 2018).

More recently, deep learning models like convolutional neural networks (CNNs) and long short-term memory (LSTM) networks have been applied with considerable success to classify both dog and cat behaviour (Hussain et al., 2022a, 2022b, 2023). A key advantage of deep learning models is their ability to automatically learn relevant features directly from raw or minimally processed time-series data, reducing the reliance on extensive manual feature engineering. Conversely, many of these processes are black boxes, making deep learning models particularly hard to understand.

A systematic review of the literature on the validation of behaviour classification for domestic cats and dogs was conducted. The papers included in Table 2.4 were retrieved using Google Scholar. The search keywords that were included were: “cat”, “domestic cat”, “feline”, “dog”, “domestic dog”, “canine”, “behaviour”, “classification”, “machine learning”, “accelerometer”, “wearable sensor”. Papers were only included if they were in English or Dutch. Despite the growing body of research, cats are underrepresented in this area compared to dogs (Table 2.4). This is consistent with the trend towards dogs for the availability of commercial companion animal trackers, as previously outlined.

Table 2.4 Overview of used ML methods in behaviour classification using accelerometer data in domestic dogs and cats, including number of included behaviours, whether behavioural classes were balanced, and accuracy and F1-score.

Paper	Animal	Number of behaviours[1]	ML model(s)[1,2]	Classes balanced	Overall accuracy[3]	Overall F1-score[3]
Abd El-latif et al., 2024	Dog	7	CNN-LSTM	No & yes	86.7 – 96.7%	88.0 – 96.7%
Aich et al., 2019	Dog	7	RF, SVM, KNN, NB, ANN	Yes	84.5 – 96.6%	82.8 – 93.7%
Chambers et al., 2021	Dog	2-10	FilterNet	No	n.r.	n.r.
den Uijl et al., 2017	Dog	8	n.s. (proprietary)	No	n.r.	n.r.
Eerdekens et al., 2022	Dog	8	RF, CNN	No	95.6 – 96.4%	n.r.
Ferdinandy et al., 2020	Dog	8	SVM	No	41.0 -58.0%	n.r.
Galea et al., 2021	Cat	12	RF, SOM	No	98.9%, 99.6%	n.r.
Gerencsér et al., 2013	Dog	7	SVM	No	75.3 – 91.3%	n.r.
Hussain et al., 2022a	Dog	10	CNN	Yes	96.9%	n.r.
Hussain et al., 2022b	Dog	10	LSTM	Yes	94.3%	n.r.
Hussain et al., 2023	Cat	10	ANN, CNN, LSTM	Yes	93.3 – 95.9%	n.r.
Kestler & Wilson, 2015	Cat	10	RF	No	97.0%	n.r.
Kumpulainen et al., 2018	Dog	7	LDA, QDA	No	72.7 – 76.0%	n.r.
Kumpulainen et al., 2021	Dog	7	LDA, QDA, SVM, CT	No	70.6 – 91.4%	n.r.
Ladha et al., 2013	Dog	17	KNN	No	68.6%	n.r.
Marcato et al., 2023	Dog	5	RF	No	n.r.	81.0 – 90.0%
Muminov et al., 2022	Dog	6	SVM, KNN, CT, NB	No	n.r.	79.0 – 88.0%
Or, 2024	Dog	7	Transformer, LSTM, LSTM-CNN, Bidirectional-LSTM	No	97.6 – 98.5%	94.6 – 98.1%
Wang et al., 2022	Dog	3-9	SVM, CT, NB, LSTM	Yes	n.r.	66.0 – 94.7%
Winters et al., 2015	Dog	11	RF	No	88.6%	n.r.

[1] n.s. = not specified.

[2] CNN = convolutional neural network; LSTM = long short-term memory; RF = random forest; SVM = support vector machine; KNN = k-nearest neighbour; NB = naïve bayes; ANN = artificial neural network; SOM = self-organising map; LDA = linear discriminant analysis; QDA = quadratic discriminant analysis; CT = classification tree.

[3] n.r. = not reported.

2.3.4 Modelling: training and validating the classifier

Once a feature set has been engineered and a ML algorithm selected, the next step is to train a classification model and evaluate its performance. The standard procedure for this involves splitting the prepared, labelled dataset into at least two mutually exclusive subsets: a training set and a testing (or validation) set (Valletta et al., 2017). The model learns the complex patterns and relationships between the features and their corresponding behavioural labels from the training data. Its performance is then evaluated on the unseen testing data to assess how well it generalises to making accurate classifying new, previously unseen data (Valletta et al., 2017). This process is essential to ensure the model is not under- or overfitting, as previously described, but learns the underlying patterns of behaviour. While this training and validation framework is standard in machine learning, its application to animal behaviour presents unique challenges, primarily due to individual variation. Animals, even of the same species and breed, exhibit individual differences in their movement patterns, gaits, and behavioural expressions (Gerencsér et al., 2013). A model trained on a small number of individuals may fail to generalise effectively to new animals whose movement signatures differ slightly. This creates the risk that the model learns the individual patterns of the specific animals that make up the training set, rather than a generalisable representation of behaviour. For example, one study on dogs that classification accuracy for a single-subject model was over 90%, but this dropped to over 70% when the model was applied to different dogs of the same breed (Gerencsér et al., 2013). This highlights a critical requirement for robust validation methods.

To address these challenges, the method of splitting the data for cross-validation is crucial. A common technique is k-fold cross validation, where the data is randomly divided into k equal-sized folds. The model is iteratively trained on k-1 folds and tested on the remaining fold (Reitermanová, 2010; Ringnér, 2008). However, when using data from multiple individuals, a simple random split is not the most appropriate and can lead to overestimated accuracy metrics (Ferdinandy et al., 2020). This is because the data points from a single animal are highly correlated, and a random split will almost certainly lead to data from the same individual being present in both the training and testing sets (Ferdinandy et al., 2020). Therefore, a more robust validation strategy is the leave-one-subject-out cross validation (Ferdinandy et al., 2020). With this approach, the data is split by individual, ensuring that all data from one animal is held out as the validation set, while the model is trained on the data from all other animals. This process is repeated for each subject, and the performance metrics are averaged across all folds (Ferdinandy et al., 2020). This method provides a more realistic and conservative estimate of the ability of the model to generalise to a new, unseen population, which is the ultimate goal for most applications in animal behaviour research.

2.3.4.1 *Tuning and optimising the model*

A ML model consists of both parameters and hyperparameters (Hossain, 2024). Parameters are values that are learned and adjusted during the training process and directly affect the predictions of the model (Hossain, 2024; Sarkar, 2018). Hyperparameters are set before training the model and do not change during the training process (Hossain, 2024). The hyperparameters control the training process and can improve the performance of the model if tuned properly (Hossain, 2024; Sarkar, 2018). Different ML algorithms have different sets of hyperparameters, which can be visualised as a n-dimensional plot, where n is the number of hyperparameters (Figure 2.6; Hossain, 2024; Sarkar, 2018). Hyperparameter tuning is the process of finding the best possible settings for each hyperparameter. As mentioned before, to prevent data leakage, hyperparameter tuning is best done on a separate validation dataset.

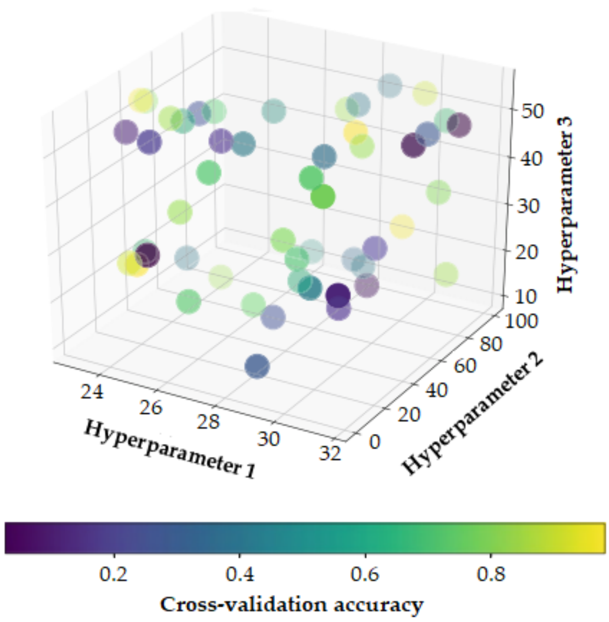

Figure 2.6. Example of a hyperparameter space consisting of three different hyperparameters. Adapted from Hossain (2024).

Though different algorithms have different hyperparameters, there are general hyperparameter tuning techniques that can be used. Examples of hyperparameter tuning techniques are:

- Manual search (Hossain, 2024): The data scientist or engineer manually selects and adjusts the hyperparameters of the model, until a satisfactory model performance is achieved.
- Grid search (Hossain, 2024; Sarkar, 2018): A grid of values for the hyperparameters is specified by the data scientist or engineer, and the model is fitted using all possible combinations (Figure 2.7a).
- Random search (Hossain, 2024; Sarkar, 2018): A random selection of combinations that are defined in the grid are fitted (Figure 2.7b).
- Bayesian optimisation (Hossain, 2024): Uses probabilistic models to find the optimal hyperparameters and rather than fitting every possible combination or a random selection of combinations, it considers the model performance of previous hyperparameter sets and selects the next hyperparameter set based on this information (Figure 2.7c).

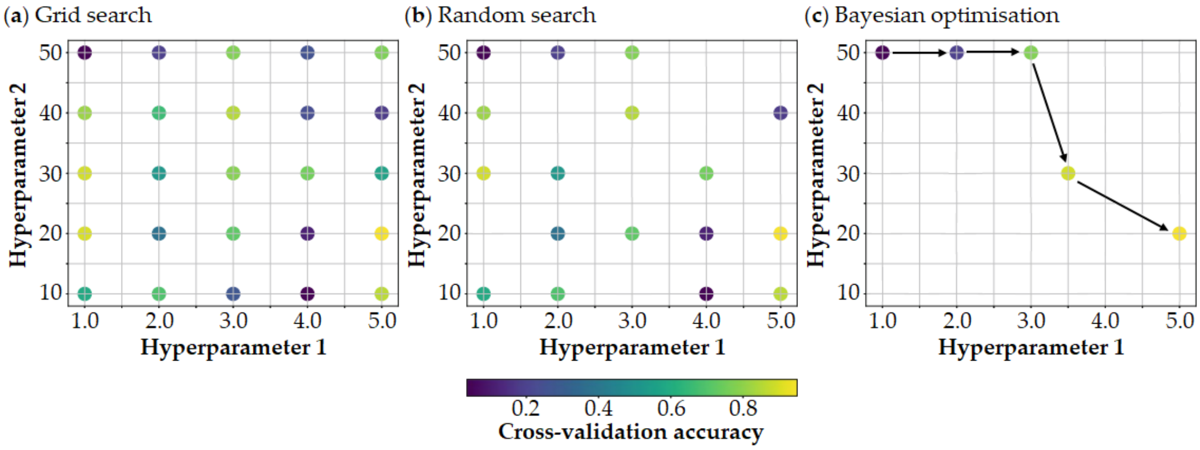

Figure 2.7. Examples of (a) grid search (b) random search, and (c) Bayesian optimisation as hyperparameter tuning techniques. Adapted from Hossain (2024).

2.3.5 Evaluating classifier model performance

For each trained model, the performance should be assessed so the optimal model can be selected. There are different evaluation metrics available to assess the performance of a classifier model, all of which are derived from a confusion matrix. A confusion matrix is a table in which the predicted class labels are compared to the actual observed class labels (Geetha, 2023; Hossain, 2024; Sarkar, 2018). A distinction can be made between a confusion matrix for binary (two classes) and multiclass classification (> two classes). In a confusion matrix for binary classification, four possible outcomes can be observed when comparing the predicted class labels to the observed class labels (Figure 2.8):

- True positive (TP): occurs when the class label is correctly predicted or classified.
- True negative (TN): occurs when the class label is correctly not predicted or classified.
- False positive (FP): occurs when the class label is incorrectly predicted or classified.
- False negative (FN): occurs when the class label is incorrectly not predicted or classified.

		Observed	
		C_1	C_2
Predicted	C_1	TP	FP
	C_2	FN	TN

Figure 2.8. Confusion matrix for binary classification. TP = true positive, TN = true negative, FP = false positive, FN = false negative.

Using the four outcomes, several key evaluation metrics can be calculated.

2.3.5.1 *Accuracy*

Accuracy is the most straightforward metric, representing the proportion of correctly classified datapoints out of the total number of datapoints (equation 2.10; Hossain, 2024; Sarkar, 2018).

2.10) $$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)}$$

While accuracy is the most commonly reported performance metric in animal behaviour studies (see Table 2.4), it is sensitive to class prevalence. Animal activity budgets are naturally imbalanced, which can result in misleading accuracies. A cat, for example, may spend around 61% of its time recumbent, 2% eating and 15% grooming (Panaman, 1981). In such a scenario, a model could achieve a deceptively high accuracy by simply classifying every instance as "recumbent", while failing to identify any of the other important, but rarer behaviours. Therefore, relying solely on accuracy to evaluate the performance of a model would provide a poor evaluation of the true performance of the model. To overcome this, it is important to use metrics that are less sensitive to unbalanced datasets, such as precision, recall, and the F1-score.

2.3.5.2 *Precision, recall, and F1-score*

Precision, also known as the positive predictive value (PPV), measures the proportion of correctly predicted or classified positive datapoints out of the total of predicted positives (equation 2.11; Geetha, 2023; Hossain, 2024; Sarkar, 2018). It answers the question: "Of all the times the model predicted a behaviour, how often was it correct?"

2.11) $Precision = \frac{TP}{(TP + FP)}$

Recall, also known as sensitivity or true positive rate (TPR), is the proportion of correctly predicted or classified positive datapoints out of all the actual positives (equation 2.12; Geetha, 2023; Hossain, 2024; Sarkar, 2018). It answers the question: "Of all the actual instances of a behaviour, how many did the model successfully detect?"

2.12) $Recall = \frac{TP}{(TP + FN)}$

There is a trade-off between precision and sensitivity (Geetha, 2023; Hossain, 2024; Sarkar, 2018). A model with a high precision may be too conservative, missing some true positives (low recall), whereas a model with high recall may capture most true positives but also generate more false positives (low precision). The F1-score is the harmonic mean of precision and recall, providing a single, balanced measure of model performance (equation 2.13; Geetha, 2023; Hossain, 2024; Sarkar, 2018).

2.13) $F1\ score = 2 \times \frac{precision \times sensitivity}{precision + sensitivity}$

It is particularly valuable for imbalanced datasets because it requires both high precision and recall to achieve a high score. If either precision or recall is low, it results in a low F1-score, making it a much more robust metric than accuracy for evaluating how well a model performance on less frequent behaviours.

2.3.5.3 *Other metrics*

Another important metric is the specificity, also called the true negative rate (TNR), which measures the proportion true negative instances that were correctly identified (equation 2.14; Geetha, 2023; Hossain, 2024).

2.14) $Specificity = \frac{TN}{(TN + FP)}$

Additionally, the receiver operating characteristic (ROC) and the area under the curve (AUC) are advanced methods for assessing a classifiers performance. The ROC curve plots the recall (equation 2.12) against the false positive rate (FPR), where each prediction represents a single point on the plot (Figure 2.9; Geetha, 2023; Sarkar, 2018). The FPR is the proportion of the negative classes wrongly predicted or classified as positive and the total number of actual negatives (equation 2.15). While the ROC is visually important, it does not have numerical value that can be used to compare models (Geetha, 2023; Sarkar, 2018). For this, the AUC can be used, which is determined by the area under the ROC curve.

2.15) $FPR = \frac{FP}{(FP + TN)}$

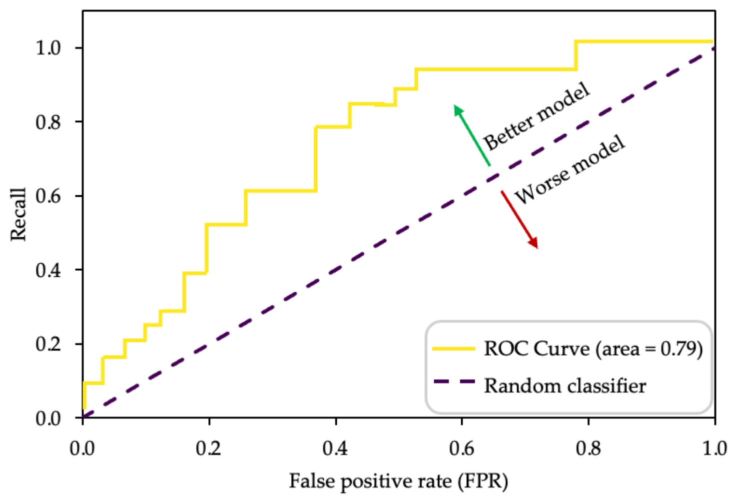

Figure 2.9. Example of a receiver operating characteristic (ROC) curve. Adapted from GeeksforGeeks (2024).

Though not common to evaluate the performance of a classifier model, Cohen's kappa (κ) can be used to evaluate the agreement between the observed (by the observer) and predicted (by the ML model) classes (equation 2.16; Chicco et al., 2021).

2.16) $\kappa = \frac{2 \times (TP \times TN - FN \times FP)}{(TP + FP) \times (FP{+}TN) \times (TP{+}FN) \times (FN{+}TN)}$

2.3.5.4 *Multi-class evaluation*

In a multi-class problem, such as classifying several distinct behaviours, performance metrics are generally calculated for each class using a 'one-versus-rest' approach, whereas a binary confusion matrix is created for each class with its corresponding FP, FN and TN values (see

Figure 1.10a). When considering all classes, however, and determining the overall performance metrics of the ML model, only the TP can be determined (Figure 2.10b).

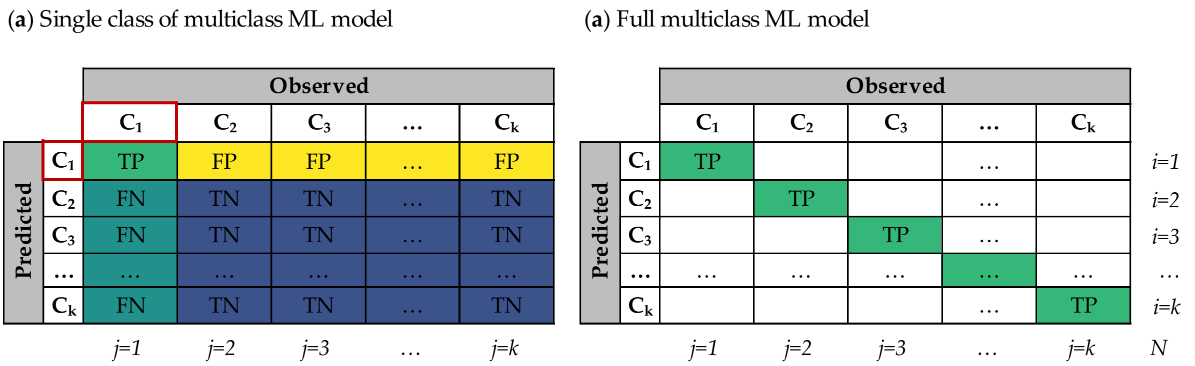

Figure 2.10. Confusion matrix when determining performance metrics for (a) a single class (C_1 selected for example) and (b) a full multiclass ML model. TP = true positive, TN = true negative, FP = false positive, FN = false negative, N = total number of observations.

The overall accuracy of the full multiclass ML model can be determined using equation 2.17, where $\sum_{i=1}^{k} TP(C_i)$ is the sum of all TP observations and N is the total number of observations (Geetha, 2023; Markoulidakis et al., 2021).

2.17) $$Overall\ accuracy = \frac{\sum_{i=1}^{k} TP(C_i)}{N}$$

2.3.5.5 *Bias and variance: over- and underfitting of the model*

Bias and variance are important measures to evaluate and tune ML model(s). Bias is the error that occurs due to the difference between the model's predicted value or class, and the actual value or class (Geetha, 2023; Hossain, 2024; Sarkar, 2018). Bias is affected by the assumptions that are made by the model. A low bias means fewer assumptions were made to train to model, while a high bias means more assumptions were made to train the model. High bias leads to underfitting, where the model fails to capture the underlying patterns in the data. A model with high bias will perform poorly on both the training and validation dataset. Examples to reduce high bias include the use of a more complex model, increasing the number of features, and/or increasing the size of the training dataset (Geetha, 2023; Hossain, 2024; Sarkar, 2018).

Variance refers to the sensitivity of the ML model to fluctuations in the training dataset (Geetha, 2023; Hossain, 2024; Sarkar, 2018). The higher the variance of a model, the more sensitive it is to fluctuations. A high variance leads to overfitting, where the model has learned the noise and errors in the training dataset along with the underlying pattern (Geetha, 2023;

Hossain, 2024; Sarkar, 2018). A model with high variance results in excellent performance on the training dataset, but poor performance on the validation dataset. Examples to reduce high variance include cross validation, reduction of the number of features and/or simplifying the model (Geetha, 2023; Hossain, 2024; Sarkar, 2018).

While an ideal model would have both a low bias and variance, there is a trade-off between bias and variance as a model cannot be simultaneously more and less complex at the same time (Figure 2.11; Geetha, 2023; Hossain, 2024; Sarkar, 2018). Thus, reducing the variance of a model will increase its bias, and *vice versa*.

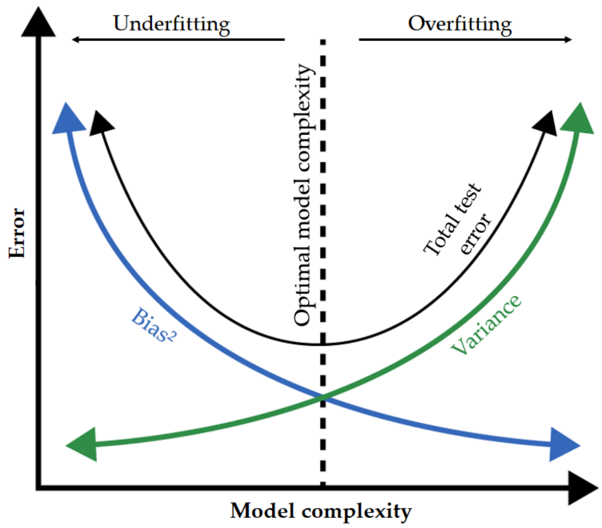

Figure 2.11. Visualisation of the Bias-variance trade-off, including underfitting, overfitting and optimal model complexity. Adapted from GeeksforGeeks (2023).

2.4 Scientific aims

Following a review of the literature, it became clear that there is a scientific knowledge gap regarding domestic cat behaviour. This is not surprising considering its complexity, the myriad of factors that can possibly affect it, and the labour-intensiveness of traditional behavioural observation studies. The use of accelerometers and ML techniques can reduce the labour-intensiveness of animal behavioural studies and though some ML models have been developed for domestic cats, they are severely underrepresented and not validated compared to domestic dogs. Three main scientific aims have been defined:

1. Develop and validate a machine learning model to classify cat behaviours using accelerometer data (Chapter 3).
2. Apply the validated model to investigate how daylength, seasons and meteorological conditions are associated with changes in the behaviour of domestic cats living in a semi-outdoor research environment (Chapter 4).
3. Apply the validated model to understand the influence of different home environments, including factors like outdoor access and the presence of other animals or children, on the behaviour of privately owned companion cats (Chapter 5).
4. Compare the behaviour of domestic cats living in a semi-outdoor research environment to those of privately owned cats living indoors only or having outdoor access (Chapter 5).

Originally, a fourth scientific aim was included: validating the use of an accelerometer to approximate energy expenditure in domestic cats. Data collection for this study was completed, and blood plasma samples were shipped to a commercial laboratory for analyses. The laboratory had the samples in their possession for 18 months but were unable to analyse the samples. This laboratory was the only one within in New Zealand that were capable to analyse the samples, and currently, there is no alternative within New Zealand. We are currently in contact with another laboratory outside of New Zealand to have the samples analysed, however, analyses will take another three to six months. Unfortunately, this study is therefore no longer included as a separate chapter in the thesis, however, considering the fundamental importance of this work to the thesis, part of this trial can be found in Appendix I.

Chapter 3

Validation of a machine learning model to classify domestic cat behaviour using accelerometer data

Image generated with Meta AI

This chapter has been published as;

Smit, M., Ikurior, S. J., Corner-Thomas, R. A., Andrews, C. J., Draganova, I., & Thomas, D. G. (2023). The Use of Triaxial Accelerometers and Machine Learning Algorithms for Behavioural Identification in Domestic Cats (*Felis catus*): A Validation Study. *Sensors (Basel, Switzerland)*, *23*(16), 7165. https://doi.org/10.3390/s23167165

See Appendix II for published paper.

Chapter 3 Validation of a machine learning model to classify domestic cat behaviour using accelerometer data

3.1 Introduction

Animal behaviour can provide a reliable and non-invasive indication of animal health and welfare. In domestic cats (*Felis catus*), behavioural changes can indicate illness, pain or distress (Horwitz & Rodan, 2018). Behavioural monitoring of pet cats is often carried out by their owner(s). However, owner observation is subjective, and they cannot monitor their companion animal continuously and may miss early and subtle signs of illness. This is exacerbated by the fact that changes in behaviour in response to illness and/or pain can often be subtle and well disguised by the cat (Horwitz & Rodan, 2018). In addition, any behavioural research trial using traditional methods, scoring behaviour manually either directly or from video recordings, is labour-intensive. Alternatives such as accelerometers have the potential to allow continuous monitoring of the behaviour of animals, including domestic cats.

To date, few studies in domestic cats have used accelerometer data to distinguish between, or classify, specific behaviours (Galea et al., 2021; Watanabe et al., 2005). Accelerometers can measure body movement in terms of acceleration in one, two or three orthogonal planes: craniocaudal (surge; forwards/backwards), mediolateral (sway; left/right) and dorsoventral (up/down; Brown et al., 2013). Measuring these accelerations in multiple directions allows for detection of both dynamic (motion) and static (gravity) accelerations (Brown et al., 2013; John & Freedson, 2012). Watanabe et al. (2005) successfully distinguished drinking (100% accuracy), eating (68% accuracy), trotting (78% accuracy) and galloping (71% accuracy) in a single domestic cat using acceleration data only along the craniocaudal plane (forwards/backwards). Galea et al. (2021) developed two classifying models for twelve different behaviours from triaxial acceleration data from ten domestic cats, using the random forest (RF) and self-organising map (SOM) machine learning (ML) techniques.

The location of the accelerometer on the animal is an important factor to consider. The placement of the device depends on the animal species, potential effects of the attachment site on the animal's behaviour, the behaviours of interest and method of attachment of the accelerometer on a site (Brown et al., 2013; Wilson et al., 2008). For example, an accelerometer attached to the back of an animal is less likely to register the fine-scale head movements involved in eating that may be detectable by a collar-mounted accelerometer (Brown et al., 2013). In domestic cats, the most common site of accelerometer attachment is ventrally, using a collar. Attachment to a collar, however, can result in rotation of the accelerometer and residual movement (i.e., movement of the device after physical movement stops) which is influenced by the looseness of the collar, weight of the accelerometer, and the animal's behaviour (Brown et al., 2013; Wilson et al., 2008). For example, greater model accuracy was found in dogs with accelerometers attached to a harness than a collar (Kumpulainen et al., 2021). It is therefore important to classify behaviours of interest before determining accelerometer placement location.

Machine learning techniques are often used to train models to classify behaviours from accelerometer data. Depending on the dataset, some ML techniques might be a better fit than others. Nathan et al. (2012) reported that the RF technique had the highest accuracies for classifying the behaviour of free ranging griffon vultures (*Gyps fulvus*) from accelerometer data. In their study, the accuracies of five frequently used supervised ML techniques were compared: linear discriminant analysis (LDA), support vector machine (SVM), classification and regression trees (CART), RF and artificial neural network (ANN). Galea et al. (2021) compared SOM to RF and found that SOM had a higher overall accuracy than the RF (99.6% vs. 98.9%, respectively) for behaviour classification of domestic cats wearing a harness-mounted accelerometer.

The main aim of the current study was to develop and validate a machine learning model capable of classifying domestic cat behaviours from accelerometer data, from which detailed activity budgets could be determined. This study compared model performance between the two sites of attachment (collar and harness) and two ML techniques (RF and supervised SOM). It was hypothesised that both RF and SOM models of harness-mounted accelerometer data would have a better overall performance, or ability to classify behaviour, when compared with models of the collar-mounted accelerometer, due to the greater rigidity of the harness-mounted accelerometer thus reducing the risk of individual and residual device movement. However, given that the collar-mounted accelerometer was expected to be more likely to detect finer-scale head movements, it was expected that the model of the collar-mounted accelerometer would have a higher accuracy in detecting eating behaviour than harness-mounted accelerometer models. Furthermore, as the SOM model had a higher overall performance compared to the RF model in the study by Galea et al. (2021), it was also hypothesised that in the current study SOM models would have higher overall performance compared with the RF model. In addition, the models were applied to a subset of the dataset to assess how well they produced realistic activity budgets.

3.2 Material and methods

The study was conducted at the Massey University Centre for Feline Nutrition, Palmerston North, New Zealand (latitude 40° 23′ S, longitude 175° 36′ E) between 26 May and 7 July 2021. This study was approved by the Massey University Animal Ethics Committee (MUAEC 21/23).

3.2.1 Animals and design

The study comprised two phases: habituation and data collection. During the habituation phase, 16 healthy desexed male (n = 7) and desexed female (n = 9) domestic shorthair cats aged from 2.3 to 4.4 years (mean ± SD, 2.64 ± 0.62 years) and weighing between 2.6 to 5.2 kg (mean ± SD, 3.93 ± 0.89 kg) were assessed for inclusion in the study. The habituation phase lasted for five weeks: four weeks for habituation to the cat harness and one week for habituation to the accelerometers attached to both a collar and harness. Cats were already accustomed to wearing collars and thus relatively little habituation was needed for accelerometer attachment. During the habituation to the harness three cats significantly decreased movement, indicating they did not habituate to the harness. In addition, one cat persisted in biting the harnesses of other cats, thus these four animals were removed from the study. Therefore, a subset of twelve desexed male (n = 5) and female (n = 7) cats, aged from 2.3 to 4.4 years (mean ± SD, 2.75 ± 0.69 years) and weighing between 2.6 to 5.1 kg (mean ± SD, 3.85 ± 0.82 kg), who had successfully completed the habituation period, were included in the data collection phase. During the seven-day data collection period, each cat wore two accelerometers: one attached to a collar and one to a harness. During the same seven days, cats were under continuous video surveillance. Throughout both phases of the study cats were housed in two semi-outdoor colony cages, or pens, (Figure 3.1), of which approximately 40% was under cover. Other pens were positioned directly alongside both long sides of the pen. The entire research facility was enclosed by a perimeter wall. Cats were fed a complete and balanced (AAFCO, 2021) commercial canned diet (Heinz Wattie's Ltd., Hastings, New Zealand) *ad libitum* on a daily basis around 11 AM and had *ad libitum* access to water.

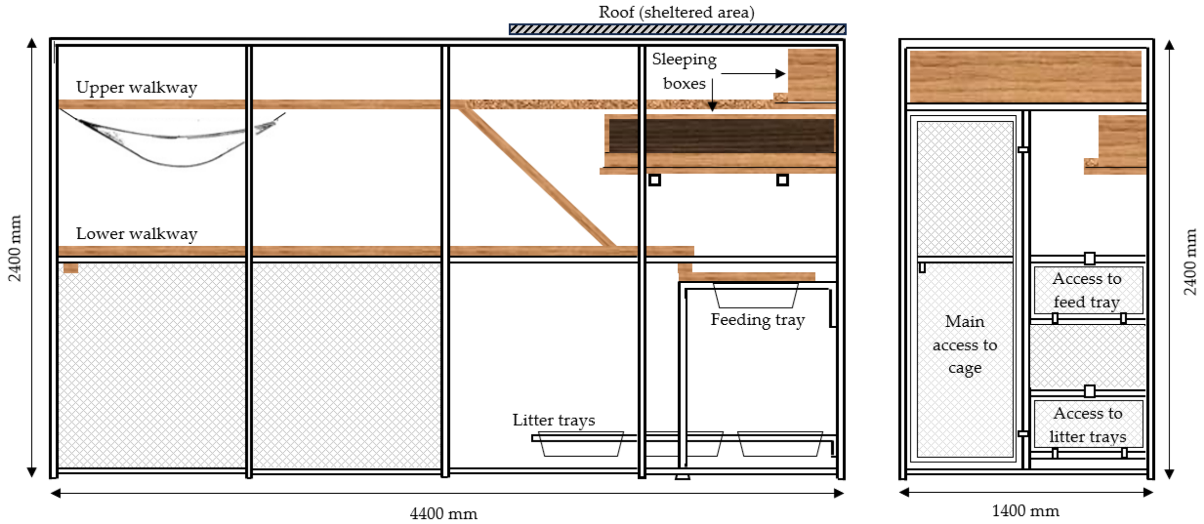

Figure 3.1. Colony cages as seen from the side (left) and front (right), measuring 1400 x 2400 x 4400 mm.

3.2.1.1 Sample size

The target sample size of n = 12 cats was determined *a priori* using a power analysis informed by previous accelerometer validation studies in cats and dogs (Andrews, 2015; Belda et al., 2018; Hansen et al., 2007). The power analysis was based on validating overall physical activity. Using the most conservative correlation coefficient ($R^2 = 0.65$) from a relevant feline study (Andrews, 2015), a power analysis for a Spearman rank correlation test (power = 0.80, a = 0.05) indicated a required sample size of n = 12. To account for a potential 25% dropout rate during harness habituation, an initial cohort of 16 cats was recruited.

3.2.2 Data collection

Cats were fitted with a collar and harness to which an ActiGraph wGT3X-BT accelerometer (weighing 19 grams and measuring 33 × 46 × 15 mm) was attached (ActiGraph, Pensacola, FL, USA). The accelerometer was positioned ventrally on the collar (Figure 3.2a), and dorsally on the left shoulder blade on the harness (Figure 3.2b). The orientation of the accelerometers was uniform across all cats for each mounting location. For the collar-mounted accelerometer, the orientation of the *X*-, *Y*- and *Z*-axis were lateral, dorso-ventral and cranio-caudal, respectively, whereas for the harness-mounted accelerometer the orientation of the *X*-, *Y*- and *Z*-axis were cranio-caudal, dorso-ventral and lateral, respectively. Acceleration data were sampled at a frequency of 30 Hz (raw acceleration data), with a dynamic range of ± 8 *g*. For each cat, a unique pattern of reflective tape was placed on the two accelerometers to allow for cat identification under infrared light.

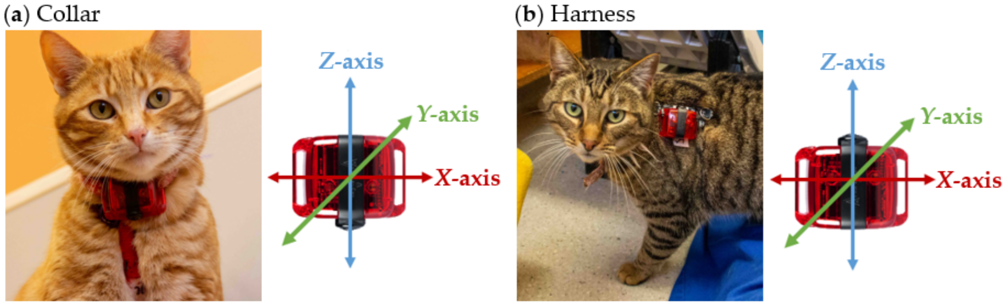

Figure 3.2. Placement and orientation of the ActiGraph wGT3X- BT accelerometer on a (a) collar and (b) harness.

Cats were filmed in real-time using a 4K Swann® security camera system (Swann Communications USA, CA, USA) capable of automatically switching between natural and infrared light, enabling continuous observation under natural light and dark conditions. A selection of active (climbing, jumping, fighting, playing, rolling, rubbing, running, trotting, walking), inactive (lying, sitting, standing), maintenance (digging, drinking, eating, grooming, littering, scratching, shaking), and other (other, out of sight, allogrooming, human contact) behaviours were then retrospectively scored using BORIS (Friard & Gamba, 2016) by a single scorer (Table 3.1). These behaviours were selected based on biological relevance and appearance in the video-recordings. Behaviours were scored from data collected on day 1 of the data collection period between 9 AM and 2 PM continuously as a state and were then exported using a one second (s) time interval.

Table 3.1. Ethogram including definitions of scored behaviours. Adapted from Stanton et al. (2015). All behaviours were scored as states.

Behaviour	Description
Active	
Climbing	Cat ascends and/or descends an object or structure.
Jumping horizontal	Cat leaps from one point to another horizontally.
Jumping vertical	Cat leaps from one point to another vertically.
Fighting[1]	Cat engages in aggressive physical combat with another cat.
Playing[1]	Cat interacts in a non-serious manner with another cat.
Rolling	While lying on the ground, cat rotates body from one side to another. During the roll, the back is rubbed against ground, the belly is exposed, and all paws are in the air. Cat may continue rolling repeatedly from side to side.
Rubbing	Cat rubs body against a surface or object.
Running[1,2]	Forward locomotion with a fast, four-beat, and asymmetric gait. Has a suspension phase. Fastest gait.
Trotting[1,2]	Forward locomotion with a swift, two-beat and symmetric gait. Body is supported by two diagonal legs during contact with ground. Slower than running, quicker than walking.
Walking[1,2]	Forward locomotion at a slow, four-beat and symmetric gait with limbs moving sequentially. Includes slow walk (three or four feet in contact with the ground at any time), fast walk (two or three feet in contact with the ground at any time). Slowest gait.
Inactive	
Lying	Cat's body is in contact with the ground in a horizontal position, including on its side, back, belly, or curled in a circular formation. This behaviour includes crouch, lying and sleeping as defined by (Stanton et al., 2015).
Sitting	Cat is in an upright position, with the hind legs flexed and resting on the ground, while front legs are extended and straight.
Standing	Cat is in an upright position and immobile, with all four paws on the ground and legs extended, supporting the body.
Maintenance	
Digging	Cat breaks up or moves substrate around with its paws.
Drinking	Cat ingests water (or other liquids) by lapping with the tongue.
Eating	Cat ingests food (or other edible substances) by means of chewing with the teeth and swallowing.
Grooming	Cat cleans itself by licking, biting, or chewing the fur on its body. May also include licking of a front paw and wiping it over the head.
Littering	Cat urinates or defecates.
Scratching	Cat scratches its body using the claws of its hind feet.
Shaking	Cat rotates its abdomen or head rapidly from side to side.
Other	
Other	Any behaviour that does not fit into one the behaviours included in this ethogram.
Out of sight	Cat is not visible to the observer.
Allogrooming	Cat licks the fur of another cat's head or body.
Human contact	Cat has direct contact with a human either being pet or is being held or carried.

[1] Beaver, 2003, [2] McGowan et al., 2022.

3.2.3 Data pre-processing and partitioning of the dataset

All data computation and statistical analyses were carried out using RStudio version 4.1.1 (RStudio Team, 2021). The R code, including used R-packages, have been published in a GitHub repository (Smit, 2022).

3.2.3.1 Data pre-processing

Raw acceleration data from all seven days of data collection were exported from the devices using the proprietary ActiLife® software (version 6.13.4; ActiGraph, Pensacola, FL, USA). A total of 32 features were derived from the raw accelerometer data and summarised into 1 second epochs (i.e., time interval): mean acceleration (X, Y, Z), sum acceleration (X, Y, Z), minimum (min) acceleration (X, Y, Z), maximum (max) acceleration (X, Y, Z), standard deviation (sd) of acceleration (X, Y, Z), skewness (X, Y, Z), kurtosis (X, Y, Z), correlation (XY, XZ, YZ), vector magnitude (VM; mean, sum, min, max, sd, skewness, kurtosis), and overall dynamic body acceleration (ODBA; see Table 3.2 for a detailed description of each feature). This selection of features resulted in a classifier model with the highest metrics (Tatler et al., 2018) and based on the features selected by (Galea et al., 2021).

Table 3.2. Description of features derived from the raw (30Hz) accelerometer data.

Feature	Description
Mean	Mean, calculated for every second from the raw acceleration data (30 measures per second).
Sum	Sum, calculated for every second from the raw acceleration data. $Sum_{(Axis)} = \sum_{i=1}^{N} Axis_i$
Minimum (min)	Minimum value of the 30 measures recorded within each second.
Maximum (max)	Maximum value of the 30 measures recorded within each second.
Standard deviation (sd)	Measures the spread of the data.
Skewness	Asymmetry of the distribution.
Kurtosis	Weight of the tails relative to a normal distribution.
Correlation	Correlation between the X- and Y-axis, X- and Z-axis and Y- and Z-axis.
Vector magnitude (VM)	$VM = \sqrt{X^2 + Y^2 + Z^2}$
Dynamic body acceleration (DBA)[1]	$DBA = Sum_{axis} - moving\ average$
Overall dynamic body acceleration (ODBA)	$ODBA = \sum_{i=1}^{N} \lvert DBA_X \rvert + \lvert DBA_Y \rvert + \lvert DBA_Z \rvert$

[1] Accelerometer data from each axis were individually smoothed using the moving average over 1 second. The DBA was not included as an identifier variable.

3.2.3.2 *Partitioning of the dataset*

Before this dataset was partitioned for model training, validation and determination of activity budgets, it was refined by removing data points classified as "other" or "out of sight". This resulted in a final, clean labelled dataset focused on distinct, identifiable behaviours. The seven days of feature-engineered accelerometer data were divided into two main datasets: data from day one was used for model training and internal validation (internal dataset), while data from days two to seven formed activity budget dataset (Figure 3.3). The internal dataset, containing the feature engineered accelerometer data from all cats, was merged with annotated data from day one to create the labelled dataset. The labelled internal dataset was further divided into a training set (70%) for model training and a validation set (30%) for validation of the models. This split was done using random stratified sampling, ensuring that the proportion of behaviours was maintained in both subsets. The activity budget dataset was used determine the activity budget of the cats by classifying the behaviours from the remaining six days of data using the trained models, to aid in further assessment of model performance and selection.

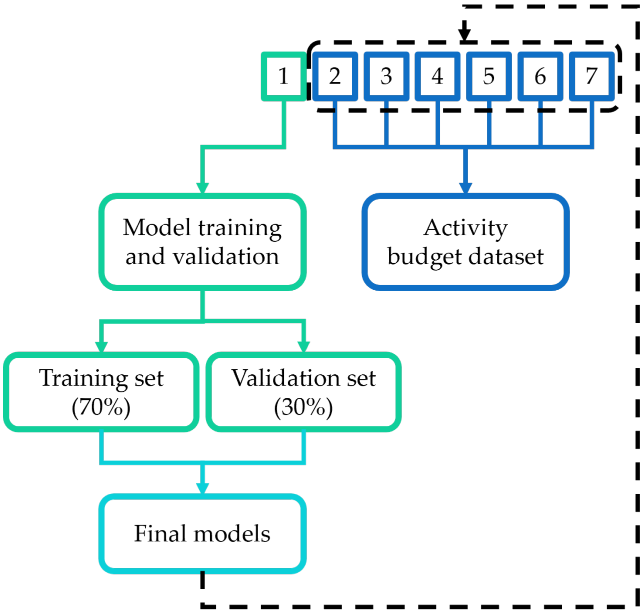

Figure 3.3. Overview of data use. Seven days of data were collected. Data from day one was used to train and validate classifier models. These models were then used to classify behaviour using accelerometer data from day two to seven to create activity budgets to assess how well the models performed in producing realistic activity budgets.

3.2.4 Training and validation of behaviour classification models

To develop behaviour classification models, a multi-stage process was implemented that included model training and validation to assess classification accuracy. Training behaviour classification models

Classification models were trained using the training set, which was created by dividing the cleaned, labelled data from day one. Two ML techniques were used to train classification models to classify behaviours in domestic cats: (I) RF and (II) supervised SOM. The RF trains a multitude of decision trees and combines the output at the end (Breiman, 2001). The SOM produces two-dimensional maps, usually a grid of nodes, of multi-dimensional and complex data, where nodes that are similar are located close to each other (Kohonen, 2001). A model was made with each modelling technique for each mounting location: RF for collar (CRF) and harness (HRF) and SOM for collar (CSOM) and harness (HSOM). The RF models were built using the R packages ‘caret’ (Kuhn et al., 2022), calling on the random forest function from ‘randomForest’ (Breiman et al., 2022). The SOM models were built using the R package ‘Kohonen’ (version 3.0.11; Wehrens & Kruisselbrink, 2018). The default hyperparameter settings were used for both the RF (mtry = $\sqrt{32}$; trees = 500; min_n = 10) and SOM (grid = 8×8; rlen = 100; alpha = (0.05, 0.01); radius = 2/3), as those have been shown to result in good animal behaviour classification models (Galea et al., 2021; Tatler et al., 2018).

To improve performance in a structured way, the models were developed through an iterative process of evaluation and refinement, referred to as modelling rounds. Behaviours with a low performance metrics (e.g., low F1-scores) were either merged with functionally similar behaviours (e.g., combining trotting and walking into active) or removed if they were consistently misclassified across behaviour classes. A new, simplified model was then trained on the refined dataset, and this process was repeated until model performance metrics no longer improved, or until only three broad behavioural categories remained (active, inactive, maintenance).

3.2.4.1 Validation of the behaviour classification models

Each trained model was validated using the validation dataset by first classifying behaviours for each second using the trained models. A confusion matrix was then generated by comparing the model-classified behaviours to the observed, annotated (ground-truth) behaviours from which true positive, true negatives, false positives, and false negatives were derived. For each model, behaviours were labelled as true positive when the behaviour was correctly classified by the model, true negative when the behaviour was correctly classified by the model as not occurring, false negative when the behaviour was observed but not classified by the model, or false positive when the behaviour was classified by the model but was not observed. For each behaviour class, the accuracy (equation 2.10), precision (equation 2.11), recall (equation 2.12), specificity (equation 2.14) and F1-score (equation 2.13) were calculated. For the full multiclass ML model, the F1-score was determined by averaging the F1-scores of all the behavioural classes, and the overall accuracy (equation 2.17) and Kappa coefficient (equation 2.16) were calculated. Results for the Kappa coefficients were interpreted according to Fleiss (Fleiss, 1981), where values > 0.75 indicated excellent agreement, 0.40 to 0.75 indicated fair to good agreement, and < 0.40 indicated poor agreement. These metrics guided the iterative refinement process described in the previous section.

3.2.5 Dirichlet regression: comparing activity budgets

This step was not designed to measure second-by-second accuracy, but to assess the ability of the models to produce stable and biologically realistic daily activity budgets. Activity budgets (proportion of time spent showing each behaviour) for acceleration data collected between days two and seven were calculated for each cat. Using the R package 'DirichletReg' (Maier, 2021), a Dirichlet regression with log link was performed as a function of mounting location (collar and harness), modelling technique (RF and SOM) and the day of observation. A Dirichlet regression allows for statistical testing between proportions (Douma & Weedon, 2019) and was performed separately for each MR. Results were considered to be significant if $p < 0.05$.

3.2.6 Intra-rater reliability

To test the intra-rater reliability of the behaviour scoring, a subset of five randomly selected 15-minute video recordings were scored by the same observer for behaviour for a second time, with a time interval of six months between the first and second scoring. Intra-rater reliability was tested using Kappa coefficient (κ) using the R package 'irr' (Gamer et al., 2022). Results for the Kappa coefficient were interpreted according to Fleiss (1981).

3.3 Results

From the first day of video footage from the 12 cats, a total of 166,754 seconds (≈ 46 h and 20 min; 3 h and 50 min per individual) of recordings were manually scored (annotated) for behaviour. For all cats, scoring was conducted between 09:00 AM and 02:00 PM, a period when cats are most active due to staff presence and feeding and exhibit the largest range of behaviours.

3.3.1 Intra-rater reliability

The behaviour scoring intra-rater reliability, comparing the agreement between the first and second behaviour scoring of video data by the scorer was found to be excellent ($\kappa = 0.93$, $p < 0.001$).

3.3.2 Performance of classification models

The performance of the classification models was evaluated on the validation dataset across four modelling rounds. Of the 24 behaviours scored (Table 3.1), four behaviours ('rolling', 'running', 'drinking', and 'human contact') were not observed at any time and were removed before model training (Figure 3.4). Similarly, 'fighting' (n = 10 s) and 'playing' (n = 1 s) were removed due to their low occurrence. 'Jumping horizontal' (n = 53 s) and 'jumping vertical' (n = 186 s) were grouped into a single category 'jumping' (Figure 3.4). Seconds (i.e., datapoints) where cats were identified as 'out of sight' (n = 38,395 s) and 'other' (n = 4,116 s), were also removed from the dataset. The final data set contained a total of 124,232 datapoints which consisted of 15 different behaviours.

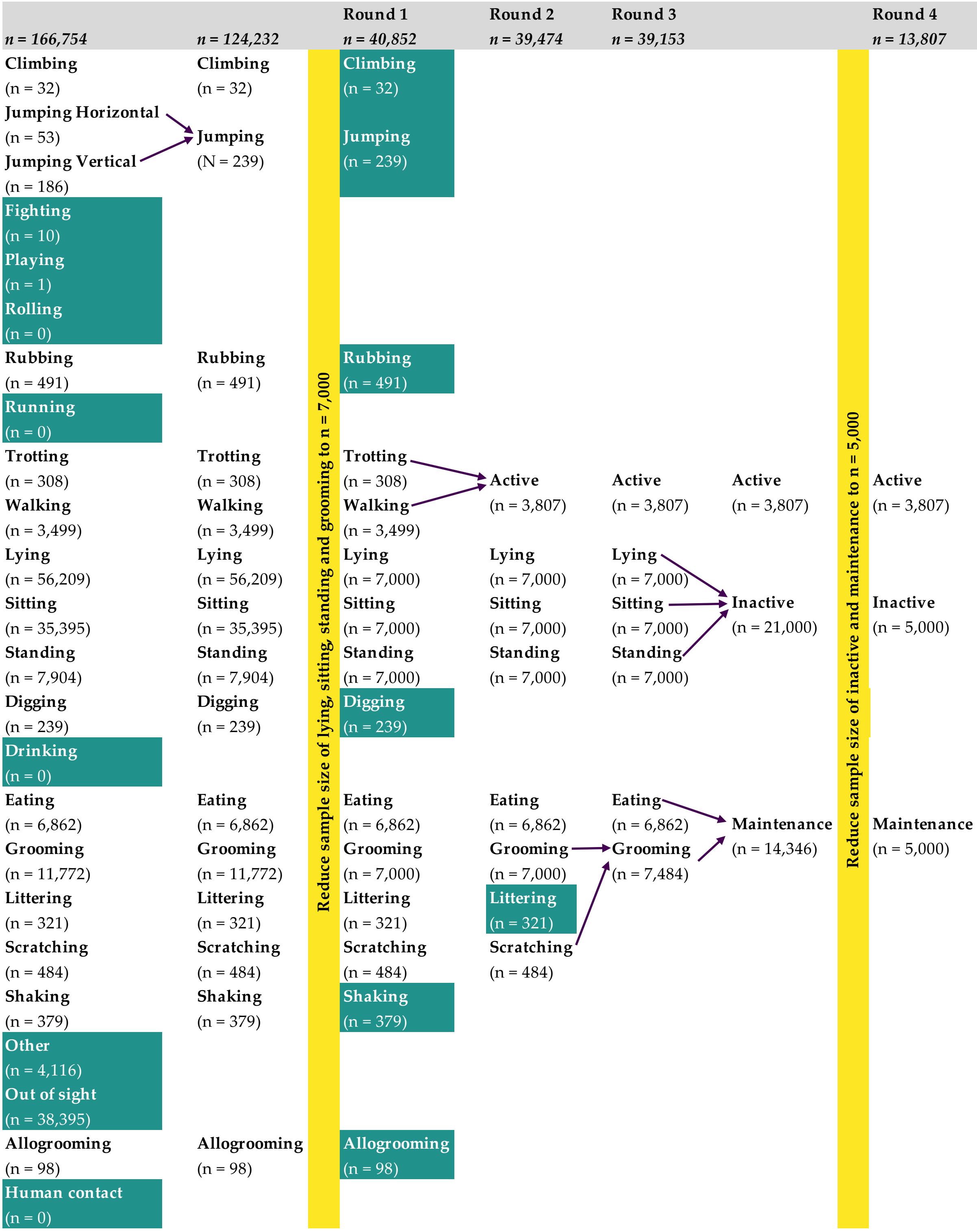

Figure 3.4. Process of behavioural selection before and between modelling rounds.

3.3.2.1 *Iterative model refinement*

Early models were highly biased towards very frequent behaviours (e.g., lying, sitting), therefore, these behaviours were down sampled to n = 7,000 datapoints (Figure 3.4). Down sampling was achieved by randomly selecting datapoints for each behaviour using the sample function in R.

Four modelling rounds were conducted which resulted in a total of 16 different behavioural classification models. Confusion matrices for each model can be found in Appendix III. The first modelling round included 15 behaviours: climbing, jumping, rubbing, trotting, walking, lying, sitting, standing, grooming, littering, digging, eating, scratching, shaking, and allogrooming. In the first modelling round, the confusion matrices showed that some behaviours were not classified by the models (true positive = 0), e.g., climbing, digging and allogrooming using the CRF model (Appendix III Modelling round 1 Tables A1-A4). Climbing, jumping, rubbing, digging, shaking and allogrooming were removed before the second modelling round due to their small sample size. Trotting was often misclassified as walking in both the CRF and HRF models in the first modelling round, and therefore the two were merged into "active".

The second modelling round included eight behaviours: active, lying, sitting, standing, grooming, littering, eating, and scratching. Scratching was often misclassified as grooming in both the CRF and HRF models of the second modelling round and was merged with grooming before the third modelling round (Appendix III Modelling round 2 Tables A5 and A6). Littering was removed as it was often misclassified as either sitting or standing.

The third modelling round included six behaviours: active, lying, sitting, standing, grooming, and eating (Appendix III Modelling round 3). The fourth and final modelling round included three behavioural categories: active, inactive (lying, sitting, standing), and maintenance (eating, grooming; Appendix III Modelling round 4). Initial models of the fourth and final modelling round showed high bias towards the inactive and maintenance category. Therefore, the number of datapoints for inactive and maintenance were further down sampled to n = 5,000 (Figure 3.3).

3.3.2.2 Classification model performance metrics

Irrespective of mounting location, the overall performance values of the SOM models were higher than those of the RF models (Table 3.3). Both Kappa and overall accuracy values were > 0.95 for all the SOM models (Table 3.3). The RF models generally showed a fair-to-good agreement (κ between 0.40 and 0.75) between the observed and classified behaviours. The harness HRF models showed excellent agreement ($\kappa > 0.75$) in the second and third modelling round (Table 3.3). For the RF models, the overall Kappa, accuracy, and F1-score values were higher for the HRF models than CRF models in modelling rounds 1-3 (Table 3.3). It was only in the fourth modelling round, containing only three behavioural categories, that the CRF models outperformed the HRF models (Table 3.3). The overall performance values for the CSOM and HSOM models were very similar, apart from modelling round three, where the overall performance values for the HSOM model was higher than that of the CSOM model (Table 3.3).

Table 3.3. Overall Kappa coefficient, accuracy and F1-score values for each model in each modelling round, mounting location (collar and harness), and modelling technique (random forest (RF), and Self Organising Map (SOM)).

Modelling round	Kappa		Accuracy		F1-Score	
	RF	SOM	RF	SOM	RF	SOM
			Collar			
1	0.642	0.962	0.700	0.968	0.479	0.828
2	0.678	0.997	0.733	0.997	0.678	0.990
3	0.684	0.953	0.739	0.961	0.679	0.959
4	0.742	0.999	0.830	0.999	0.827	0.999
			Harness			
1	0.729	0.962	0.772	0.968	0.463	0.781
2	0.753	0.996	0.795	0.997	0.727	0.993
3	0.757	0.997	0.799	0.998	0.745	0.998
4	0.739	0.999	0.827	0.999	0.824	1.000

For individual behaviours, accuracy was generally ≥ 0.85 except for eating in the CRF and HRF models of the third modelling round, where it was 0.75 and 0.79, respectively (Appendix IV). Model behaviour classification showed precision ranging from 0.25 to 1.00. The lowest precision found was for behaviours with small sample sizes (e.g., climbing; Appendix V). Sensitivity ranged from 0.02 to 1.00 for behaviours that were classified by the models (Appendix VI). Precision and sensitivity decreased as the number of false positives or false negatives, respectively, increased compared to the number of true positives. Specificity was ≥ 0.90 for individual behavioural classes, except for eating in the RF models in modelling round 3, where it was 0.72 and 0.75 for the CRF and HRF models, respectively (Appendix VII). The F1-score ranged from 0.04 to 1.00 for behaviours that were classified by the models. (Appendix VIII).

3.3.3 Dirichlet regression: comparing activity budgets

The 16 trained and validated models were used to classify the unannotated accelerometer data from days two through seven (activity budget dataset). One activity budget was determined per cat (n = 12). Per modelling round the resulting activity budgets from the different models were compared using a Dirichlet regression.

3.3.3.1 *Modelling round 1*

Observed activity budgets for modelling round 1 are presented in Table 3.4. Regardless of model, the most frequent behaviours were lying (28.20% to 52.69%) and sitting (18.74% to 28.93%). Less frequent were walking (0.45% to 4.57%), eating (3.32% to 22.67%), grooming (6.99% to 20.68%) and standing (7.70% to 8.83%). The least frequent behaviours were allogrooming (0.00% to 0.01%), climbing (0.00% to 0.03%), digging (0.00% to 0.01%), jumping (0.00% to 0.03%), littering (0.00% to 0.62%), rubbing (0.07% to 1.89%), scratching (0.00% to 1.24%), shaking (0.00% to 0.02%) and trotting (0.00%)

Table 3.4. Difference in model-classified mean ± standard error daily percentages of behaviours of research cats (n = 12) between models for modelling round 1.

	CRF[1]	HRF[1]	CSOM[1]	HSOM[1]
Allogrooming	0.00	0.01 ± 0.00	0.00	0.00
Climbing	0.00	0.03 ± 0.01	0.00	0.00
Digging	0.00	0.01 ± 0.00	0.00	0.00
Eating	4.08 ± 0.45 [b]	3.32 ± 0.30 [c]	22.67 ± 1.56 [a]	12.99 ± 1.30 [a]
Grooming	6.99 ± 0.29 [c]	7.99 ± 0.31 [c]	15.92 ± 0.75 [b]	20.68 ± 1.50 [a]
Jumping	0.01 ± 0.00	0.03 ± 0.01	0.00	0.00
Littering	0.06 ± 0.01 [b]	0.64 ± 0.25 [a]	0.00	0.00
Lying	52.69 ± 2.21 [a]	47.54 ± 2.80 [b]	28.20 ± 2.27 [d]	33.76 ± 2.04 [c]
Rubbing	0.07 ± 0.01	0.11 ± 0.04	1.89 ± 0.43	0.42 ± 0.15
Scratching	0.20 ± 0.03 [a]	0.21 ± 0.03 [a]	0.08 ± 0.02 [b]	0.00
Shaking	0.02 ± 0.00	0.01 ± 0.00	0.00	0.00
Sitting	25.29 ± 2.45 [a]	28.93 ± 2.88 [a]	23.08 ± 2.79 [b]	18.74 ± 1.89 [c]
Standing	8.08 ± 1.18 [b]	8.16 ± 0.87 [b]	7.70 ± 3.16 [c]	8.83 ± 1.08 [a]
Trotting	0.00	0.00	0.00	0.00
Walking	2.51 ± 0.33 [a]	3.02 ± 0.38 [a]	0.45 ± 0.07 [b]	4.57 ± 0.58 [a]

[1] CRF = Collar Random Forest, HRF = Harness Random Forest, CSOM = Collar Self-Organising Map, HSOM = Harness Self-Organising Map.
[a-d] Different superscripts within a behaviour indicate a significant difference ($p < 0.05$).

The Dirichlet regression analysis showed significant differences for both mounting location and the machine learning technique used (Table 3.4). Comparing mounting locations within the same modelling technique, the RF models showed significant differences between the collar (CRF) and harness (HRF) for the daily proportions of lying ($p < 0.001$), littering ($p = 0.017$) and eating ($p = 0.005$), but not for grooming, scratching, sitting and walking. For the

SOM models, differences between the collar (CSOM) and harness (HSOM) were more widespread, affecting walking, lying, sitting, standing and grooming ($p < 0.001$ for all).

When comparing the ML techniques for each specific mounting location, significant differences were also found (Tabel 3.4). For the collar-mounted devices, the RF and SOM models differed significantly for eating, grooming, lying, scratching, sitting, standing, and walking ($p < 0.001$ for all), with no differences found for rubbing ($p = 0.104$). Similarly, for the harness-mounted devices, the RF and SOM models differed for eating ($p < 0.001$), grooming ($p < 0.001$), lying ($p < 0.001$), scratching ($p < 0.001$), sitting ($p < 0.001$) and standing ($p = 0.002$), but not for rubbing and walking. Irrespective of mounting location, the SOM models produced higher estimated proportions of eating and grooming at the expense of lying and sitting.

3.3.3.2 *Modelling round 2*

Observed activity budgets for modelling round 2 are presented in Table 3.5. Regardless of model, the most frequent behaviours were lying (29.17% to 52.52%) and sitting (17.47% to 28.57%). Less frequent were active (0.09% to 3.22%), eating (3.22% to 22.15%), grooming (7.15% to 18.91%) and standing (3.99% to 8.37%). The least frequent behaviours were littering (0.00% to 0.62%) and scratching (0.00% to 1.24%).

Table 3.5. Difference in model-classified mean ± standard error daily percentages of behaviours of research cats (n = 12) between models for modelling round 2.

	CRF[1]	HRF[1]	CSOM[1]	HSOM[1]
Active	2.71 ± 0.37 [a]	3.22 ± 0.41 [a]	0.09 ± 0.01 [c]	2.64 ± 0.27 [b]
Eating	4.05 ± 0.47 [c]	3.22 ± 0.31 [d]	22.15 ± 1.68 [a]	13.95 ± 1.30 [b]
Grooming	7.15 ± 0.31 [c]	8.07 ± 0.33 [c]	18.91 ± 0.89 [a]	16.14 ± 1.50 [b]
Littering	0.07 ± 0.02	0.62 ± 0.25	0.00	0.00
Lying	52.52 ± 2.37 [a]	47.73 ± 2.92 [b]	29.17 ± 1.85 [d]	38.00 ± 2.39 [c]
Scratching	0.19 ± 0.03	0.20 ± 0.03	1.24 ± 0.42	0.00
Sitting	25.35 ± 2.58 [a]	28.57 ± 3.01 [a]	24.46 ± 3.12 [b]	17.47 ± 1.96 [c]
Standing	7.95 ± 1.25 [a]	8.37 ± 0.93 [a]	3.99 ± 2.85 [b]	11.81 ± 1.29 [a]

[1] CRF = Collar Random Forest, HRF = Harness Random Forest, CSOM = Collar Self-Organising Map, HSOM = Harness Self-Organising Map.
[a-d] Different superscripts within a behaviour indicate a significant difference ($p < 0.05$).

Similar to modelling round 1, the Dirichlet regression showed significant differences for both mounting location and machine learning technique (Table 3.5). Comparing mounting locations within the same modelling technique, the RF models showed significant differences between the collar (CRF) and harness (HRF) for the daily proportions of lying ($p < 0.001$) and eating ($p = 0.030$), but not for active, grooming, littering, scratching, sitting and standing. For the SOM models, the proportions of all predicted behaviours differed significantly between the collar (CSOM) and harness (HSOM) locations ($p < 0.05$ for all).

Significant differences were also found when comparing the ML techniques for each specific mounting location (Table 3.5). The models for collar-mounted devices (CRF *vs*. CSOM) showed significant differences for active ($p = 0.041$), lying ($p < 0.001$), sitting ($p < 0.001$), standing ($p < 0.001$), grooming ($p = 0.019$), and eating ($p = 0.004$). The models for harness-mounted devices differed significantly for ($p = 0.025$), lying ($p < 0.001$), sitting ($p < 0.001$), grooming ($p = 0.003$), and eating ($p < 0.001$). Irrespective of mounting location, the SOM models produced higher estimated proportions of eating and grooming at the expense of lying and sitting.

3.3.3.3 Modelling round 3

Observed activity budgets for modelling round 3 are presented in Table 3.6. Regardless of model, the most frequent behaviours were lying (27.82% to 53.21%) and sitting (20.66% to 28.04%). Less frequent were active (0.10% to 3.17%), eating (3.28% to 26.79%), grooming (7.59% to 13.91%) and standing (3.33% to 89.57%).

Table 3.6. Difference in model-classified mean ± standard error daily percentages of behaviours of research cats (n = 12) between models for modelling round 3.

	CRF[1]	HRF[1]	CSOM[1]	HSOM[1]
Active	2.70 ± 0.37 [a]	3.17 ± 0.40 [a]	0.10 ± 0.02 [c]	1.87 ± 0.21 [b]
Eating	3.98 ± 0.47 [c]	3.28 ± 0.31 [c]	26.79 ± 2.91 [a]	14.11 ± 1.47 [b]
Grooming	7.59 ± 0.35 [b]	8.45 ± 0.35 [b]	13.91 ± 0.99 [a]	13.20 ± 1.55 [b]
Lying	53.21 ± 2.34 [a]	49.82 ± 2.85 [a]	27.82 ± 2.98 [c]	39.58 ± 2.00 [b]
Sitting	24.88 ± 2.58 [b]	27.35 ± 3.02 [b]	28.04 ± 3.40 [a]	20.66 ± 2.21 [c]
Standing	7.64 ± 1.30 [b]	7.92 ± 0.97 [b]	3.33 ± 2.76 [c]	9.57 ± 1.00 [a]

[1] CRF = Collar Random Forest, HRF = Harness Random Forest, CSOM = Collar Self-Organising Map, HSOM = Harness Self-Organising Map, n.c. = behaviour not classified by the model.
[a-c] Different superscripts within a behaviour indicate a significant difference ($p < 0.05$).

When comparing mounting locations, the Dirichlet regression did not show significant differences for the RF models for any predicted behaviour (Table 3.6). For the SOM models, all predicted behaviours differed significantly between the collar (CSOM) and harness (HSOM) locations (eating $p = 0.012$, all other behaviours $p < 0.001$; Table 3.6)

When comparing ML techniques, the models for collar-mounted devices (CRF *vs*. CSOM) differed significantly for active, lying, and sitting (all $p < 0.001$), and for eating ($p = 0.011$; Table 3.6). Irrespective of mounting location, the SOM models produced higher estimated proportions of eating and grooming at the expense of lying and sitting.

3.3.3.4 Modelling round 4

Observed activity budgets for modelling round 4 are presented in Table 3.7. The most frequent behavioural category was inactive (51.16% to 84.46%), followed by maintenance (10.90% to 34.06%) and active (4.64% to 14.78%).

Table 3.7. Difference in model-classified mean ± standard error daily percentages of behaviours of research cats (n = 12) between models for modelling round 4.

	CRF[1]	HRF[1]	CSOM[1]	HSOM[1]
Active	4.64 ± 0.49 [b]	5.20 ± 0.61 [b]	14.78 ± 2.09 [a]	10.81 ± 0.72 [a]
Inactive	84.46 ± 0.58 [a]	83.27 ± 0.57 [a]	51.16 ± 3.27 [c]	61.98 ± 2.30 [b]
Maintenance	10.90 ± 0.47 [b]	11.53 ± 0.46 [b]	34.06 ± 1.59 [a]	27.21 ± 2.35 [a]

[1] CRF = Collar Random Forest, HRF = Harness Random Forest, CSOM = Collar Self-Organising Map, HSOM = Harness Self-Organising Map, n.c. = behaviour not classified by the model.
[a-c] Different superscripts within a behaviour indicate a significant difference ($p < 0.05$).

When comparing mounting locations, the Dirichlet regression did not show significant differences for the RF models for any predicted behavioural category (Table 3.7). For the SOM models, a significant difference was found between the collar (CSOM) and harness (HSOM) for the inactive category ($p < 0.001$).

When comparing ML techniques, significant differences were found for all three categories between the models for collar-mounted models (CRF *vs*. CSOM; $p < 0.001$ for all) and between the harness-mounted collars (HRF *vs*. HSOM; $p = 0.011$; Table 3.7). Irrespective of mounting location, the SOM models produced higher estimated proportions of time spent on active and maintenance behaviours at the expense of inactive behaviours.

3.4 Discussion

This chapter aimed to develop and validate a ML model capable of accurately classifying domestic cat behaviours from accelerometer data. An iterative methodology was applied to refine model complexity, and activity budgets were produced from a separate dataset to assess how well the developed models performed in producing realistic activity budgets. The findings highlight a crucial difference between internal performance metrics and practical application.

In this study a clear trade-off between the number of behavioural classes included in the model and its overall classification performance was found. After the initial models were trained, behaviours that were poorly classified based on their poor performance metrics were either merged with functionally similar behaviours (e.g., trotting and walking) or removed (e.g., digging). This process of simplification consistently led to improved model performance metrics across successive modelling rounds. Similar results were observed in other comparable studies where reducing the number of behavioural classes increased overall model performance (McGowan et al., 2022; Shamoun-Baranes et al., 2012). Researchers, therefore, must carefully balance the desired level of behavioural detail with the need for a reliable and accurate model. Accordingly, decisions to merge or remove behaviours should not be random but must be done carefully, based on a combination of factors, including the available sample size for each behaviour, the similarity of accelerometer signatures between behaviours and, of course, the biological relevance of behaviours to the research question.

Validation of the models with the validation dataset showed that the SOM models consistently had higher performance metrics than the RF models. However, when activity budgets were generated from days two to six using the behaviours classified by each model, inconsistencies between models became apparent, especially between the RF and SOM models. The SOM models overestimated the time cats spent eating which ranged between 14% and 28%. The overestimation of eating and grooming came at the cost time spent lying and sitting, indicating poor generalisation of the SOM models. The activity budgets generated by the RF models were more consistent across mounting locations and aligned with previously reported literature values. Literature on the activity budget of domestic cats suggests that domestic cats spend approximately 2-3% of their time on eating (Berteselli et al., 2017; Eckstein & Hart, 2000b; Huck & Watson, 2019; Panaman, 1981). The RF models consistently classified that cats spent approximately 3-4% of their time eating. In addition, there were sizeable inconsistencies between the collar and harness models of the SOM models, suggesting poor generalisability of the SOM models.

A supervised SOM is an artificial neural network that consists of an input layer, a single hidden layer, and an output layer in the form of a grid map consisting of neurons (Riese et al., 2020). There is a neighbourhood relationship between the neurons on the output grid map (Riese et al., 2020). The neurons of the hidden layer are connected to the samples in the input layer through weights which are updated with each iteration (Siqueira et al., 2022). Due to the neighbourhood relationship between neurons, changes in the weight of one neuron will affect other neurons in its neighbourhood (Riese et al., 2020). Allende et al. (2004) reported that SOMs are sensitive to outliers due to the weight of one neuron affecting its neighbouring neurons. It is reasonable to expect outliers in behavioural datasets, as behaviour can be very dynamic. A cat sitting, for example, can sit completely stationary, but it might suddenly turn its head back when hearing a noise, triggering the accelerometer due to the movement. In both cases, the cat is classified simply as sitting but will result in different accelerometer traces. It is possible that the outliers of the dataset not used to train the model were different than those included in the training dataset. This could have led to the SOM being able to classify behaviours in the training dataset with high accuracy but having problems classifying behaviours in a novel dataset. The SOM models could be improved by distinguishing more subtle differences in behaviour and posture, e.g., annotating sitting completely stationary and moving the head around while sitting separately. It should be noted, however, that adding more behaviour classes does not necessarily improve the model, but rather decreases its accuracy, as explained earlier.

Another contributing factor to the seemingly poor generalisation of the SOM models is overfitting. Overfitting occurs when a model fits the training data so well, it learns the noise in the dataset leading to a model that does not perform well on a new dataset (Dolphin, 2022). A reason why overfitting might occur is the presence of too many classification variables, making the model overcomplicated (Dolphin, 2022; Ying, 2019). The classification variables included in the current study were based on the 26 classification variables identified as most effective by Tatler et al. (2018), and the 31 used by Galea et al. (2021). The SOM models were simplified to as few as four classification variables (mean for X, Y and Z, and ODBA), but this did not improve the results (results not shown).

The poor performance of the SOM models and wider challenge of model generalisation can be attributed to several methodological limitations in the design of the methods for this chapter. A primary concern is the representativeness of the training data. The annotated data used for training and internal validation came from a single, continuous time window: between 9 AM and 2 PM from day one. This time window was deliberately chosen because the cats at the research facility have been shown to be the most active at these times (Andrews et al., 2015; Smit et al., 2022) and therefore most likely to display the widest range of behaviours. In the current study, inactive behaviours consistently had higher performance metrics than more active and dynamic behaviours, likely due to their lower variability in accelerometer signatures. This aligns with previous findings that dynamic behaviours require larger sample sizes to adequately capture their variability. Galea et al. (2021) reported that SOM models need at least 2000 observations per behaviour for high-intensity behaviours such as jumping or trotting, whereas more static behaviours, such as sitting or lying, require only around 100 observations. Expanding the annotation period to include low-activity times (e.g., evenings or nights) would primarily have added more of these already dominant inactive behaviours. Because these behaviours are frequent and easier to classify, they had to be down sampled to avoid biasing the model towards more common, static behaviours.

Behaviours with small sample sizes, such as climbing and jumping, were difficult to classify accurately and were therefore removed to improve overall model performance. The difficulty in classifying these behaviours is compounded by their duration. Most behaviours with low sensitivity and precision in the current study consisted of swift movements of short duration (< 1 second). This aligns with findings from Tatler et al. (2018), who reported similar challenges in classifying rapid, short-duration activities in dingoes (*Canis lupus dingo*) using collar-mounted accelerometers. Capturing such movements is particularly difficult in small, agile animals like cats, whose movements are quicker than those of larger species (Brown et al., 2013). The one-second epoch length used in the current study may also have contributed. Jumping, which had an average duration of 0.89 seconds (results not shown), was often misclassified as walking, likely because the brief acceleration signature was lost within the signal of walking behaviour that immediately preceded and followed it. A shorter epoch could more accurately isolate these swift movements and increase sample size of infrequent behaviours. In the current study, accelerometer data were collected at 30 Hz and summarised into one second epochs, and sample sizes could have easily been increased by selecting a shorter epoch. However, increasing the sample size will also increase the computational time to train and test the models (Tatler et al., 2018).

In any accelerometery-based behavioural classification study there is a need to simplify the complete ethogram of the animal as a full ethogram consists of over 100 behaviours (Kappel et al., 2024; Stanton et al., 2015). Many of these behaviours, however, are subtle or context-dependent and difficult to reliably distinguish with an accelerometer alone. The addition of a gyroscope, which measures how fast an object moves, and a magnetometer, that can provide information on body orientation, could increase the number of behaviours that can be distinguished. Hussain et al. (2023) reported that the addition of a gyroscope and magnetometer could improve the classification accuracy of cat behaviour.

The models trained in the current study were limited by the behaviours that were observed and annotated within the video recordings. Consequently, several biologically relevant behaviours, such as drinking, running and fighting, were either not observed at all or too infrequent to be included in the models. When the models are applied to data collected in different environments, such as private homes, it is likely to encounter behaviours it was not trained to recognise. Such untrained behaviours will therefore be misclassified into one of the existing classes, introducing a potential source or error. Care should be taken when extrapolating the classifications made by a model beyond the context in which it was developed.

An unexpected finding that further highlights these challenges, was that models for the harness-mounted accelerometers classified eating more accurately than the models for the collar-mounted accelerometers. This contradicted the initial hypothesis that collar-mounted accelerometers would be better suited for detecting subtle head movements than harness-mounted ones. This discrepancy is likely the results of the design of the feeding area in the colony cages (Figure 3.1). Cats were often observed to place their front paws in the feeding tray, while their hind paws remained on the wooden walkway surrounding the feeding tray, resulting in a forward tilted posture where the head and shoulders were lower than their hips. This change in posture during eating likely resulted in a greater change in the orientation of the harness-mounted accelerometer compared with the collar (Kumpulainen et al., 2021). In a home situation, it would be expected that food bowls would be on the ground or slightly elevated and thus will not result in the cat being tilted forward (Houpt, 2022; Laflamme & Gunn-Moore, 2014). Consequently, the model's high performance in classifying eating behaviour may not be transferable to pet cats, underscoring the need for context-specific validation of models.

The RF models classifying three categories (active, maintenance, inactive), although having the highest performance metrics, did not provide specific information on individual behaviours and were therefore not deemed the best option for future research. The RF models classifying eight or six different behaviours differed little in their performance metrics. Therefore, the RF model classifying eight behaviours was deemed the most suitable option, even though it had low sensitivity for littering. The inclusion of littering was retained as it is a medically relevant behaviour. Given that cats are more likely to wear a collar than a harness, the final model selected for subsequent analyses was the collar-mounted accelerometer and RF model that classified eight behaviours, as it represents the best balance of classification detail, practical applicability, and validated robustness. It will be used to gain more detailed insights into the behaviour of research cats (Chapter 4) and pet cats (Chapter 5).

A crucial aspect of validating any behavioural classification model, is ensuring its ability to generalise to new unseen data. This is particularly challenging in animal behaviour studies, which are often characterised by high inter-individual variation in movement patterns, activity levels, and behavioural rhythms (Andrews et al., 2015; Gerencsér et al., 2013). A model trained on a limited cohort of animals may learn the specific movement signatures of those individuals and fail to generalise to new subjects. This challenge was demonstrated in a study on dogs, which found that while a model achieved over 91% accuracy when validated on data from the same dog it was trained on, its performance dropped to around 70% when applied to a different dog of the same breed (Gerencsér et al., 2013). To better account for inter-individual variation, a validation strategy known as leave-one-individual-out cross validation is recommended. In this approach, a model is trained on data from all individuals except one, which is excluded from the validation dataset (Ferdinandy et al., 2020). This process is then repeated for every individual in the dataset, providing a more robust and realistic estimate of the performance of the model on a completely new individual. In addition to individual differences, temporal generalisability is also important, as behaviour can vary across different times of the day and between days. In the present study, both training and validation were conducted with data from a single period of high-activity on one day, and temporal generalisability was not evaluated. Day-to-day changes in behaviour can occur, for example in response to illness or changes in the environment, although, this was unlikely in the current study because the cats were healthy and housed in a stable, controlled environment with consistent routines. Care should be taken when models are applied outside of the context in which they were developed. Future studies should assess model performance and generalisability using independent datasets sampled across multiple days and time periods, including during low-activity periods, to evaluate both inter-individual and temporal robustness.

3.5 Conclusion

Despite the superior internal performance metrics of the Self-Organising Maps, the results from the activity budgets indicated poor generalisation of these models to unseen data. In contrast, the Random Forest models produced more consistent and biologically plausible activity budgets, supporting their selection as the most reliable and robust classifier for this dataset. Among the Random Forest models, the eight-behaviour model derived from a collar-mounted accelerometer was deemed the most suitable tool for subsequent chapters. The results further demonstrate that realistic activity budgets are a crucial additional step when applying ML models from controlled training conditions to applied biological research. The selected model will therefore be used in the following chapters to study the behaviour of both research and pet cats under varying environmental conditions.

Chapter 4

Longitudinal study on the associations of seasons and the behaviour of domestic cats (*Felis catus*)

Image generated with Meta AI

Part of this chapter has been published as;

Smit, M., Andrews, C. J., Draganova, I., Corner-Thomas, R. A., & Thomas, D. G. (2025). Longitudinal Study on the Effect of Season and Weather on the Behaviour of Domestic Cats (*Felis catus*). *Animals*, *15*(5), 637. https://doi.org/10.3390/ani15050637

See Appendix IX for published paper.

Chapter 4 Longitudinal study on the association of season and the behaviour of domestic cats (*Felis catus*)

4.1 Introduction

Behaviour plays a crucial role in monitoring animal welfare. To be able to correctly interpret the welfare of an animal based on its behaviour, an understanding of how animals react to their environment is essential. For domestic cats, especially those with outdoor access, this environment includes seasonal and meteorological changes. While research has established clear links between these environmental and general activity levels, less is known about their influence on specific behaviours. It is important to increase our understanding in this area, as different behaviours serve distinct biological functions and individuals may respond differently to environmental pressures.

As previously established in literature, the naturally occurring light-dark cycle is an important cue to which animals, including domestic cats, entrain its behavioural rhythm (Refinetti, 2008, 2016). However, the pattern of the light-dark cycle can fluctuate significantly throughout the year, depending on the latitude of the location. In equatorial regions, the fluctuation is minimal, but as one travels further away from the equator, the more noticeable and extreme this fluctuation becomes.

Current knowledge on the associations of seasonal changes with changes in activity primarily comes from general activity studies, where the activity of domestic cats was measured through visual observation, radio-tracking, or Global Positioning Systems (GPS). These studies have shown that the activity levels of cats can vary across seasons and living conditions. Free roaming cats, for example, have been shown to be more active in spring and summer than in autumn and winter (Goszczyński et al., 2009; Haspel & Calhoon, 1993; Merčnik et al., 2023). These studies, however, only looked at free-roaming cats and did not distinguish between pet, stray or feral cats. Horn et al. (2011) compared the activity of unowned free-roaming cats to that of free-roaming pet cats and found contrasting results. Unowned cats were most active in autumn and winter, while pet cats were more active in spring and autumn. The difference was attributed to higher energy demands during the colder months in the unowned cats, while pet cats appeared to prioritise comfort, avoiding extreme hot and cold conditions. In addition, Parker et al. (2022a) reported that research cats housed in controlled temperature and humidity, but exposed to natural daylight, were most active in spring and autumn and least active in winter. To date, it appears that no other studies on seasonal changes in activity of research cats have been published.

Different seasons are not only characterised by changes in daylength, but also by varying weather conditions. In free-roaming cats, activity has been negatively and positively correlated with temperature and rain, respectively (Goszczyński et al., 2009; Haspel & Calhoon, 1993; Merčnik et al., 2023). Konecny (1987) reported the lowest activity in feral cats was around midday, when the ambient temperature was at its highest. Izawa (1983) reported a negative correlation between temperature and activity during the day, while this correlation was positive during the night. A questionnaire-based study, including both indoor-only and free-roaming pet cats, found that extreme weather events affected specific behaviours of pet cats (Palestrini et al., 2022). Sudden decreases in temperature were associated with an increase in eating behaviour, whereas intake decreased in hot weather (temperature not specified). Grooming behaviour tended to increase in the colder seasons, however, there was a lack of detail on what constituted excessively hot temperatures, and owner-reported data is subjective. While activity can provide valuable insights into activity patterns, it does not capture the full range of behaviours that cats display. Thus, examining specific behaviours is essential to fully understand how environmental conditions shape domestic cat behaviour.

The existing literature further highlights that most research has focused on either free-roaming cats, whose behaviour is driven by factors like hunting and territorial defence, or on fully indoor-housed research cats, who are not exposed to weather. This leaves a significant gap in our understanding of how specific, quantified weather variables directly influence the behaviour of domestic cats in semi-outdoor environments, where they are exposed to the elements but do not engage in free-roaming behaviours. Therefore, the primary aim of this chapter is to determine how daylength, weather and seasonal factors are associated with changes in the behaviour of group-housed cats with semi-outdoor access over time. Behaviour of the cats was classified using the in Chapter 3 validated random forest model classifying eight different behaviours (active, sitting, standing, grooming, littering, eating, scratching) from a collar-mounted accelerometer. Given that the study animals are provided with food and shelter, similar to the free-roaming pet cats described by (Horn et al., 2011), it was hypothesised that cats would prefer thermal comfort, resulting in a negative correlation between temperature and active behaviours. Based on the consistent findings across multiple studies (Goszczyński et al., 2009; Harper, 2007; Haspel & Calhoon, 1993; Izawa, 1983), it was hypothesised that rainfall would have a clear negative association with active behaviours, as the cats would likely reduce their use of unsheltered portions of their enclosure during wet weather. Finally, considering the distinct effect of daylength observed in indoor research cats (Parker et al., 2022a), versus the direct influence of meteorological conditions on free-roaming cats, it was hypothesised that both daylength and weather patterns would significantly influence behavioural patterns.

4.2 Material and methods

The study was conducted at the Massey University Centre for Feline Nutrition, Palmerston North, New Zealand (latitude 40° 23′ S, longitude 175° 36′ E). The study was approved by the Massey University Animal Ethics Committee (MUAEC 22/23).

4.2.1 Data collection

Eight healthy, desexed male (n = 4) and desexed female (n = 4) domestic shorthair cats were group housed in a single semi-outdoor colony cage for a year (Figure 3.1). At the start of the trial, the average ± standard deviation age of the cats was 4.2 ± 0.8 years, and bodyweight was 4.2 ± 0.9 kg. Bodyweight was measured on a weekly basis for every cat throughout the trial. Cats were fed a complete and balanced (AAFCO, 2021) commercial canned diet (Heinz Wattie's Ltd., Hastings, New Zealand) and had *ad libitum* access to water for the duration of the study.

4.2.1.1 Accelerometer data

Accelerometer data were collected using the collar attachment method as described in Chapter 3. Accelerometer data were downloaded, and feature engineered as described in Chapter 3. Using the feature engineered data, the behaviour of the cats was classified using a random forest model that classifies eight different cat behaviours using data from a collar-based accelerometer: active (walking and trotting), eating, grooming, littering, lying, scratching, sitting, and standing. This model was chosen from Chapter 3 as it provided the best trade-off between retaining a greater number of biologically relevant behaviours (n = 8) while maintaining an acceptable overall F1-score (68%). Accelerometer data were collected for seven consecutive days, every four weeks, for a full year, starting in December 2022, and ending in November 2023 (Figure 4.1). Events that deviated from the normal, or disturbances in the normal routine at the Centre for Feline Nutrition were noted.

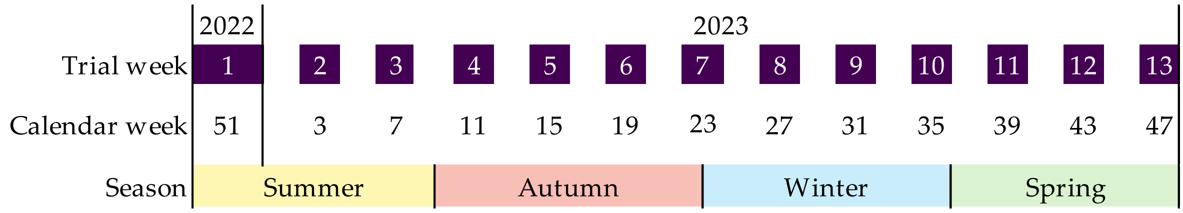

Figure 4.1. Timeline of accelerometer data collection including calendar year and week, trial week and the season.

4.2.1.2 Weather data

A Vantage Pro2™ ISS weather station (Davis Instruments, Hayward, CA, U.S.A.) was used at the Centre for Feline Nutrition to collect weather data. The weather station was connected to a solar panelled gateway EnviroMonitor System (Davis Instruments, Hayward CA, U.S.A.), which sent hourly aggregated weather data via cellular connection to WeatherLink.com, from the weather data were downloaded. A total of 20 weather variables could be downloaded, of which eight were selected: average temperature (°C), minimum and maximum temperature (°C), average relative humidity (%), average THW (temperature, humidity & windchill) index (°C), average wind speed (m/s), and total rainfall (mm; Table 4.1). The heat index and THW index were selected to account for any possible high correlation between temperature, humidity and wind. The other six weather variables were selected based on their established biological relevance to feline behaviour and thermoregulation, as reported in previous literature (Goszczyński et al., 2009; Harper, 2007). Four seasons were recognised: summer (December – February), autumn (March – May), winter (June – August), and spring (September – November). Weather data were continuously recorded throughout the study.

Table 4.1. Units and definitions of selected weather variables.

Weather variable	Unit	Definition[1]
Temperature	°C	Average temperature over the 60-minute period (each full hour).
Minimum temperature	°C	Minimum temperature recorded over the 60-minute period (each full hour).
Maximum temperature	°C	Maximum temperature recorded over the 60-minute period.
Relative humidity	%	Average saturation of the air with water at its current temperature over the 60-minute period.
Heat index	°C	Average calculated temperature per 60-minute period that takes temperature and humidity into account to determine how hot the air feels.
THW index	°C	Average calculated temperature per 60-minute period that takes temperature, humidity, the heating effects of sunshine and cooling effects of the wind (wind chill) into account to determine what it feels like in the shade.
Rainfall	mm	The total rainfall recorded during the 60-minute period
Wind speed	m/s	The average wind speed recorded during the 60-minute period.

[1] (Davis Instruments, 2024).

The R-package 'suncalc' (Thieurmel & Elmarhraoui, 2022) was used to obtain daily data on the exact times of light phases based on the specific coordinates of the weather station within the Centre for Feline Nutrition (-40.390344, 175.615829). From these times, the daylength, or total amount of light in seconds between sunrise and sunset, was determined for each day (00:00:00 – 23:59:59).

4.2.2 Data analysis

All data computation and statistical analyses were carried out using RStudio version 4.1.1 (RStudio Team, 2021). The data were cleaned by removing acceleration data from those times each cat was not wearing the collar and corresponding weather data were also removed. Seasons were assigned to the individual datapoints in the dataset based on the calendar date. The proportion of each behaviour was determined for every day of data collection, trial week and season for every cat. Boxplots were created using daily and weekly proportions to identify outliers in the proportional data. Outliers in the dataset were identified using boxplots and were removed if they occurred during a noted event or disturbance. Generalised linear mixed models (GLMM), using the R package 'glmmTMB' (Brooks et al., 2024), with a beta distribution and logit link to account for the proportional nature of the data, were used to evaluate the association of season and weather variables with changes in cat behaviour. To evaluate the association of season, three GLMMs were created for each behaviour: (1) a simple model with no predictors, (2) an intermediate model with only cat as a random effect, and (3) a full model that included cat as a random effect and the season as a fixed effect as in equation 4.1:

(4.1) $$logit\left(\mu_{ij}\right) = \beta_0 + \beta_1 X_{ij} + b_j$$

where μ_{ij} is the expected seasonal proportion of time cat j spends on the behaviour in observation i, β_0 is the overall intercept, β_1 is the fixed effect of season, X_{ij} indicates the specific season of observation i for cat j, and $b_j \sim \mathcal{N}(0, \sigma_b^2)$ is the random intercept for cat j to account for individual differences.

The three models were compared with an ANOVA to determine which factors improved the model, and the marginal and conditional R^2 of the full models were determined. The marginal R^2 value is the variance explained by only the fixed effect, whereas the conditional R^2 value is the variance explained by both the random and fixed effects. Bodyweights were averaged over the seasons for each cat and analysed using a linear mixed-effects model to determine seasonal differences. To determine differences between seasons, pairwise comparisons of estimated marginal means were conducted for each behaviour and bodyweight, using the R package 'emmeans' (Lenth et al., 2024). A Tukey adjustment was used to correct for multiple pairwise comparisons. Results were considered significant if $p \leq 0.05$, and a trend if $0.05 > p < 0.10$.

Daily averages for temperature (including minimum and maximum), relative humidity, THW, index and wind speed, and sum of rainfall were calculated. These daily averages were merged with daily behavioural proportions and the associations of weather conditions with cat behaviours were statistically tested using a GLMM with a beta distribution and logit link. Because the weather data were on different scales with different units, they were scaled using the scale function in R prior to statistical modelling. Similar to the GLMM testing above, three GLMMs were performed: with the same simple and intermediate models as described above. The full model included cat and day of the trial as a random effect to account for the repeated nature of the data, and weather conditions as fixed effects. The full model followed the same mathematical formulation and assumptions as in equation 4.1, but with the fixed effect being one weather variable. The marginal and conditional R^2 values for each model were determined. First, univariate GLMMs were performed to determine the main effects of each selected variable on each behaviour. For each behaviour, weather variables that improved the model ($p < 0.10$) were then combined in a final multivariate model. A backwards stepwise procedure was used to remove variables for which $p\ ^{3}\ 0.10$ until only those remained for which $p < 0.10$. The 95% confidence intervals for the estimated coefficients were determined. Results of all the statistical testing were considered significant if $p \leq 0.05$, and a trend if $0.05 > p < 0.10$. In addition, correlation coefficients between the weather variables and daylength were determined, which were interpreted as defined in Table 4.2.

Results are presented as the mean ± standard error (SE).

Table 4.2. Interpretation of correlation coefficients (Mukaka, 2012).

Correlation coefficient	Interpretation
0.90 to 1.00 (-0.90 to -1.00)	Very high positive (negative) correlation
0.70 to 0.90 (-0.70 to -0.90)	High positive (negative) correlation
0.50 to 0.70 (-0.50 to -0.70)	Moderate positive (negative) correlation
0.30 to 0.50 (-0.30 to -0.50)	Low positive (negative) correlation
0.00 to 0.30 (0.00 to -0.30)	Negligible correlation

4.3 Results

The study was extended by three months due to faulty weather station equipment so was completed in February 2024. The accelerometer data collected between December 2022 and February 2023 were not included in this study but were used in Chapter 5. Data collected between March 2023 and February 2024 were included in the data analyses (Figure 4.2). Data collection originally scheduled for calendar week 43 (trial week 9) was postponed by a week until week 44 due to illness of the researcher (Figure 3.2). One of the cats was humanely euthanised due to an illness unrelated to the study, therefore, only data from seven cats were included in the data analyses. One week of data was not collected for two cats, one in trial week 9 and one in trial week 12, due to animal illness at the time.

	2023											2024	
Trial week	1	2	3	4	5	6	7	8	**9**	10	11	12	13
Calendar week	11	15	19	23	27	31	35	39	**44**	47	51	2	6
Season	Autumn				Winter			Spring			Summer		

Figure 4.2. Final timeline of data collection including calendar year and week, trial week and the season. The trial week highlighted in yellow was postponed by a week.

Weekly proportional data boxplots for each individual cat allowed the identification of a small number of outliers in the dataset (Figure 4.3). The outliers each were identified to a single cat (see Appendix X for outlier identification labels). The majority of outliers for grooming and scratching were consistently attributed to a single cat (Cho) across all seasons, suggesting and individual pattern that was not representative of the group. She was later diagnosed with idiopathic dermatitis, and therefore, her grooming and scratching data were removed. Though not visible in Figure 4.3, large variations in many behaviours were observed for all cats in trial week 5 when compared to other trial weeks (Appendix XI). On day two of trial week 5, one cat (Cho) was accidentally placed in the wrong colony cage for one day, after which she was placed back in the colony cage with the other cats included in this trial. Given the large variation for several behaviours in the boxplots for this week across all cats, it was assumed that this affected the behaviour of all cats in the colony cage. For this reason, the behavioural data of trial week 5 were removed from the dataset for all cats and excluded from data analyses. Large variations in behaviour were observed for Nimbus in trial week 10, but no events or disturbances were reported for that week, and, therefore, this data was not removed (Appendix XI Figure A7).

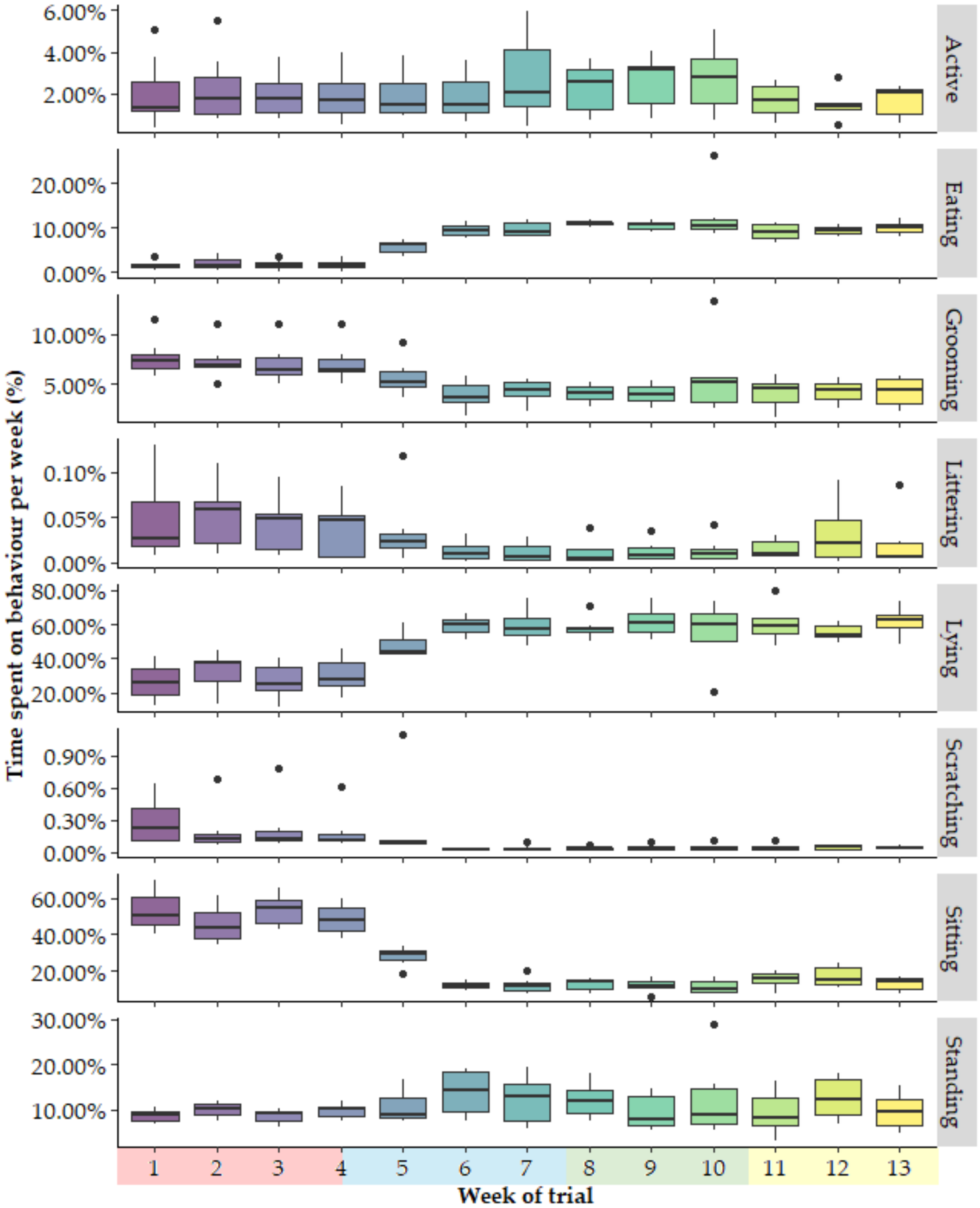

Figure 4.3. Boxplots of weekly proportional behaviour data (n = 7). Seasons are indicated along the x-axis by colours: red = autumn, blue = winter, green = spring, yellow = summer.

4.3.1 Seasonal differences

For each cat (n = 7) one seasonal proportion for each behaviour was determined, resulting in seven datapoints per behaviour, per season that were included in the GLMM models.

4.3.1.1 Bodyweight

Six cats were included in the analysis due to health-related weight loss in one cat (Mrs. Norris), with no significant differences in average bodyweight across seasons (of 4.2 ± 0.4 kg;

p > 0.05). While no seasonal pattern was observed in the average bodyweight, individual trends varied (Figure 4.4).

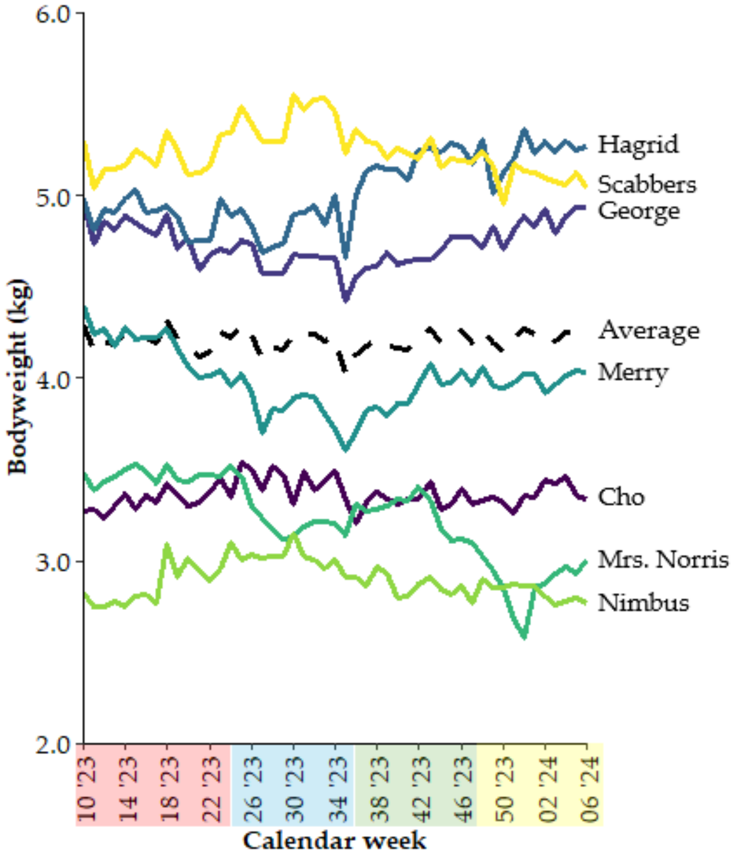

Figure 4.4. Weekly bodyweight (kg), expressed per calendar week, of all individual cats (n = 7) included in the study. Seasons are indicated along the x-axis by colours: red = autumn, blue = winter, green = spring, yellow = summer.

4.3.1.2 Active

Inclusion of cat as a random effect in the GLMM improved the model ($R^2_{conditional}$ = 0.54; p = 0.003), whereas the inclusion of season as a fixed effect did not ($R^2_{marginal}$ = 7.8%; $R^2_{conditional}$ = 66.4%; p > 0.05). Although differences were not statistically significant, the proportion of time cats spent in active behaviours (walking and trotting) was highest during spring (2.47 ± 0.27%; followed by winter (2.23 ± 0.49%) and autumn (2.05 ± 0.55%), and lowest in summer (1.56 ± 0.54%; Figure 4.5). These values reflect comparisons of mean time spent in active behaviours across four periods rather than causal effects of season.

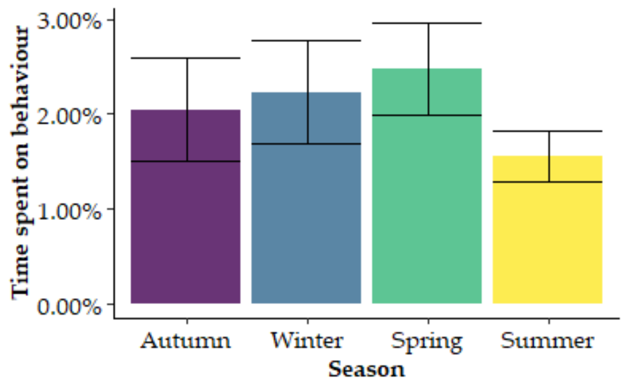

Figure 4.5. Average time spent on active behaviours (walking and trotting) by cats (n = 7), as classified by the model, across four time periods within a year (autumn, winter, spring, summer).

4.3.1.3 *Eating*

Inclusion of cat as a random effect in the GLMM did not improve the model ($p > 0.05$), whereas the inclusion of season as a fixed effect did ($R^2_{marginal} = 94.5\%$; $R^2_{conditional} = 95.0\%$; $p < 0.001$). Cats spent the most time eating in spring (11.34 ± 0.48%), followed by summer (9.52 ± 0.48%) and winter (7.73 ± 0.83%), and the least in autumn (1.73 ± 0.42%; Figure 4.6). Time spent eating was lower in autumn compared to the three other seasons ($p < 0.001$) and was lower in winter than in both spring ($p < 0.001$) and summer ($p = 0.035$). A trend was found for the difference between spring and summer ($p = 0.057$). These values reflect comparisons of mean time spent in eating behaviour across four periods rather than causal effects of season.

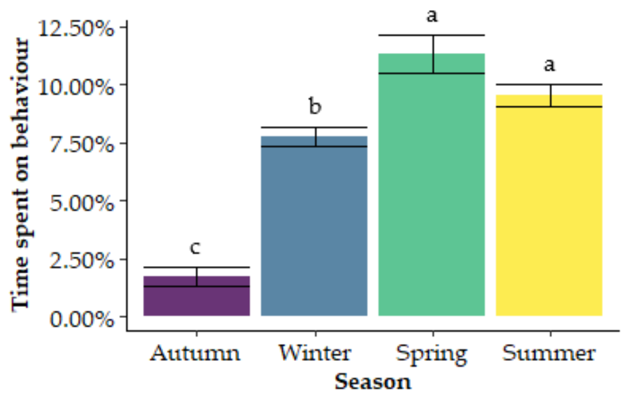

Figure 4.6. Average time spent on eating behaviour by cats (n = 7), as classified by the model, across four time periods within a year (autumn, winter, spring, summer). $^{a\text{-}c}$ **Different superscripts indicate significant differences ($p \leq 0.05$).**

4.3.1.4 *Grooming*

Inclusion of cat as a random effect in the GLMM did not improve the model ($p > 0.05$), whereas the inclusion of season as a fixed effect did ($R^2_{marginal} = 41.0\%$; $R^2_{conditional} = 81.1\%$; $p < 0.001$). Cats groomed most in autumn (6.83 ± 0.47%) than during winter (4.57 ± 0.70%; $p < 0.001$), spring (4.46 ± 0.56%; $p < 0.001$), and summer (4.04 ± 0.47%; $p < 0.001$ Figure 4.7). A trend was found for the difference between winter and summer (p = 0.083) and no differences were found between spring and either winter or summer ($p > 0.05$). These values reflect comparisons of mean time spent in grooming behaviour across four periods rather than causal effects of season.

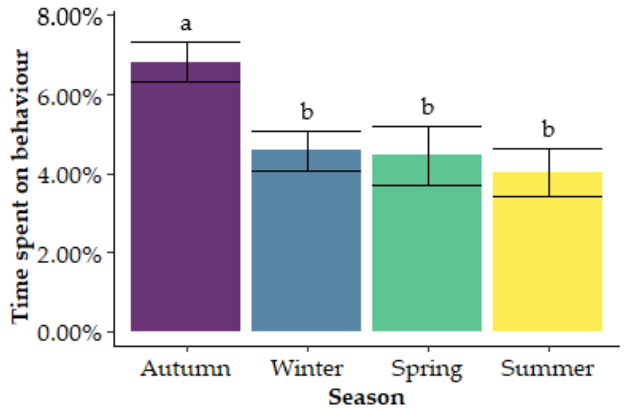

Figure 4.7. Average time spent on grooming behaviour by cats (n = 6), as classified by the model, across four time periods within a year (autumn, winter, spring, summer). [a-b] Different superscripts indicate significant differences ($p \leq 0.05$).

4.3.1.5 Littering

Inclusion of cat as a random effect in the GLMM did not improve the model ($p > 0.05$), whereas the inclusion of season as a fixed effect did ($R^2_{marginal}$ = 25.0%; $R^2_{conditional}$ = 37.9%; p = 0.037). Cats littered most in autumn (0.046 ± 0.012%), followed by summer (0.022 ± 0.004%), winter (0.017 ± 0.004%), and spring (0.013 ± 0.009%; Figure 4.8). Time spent littering was higher in autumn compared to winter (p = 0.022), spring (p = 0.002) and summer (p = 0.021). No differences were found between winter, spring and summer ($p > 0.05$). These values reflect comparisons of mean time spent in littering behaviour across four periods rather than causal effects of season.

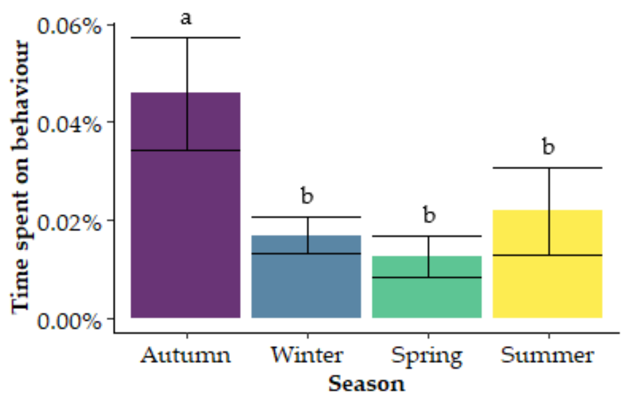

Figure 4.8. Average time spent on littering behaviour by cats (n = 7), as classified by the model, across four time periods within a year (autumn, winter, spring, summer). [a-b] Different superscripts indicate significant differences ($p \leq 0.05$).

4.3.1.6 *Lying*

Inclusion of cat as a random effect in the GLMM did not improve the model ($p > 0.05$), whereas the inclusion of season as a fixed effect did ($R^2_{marginal} = 87.7\%$; $R^2_{conditional} = 92.7\%$; $p < 0.001$). Cats spent most time lying in summer (60.33 ± 3.92%), followed by spring (58.29 ± 3.37%) and winter (52.88 ± 3.52%), and autumn (28.68 ± 3.93%; Figure 4.9). Time spent on lying was lowest in autumn compared to all other seasons ($p < 0.001$). A trend was found for the difference between winter and summer ($p = 0.076$), and no difference was found between spring and summer ($p > 0.05$). These values reflect comparisons of mean time spent in lying behaviour across four periods rather than causal effects of season.

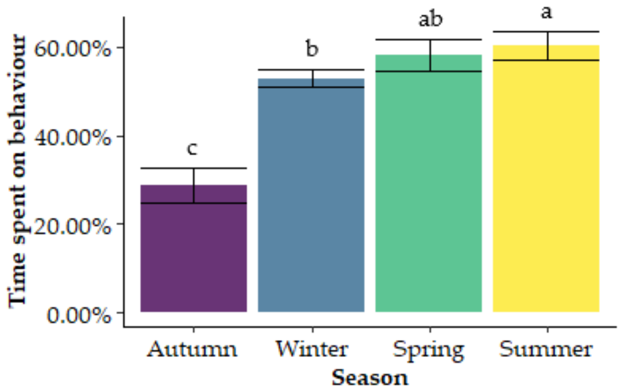

Figure 4.9. Average time spent on lying behaviour by cats (n = 7), as classified by the model, across four time periods within a year (autumn, winter, spring, summer). [a-c] Different superscripts indicate significant differences ($p \leq 0.05$).

4.3.1.7 *Scratching*

Inclusion of cat as a random effect in the GLMM did not improve the model ($p > 0.05$), whereas the inclusion of season as a fixed effect did ($R^2_{marginal} = 59.9\%$; $R^2_{conditional} = 93.2\%$; $p < 0.001$). Cats scratched most in autumn (0.16 ± 0.03%), followed by winter (0.05 ± 0.00%), summer (0.04 ± 0.02%) and spring (0.03 ± 0.01%; Figure 4.10). Cats spent the most time spent scratching in autumn compared to the other three seasons ($p < 0.001$). Scratching was higher in winter compared to both spring ($p = 0.008$) and summer ($p = 0.014$). No difference was found between spring and summer ($p > 0.05$). These values reflect comparisons of mean time spent in scratching behaviour across four periods rather than causal effects of season.

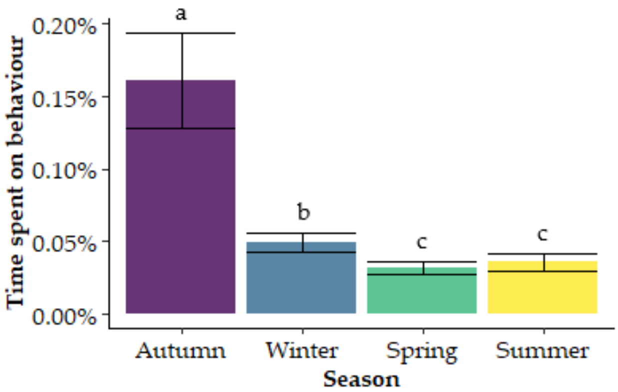

Figure 4.10. Average time spent on scratching behaviour by cats (n = 6), as classified by the model, across four time periods within a year (autumn, winter, spring, summer). [a-c] **Different superscripts indicate significant differences ($p \leq 0.05$).**

4.3.1.8 Sitting

Inclusion of cat as a random effect in the GLMM did not improve the model ($p > 0.05$), whereas the inclusion of season as a fixed effect did ($R^2_{marginal} = 93.5\%$; $R^2_{conditional} = 93.5\%$; $p < 0.001$). Cats sat most in autumn (50.77 ± 3.73%), followed by winter (20.10 ± 1.14%), summer (14.35 ± 0.97%) and spring (11.98 ± 1.61%; Figure 4.11). Cats spent more time sitting in autumn compared to the other three seasons ($p < 0.001$). Cats spent more time sitting in winter compared to both spring ($p < 0.001$) and summer ($p = 0.013$) and no difference was found between spring and summer ($p > 0.05$). These values reflect comparisons of mean time spent in sitting behaviour across four periods rather than causal effects of season.

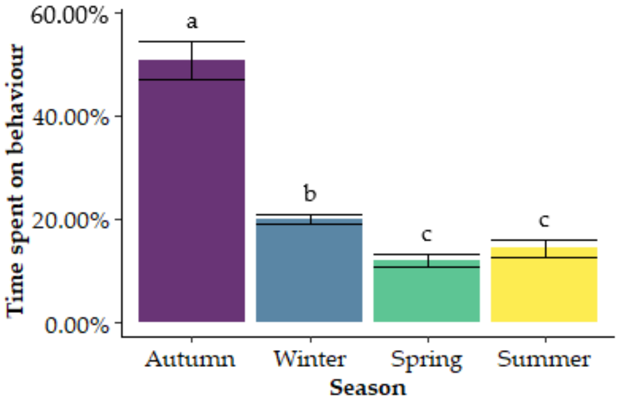

Figure 4.11. Average time spent on sitting behaviour by cats (n = 7), as classified by the model, across four time periods within a year (autumn, winter, spring, summer). [a-c] **Different superscripts indicate significant differences ($p \leq 0.05$).**

4.3.1.9 Standing

Neither inclusion of cat as a random effect or the inclusion of season as a fixed effect improved the model ($R^2_{marginal} = 13.2\%$; $R^2_{conditional} = 49.8\%$; $p > 005$). Despite not being significantly different, cats stood most in winter (12.20 ± 1.38%), followed by spring (11.32 ± 1.79%), summer (10.10 ± 1.46%) and autumn (9.15 ± 0.53%; Figure 4.12). These values reflect comparisons of mean time spent in standing behaviour across four periods rather than causal effects of season.

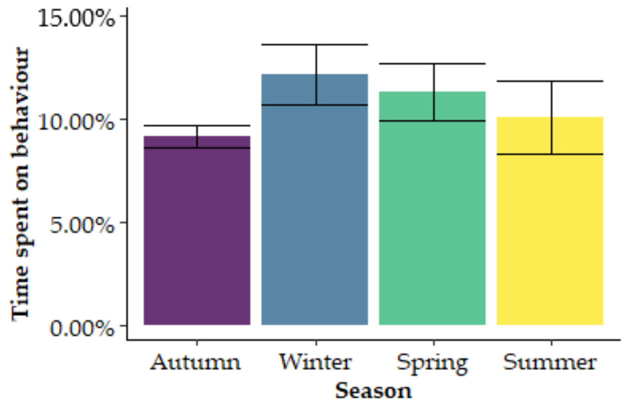

Figure 4.12. Average time spent on standing behaviour by cats (n = 7), as classified by the model, across four time periods within a year (autumn, winter, spring, summer).

4.3.2 Weather

Daylength ranged from 9 hours and 17 minutes in winter to 15 hours and 3 minutes in summer (Figure 4.13. The lowest temperature recorded was -2.3 °C, and the highest was 34.5 °C. The lowest monthly average temperature recorded was 7.0 °C in August, while the highest was 19.0 °C in January (Figure 4.13). The temperature gradually decreased from March 2023 until August 2023, after which it gradually increased until January 2024. In autumn, the average temperature was 13.4 °C (range from 1.1 °C to 28.1 °C), in winter 7.9 °C (-2.3 °C to 18.2 °C), in spring 12.2 °C (-0.7 °C to 27.5 °C) and in summer 17.8 °C (3.4 °C to 34.5 °C).

The average relative humidity was lowest in summer (55.8%), followed by spring (60.0%), autumn (65.8%) and winter (67.9%; Figure 4.13). The maximum recorded relative humidity was 79% across all seasons. The lowest recorded relative humidity for autumn, winter, spring and summer were 36%, 37%, 16% and 18%, respectively.

Spring was the windiest season, with an average of 1.77 m/s and highest recorded wind speed of 12.5 m/s, while autumn was the least windy, with an average of 0.93 m/s and highest recorded winds speed of 8.5 m/s (Figure 4.13). The average windspeeds in winter and summer were 0.95 m/s and 1.21 m/s, respectively, with the highest recorded windspeeds 11.6 m/s and 9.4 m/s, respectively.

The THW-index followed the same pattern as temperature (Figure 4.13). The averages for the THW-index for autumn, winter, spring and summer were 12.8 °C, 7.2 °C, 11.0 °C and 17.1 °C, respectively.

The wettest season was autumn, with a total of 294 mm of rainfall, while the driest season was summer, with a total of 106 mm (Figure 4.13). A total of 234 mm and 288 mm of rain fell in winter and spring, respectively.

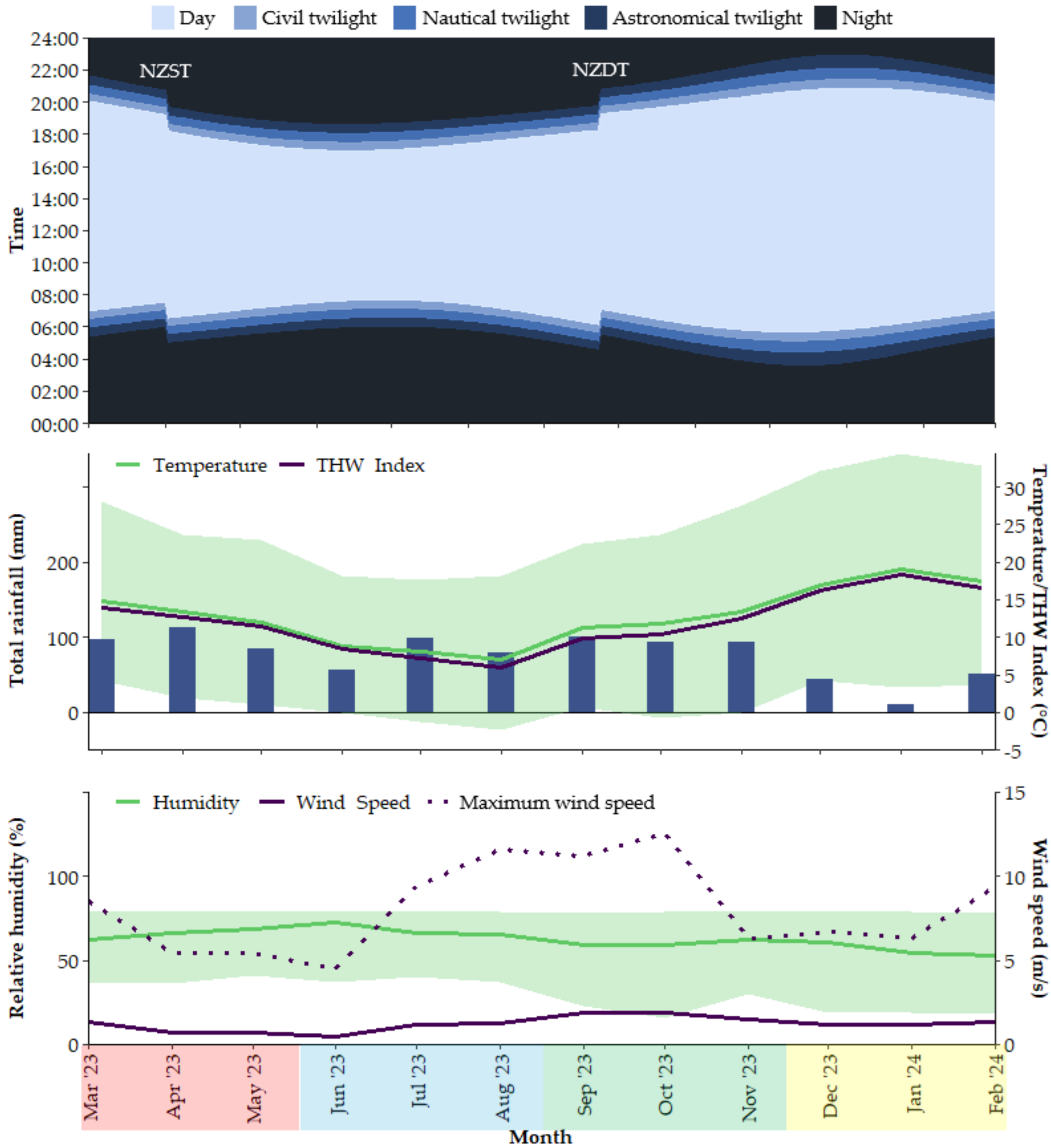

Figure 4.13. Change in daylength and monthly averages for total rainfall, temperature (± minimum and maximum), THW index, relative humidity (± minimum and maximum) and wind speed (+ maximum) from March 2023 till February 2024. Seasons are indicated with colours (red = autumn, blue = winter, green = spring, yellow = summer). NZST = New Zealand Standard Time, NZDT = New Zealand Daylight Time.

Correlation coefficients between weather conditions and daylength are presented in Table 4.3. A very high correlation was found between the heat index and temperature (1.00), the THW index and temperature (0.99), and the heat index and THW index (0.99). A high correlation between temperature and relative humidity (-0.71) was found. Moderate correlations were found between the heat index and relative humidity (-0.67), THW index and relative humidity (-0.64), daylength and temperature (0.51), daylength and heat index (0.51), and the daylength and THW index (0.50). A low correlation was found between wind speed and relative humidity (-0.46). All other correlations were negligible.

Table 4.3. Correlation matrix with correlation coefficients of weather conditions and daylength.

	Temperature	Relative humidity	Wind speed	Heat index	THW index	Rainfall	Daylength
Temperature	1.00						
Relative humidity	-0.71	1.00					
Wind speed	0.27	-0.46	1.00				
Heat index	1.00	-0.67	0.25	1.00			
THW index	0.99	-0.64	0.15	0.99	1.00		
Rainfall	-0.04	0.16	0.08	-0.03	-0.05	1.00	
Daylength	0.51	-0.36	0.13	0.51	0.50	-0.04	1.00

4.3.2.1 *Effect of daylength and weather on behaviour*

To determine the effect of daylength and weather variables, daily proportions, based on the date, of each behaviour were determined for each cat (n = 7). Because proportions were determined based on the date (00:00:00 – 23:59:59), the final dataset used for the GLMMs contained 656 observations after data cleaning and outlier removal. Due to the removal of all grooming and scratching behaviour of one cat, the final number of observations for these behaviours was 560. The results presented are based on the model estimates from the transformed (logit) scale of the beta regression.

Inclusion of cat as a random effect improved the GLMM for active, eating, grooming, littering, lying, scratching and standing behaviour (all $p < 0.001$). Inclusion of day as a random effect improved the GLMM for active, eating, lying, scratching, sitting and standing behaviour (all $p < 0.001$).

The effect of daylength, temperature, relative humidity, wind speed and rain were first determined separately for each behaviour. Daylength was positively associated with eating

($p < 0.001$) and lying ($p < 0.001$) and negatively associated with grooming ($p < 0.001$), littering ($p = 0.035$), scratching ($p = 0.004$), and sitting ($p < 0.001$). There was a negative trend of daylength on active behaviour ($p = 0.076$). No association was observed between daylength and standing behaviour ($p > 0.05$). The β_1 estimates, 95% confidence intervals and *p*-values are reported in Table 4.4.

Table 4.4. Fixed-effect estimates (β_1), 95% confidence interval (CI) and *p*-values for the association of daylength with cat behaviours (univariate GLMMs). Estimates are presented on the logit scale.

Behaviour	β_1	95% CI	*p*-value
Active	-0.05	[-0.10, 0.01]	0.076
Eating	0.50	[0.33, 0.67]	<0.001
Grooming	-0.11	[-0.17, -0.05]	<0.001
Littering	-0.07	[-0.14, -0.01]	0.035
Lying	0.28	[0.16, 0.39]	<0.001
Scratching	-0.22	[-0.37, -0.07]	0.004
Sitting	-0.43	[-0.61, -0.25]	<0.001
Standing	-0.02	[-0.07, 0.02]	0.334

Temperature was positively associated with scratching behaviour ($p = 0.011$) and negatively associated with active ($p < 0.001$) and standing ($p < 0.001$) behaviour. Positive trends were observed for temperature and grooming ($p = 0.052$) and sitting ($p = 0.071$). No associations were observed for temperature and eating, littering, or lying behaviour ($p > 0.05$). The β_1 estimates, 95% confidence intervals and *p*-values are reported in Table 4.5.

Table 4.5. Fixed-effect estimates (β_1), 95% confidence interval (CI) and *p*-values for the association of temperature with cat behaviours (univariate GLMMs). Estimates are presented on the logit scale.

Behaviour	β_1	95% CI	*p*-value
Active	-0.09	[-0.14, -0.05]	<0.001
Eating	-0.05	[-0.23, 0.13]	0.600
Grooming	0.06	[-0.00, 0.12]	0.052
Littering	0.04	[-0.02, 0.10]	0.167
Lying	-0.08	[-0.20, 0.04]	0.173
Scratching	0.18	[0.04, 0.32]	0.011
Sitting	0.17	[-0.02, 0.35]	0.071
Standing	-0.07	[-0.10, -0.03]	<0.001

Relative humidity was positively associated with sitting behaviour ($p = 0.037$), and negatively with eating ($p = 0.002$) and lying ($p = 0.005$) behaviour. A positive trend was observed for littering behaviour ($p = 0.059$). No associations were observed for relative humidity and active, grooming, scratching, or standing behaviour ($p > 0.05$). The β_1 estimates, 95% confidence intervals and p-values are reported in Table 4.6.

Table 4.6. Fixed-effect estimates (β_1), 95% confidence interval (CI) and p-values for the association of relative humidity with cat behaviours (univariate GLMMs). Estimates are presented on the logit scale.

Behaviour	β_1	95% CI	p-value
Active	0.03	[-0.02, 0.08]	0.286
Eating	-0.26	[-0.43, -0.09]	0.002
Grooming	0.01	[-0.05, 0.07]	0.729
Littering	0.06	[-0.00, 0.12]	0.059
Lying	-0.17	[-0.28, -0.05]	0.005
Scratching	0.04	[-0.11, 0.18]	0.620
Sitting	0.19	[0.01, 0.37]	0.037
Standing	0.01	[-0.03, 0.05]	0.693

Wind speed was positively associated with active ($p = 0.001$), eating ($p < 0.001$), and lying ($p = 0.006$) behaviour, and negatively with littering ($p = 0.003$), scratching ($p = 0.036$), and sitting ($p = 0.003$). A negative trend was observed for grooming behaviour ($p = 0.058$). No associations were observed between wind speed and standing behaviour ($p > 0.05$). The β_1 estimates, 95% confidence intervals and p-values are reported in Table 4.7.

Table 4.7. Fixed-effect estimates (β_1), 95% confidence interval (CI) and p-values for the association of wind speed with cat behaviours (univariate GLMMs). Estimates are presented on the logit scale.

Behaviour	β_1	95% CI	p-value
Active	0.08	[0.03, 0.13]	0.001
Eating	0.30	[0.12, 0.48]	<0.001
Grooming	-0.06	[-0.12, 0.00]	0.058
Littering	-0.10	[-0.17, -0.04]	0.003
Lying	0.17	[0.05, 0.29]	0.006
Scratching	-0.16	[-0.31, -0.01]	0.036
Sitting	-0.27	[-0.46, -0.09]	0.003
Standing	0.02	[-0.02, 0.06]	0.402

Rainfall showed a negative trend with grooming ($p = 0.077$) and scratching ($p = 0.086$) behaviour. No associations were observed between rainfall and active, eating, littering, lying, sitting, or standing behaviour ($p > 0.05$). The β_1 estimates, 95% confidence intervals and p-values are reported in Table 4.8.

Table 4.8. Fixed-effect estimates (β_1), 95% confidence interval (CI) and *p*-values for the association of rainfall with cat behaviours (univariate GLMMs). Estimates are presented on the logit scale.

Behaviour	β_1	95% CI	*p*-value
Active	0.01	[-0.04, 0.07]	0.645
Eating	0.07	[-0.14, 0.28]	0.505
Grooming	-0.06	[-0.13, 0.01]	0.077
Littering	-0.03	[-0.10, 0.04]	0.474
Lying	0.00	[-0.14, 0.14]	0.969
Scratching	-0.14	[-0.31, 0.02]	0.086
Sitting	-0.11	[-0.32, 0.10]	0.307
Standing	0.01	[-0.04, 0.06]	0.685

A moderate correlation was detected between daylength and temperature. Izawa (1983) reported a negative effect of temperature during the day and a positive effect during the night. Therefore, an interaction term between daylength and temperature was included in the final multivariate GLMM for active behaviours, grooming, scratching and sitting. The retained factors and the marginal and conditional R^2 values for each GLMM can be found in Table 4.9. The β_1 estimates, 95% confidence intervals and *p*-values are reported in Table 4.10.

Table 4.9. Results of the final multivariate GLMMs for daylength and weather variables including the marginal and conditional R^2 values.

GLMM	Final multivariate model	Marginal R^2 (%)	Conditional R^2 (%)
Active	Daylength × Temperature + Wind speed	5.62	49.01
Eating	Daylength + Wind speed	27.02	85.95
Grooming	Daylength × Temperature	15.90	60.92
Littering	Wind speed	1.14	4.67
Lying	Daylength + Wind speed	18.17	81.51
Scratching	Daylength × Temperature + Wind speed	25.09	59.99
Sitting	Daylength × Heat index + Wind speed	51.97	84.57
Standing	Temperature	2.03	29.17

Table 4.10. Fixed-effect estimates (β_1), 95% confidence interval (CI), and p-values for final multivariate GLMMs. Estimates are presented on the logit scale.

Retained factor(s)	β_1	95% CI	*p*-value
Active			
Daylength × Temperature	-0.08	[-0.12, -0.03]	<0.001
Wind speed	0.10	[0.05, 0.14]	<0.001
Eating			
Daylength	0.45	[0.29, 0.62]	<0.001
Wind speed	0.20	[0.04, 0.36]	0.013
Grooming			
Daylength × Temperature	-0.09	[-0.14, -0.03]	0.001
Littering			
Wind speed	-0.10	[-0.17, -0.04]	0.003
Lying			
Daylength	0.25	[0.13, 0.37]	<0.001
Wind speed	0.12	[0.00, 0.23]	0.047
Scratching			
Daylength × Temperature	-0.23	[-0.52, -0.22]	<0.001
Wind speed	-0.12	[-0.24, 0.00]	0.051
Sitting			
Daylength × Heat index	-0.32	[-0.45, -0.19]	<0.001
Wind speed	-0.18	[-0.31, -0.06]	0.005
Standing			
Temperature	-0.07	[-0.10, -0.03]	<0.001

For active behaviour, a significant negative interaction was detected between daylength and temperature ($p < 0.001$), indicating that the association between temperature and active behaviours varied across daylength (Figure 4.14). Wind speed was positively associated with active behaviours ($p < 0.001$). The model explained 4.6% of the variance with the fixed effects and 49.0% when including the random effects.

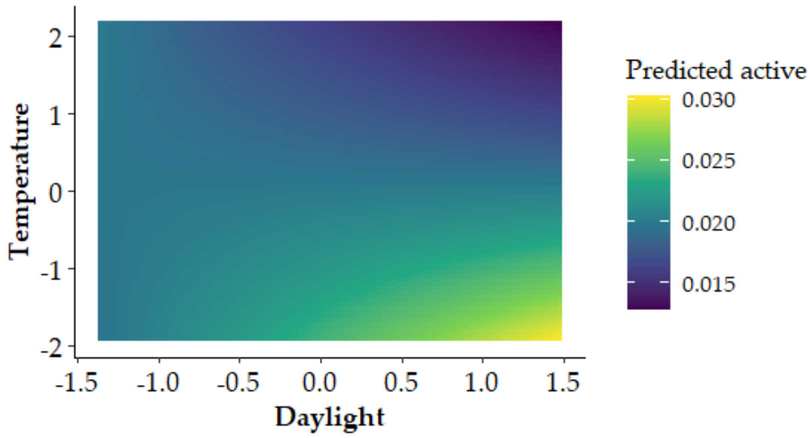

Figure 4.14. Heat map showing the modelled interaction between daylength and temperature (both on the logit scale) in relation to the proportion of time cats spent in active behaviour. Colours represent the predicted proportion of active behaviours across the observed ranges of daylength and temperature.

For eating behaviour, both daylength ($p < 0.001$) and wind speed ($p = 0.013$) were positively associated with eating. The model explained 27.0% of the variance with the fixed effects and 86.0% when including the random effects.

For grooming behaviour, a significant interaction between daylength and temperature was observed for grooming behaviour ($p = 0.001$), with temperature showing a stronger positive association with grooming during shorter days, while this association decreased as daylength increased (Figure 4.15). The model explained 15.9% of the variance with the fixed effects and 60.9% when including the random effects.

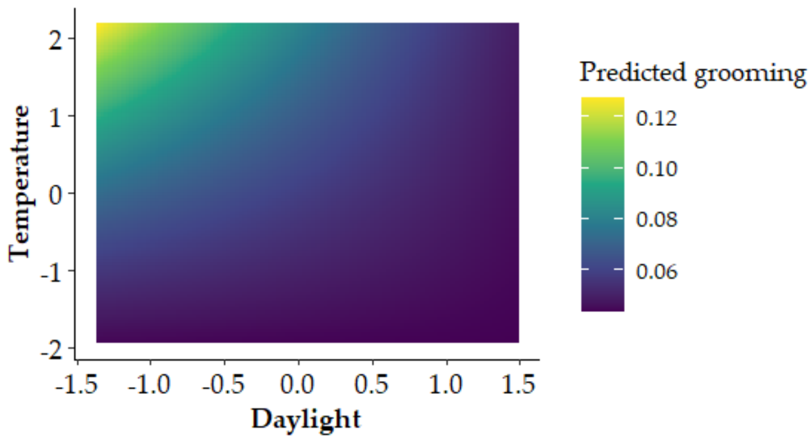

Figure 4.15. Heat map showing the modelled interaction between daylength and temperature (both on the logit scale) in relation to the proportion of time cats spent grooming. Colours represent the predicted proportion of grooming behaviour across the observed ranges of daylength and temperature.

For littering behaviour, only wind speed showed a significant negative association ($p = 0.003$). The model explained 1.1% of the variance with the fixed effect and 4.7% when including the random effects.

For lying behaviour, daylength ($p < 0.001$) and wind speed ($p = 0.047$) were positively associated with lying. The model explained 18.2% of the variance with the fixed effects and 81.5% when including the random effects.

For scratching behaviour, a significant interaction between daylength and temperature was observed for grooming behaviour ($p < 0.001$), with temperature showing a stronger positive association with scratching during shorter days, while this association decreased as daylength increased (Figure 4.16). The model explained 25.1% of the variance with the fixed effects and 60.0% when including the random effects.

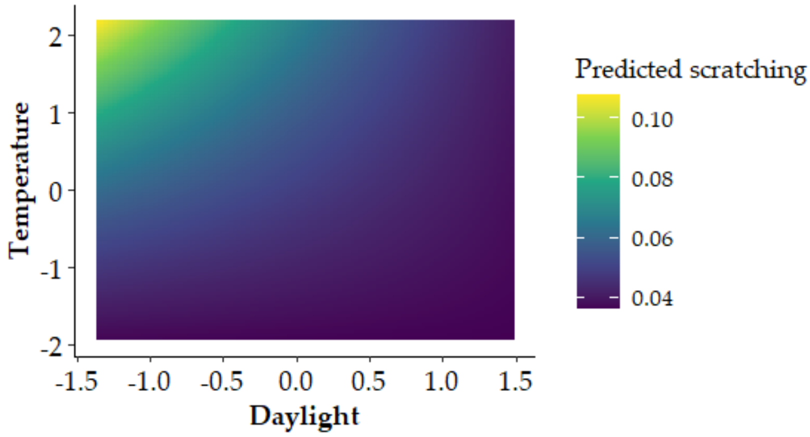

Figure 4.16. Heat map showing the modelled interaction between daylength and temperature (both on the logit scale) in relation to the proportion of time cats spent on scratching. Colours represent the predicted proportion of scratching behaviour across the observed ranges of daylength and temperature.

For sitting, both temperature and relative humidity were found to be significant in the univariate GLMMs (Table 4.9). Since a high correlation was detected between temperature and relative humidity, the heat index, accounting for both, was included in the final multivariate GLMM. A significant interaction between daylength and the heat index was observed for sitting behaviour ($p < 0.001$), with the heat index showing a stronger positive association with sitting during shorter days, while this association decreased as daylength increased (Figure 4.17). Wind speed was negatively associated with sitting ($p = 0.005$). The model explained 52.0% of the variance with the fixed effects and 84.6% when including the random effects.

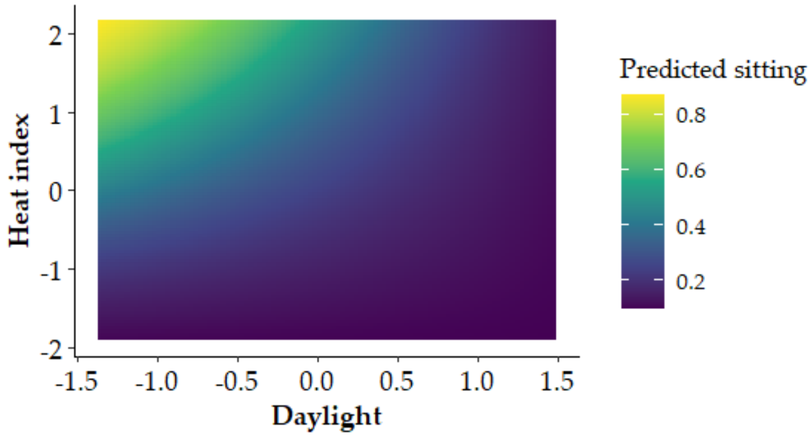

Figure 4.17. Heat map showing the modelled interaction between daylength and the heat index (both on the logit scale) in relation to the proportion of time cats spent on sitting. Colours represent the predicted proportion of sitting behaviour across the observed ranges of daylength and temperature.

For standing behaviour, only temperature showed a significant negative association ($p < 0.001$). The model explained 2.0% of the variance with the fixed effect and 29.2% when including the random effects.

4.4 Discussion

This study utilised a validated machine learning model to conduct a detailed, longitudinal analyses of domestic cat behaviour, providing novel insights how seasonal changes and daily meteorological conditions are associated with changes in cat behaviour. The findings revealed that while certain behaviours are shaped by short-term weather conditions, others seem entrained to more profound biological cycles, such as photoperiod. Furthermore, this research confirmed that accelerometer-based monitoring is a powerful tool to understand nuanced behavioural changes in response to environmental drivers.

Changes in bodyweight, in healthy individuals, are the result of an imbalance in energy requirements and energy intake (Case et al., 2011). In this study, no seasonal differences in average bodyweight were observed. However, substantial individual variations were present; some cats gained weight approaching winter, mirroring findings by Bermingham et al. (2024) in the same research facility, while other individuals showed the opposite trend. The literature on feline energy requirements is similarly inconsistent. Serisier et al. (2014) reported that cats housed either indoors or indoor/outdoor and fed *ad libitum*, consumed the most food during winter, and the least during summer. Despite this, they maintained bodyweight, suggesting increased energy requirements during winter (Serisier et al., 2014).

The analysis of seasonal and meteorological associations with cat behaviour revealed a clear and consistent pattern. By disentangling the broad "season" category into its key meteorological components, this study provides a more in-depth understanding of the environmental factors drive feline activity budgets. Behaviours related to activity and rest were strongly linked to immediate environmental conditions. This aligns with findings from studies on free-ranging cats, which report that that activity levels increase with rising ambient temperature and decrease during periods of rainfall (Goszczyński et al., 2009; Haspel & Calhoon, 1993). In the current study neither a significant association nor a clear trend between season and time spend on active behaviours was found. Instead, the multivariate GLMM identified a significant negative interaction between daylength and temperature, suggesting that variation in activity was primarily driven by specific environmental variables rather than season per se. Similar decreases in activity during the warmest part of the day have been reported in rural cats in Poland (Goszczyński et al., 2009), while cats in Japan and the United Kingdom have been observed to shift towards more nocturnal activity in summer to avoid peak daytime heat (Dunford et al., 2024; Izawa, 1983). Concurrently, cats in the present study spent more time lying during long, warmer days, supporting the role of temperature and photoperiod in shaping resting behaviour. These findings are consistent with earlier work in the same research colony, where accelerometry revealed a negative correlation between overall physical activity and ambient temperature (Smit et al., 2022).

Beyond activity and rest, several other behaviours also displayed seasonal peaks that were clarified by specific meteorological drivers. Eating behaviour, for example, was highest during spring, coinciding with longer daylength and increased wind speeds—two defining features of the season in the study area. Although less commonly reported in the literature, this result suggests that seasonal increases in activity during spring may elevate energetic demands, which in turn manifest as increased food intake. However, care should be taken, as time spent eating does not necessarily equal amount eaten, and therefore does not infer energy intake.

Perhaps the most insightful finding that emerged was the fact that grooming and scratching behaviours were both more prevalent during autumn. This was most likely associated with the feline hair growth cycle. Seasonal changes in coat dynamics are primarily regulated by photoperiod, with an increase in hair growth during autumn to develop a dense and insulating winter coat (Hendriks et al., 1997, 1998). This interpretation is consistent with reports that the onset of hair follicle inactivity in autumn reduces hair loss (Baker, 1974; Ryder, 1976), resulting in greater coat density and, consequently, more grooming and scratching activity. Interestingly, although cats typically shed their winter coat in spring and summer (Hendriks et al., 1998), and thus a second peak in grooming and scratching might be expected, no such increase was observed in this study. The absence of this anticipated pattern suggests that autumn represents the more biologically salient phase of coat turnover in this colony, or that other factors, such as housing conditions or the semi-outdoor environment, modulated the spring/summer shedding response. A key finding was the association between wind speed and posture-related behaviours. Statistical models revealed a significant positive association between wind and lying behaviour and a corresponding negative association with sitting, with smaller changes in other behaviours. Because these data are based on proportions, increases in some behaviours are necessarily accompanied by decreases in others. Observational data collected from video recordings in Chapter 3 indicated that cats frequently performed stationary maintenance behaviours, such as sitting and grooming, in the unsheltered, open-air portion of their enclosure. An increase in wind speed likely made these exposed areas less comfortable, prompting cats to seek the sheltered indoor section. Lying rather than sitting under such conditions reduces the body surface area exposed to moving air, thereby limiting wind-driven heat loss. This posture-based thermoregulatory response has been documented in a range of mammals, including domestic cats, as a means to conserve body heat under cooler or windy conditions (Withers et al., 2016). The observed changes in other behaviours, such as grooming and scratching, likely reflect this spatial shift but are of less biological relevance. Overall, these results suggest that wind was primarily associated with how cats allocate time between postures, consistent with behavioural thermoregulation, rather than indicating broader shifts in activity patterns.

Across all analyses, the individual cat and day were a highly significant random effects, often explaining a larger portion of the behavioural variance than the fixed environmental factors.

This is a critical finding, underscoring that cats are not uniform in their response to environmental stimuli. Factors such as age, personality, and social dynamics within the group likely play a profound role in shaping individual behavioural strategies. This result strongly supports the argument for an individual-based monitoring approach, as group-level averages can obscure significant individual differences in welfare and behavioural patterns.

The study further demonstrated the real-world challenge of collecting longitudinal data, where unexpected events can impact data integrity. The reintroduction of a cat into the colony cage caused significant behavioural disruptions across the entire group, necessitating the removal of a full week of data from the analysis. Changes in routine, such as relocation or the reintroduction of an absent individual, have been identified as stressors in domestic cats (Amat et al., 2016; McKeown et al., 1988). Firstly, this observation carries significant practical implications for the management of colony-housed cats. It underscores the need of implementing adequate acclimation periods when a new cat is introduced, especially prior to behaviour-related studies. Without a sufficient period of stabilisation, behavioural data may reflect short-term social stress rather than the baseline patterns under investigation. In addition, it quantitatively demonstrated the sensitivity of the colony's social dynamics and highlighted the need for clearly defined, *a priori* criteria for identifying and handling outliers in behavioural datasets to ensure analytical consistency.

The interpretations presented must be considered in light of several methodological limitations. First, the study was conducted on a small population of seven research cats in a specific semi-outdoor environment in New Zealand. This limits the statistical power and the generalisability of the findings to pet cats in different housing conditions or to cats in different climatic zones. Second, the study relied on the classification accuracy of the ML model developed in Chapter 2, which itself has limitations. While the RF model was the most robust choice, its ~73% accuracy means there is inherent uncertainty in the behavioural classifications that form the basis of this chapter's analysis. This is particularly relevant for behaviours such as eating, for which the proportions in the later stages of the trial (~10%) exceeded values commonly reported in literature (~3%; Berteselli et al., 2017; Eckstein & Hart, 2000b; Huck & Watson, 2019; Panaman, 1981). No notable event(s) occurred that could explain this increase in behaviours being classified as eating by the model, suggesting that the observed changes in absolute activity budgets for some behaviours may reflect time-dependent classification error rather than true biological changes. Importantly, the direction of the associations between weather variables and classified behaviour in this study is largely consistent with previously published findings (as discussed above), indicating that, despite inevitable classification error, the RF is informative for detecting relative behavioural patterns and environmental associations. Nevertheless, the absence of continuous external validation data across this study limits the certainty with which changes in absolute behavioural proportions can be interpreted, and further validation using independently annotated datasets across multiple time periods would be valuable to strengthen future studies.

A third methodological consideration relates to the temporal resolution of the analysis. Weather conditions can change rapidly, and a key decision was to aggregate behavioural and meteorological data at a daily level rather than hourly. This approach was chosen deliberately after initial exploratory analysis at an hourly resolution revealed a significant analytical challenge. The large increase in statistical power from using hourly data ($n > 15{,}000$ datapoints) resulted in nearly every weather variable being significantly associated with every behaviour. Machine learning methods are better equipped to handle such large volumes of data, but their strength lies in prediction rather than inference. They can effectively predict how a behaviour in response to a set of weather conditions, but it does not easily provide interpretable coefficients that explain the underlying nature of the that relationship. The primary goal of the current study was to understand how and why a specific weather variable is associated with behaviour. Aggregating data at a daily level allowed for determination of the more substantial and consistent associations between daily weather patterns and domestic cat behaviour. Future research, however, could benefit from a dual approach. The daily-level inferential analysis presented here, which identifies key environmental drivers, could be complemented by predictive ML models trained on hourly data. Such models would be invaluable for developing forecasting tools, for instance by predicting periods of high or low activity based on weather forecasts, and could potentially uncover complex, non-linear interactions that traditional statistical models might miss. This would allow for both a robust biological interpretation of behaviour and the development of powerful predictive applications.

4.5 Conclusion

In conclusion, this chapter successfully demonstrates that accelerometer data paired with ML models can serve as a powerful tool for conducting detailed, longitudinal studies of domestic cat behaviour. The findings disentangle the influence of overarching seasonal rhythms from immediate meteorological drivers, showing that grooming and scratching are likely linked to innate physiological cycles, while other behaviours are adjusted in response to daily weather. The study highlights the profound influence of individual variability and underscores the importance of considering housing context when interpreting behavioural responses to the environment. These findings from a controlled, semi-outdoor setting provide a crucial baseline and a refined set of questions for the investigation into the more complex, multi-variate home environments of pet cats, which will be explored in the subsequent chapter.

Chapter 5

Applying a validated machine learning model to assess environmental influences on the behaviour of domestic cats

Image generated with Meta AI

Part of this chapter has been published as:

Smit, M., Corner-Thomas, R. A., Draganova, I., Andrews, C. J., & Thomas, D. G. (2024). How Lazy Are Pet Cats Really? Using Machine Learning and Accelerometry to Get a Glimpse into the Behaviour of Privately Owned Cats in Different Households. *Sensors (Basel, Switzerland)*, *24*(8), 2623. https://doi.org/10.3390/s24082623.

See Appendix XII for published paper.

Chapter 5 Applying a validated machine learning model to assess environmental influences on the behaviour of domestic cats

5.1 Introduction

Animal behaviour is a key indicator of welfare and environmental adaptation, providing critical insights into the health and well-being of an animal (Mellor et al., 2020; Mellor & Reid, 1994). As one of the most popular companion animals, the domestic cat (*Felis catus*) has an estimated global population of over 400 million (Euromonitor International, 2024), with a significant presence in New Zealand (Companion Animals New Zealand, 2020). Understanding feline behaviour is not only essential for monitoring welfare, but also to strengthen the human-animal bond. (Companion Animals New Zealand, 2020). Given that behavioural changes can be important indicators of pain, illness or distress, a comprehensive understanding of behavioural drivers is crucial for owners, veterinarians and welfare scientists.

Studies have shown that domestic cat behaviour is influenced by a combination of natural rhythms, environmental factors, and human interaction. Feral cats, free from human influence, typically exhibit a bimodal, crepuscular/nocturnal activity pattern, with peaks around dawn and dusk (Konecny, 1987; Lavery et al., 2020). However, this pattern is flexible. In the presence of humans, cats often shift their activity to be more diurnal, aligning their active periods with the routines of their owners or caretakers (Piccione et al., 2013; Smit et al., 2022). Environmental seasonal weather variables are another important driver of feline behaviour patterns. Studies have quantified the impact of weather, finding that variables like temperature, humidity, precipitation, and day length can account for a substantial portion of the variance in activity levels (Dunford et al., 2024; Goszczyński et al., 2009; Haspel & Calhoon, 1993; Izawa, 1983). Physiologically, cats exhibit clear seasonal cycles, such as changes in coat growth and shedding, which are primarily driven by photoperiod (Baker, 1974; Hendriks et al., 1997, 1998; Ryder, 1976) and are linked to maintenance behaviours such as grooming, as became apparent in Chapter 4.

While outdoor access and owner presence can affect activity, most research has been conducted outside the complex home environment, such as in shelters, catteries, or laboratories, limiting its direct applicability to companion cats living in a domestic setting (Foreman-Worsley & Farnworth, 2019). Few studies have looked at how the combined effects of factors cat are exposed to in a complex home environment, including for example the presence of other companion animals or children, affect cat behaviour. Rather, studies have focused on a single factor (Foreman-Worsley & Farnworth, 2019). While such studies can be useful for identifying how specific environmental factors may affect cat behaviour and welfare, they do not resemble the complex, multi-factorial home environment. As a result, the interactions between environmental variables, human presence, and seasonal factors in domestic settings remain poorly understood.

It is not surprising that little is known about the effects of a complex environment on cat behaviour. Behavioural studies are labour-intensive and have traditionally been conducted using observational methods by either scoring behaviours in real time or from video recordings (Martin & Bateson, 1993). With scan sampling, infrequent behaviours can easily be missed, and with live continuous scoring only one animal per observer can be scored at a time. There is also the risk of observer fatigue if a long period is required for behavioural scoring. In addition, it is challenging to observe an animal under low-light and dark circumstances. The majority of studies reviewed by Foreman-Worsley and Farnworth (2019) scored behaviour using scan (i.e., instantaneous) sampling, which involves the observer recording the behaviour of individual animals at predetermined time intervals (Altmann, 1974). With this method, there is a risk of missing infrequent and/or short-lasting behaviours. These significant methodological limitations highlight the need for an automated approach that can operate continuously and objectively, capturing a complete behavioural repertoire without the constraints of human observation. The use of accelerometers combined with machine learning techniques offers such solution, making it possible to quantitatively study the effects of the home environment on domestic cat behaviour.

This chapter applied an in Chapter 3 validated random forest model, capable of classifying eight behaviours from a collar-mounted accelerometer, to address two primary scientific aims. The first aim is to compare seasonal activity budgets and daily behavioural rhythms of pet cats, with differing levels of outdoor access, with semi-outdoor housed research cats. The second aim is to specifically identify and quantify the influence of several household and social factors on the behaviour of these pet cats. Based on these aims, several hypotheses were formulated. It was hypothesized that cats with outdoor access would be more active than confined cats and that their daily activity patterns would be strongly aligned with natural sunrise and sunset, whereas the activity patterns of the research cats and confined cats would be influenced more by the routines of the caretakers and their owners, respectively. Furthermore, considering physiological and environmental drivers, it was hypothesised that activity levels would decline with age and that free-roaming cats would adapt their behaviour to prioritise thermal comfort in response to seasonal weather changes.

5.2 Material and methods

This chapter consists of two parts: the first is on the association of different factors in a home environment with the behaviour of pet cats, and the second compared the behaviour of pet and research cats. For both parts, the accelerometer data were collected using the collar attachment method, downloaded, and feature engineered as described in Chapter 3.

5.2.1 Collecting behavioural data of pet cats

The study was conducted in the Manawatū-Whanganui region, New Zealand. The study was approved by both the Massey University Human Ethics (MUHEC 4000025773) and Massey University Animal Ethics Committees (MUAEC 22/24).

5.2.1.1 Owner and cat recruitment

Voluntary response sampling was used to recruit participants and their cat(s) by distributing flyers to local veterinary clinics and throughout Massey University in Palmerston North (Appendix XIII). The flyer provided information about the study and referred potential participants to a screening questionnaire that included questions about demographics, housing of the cat, and some general information about the cat(s) (Appendix XIV).

Prior to the study, a total of 61 cat owners (n = 89 cats) were recruited for the study. Owners/cats were excluded from the study if the questionnaire was incomplete (n = 15), if they lived outside the Manawatū-Whanganui region (n = 13), or if they fell outside the age range of 1 to 10 years (n = 6). As some health conditions are known to affect behaviour, cats were also excluded if they suffered from a mobility-related illness (e.g., osteoarthritis), a urinary tract and/or kidney disease, diabetes, and/or hyperthyroidism (n = 4). After excluding cats that did not meet the inclusion criteria (n = 29), a total of 60 eligible cats remained. The owners of these 60 cats were invited to participate in the trial. Participation was voluntary, and owners were able to withdraw their cat(s) at any time.

From the questionnaire, several variables were extracted for each cat (Table 5.1): sex of the cat (male, female; neutered, entire), age group (kitten, junior, prime, mature, senior, geriatric) , housing (exclusively indoors, free-roaming, exclusively outdoors, other), number of cats in household (one, two, three or more), presence of at least one dog (no, yes), presence of at least one child (£ 18 years; no, yes).

Table 5.1. Variables extracted from the questionnaire, or collected during an appointment, and their respective categories.

Variable	Categories
Sex of cat	Entire female Entire male Neutered female Neutered male
Age group[1]	Kitten (0–6 months) Junior (7 months–2 years) Prime (3–6 years) Mature (7–10 years) Senior (11–14 years) Geriatric (≥15 years)
Housing[2]	Exclusively indoors Indoors with unlimited outdoor access (free-roaming) Exclusively outdoors Other (owner could specify)
Number of cats in household	One Two Three or more
Presence of at least one dog	No (absent; no dog(s) in household) Yes (present; at least one dog in household)
Presence of at least one child (<18 years)	No (absent; no child(ren) in household) Yes (present; at least one child in household)

[1] (Pittari et al., 2009; Vogt et al., 2010)

[2] Examples of limited outdoor access include harnessed walks, a catio, or supervised garden access.

5.2.1.2 *Data collection*

Data were collected over two periods: summer (1 December 2022 until 28 February 2023) and winter (1 June 2023 until 31 August 2023). An appointment was organised with each participant, during which their cat(s) was weighed and assigned a body condition score (BCS; 9-point scale; Laflamme, 1997) by the same researcher for the whole study. Owners were also asked whether they fed their cats a wet diet, dry diet, or a mix of a wet and dry diets. During each sampling period, owners habituated their cats to wearing a quick release collar to which an accelerometer was attached over a six-day period, followed by seven consecutive days of data collection (Table 5.2). Accelerometer data were collected using the collar attachment method as described in Chapter 3. At the end of the data collection period, collars and accelerometers were retrieved. If a cat lost its collar during the first or second collection period, their data were excluded from the data analyses.

Table 5.2. Training schedule for owners to habituate their cat(s) to wearing the collar with accelerometer, followed by seven days of data collection.

Training Day						Data collection
1	2	3	4	5	6	Day 7–14
2 h	4 h	6 h	8 h	24 h	-	

Dash (-) indicates that the collar was not worn by the cat.

5.2.1.3 *Behaviour classification*

Accelerometer data were downloaded as outlined in Chapter 3. Any time periods during which a cat was not wearing the collar, for example due to it being lost or temporarily removed, were excluded prior to behaviour classification using the selected machine learning model. Cleaned accelerometer data was feature engineered as described in Chapter 3. Using the feature engineered data, the behaviour of the cats was classified using a random forest model that classifies eight different cat behaviours using data from a collar-based accelerometer: active (walking and trotting), eating, grooming, littering, lying, scratching, sitting, and standing. This model was chosen as it provided the best trade-off, retaining a greater number of biologically relevant behaviours (n = 8) while maintaining an acceptable overall F1-score (68%) for this longitudinal study. However, one of the major concerns for this model, was its applicability to pet cats due to the discrepancy in posture during eating. Therefore, additional data on eating behaviour were collected using the research cats. Eight cats were housed in individual cages (80 × 80 × 110 mm; Figure 5.1a) and fed while wearing a collar-mounted accelerometer and being video recorded (Figure 5.1b). Accelerometer data were collected using the collar attachment method as described in Chapter 3. Cats were kept in the individual cages for two hours and data was collected for five consecutive days. Video recordings were scored continuously for eating behaviour (state) using BORIS (Friard & Gamba, 2016) and the annotated data was exported using a one second (s) time interval. The annotated data was then merged with the accelerometer data based on the timestamp. The eating datapoints from the original labelled dataset containing the eight behaviours from Chapter 3 were removed and replaced with the new datapoints for eating behaviour and the model, including the same eight behaviours, was retrained using the random forest technique and validated as described in Chapter 3. The F1 scores of the old and new model were compared. In addition, both the original selected RF model as the newly trained one were used to classify the behaviours of the pet cats. Activity budgets were determined for both and compared to one another, a method previously used to determine the generalisability from one setting to another (Hammond et al., 2016).

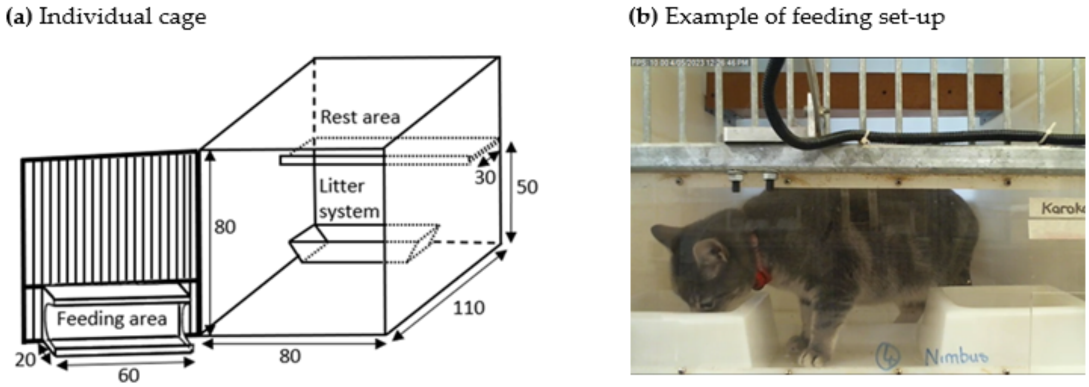

Figure 5.1. (a) Individual cage measuring 80 × 80 × 100 mm and (b) screenshot from video-recording of a cat eating.

5.2.2 Research cat data

Data for the research cat consisted of data collected in Chapter 4. Though the weather station malfunctioned during the initial scheduled summer period (December 2022 – February 2023), accelerometer data was collected. The accelerometer data from this period, alongside the accelerometer data collected in the winter of 2023 (June – August) were used to compare the behaviour of research cats to that of the pet cats, ensuring data that was compared was collected in the same periods. The accelerometer data of the research cats was quantified using the random forest model for the collar-mounted accelerometer, classifying the same eight behaviours described above.

5.2.3 Statistical analysis

Weekly behaviour proportions were determined because data of the pet cats was collected in different weeks, days and with different start and end times. Similarly, the summer and winter season data collection for the research cats contained more than one week of data, thus seasonal behaviour proportions were determined for the research cats to allow for comparisons between the pet and research cats. All data processing and computation was carried out using RStudio version 4.1.1 (RStudio Team, 2021).

5.2.3.1 Comparing the behaviour of research and pet cats

A generalised linear mixed model (GLMM; R package 'glmmTMB' (Brooks et al., 2024)), was used to analyse the association between season × housing and each of the eight behaviours. Three GLMMs were performed for each behaviour: (1) a simple model with no predictors, (2) an intermediate model with cat as a random effect, and (3) a full model that included cat as a random effect and the interaction of season × housing as a fixed effect (equation 4.1).

$$logit\ (\mu_j) = \beta_0 + \beta_1 Season_j + \beta_2 Housing_j + \beta_3 (Season_j \times Housing_j) + b_j \quad (4.1)$$

where μ_j is the expected seasonal proportion of time cat j spends on the behaviour, β_0 is the overall intercept, β_1 is the fixed effect of season, $Season_j$ indicates the specific season for cat j, β_2 is the fixed effect of housing, $Housing_j$ indicates the housing type for cat j, β_3 is the interaction between season and housing, and $b_j \sim \mathcal{N}(0, \sigma_b^2)$ is the random intercept for cat j to account for individual differences.

The three models were compared with an ANOVA to determine which factors improved the model, and the marginal and conditional R^2 of the full models were determined. The marginal R^2 value is the variance explained by only the fixed effect, whereas the conditional R^2 value is the variance explained by both the random and fixed effects. To determine differences between seasons × housing, pairwise comparisons of estimated marginal means were conducted for each behaviour, using the R package 'emmeans' (Lenth et al., 2024). A Tukey adjustment was used to correct for multiple pairwise comparisons. Results were considered significant if $p \leq 0.05$, and a trend if $0.05 > p < 0.10$.

In addition, hourly behaviour proportions were calculated per season and housing condition to visualise patterns in behaviour throughout the day. Hourly data was not statistically analysed.

5.2.3.2 *The influence of household and social factors on pet cat behaviour*

Cat bodyweight (BW) and body condition score (BCS) were analysed using linear mixed-effects models to account for repeated measurements within cats using the R package 'lmerTest' (Kuznetsova et al., 2020). To determine differences between seasons × housing, pairwise comparisons of estimated marginal means were conducted for each behaviour, using the R package 'emmeans' (Lenth et al., 2024). A Tukey adjustment was used to correct for multiple pairwise comparisons. Results were considered significant if $p \leq 0.05$, and a trend if $0.05 > p < 0.10$.

Weekly behaviour proportions were determined because data of the pet cats was collected in different weeks, days and with different start and end times. Eight categorical environmental and social factors were selected for statistical analysis: season, age group, sex of the cat, diet, housing, number of cats in the household, presence of at least one dog in the household, and the presence of at least one child (<18 years). Similar to the GLMM testing above, three GLMMs were performed: with the same simple and intermediate models as described above. The full model included cat as a random effect and the selected environmental and social variables as fixed effects (equation 4.2):

(3.1) $$logit\left(\mu_{ij}\right) = \beta_0 + \beta_1 X_{ij} + b_j$$

where μ_j is the expected seasonal proportion of time cat *j*, β_0 is the overall intercept, β_1 is the fixed effect of the selected variable, X_{ij} indicates the specific category for the selected variable for cat *j*, and $b_j \sim \mathcal{N}(0, \sigma_b^2)$ is the random intercept for cat *j* to account for individual differences.

The marginal and conditional R^2 values for each model were determined. First, univariate GLMMs were performed to determine the main effects of each selected variable on each behaviour. For each behaviour, weather variables that improved the model ($p < 0.10$) were then combined in a final model. A backwards stepwise procedure was used to remove variables for which p ³ 0.10 until only those remained for which $p < 0.10$. To determine differences between the categories of the variables, pairwise comparisons of estimated marginal means were conducted for each behaviour, using the R package 'emmeans' (Lenth et al., 2024). A Tukey adjustment was used to correct for multiple pairwise comparisons. Results of all statistical testing were considered significant if $p \leq 0.05$, and a trend if $0.05 > p < 0.10$.

5.3 Results

First, a new model was trained. Based on these results, one model (new or old) was selected as the best for use in pet cats. Using the selected model, behavioural proportions were determined for the pet cats and compared to those of the research cats. Lastly, the influence of several household and social factors on pet cat behaviour was determined.

5.3.1 Retraining the machine learning model

The random forest model classifying eight different behaviours from a collar-mounted accelerometer from Chapter 3 was retrained with the newly annotated eating behaviour. The newly trained model had a F1-score of 68%, which was the same as the old model (see Chapter 3). However, when behavioural proportions were determined for the pet cat dataset, the new model predicted pet cats spent 25% of their time on eating behaviour, whereas the old model predicted 5.5%. As discussed in Chapter 3, time spent on eating has consistently been reported to be around 3 to 4%. Considering the overestimation of the new model for eating behaviour, the old model was selected for the classification, and subsequent proportion determination, of the pet cat behaviours.

5.3.2 Comparing the behaviour of research and pet cats

Results for this section are presented as the seasonal mean ± standard error (SE) as determined with the classification model. The final dataset contained research cats (n = 7), indoor pet cats (n = 10) and free-roaming pet cats (n = 18). The presented values reflect comparisons of the mean time spent in showing active behaviours across two periods rather than causal effects of season.

The variance in time spent exhibiting active behaviours explained by the model improved when including both cat as the random effect ($p = 0.006$) and the interaction of season ´ housing as a fixed effect ($p = 0.002$). The fixed effect of season ´ housing alone explained 22.9% of the variance, and the combination of the fixed and random effects explained 59.8%. No difference was seen in time spent showing active behaviours between summer and winter either among the research (2.0 ± 0.36% and 2.2 ± 0.54%, respectively; $p > 0.05$) or indoor pet cats (2.0 ± 0.36% and 2.2 ± 0.23%, respectively; $p > 0.05$; Figure 5.2). In addition, there were no differences in active behaviours between the research and indoor pet cats in either season ($p > 0.05$). Free-roaming pet cats spent more time active in summer (3.9 ± 0.39%) than in winter (2.7 ± 0.33%;

p < 0.001). During summer, free-roaming pet cats also spent more time active than both research (p = 0.004) and indoor pet cats (p < 0.001). In winter, however, no differences in active behaviours (p > 0.05) were observed between housing conditions.

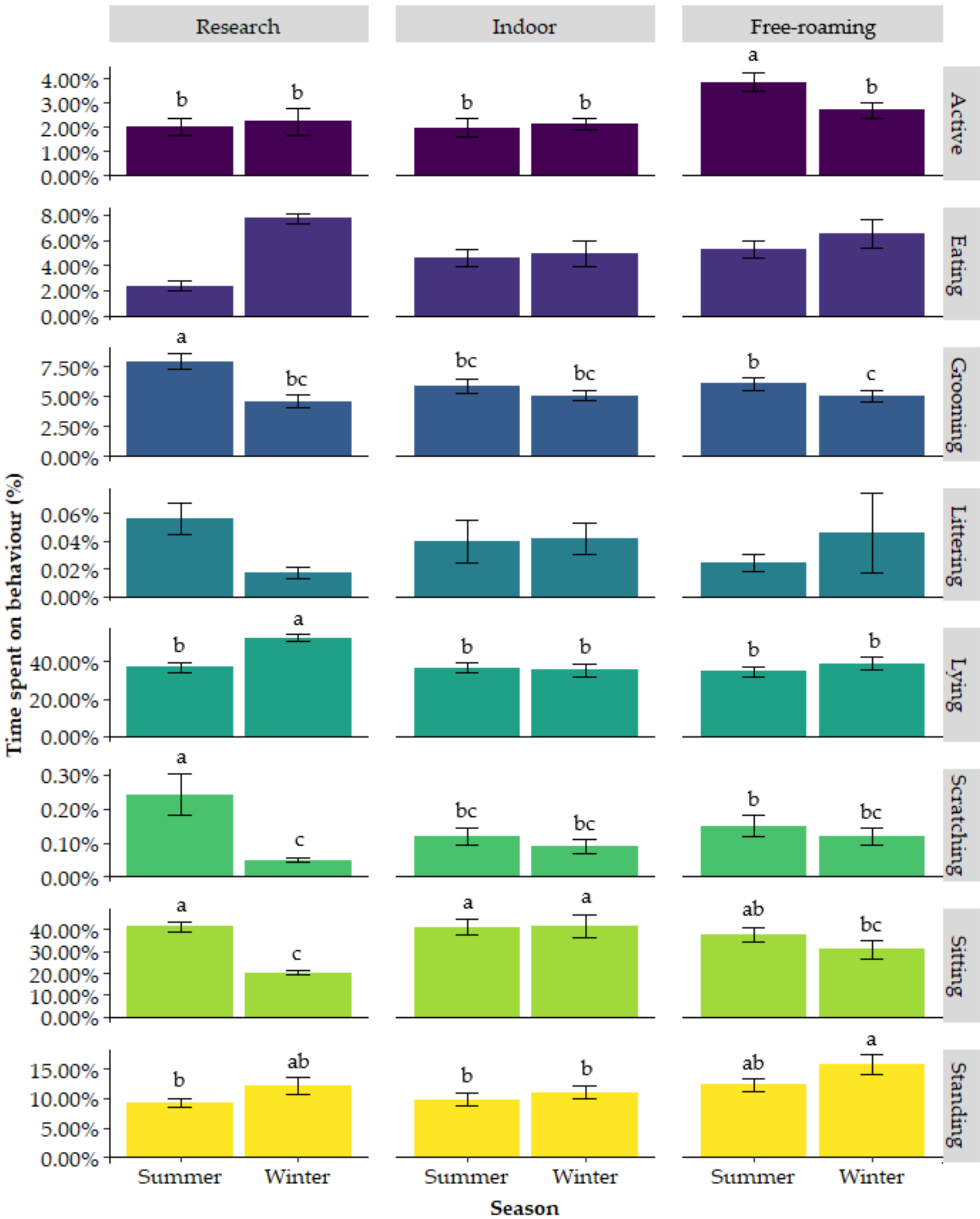

Figure 5.2. Average time spent on behaviours (classified with the model) across two periods within a year (summer and winter) of research cats (n = 7 cats × 3 weeks per period), indoor pet cats (n = 10 cats × 1 week per period), and free-roaming (n = 18 cats × 1 week per period) pet cats. [a-c] Within a behaviour, bars with different superscripts differ significantly (p < 0.05).

The variance in time spent eating explained by the model did not improve when either cat was included as a random effect or the interaction of season ´ housing was included as a fixed effect ($p > 0.05$). The model with the random effect of cat and interaction explained 21.2% of the variance. Research cats spent 2.4 ± 0.39% and 7.7 ± 0.41% of their time eating during summer and winter, respectively (Figure 5.2). The indoor pet cats spent 4.6 ± 0.71% and 4.9 ± 1.01% of their time eating during summer and winter, respectively. Free-roaming pet cats spent 5.3 ± 0.66% and 6.5 ± 1.10% of their time eating during summer and winter, respectively.

The variance in time spent grooming explained by the model improved with the inclusion of the interaction of season ´ housing as a fixed effect ($p = 0.009$), but not when cat was included as a random effect ($p > 0.05$). The fixed effect explained 19.1% of the variance in time spent grooming, and both the random and fixed effect explained 38.0%. Research cats spent more time grooming during summer (7.9 ± 0.66%) than in winter (4.6 ± 0.50%; $p < 0.001$; Figure 5.2) as did free-roaming pet cats (6.0 ± 0.58% and 5.0 ± 0.40%, respectively; $p = 0.049$). Time spent grooming did not differ for indoor cats between summer (5.9 ± 0.64%) and winter (5.0 ± 0.40%; $p > 0.05$). During summer, research cats spent more time grooming than both indoor ($p = 0.033$) and free-roaming pet cats ($p = 0.022$). During winter there were no differences in time spent grooming between housing conditions ($p > 0.05$).

The variance in time spent littering explained by the model did not improve when including either cat as the random effect or the interaction of season ´ housing as the fixed effect ($p > 0.05$). The model with the random cat effect and fixed interaction effect explained 65.6% of the variance. Research cats spent 0.06 ± 0.011% and 0.02 ± 0.004% of their time littering during summer and winter, respectively (Figure 5.2), whereas indoor pet cats spent 0.04 ± 0.015% and 0.04 ± 0.011% and free-roaming pet cats spent 0.02 ± 0.006% and 0.05 ± 0.029%, respectively (Figure 4.2).

The variance in time spent lying explained by the model improved with the inclusion of the interaction of season ´ housing as a fixed effect ($p = 0.019$) but not when including cat as a random effect ($p > 0.05$). The model with the random cat effect and fixed interaction effect explained 36.6% of the variance. Research cats spent more time lying in winter (52.9 ± 2.03%) than summer (36.9 ± 2.89%; $p = 0.009$; Figure 5.2). No difference in time spent lying between summer and winter were found for either the indoor (36.9 ± 2.95% and 35.4 ± 3.29%, respectively; $p > 0.05$) or free-roaming pet cats (34.8 ± 2.48% and 39.2 ± 3.34%, respectively; $p > 0.05$). In winter, research cats spent more time lying than both indoor ($p = 0.001$) and free-roaming pet cats ($p = 0.004$).

The variance in time spent scratching explained by the model improved with the inclusion of the interaction of season ´ housing as a fixed effect ($p = 0.002$) but not when including cat as a random effect ($p > 0.05$) in the model. The model with the random cat effect and fixed interaction effect explained 45.9% of the variance. Research cats spent more time scratching during summer (0.24 ± 0.060%) than during winter (0.05 ± 0.006%; $p < 0.001$; Figure 5.2). No differences in time spent scratching were found between summer and winter for both indoor (0.12 ± 0.025% and 0.09 ± 0.020, respectively; $p > 0.05$) and free-roaming pet cats (0.15 ± 0.030% and 0.12 ± 0.024%, respectively; $p > 0.05$). No differences in time spent grooming between housing conditions were found during winter ($p > 0.05$).

The variance in time spent sitting explained by the model was improved by the inclusion of the interaction of season ´ housing as a fixed effect ($p = 0.006$) but not the random effect of cat ($p > 0.05$). The model with the random cat effect and fixed interaction effect explained 40.7% of the variance. Research cats spent more time sitting in summer (41.4 ± 2.33%) than in winter (20.1 ± 0.097%; $p = 0.004$; Figure 5.2). For free-roaming pet cats, a trend was found for the difference in time spent sitting during summer (37.5 ± 3.01%) and winter (30.8 ± 4.19%; $p = 0.061$). For indoor pet cats, no differences in time spent sitting were found between summer (40.7 ± 3.57%) and winter (41.3 ± 5.32%; $p > 0.05$). During winter, indoor pet cats spent more time sitting than both research ($p = 0.002$) and free-roaming pet cats ($p = 0.021$). Time spent sitting did not differ between the research free-roaming pet cats in winter ($p > 0.05$), and no differences in time spent sitting between housing conditions were found during summer ($p > 0.05$).

The variance in time spent standing explained by the model was improved by the inclusion of the interaction of season ´ housing as the fixed effect ($p = 0.025$), but not when including cat as the random effect ($p > 0.05$) in the model. The model with the random cat effect and fixed interaction effect explained 21.3% of the variance. For free-roaming pet cats, a trend was found for the difference in time spent standing between summer (12.4 ± 1.08%) and winter (15.6 ± 1.70%; $p = 0.066$; Figure 5.2). No differences in time spent standing were observed between summer and winter for research cats (9.3 ± 0.71% and 12.2 ± 1.46%, respectively; $p > 0.05$) and indoor pet cats (9.8 ± 1.07% and 11.0 ± 1.03%, respectively; $p > 0.05$). During winter, free-roaming pet cats spent more time standing than indoor pet cats ($p = 0.024$), but not research cats ($p > 0.05$). No differences in time spent standing between housing conditions were found during summer ($p > 0.05$).

5.3.2.1 Daily pattern in behaviour

A bimodal pattern of behaviour was observed in both summer and winter, regardless of housing condition, which was primarily driven by active behaviours and eating (Figure 5.3). Free-roaming pet cats showed a clear bimodal pattern during both summer and winter; however, it was less prominent during summer for indoor pet cats. Among research cats, the bimodal pattern was less prominent during winter than during summer. In addition, regardless of season, research cats were most active between 07:00 and 12:00, which was when daily cleaning and feeding routines took place. A second peak was observed around the time of sunset in both summer and winter, though the peak was slightly more pronounced in summer than winter. For the pet cats, the peaks occurred around sunrise and sunset in both summer and winter. Free-roaming pet cats remained more active between sunset and sunrise in summer than in winter. This nightly activity was not observed in research cats and indoor pet cats.

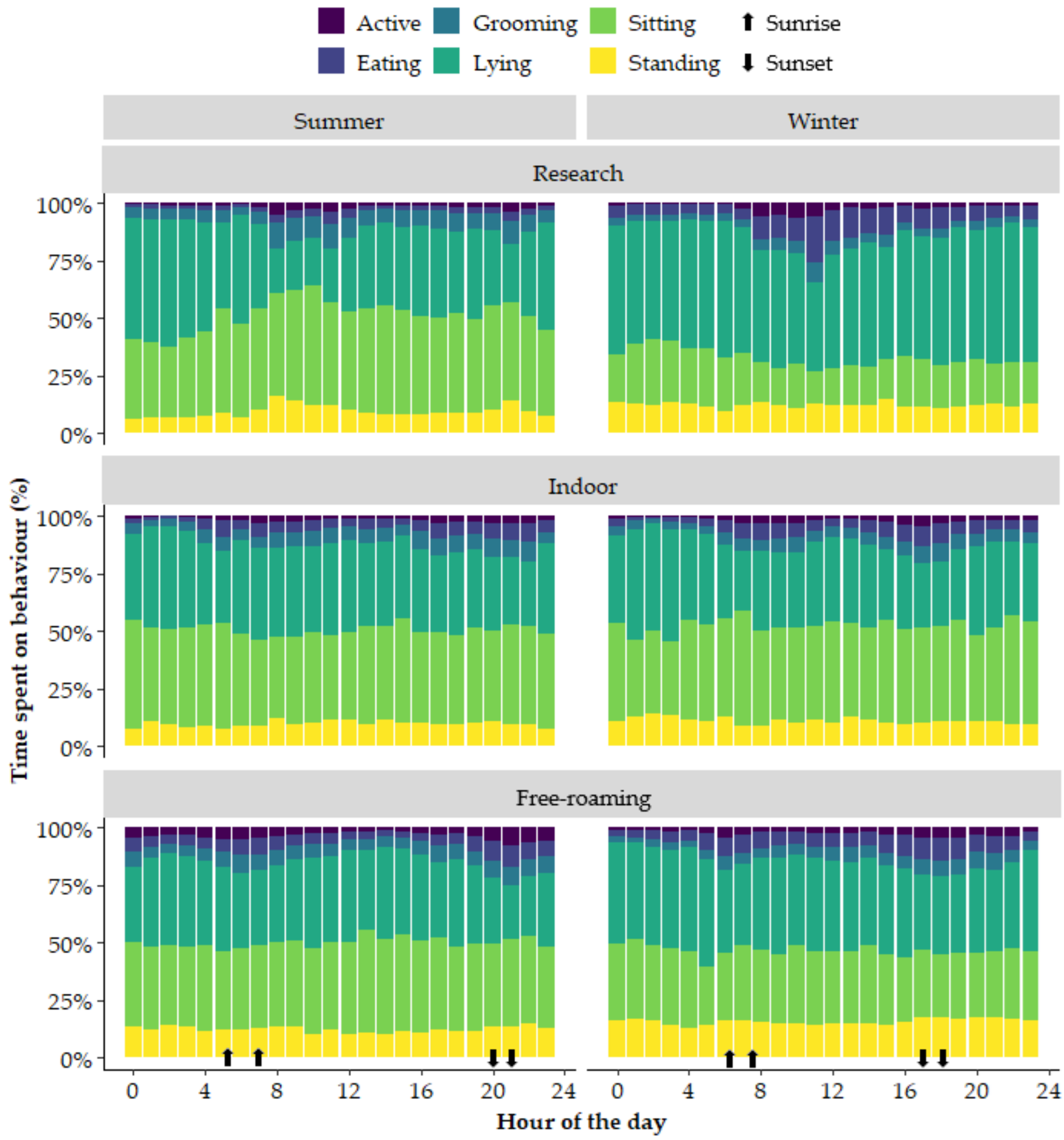

Figure 5.3. Daily behaviour patterns (classified with the model), expressed per hour of the day, across two periods (summer and winter) of research cats (n = 7 × 21 days), indoor pet cats (n = 10 × 7 days), and free-roaming (n = 18 × 7 days) pet cats. Earliest and latest sunrise and sunset times for each period are indicated with arrows. Littering and scratching behaviour were removed from the plot due to their low proportion.

5.3.3 The influence of household and social factors on pet cat behaviour

Of the 60 eligible cats identified from the questionnaire, owners of 18 cats did not respond to the invitation to participate in the study, resulting in a total of 42 cats that participated in the first collection period (summer). Of those 42, five lost their collars and two did not adapt to wearing the monitor according to their owners and were thus excluded from the trial. Reasons given for failure to habituate to wearing the monitor included changes in behaviour (as observed by the owner, such as excessive grooming and/or scratching, and removal of the collar by the cat. One cat was euthanized due to reasons unrelated to this study between the first and second collection period, one cat was withdrawn from the study by the owner, and two cats were not booked in for the second collection period by the owner. The second collection period therefore included 33 cats, of which five cats lost their collar, resulting in a final sample size of 28 cats. Only data from these 28 cats were included in the data analysis.

All cats that participated in the study were desexed; therefore, hereafter they will be referred to as female and male. The remaining cohort of cats only contained cats in the junior, prime and mature categories. Cats were fed either a dry diet or a combination of dry and wet diets (e.g., canned or pouched). Cats that completed the study were either housed indoors with unlimited outdoor access (free-roaming; n = 18), or indoors with limited outdoor access (indoor; n = 10). In one household with two cats participating in the study, a child was born between the first and second collection, which transitioned these cats from a child-free household to a household with a child. In one of the households, a second cat was introduced between the first and second collection period, resulting in a change in classification from a single cat to a multi-cat household. The maximum number of cats in a household for the cats who completed the study was three. Therefore, the third category was renamed to "three". Final sample sizes per season for each category within each variable are presented in Table 5.3. The sample sizes in Table 5.3 are also the sample sizes used in the GLMMs.

Table 5.3. Number of cats in each variable category in the summer and winter study periods.

	Seasonal period			**Seasonal period**	
	Summer	Winter		Summer	Winter
Sex			**Dogs**		
Female	17	17	Absent	19	19
Male	11	11	Present	9	9
Age group[1]			**Number of cats in household**		
Junior	10	10	One	12	11
Prime	12	12	Two	9	10
Mature	6	6	Three	7	7
Housing[2]			**Children (< 18 years)**		
Indoor	10	10	Absent	20	18
Free-roaming	18	18	Present	8	10

[1] Junior = 1-2 years, prime = 3 to < 7 years, mature = 7 to < 11 years.
[2] Indoor = cats with indoor only access, free-roaming = cats having both indoor and outdoor access.

5.3.3.1 Bodyweight and body condition score

A significant interaction effect of season ′ housing on both bodyweight (t_{23} = 3.29; p = 0.004) and BCS (t_{22} = 3.66; p = 0.001) was found. Free-roaming pet cats were significantly heavier in winter (4.98 ± 0.18 kg) than in summer (4.63 ± 0.17 kg; p = 0.001), whereas indoor pet cats showed little difference between winter (4.60 ± 0.27kg) and summer (4.56 ± 0.30). Little differences in bodyweight between free-roaming and indoor pet cats were found in either winter or summer. Free-roaming pet cats had a significantly higher BCS in winter (6.73 ± 0.24) than in summer (6.20 ± 0.18; p = 0.002), whereas indoor pet cats showed little difference between winter (5.67 ± 0.32) and summer (5.89 ± 0.33). In winter, free-roaming pet cats tended to have a higher BCS than indoor pet cats (p = 0.062). In summer, little difference was found between the free-roaming and indoor pet cats.

5.3.3.2 Behaviour

Time spent on behaviours are presented as the observed mean ± standard error. Chapter 4 clearly showed that exposure to changing weather was associated with changes in the behaviour of cats. Because indoor pet cats are not exposed to the weather outdoors, whereas free-roaming cats can be, an interaction term between the two was included in the multivariate GLMM if both were found to be significant in the univariate GLMM.

The β_1 estimates, 95% confidence intervals and p-values for the univariate GLMM of time spent on active behaviours are reported in Table 5.4. The univariate GLMMs indicated significant associations with season (p = 0.028) and housing (p = 0.010), as well as a significant quadratic association with age group (p = 0.048). Cats spent less time on active behaviours in winter (2.5% ± 0.23%) compared with summer (3.2% ± 0.33). Free-roaming pet cats spent more time on active behaviours (3.28% ± 0.31) than indoor pet cats (2.06 ± 0.27%). Junior cats spent more time on active behaviours (3.8% ± 0.44%) than both prime (2.3 %± 0.25%; p < 0.001) and mature cats (2.3% ± 0.40; p = 0.008), while there was no difference between prime and mature cats. Following a backwards stepwise procedure, the final GLMM included the interaction "season × housing" and the quadratic association with age group. In summer, free-roaming pet cats spent more time on active behaviours (3.86% ± 0.39%) than indoor pet cats (1.98% ± 0.36%; p < 0.001). Free-roaming pet cats spent more time on active behaviours in summer than in winter (2.69% ± 0.33%; p = 0.004). Indoor pet cats spent less time on active behaviours in summer than free-roaming pet cats in winter (p < 0.001). No difference was found between indoor (2.15% ± 0.23%) and free-roaming pet cats in winter. Inclusion of cat as a random effect significantly improved the variance explained by the models (p = 0.046), as did inclusion of the fixed effects (p < 0.001). The fixed effects alone explained 46.8% of the variance, while inclusion of cat as a random effect improved that to 57.5%.

Table 5.4. Results of GLMMs examining household and social variables associated with active behaviours (walking and trotting), as classified with the model. Presented are the estimates (β_1), 95% confidence interval (CI), *p*-values and reference category. Estimates are presented on the logit scale.

Variable	Estimate	95% CI	*p*-value	Reference category
		Univariate GLMMs		
Season	-0.22	[-0.43, -0.01]	0.029	Winter
Age group (linear)	-0.38	[-0.65, -0.13]	0.003	Junior
Age group (quadratic)	0.23	[-0.00, 0.46]	0.047	Junior
Sex	0.19	[-0.15, 0.52]	0.255	Neutered male
Housing	0.41	[0.09, 0.74]	0.010	Free-roaming
Children	-0.06	[-0.41, 0.27]	0.730	Present
Number of cats in household (linear)	-0.17	[-0.46, 0.12]	0.252	One
Number of cats in household (quadratic)	-0.01	[-0.29, 0.27]	0.935	One
Dogs in household	0.10	[-0.26, 0.45]	0.573	Present
		Final multivariate GLMM: Season × Housing + Age group		
Season × housing	-0.49	[-0.91, -0.07]	0.019	Winter free-roaming
Age group (quadratic)	-0.31	[0.10, 0.52]	0.002	Junior

The β_1 estimates, 95% confidence intervals and *p*-values for the univariate GLMM of time spent on grooming behaviour are reported in Table 5.5. The univariate GLMMs indicated a significant association with season ($p = 0.045$), while trends were observed for age group ($p = 0.071$) and the presence of children in the household ($p = 0.061$). Cats spent less time grooming in winter (5.0% ± 0.35%) than in summer (6.0% ± 0.43%; $p = 0.045$). Junior cats tended to spend more time grooming (6.3% ± 0.49%) than prime cats (5.1% ± 0.49%; $p = 0.06$%). No differences were observed in time spent on grooming between junior and mature (5.0% ± 0.38%), and prime and mature cats. Cats in households with at least one child present tended to spend less time grooming (4.6% ± 0.39%) than cats in child-free households (5.8% ± 0.37%; $p = 0.057$). Following a backwards stepwise procedure, the final GLMM included season and the presence of children in the household, although both only showed trends. Cats tended to spend less time grooming in winter than summer ($p = 0.058$), and less in child-free households than in households with at least one child present ($p = 0.071$). In the final model, inclusion of the fixed effects significantly improved the model ($p = 0.030$), explaining 13.1% of the variance. Though inclusion of cat did not significantly improve the variance explained by the model, inclusion of it led to the model explaining 27.8% of the variance.

Table 5.5. Results of GLMMs examining household and social variables associated with grooming behaviour, as classified with the model. Presented are the estimates (β_1), 95% confidence interval (CI), *p*-values and reference category. Estimates are presented on the logit scale.

Variable	Estimate	95% CI	*p*-value	Reference category
		Univariate GLMMs		
Season	-0.18	[-0.35, 0.00]	0.045	Winter
Age group (linear)	-0.16	[-0.35, 0.01]	0.071	Junior
Age group (quadratic)	0.10	[-0.06, 0.26]	0.213	Junior
Sex	0.07	[-0.15, 0.28]	0.524	Neutered male
Housing	-0.02	[-0.23, 0.20]	0.881	Free-roaming
Children	-0.21	[-0.44, 0.01]	0.061	Present
Number of cats in household (linear)	-0.13	[-0.32, 0.05]	0.163	One
Number of cats in household (quadratic)	-0.05	[-0.22, 0.13]	0.590	One
Dogs in household	-0.04	[-0.27, 0.18]	0.722	Present
		Final multivariate GLMM: season + presence of child(ren)		
Season	-0.16	[-0.34, 0.01]	0.058	Winter
Children	-0.20	[-0.42, 0.02]	0.071	Present

The β_1 estimates, 95% confidence intervals and *p*-values for the univariate GLMM of time spent on sitting behaviour are reported in Table 5.6. The univariate GLMMs indicated a significant association with the number of cats in the households ($p = 0.039$), and a trend for housing ($p = 0.067$) and presence of children ($p = 0.074$). Cats in households with three cats tended to spend more time sitting (42.6% ± 4.73%) than cats in single-cat households (32.3% ± 2.88%; $p = 0.098$). No difference was observed for time spent sitting between one- and two- (37.5% ± 3.26%), and two- and three-cat households. Indoor-housed cats tended to spend more time sitting (41.1% ± 3.53%) than free-roaming pet cats (34.1% ± 2.37%; $p = 0.072$), and cats in child-free households tended to spend more time sitting (40.1% ± 2.76%) than cats in households with at least one child present (29.2% ± 3.72%; $p = 0.064$). Following a backwards stepwise procedure, the final GLMM included the number of cats in the household and the presence of children. Cats in three-cat households spent more time sitting than cats in single-cat households ($p = 0.021$). No differences in time spent sitting were observed between cats in one- and two-cat, and two- and three-cat households. In the final model, inclusion of the fixed effect significantly improved the model ($p = 0.016$). The fixed effects alone explained 36.6% of the variance, while inclusion of cat as a random effect did not improve this at all (36.6%).

Table 5.6. Results of GLMMs examining household and social variables associated with sitting behaviour, as classified with the model. Presented are the estimates (β_1), 95% confidence interval (CI), *p*-values and reference category. Estimates are presented on the logit scale.

Variable	Estimate	95% CI	*p*-value	Reference category
		Univariate GLMMs		
Season	-0.22	[-0.56, 0.12]	0.199	Winter
Age group (linear)	0.10	[-0.23, 0.42]	0.556	Junior
Age group (quadratic)	-0.04	[-0.32, 0.25]	0.800	Junior
Sex	0.12	[-0.23, 0.46]	0.505	Neutered male
Housing	-0.32	[-0.66, 0.03]	0.067	Free-roaming
Children	-0.34	[-0.75, 0.02]	0.074	Present
Number of cats in household (linear)	0.31	[0.01, 0.60]	0.039	One
Number of cats in household (quadratic)	0.00	[-0.29, 0.29]	0.996	One
Dogs in household	-0.28	[-0.64, 0.08]	0.130	Present
Final multivariate GLMM: Number of cats in household + presence of child(ren)				
Number of cats in household (linear)	0.39	[0.10, 0.68]	0.008	One
Children	-0.45	[-0.81, -0.10]	0.012	Present

The β_1 estimates, 95% confidence intervals and *p*-values for the univariate GLMM of time spent on standing behaviour are reported in Table 5.7. The univariate GLMMs indicated significant associations with housing ($p = 0.016$) and presence of children ($p = 0.001$). Indoor-housed pet cats spent less time standing (10.4% ± 0.77) than free-roaming cats (14.0% ± 1.00%). Cats in child-free households spent less time standing (10.9% ± 0.50%) than cats in households with at least one child present (17.6% ± 2.38%). To test for any interaction between housing and presence of children, a new variable was created, as the dataset did not contain any indoor cats where there was at least one child present. The new variable contained three categories: child-free indoor (reference category), child-free free-roaming and free-roaming with at least on child present. The final model included this new variable, and a significant association was observed ($p = 0.003$). Free-roaming pet cats in households with at least one child present spent more time standing (16.4% ± 1.77%) than indoor cats living in child-free households (10.4% ± 0.74%; $p = 0.003$). Free-roaming pet cats in child-free households tended to spend less time standing (11.6% ± 0.77%) than free-roaming cats in in households with children. No difference was observed between indoor and free-roaming pet cats in child-free households. In the final model, the fixed effects alone explained 25.1% of the variance ($p = 0.003$). Though not significant, inclusion of cat as a random effect increased the variance explained by the model to 30.9%.

Table 5.7. Results of GLMMs examining household and social variables associated with standing behaviour, as classified with the model. Presented are the estimates (β_1), 95% confidence interval (CI), *p*-values and reference category. Estimates are presented on the logit scale.

Variable	Estimate	95% CI	*p*-value	Reference category
		Univariate GLMMs		
Season	0.19	[-0.04, 0.42]	0.104	Winter
Age group (linear)	-0.16	[-0.39, 0.07]	0.171	Junior
Age group (quadratic)	-0.01	[-0.21, 0.18]	0.886	Junior
Sex	0.04	[-0.20, 0.27]	0.754	Neutered male
Housing	0.29	[0.05, 0.53]	0.016	Free-roaming
Children	0.43	[0.18, 0.71]	0.001	Present
Number of cats in household (linear)	-0.07	[-0.28, 0.14]	0.534	One
Number of cats in household (quadratic)	-0.04	[-0.23, 0.17]	0.724	One
Dogs in household	0.09	[-0.16, 0.33]	0.452	Present
		Final multivariate GLMM: Housing × Presence of child(ren)		
Housing × Children[1]	0.12	[-0.18, 0.40]	0.388	Absent
	0.47	[0.20, 0.77]	0.001	Present

[1] A new variable was created as there were no indoor-only cats in households with children

The β_1 estimates, 95% confidence intervals and *p*-values for the univariate GLMM of time spent on scratching behaviour are reported in Table 5.8. The univariate GLMMs indicated trends for the association with season ($p = 0.097$) and number of cats in the household ($p = 0.096$). Cats tended to spend more time scratching in summer (0.14% ± 0.02%) than in winter (0.11% ± 0.02%). Though a trend was observed for the association with number of cats in the household, the pairwise comparison did not reveal any trends between households with one, two or three cats.

Table 5.8. Results of GLMMs examining household and social variables associated with scratching behaviour, as classified with the model. Presented are the estimates (β_1), 95% confidence interval (CI), *p*-values and reference category. Estimates are presented on the logit scale.

Variable	Estimate	95% CI	*p*-value	Reference category
		Univariate GLMMs		
Season	-0.25	[-0.56, 0.05]	0.097	Winter
Age group (linear)	-0.05	[-0.46, 0.34]	0.787	Junior
Age group (quadratic)	0.06	[-0.28, 0.41]	0.714	Junior
Sex	-0.10	[-0.52, 0.33]	0.649	Neutered male
Housing	0.13	[-0.29, 0.58]	0.529	Free-roaming
Children	-0.13	[-0.58, 0.29]	0.556	Present
Number of cats in household (linear)	-0.31	[-0.69, 0.05]	0.096	One
Number of cats in household (quadratic)	-0.24	[-0.57, 0.10]	0.158	One
Dogs in household	-0.08	[-0.53, 0.36]	0.733	Present

Changes in time spent eating, littering and lying were not associated with any variables (see Appendix XV for tables containing the GLMM results).

5.4 Discussion

Foreman-Worsley and Farnworth (2019) identified substantial gaps in our knowledge of how pet cats respond and interact with their multifactorial home environment. By applying a validated machine learning model to quantify behaviour from accelerometer data of privately owned cats, this study aimed to bridge this gap and provide objective, quantitative data on the influence of household and environmental factors on feline behaviour. The findings demonstrate how the behaviour of cats changes in response to age, social complexity, and housing conditions, confirming several hypotheses and offering new insights into their lives in domestic settings.

The comparison between research cats and pet cats revealed both differences, but also some similarities, in behaviour that reflect both housing conditions and the broader environmental context. A foundational similarity observed across all populations, from feral cats to research cats in colonies and pet cats in homes, is the presence of a crepuscular, or bimodal, pattern in activity. Studies of feral cats consistently report activity peaks near dawn and dusk, a rhythm believed to be inherited from their wild ancestors and synchronised with prey availability (Konecny, 1987; Lavery et al., 2020). In line with this, the current study confirms that this fundamental biological rhythm persists through domestication: the bimodal pattern observed in both research and pet populations appears to be primarily driven by behaviours associated with physical activity and feeding, reflecting the inherited nature of these peaks. Previous studies on indoor-housed research cats also reported a bimodal pattern driven by physical activity and eating (Parker et al., 2019, 2022a, 2022b). However, while the underlying rhythm is shared, its expression is strongly influenced by the environment, particularly human influence.

The activity of research cats was strongly synchronised with the schedules of their caretakers, showing a prominent peak between 07:00 and 12:00 that coincided with daily cleaning and feeding regimes. A similar prolonged morning peak and second less pronounced peak around sunset have previously been observed in the same population of research cats (Smit et al., 2022). A study with pet cats found that indoor-housed cats with one hour of garden access per day were more active when their owners were at home, whereas the cats with more extensive and unrestricted outdoor access was primarily nocturnal and maintained a robust daily activity independent of the schedule of the owner (Piccione et al., 2013). In the current study, the free-roaming pet cats showed a clear bimodal pattern aligning with dusk and dawn in both summer and winter. Indoor cats also displayed a bimodal rhythm, though it was more pronounced in winter than in summer. The winter peaks may have been reinforced by the overlap between sunrise/sunset and typical owner work schedules, suggesting that natural crepuscular tendencies and human routines acted in combination. In summer, two evening peaks were visible, one aligning with owner return times and the other with sunset, indicating that both inherited rhythms and owner presence influenced activity. The weaker overall bimodality in summer may further reflect seasonal changes in household routines, such as school holidays, when cats are exposed to more frequent human interaction throughout the day.

The time allocated to maintenance behaviours, specifically grooming and scratching, also revealed a clear contrast based on environmental exposure, directly linking behaviour to underlying physiological cycles. A pronounced similarity was found between research cats and free-roaming pet cats, both of which spent significantly more time grooming and scratching in summer than in winter. This pattern strongly correlates with the natural hair growth and shedding cycle in domestic cats, which is primarily driven by photoperiod (Baker, 1974; Hendriks et al., 1997; Ryder, 1976). As cats shed their denser winter coat in response to increasing daylight hours and temperatures, grooming activity logically increases to manage the moult. Conversely, indoor-only privately owned cats did not show this seasonal pattern. Their lack of exposure to natural, fluctuating light cycles and temperatures, coupled with their exposure to artificial lighting in winter, likely disrupts the environmental cues that trigger a pronounced seasonal moult. As a result, they do not have the same physiological need to grow a thick winter coat, and their grooming behaviour remains relatively constant throughout the year. It is also possible that owners aid the moulting of their indoor-housed cats by means of brushing, lowering the increased need for self-grooming during the moult. Interestingly, the research cats spent significantly more time grooming compared to even the free-roaming pet cats. This may be explained by their housing conditions; unlike free-roaming pet cats who can retreat indoors during inclement weather, the research cats were exposed to the outdoors year-round. This constant exposure may necessitate a thicker denser coat for insulation, which in turn requires more intensive grooming to maintain during the moult.

These changes in active and maintenance behaviours are intrinsically linked to the time allocated for rest, governed by the principle of a finite time budget. When a cat spends less time on one behaviour, it must spend more time on another. This was clearly demonstrated in the free-roaming cats, whose reduced winter activity corresponded with a marked increase in lying behaviour, representing an energy conservation strategy to cope with the thermal challenges of winter. It is hypothesised that the reduction in active behaviour is the result of cats spending more time indoors, prioritising thermal comfort, as has been previously reported in free-roaming pet cats (Horn et al., 2011). The research cats showed a similar pattern, spending more time lying down in winter, most likely within their sleeping boxes, which provided shelter and insulation. Interestingly, both research and free-roaming cats also spent more time eating in winter than in summer, suggesting higher energy demands for thermoregulation. Correspondingly, free-roaming cats exhibited increases in both body weight and body condition score during winter. These findings provide physiological support for the behavioural patterns observed, indicating that the reduced activity and increased feeding in winter may contribute to seasonal gains in body mass and condition. However, caution is warranted when interpreting this result: time spent eating does not necessarily equate to the quantity of food consumed or actual energy intake. Individual cats may eat at different rates or take larger or smaller bites, so further research is needed to clarify this relationship. The association was more pronounced in the research cats, possibly because they lacked the option of retreating indoors for warmth, unlike the free-roaming cats. Together, these patterns highlight how behavioural trade-offs in activity, rest, and feeding reflect adaptive strategies to maintain energy balance in colder conditions.

Previous studies using accelerometers have shown that overall physical activity in cats declines with age, as measured by activity counts. (Naik et al., 2018) reported a 6–7% yearly reduction in daily activity, although their sample was relatively small (n = 19) and skewed towards younger cats (mean age 4.6 years). Similarly, (Smit et al., 2022) found that research cats in the kitten (0–6 months) and junior (7 months–2 years) age groups were more active than cats in the prime (3–6 years), mature (7–10 years), and senior (11–14 years) groups, with no differences observed among the older groups. In the current study, a comparable pattern was observed in pet cats: juniors (7 months–2 years) spent significantly more time on active behaviours than both prime (3–6 years) and mature (7–10 years) cats, while activity levels did not differ between prime and mature individuals. Beyond locomotor activity, age also tended to be negatively associated with time spent grooming, which may further contribute to the overall decline in activity with age. This aligns with previous evidence that grooming and scratching can produce high activity counts (Andrews et al., 2015; Lascelles et al., 2008) and that owners often report reduced grooming in older cats (Sordo et al., 2020). Together, these findings suggest that age-related decreases in overall activity, recorded by accelerometers, are likely driven by declines in both locomotor and grooming behaviours. Importantly, reduced grooming in older cats may have practical implications for caretakers, as seniors (11–14 years) and geriatrics (≥15 years) may require additional grooming assistance, such as regular brushing, to maintain coat condition and skin health.

The domestic environment is a complex ecosystem the behaviour of a cat is not only shaped by physical factors but also by the intricate social dynamics of the household. The current study’s findings align with literature suggesting that the presence of other cats and children significantly alters a cat's daily time budget, particularly the balance between resting and vigilant behaviours. However, interpreting these changes requires careful consideration, as a statistically significant association does not always equate to a negative impact on welfare. Domestic cats have the capacity for social living, but cohabitation in multi-cat households can introduce social challenges, often stemming from competition over resources (Carlstead et al., 1993; Ramos et al., 2013). In the current study, the number of cats in a household significantly influenced time spent sitting, with cats in three-cat households spending more time sitting than those in single-cat homes. This behaviour likely reflects increased vigilance and a need to monitor conspecifics to navigate social order in a spatially limited environment. However, links between group size and physiological stress are complex: studies measuring fecal glucocorticoid metabolites have not found consistent differences in baseline stress levels between single- and multi-cat households (Finka & Foreman-Worsley, 2022; Ramos et al., 2013). Research in pet cats has further highlighted that social outcomes depend on factors such as early socialisation, familiarity, and relatedness (Bradshaw & Hall, 1999; Finka & Foreman-Worsley, 2022; Karsh & Turner, 1988). Related cats tend to interact more frequently and have overlapping home ranges, whereas unrelated cats time-share resources and maintain partial spatial separation to reduce conflict (Barratt, 1997; Bernstein & Strack, 1996). Overall, the increased sitting observed in multi-cat households likely represents a low-energy behavioural strategy for managing complex social dynamics rather than a direct indicator of compromised welfare.

The presence of children in households had a clear impact on cat behaviour, influencing both postural and maintenance activities. In homes with at least one child, cats spent more time standing and tended to spend less time grooming, suggesting a shift towards heightened alertness or readiness to react to unpredictable interactions (Hart et al., 2018). Reduced grooming, typically performed when a cat feels relaxed, further supports the interpretation that cats may experience sustained arousal in the presence of children. However, an alternative perspective is that children provide dynamic environmental enrichment, prompting curiosity and engagement rather than stress. Survey-based studies indicate that cats are often perceived as less affectionate towards children than adults, particularly younger children (3-5 years), which may generate conflict and affect the welfare of both parties (Groenewoud et al., 2023; Hart et al., 2018; Melson, 1990). In the present study, children were defined broadly as any household member under 18 years of age. This wider grouping may have masked age-specific associations suggested in the literature, since only a limited number of households contained children in each developmental stage. Future research with larger samples and finer age distinctions will be important for disentangling whether cat behaviour differs across child developmental stages.

Although interactions between cats and dogs in shared households are less well-studied, existing evidence suggests that cohabitation does not inherently disrupt the cat's time budget. In the current study, the presence of a dog was not a significant predictor of time spent sitting, standing, or grooming, suggesting that dog presence alone does not strongly influence cat behaviour. Prior research indicates that early exposure is critical: cats are more likely to be amicable towards dogs if the first encounter occurs before six months of age, and both species are capable of interpreting each other's body language, even when postures have opposite meanings (Feuerstein & Terkel, 2008). These observations indicate that cohabitation with dogs can be managed successfully, but outcomes likely depend on individual temperament, socialisation history, and household management strategies that allow cats access to safe, dog-free spaces. More research is warranted to understand the nuanced dynamics of cat-dog relationships and their implications for feline welfare.

While this study provides valuable insights into the lives of pet cats, its findings must be interpreted in light of several methodological limitations. The most significant of these is the application of a machine learning model trained on research cats in a semi-outdoor colony to a population of pet cats in more complex and variable home environments. The Random Forest model was validated on these research cats, achieving an overall accuracy of approximately 73% and an F1-score of 68%. However, the domestic setting introduces factors and behavioural contexts that were not present in the training environment, which presents critical challenges to the performance of the model. The accuracy of a model is dependent on the environment in which it was trained, and its performance may decline when applied to a new context (Rast et al., 2020). The home environment contains behaviours the model was not trained on (e.g., specific types of play, complex social interactions), which may be misclassified into one of the existing eight categories. This limitation was demonstrated practically when addressing the postural differences in eating behaviour between the research and pet cats. In the research setting, cats ate from bowls placed on the floor of their individual feeding cages, a posture that proved to be unique to that setup. Recognising this discrepancy, an attempt was made to retrain the model using new data captured from research cats eating in a posture more analogous to that of pet cats. However, this newly trained model, despite having an identical F1-score, performed poorly on the pet cat dataset, erroneously classifying 25% of their daily time budget as "eating". This is a grave overestimation compared to the 2–

3% consistently reported in the literature (Berteselli et al., 2017; Eckstein & Hart, 2000b; Huck & Watson, 2019; Panaman, 1981). Consequently, the original model, which predicted a more biologically plausible 5.5% eating time, was used for the final analysis. This outcome powerfully illustrates the challenge of model generalisability and underscores that even with retraining efforts, accelerometer signatures for the same behaviour can differ significantly across contexts.

Despite these significant concerns, the ability of the model to consistently and successfully identify the bimodal activity pattern in the pet cats, a foundational and well-documented rhythm in feline behaviour, lends significant credibility to its overall validity in this new context. The clear detection of this fundamental biological pattern suggests the model is capturing genuine, meaningful behavioural signals rather than context-specific artifacts, supporting its utility for assessing broad activity budgets and rhythms in pet cats. Importantly, this supports the value of the model for detecting relative behavioural patterns and environmental associations, even if absolute behavioural proportions should be interpreted with caution in the absence of external validation.

The study was ultimately limited by a small final sample size (n = 28), which reduces statistical power, particularly when subdividing the cohort to analyse different factors like housing or the presence of children. This limitation was compounded by a high rate of participant dropout; of the 42 cats that began the study, 14 were lost to follow-up, representing a 33% dropout rate. This constrained the statistical power and the ability to draw more definitive conclusions from the data.

The study design cannot fully distinguish between direct environmental associations and indirect associations mediated through owner behaviour. For instance, cats in households with children might behave differently not only due to the children's presence but also because owners in such households may interact with their cats differently, alter feeding schedules, or manage the home environment in ways that were not measured.

5.5 Conclusion

This study successfully demonstrated that a validated ML model can be effectively applied to compare the behaviour of research cats and pet cats, quantifying the significant associations of the home environment with domestic cat behaviour. The research confirms that while cats share a fundamental bimodal activity rhythm, its expression is markedly shaped by housing, human schedules, and social context. Free-roaming pet cats adapt their activity levels to seasonal weather, whereas confined cats adapt their resting behaviours. Within the home, factors such as the presence of other animals, children, and owner routines further modulate the daily life of a cat. Despite methodological limitations, this work provides an essential contribution by offering objective, quantitative data on how domestic cats respond to their multifactorial home environments, highlighting the critical importance of considering environmental context when extrapolating findings from research settings to companion animals and advancing our understanding of how to better support their welfare.

Chapter 6

General discussion & conclusion

Image generated with Meta AI

Chapter 6 General discussion & conclusion

6.1 General discussion

This thesis was fundamentally aimed at bridging a significant knowledge gap regarding the complex behaviour of domestic cats, particularly how environmental factors shape their activity patterns and time budgets. Despite a global population of companion cats estimated at over 445 million, in-depth, longitudinal studies of their behaviour have been constrained by the labour-intensive and subjective nature of traditional observational methods. To overcome these limitations, the central objective of this research was to develop, validate, and apply machine learning (ML) models integrated with accelerometer data to quantitatively and continuously analyse domestic cat behaviour.

The research proceeded through a structured, multi-phase approach designed to move from technical development to real-world application, with each chapter representing a progressive step in this ambitious research trajectory. The initial phase (Chapter 3) focused on the model development and validation, establishing the necessary ML framework for classifying behaviour from acceleration signals. This foundational work was crucial for establishing the methodology before its deployment. Following this, the subsequent phases applied the validated tool to different cat populations and environmental contexts. Chapter 4 investigated the influence of seasonal and meteorological conditions on research cats housed in a semi-outdoor environment, allowing for an analysis of behaviour in response to natural environmental fluctuations. Finally, Chapter 5 extended this application to pet companion cats, examining how a range of factors within the complex home environment, including housing type, outdoor access, and the presence of other animals or children, can be associated to changes in behaviour. This comprehensive pathway ensured that the methodology was first rigorously established before being used to gain novel insights into how cats adapt their time budgets in response to both natural cycles and the domestic environment.

6.1.1 Key findings and implications

The foundation of this work lay in developing a robust machine learning model for domestic cat behaviour classification from accelerometer data. The iterative refinement of models demonstrated a clear trade-off between number of behavioural classes and the resulting classification accuracy. Both overall accuracy and the F1-score consistently improved as the number of behaviours was simplified by either removing or merging functionally similar ones. This aligns with findings from past animal accelerometry work that reported the same trade-off (McGowan et al., 2022; Shamoun-Baranes et al., 2012). These findings highlight an important methodological consideration for behavioural machine learning: the need to balance biological detail with statistical robustness, and to carefully evaluate which behaviours can be removed or merged without compromising the scientific or welfare relevance of the model.

A pivotal finding arose from the comparison of the Self-Organizing Map (SOM) and Random Forest (RF) classifiers. While SOM models achieved superior internal validation metrics, with accuracy and F1-scores often exceeding 95%, they performed poorly when determining the activity budgets. When applied to unannotated, real-world data, the SOM models generated biologically unrealistic activity budgets, consistently overestimating time spent on maintenance behaviours like eating (predicting 13-28% of the time) and grooming. In contrast, the RF models, despite lower internal metrics, produced activity budgets that aligned closely with previously reported values, especially for eating. The RF models estimated that cats spent between 3–4% of their time eating, which was in agreement with the 2–3% previously reported (Berteselli et al., 2017; Eckstein & Hart, 2000b; Huck & Watson, 2019; Panaman, 1981). These findings underscore the additional benefit of generating activity budgets using the models, confirming that models must be assessed on their ability to generalise to new, unseen data, a point supported by literature cautioning against relying solely on (internal) performance metrics (Ferdinandy et al., 2020; Rast et al., 2020).

The influence of device mounting location also emerged as an important consideration. Harness-mounted accelerometers showed slightly higher performance metrics than collar-mounted devices, particularly for eating behaviour, likely due to posture-related orientation shifts. However, the differences between mounting sites were small, suggesting that collar-mounted devices, which are more practical for privately owned cats, do not compromise classification accuracy. This outcome is consistent with previous companion animal studies showing that mounting site influences classification to some extent but does not necessarily undermine model reliability (Tatler et al., 2018).

Taken together, these results demonstrate that the Random Forest model with eight behavioural classes, trained from collar-mounted accelerometer data, provided the best balance of classification detail, robustness, and practical applicability. Importantly, this work underscores that careful model selection cannot rely on internal validation alone but must incorporate and biological relevance. In this way, the models developed here move beyond proof-of-concept to provide a reliable and welfare-relevant tool for behavioural monitoring in domestic cats.

While the development and validation of the behavioural classification model was a critical first step, its value extends beyond methodological advancement. The subsequent chapters applied this tool to real-world contexts, moving from proof-of-concept to generating novel biological insights. In Chapter 4, the model was used to examine how seasonal and meteorological conditions influence the behaviour of semi-outdoor research cats, providing a fine-grained view of how natural environmental fluctuations shape discrete activities. Chapter 5 extended this application to pet cats, disentangling the associations of housing, outdoor access, and social dynamics within the home with domestic cat behaviour. Together, these chapters demonstrate how accelerometer-based machine learning can move beyond generic activity measures to reveal how specific environmental factors modulate specific feline behaviours, thereby offering insights of both scientific and welfare relevance. The findings from Chapter 4, which focused on a longitudinal study of research cats in a semi-outdoor colony, revealed significant seasonal associations with most behaviours. The analysis showed that time spent grooming and scratching was highest in autumn compared to all other seasons. Similarly, sitting and littering behaviours also peaked in autumn. Conversely, time spent lying was lowest in autumn and highest in summer. Eating behaviour was lowest in autumn and highest in spring, while active behaviours were displayed most in spring and least in summer. When these behaviours were analysed against meteorological drivers, the results disentangled the influence of overarching seasonal rhythms from immediate weather. Daylength was found to have a significant negative association with grooming, scratching, and sitting, while temperature had a significant positive association with scratching and a negative association with active and standing behaviours. This supports the conclusion that grooming and scratching are likely linked to innate physiological cycles cued by photoperiod, while other behaviours are adjusted in response to daily weather conditions like temperature and wind speed.

Chapter 5, which investigated pet cats, provided a comparative analysis and examined household factors. In a direct comparison between summer and winter, both research cats and free-roaming pet cats spent significantly more time grooming in summer than in winter, a seasonal difference not observed in indoor-only cats. Research cats also spent more time scratching in summer than in winter, while no seasonal difference was found for pet cats in this behaviour. For active behaviours, only free-roaming cats were significantly more active in summer than in winter. These seasonal behavioural changes were mirrored by physiological measures: free-roaming cats exhibited increases in body weight and body condition score during winter. This suggests that reduced activity and increased time spent resting and feeding in winter may contribute to seasonal gains in body mass and condition, reflecting adaptive energy management. Regarding household factors, the presence of children tended to be associated with less time spent grooming and sitting, but more time standing. The number of cats in the household also influenced sitting time, with cats in three-cat households tending to sit more than those in single-cat households. Collectively, these findings highlight how both environmental conditions and household composition shape behavioural rhythms and physiological outcomes in domestic cats.

The seasonal increase in body weight and body condition score observed in free-roaming pet cats during winter appears to be linked to reductions in active behaviours, as physical activity is an important component of energy expenditure (Case et al., 2011). These cats also spent more time lying down in winter, reflecting an energy conservation strategy, and, although not statistically significant, tended to spend more time eating compared with summer. Importantly, the outdoor environment provides enrichment opportunities that indoor spaces may lack, which can stimulate activity and play. This suggests that providing appropriate enrichment or playtime, particularly when outdoor access is limited or during periods of low activity, may help maintain energy balance and mitigate seasonal gains in body weight and condition. However, it should be noted that time spent eating does not necessarily equate to energy intake, and feeding strategies should still be tailored to activity levels to reduce the risk of unhealthy weight gain.

The presence of children in a household can influence feline behaviour in multifaceted ways. On one hand, children can provide dynamic environmental enrichment, stimulating curiosity and engagement in cats (Bradshaw, 2018). On the other hand, the presence of children may lead to increased arousal in cats, as indicated by the by heightened alertness (standing and sitting) and reduced grooming behaviours in Chapter 5. Cats have been reported to generally show less affection toward younger children than adults, and the child's behaviour is often the limiting factor (Hart et al., 2018). This may be due to the interaction styles of children, which can be perceived as by cats as threatening (Mertens, 1991; Mertens & Turner, 1988). Grooming is a vital maintenance behaviour for cats, serving not only to maintain hygiene but also to regulate body temperature, manage ectoparasites, and alleviate stress (Eckstein & Hart, 2000a, 2000b; Kim et al., 2019). A decrease in grooming time, as observed in Chapter 5, suggests that cats may experience sustained arousal or stress in the presence of children, potentially impacting their overall well-being. From a welfare perspective, this underscores the critical importance of providing cats in socially complex homes with secure, elevated, and inaccessible retreat spaces. Such spaces allow cats to self-regulate their social exposure, mitigate potential stress, and perform necessary maintenance behaviours without disruption. Ensuring that cats have access to these safe zones is essential for their physical and psychological health in multi-child households.

Although Chapters 4 and 5 addressed distinct contexts, several findings converge on shared biological processes that are best understood when considered together. For example, the apparent discrepancy in seasonal peak of grooming behaviour between Chapter 4 and Chapter 5 (Table 6.1). In Chapter 4, the detailed seasonal analysis of research cats revealed a distinct and significant peak in grooming and scratching behaviour during autumn. However, the analysis in Chapter 5 found that both research cats and free-roaming pet cats spent significantly more time grooming in summer than in winter, a finding that was not apparent in the seasonal data from Chapter 4. The inconsistency is likely not a contradiction but rather a reflection of the biannual moulting cycle in domestic cats. Feline hair growth and shedding are primarily regulated by photoperiod, resulting in two distinct moulting periods per year: the shedding of the heavy winter coat in spring and early summer as daylength increases, and the shedding of the lighter summer coat in autumn as daylength shortens to make way for a denser winter pelage (Baker, 1974; Hendriks et al., 1997, 1998; Ryder, 1976). The finding in

Chapter 5, that grooming was higher in summer than in winter, likely captures the physiological response to the first of these moults. As cats shed their thick winter undercoat in response to increasing daylight and temperatures, an increase in grooming is a necessary maintenance behaviour (Baker, 1974; Hendriks et al., 1997, 1998; Ryder, 1976). The detailed seasonal analysis in Chapter 4, however, with its finer temporal resolution, appears to have captured the pronounced peak of the second moulting period in autumn. Therefore, the findings of the two chapters are not mutually exclusive; they simply highlight different phases of the same continuous, year-long physiological process. The summer-over-winter comparison in Chapter 5 demonstrates the predictable increase in maintenance during the warmer shedding period, while the autumn peak identified in Chapter 4 pinpoints the climax of the coat's preparation for winter. This interpretation is further supported by literature showing that seasonal hair loss in cats has a sinusoidal pattern, with a net loss of hair occurring in spring and a net build-up in autumn (Hendriks et al., 1998). The link between grooming peaks and the moulting cycle has direct welfare implications. The increased need for coat maintenance during spring/summer and autumn represents a predictable physiological event. Providing enhanced grooming opportunities during these periods, such as grooming brushes or textured surfaces for self-grooming, could be a simple and effective enrichment strategy to support a cat's natural behaviour and improve its comfort.

Table 6.1. Overview of observed activity budgets reported in the different research chapters, including an average per housing condition.

	Research cats							Indoor pet cats			Free-roaming pet cats		
Season	Winter	Summer	Autumn	Winter	Spring	Summer	Average	Summer	Winter	Average	Summer	Winter	Average
Year	2021	2022/2023	2023	2023	2023	2023/2024		2022/2023	2023		2022/2023	2023	
Chapter	2	4	3	3 & 4	3	3		4	4		4	4	
	Time spent on behaviour (%)												
Active	2.71	2.03	2.05	2.23	2.47	1.56	2.18	1.98	2.15	2.07	3.86	2.69	3.28
Eating	4.05	2.39	1.73	7.75	11.34	9.52	6.13	4.58	4.90	4.74	5.26	6.54	5.90
Grooming	7.15	7.91	6.83	4.57	4.46	4.04	5.83	5.85	5.03	5.44	6.02	5.00	5.51
Littering	0.07	0.06	0.05	0.02	0.01	0.02	0.04	0.04	0.04	0.04	0.02	0.05	0.04
Lying	52.52	36.95	28.68	52.88	58.29	60.33	48.27	36.90	35.44	36.17	34.83	39.18	37.01
Scratching	0.19	0.24	0.16	0.05	0.03	0.04	0.12	0.12	0.09	0.11	0.15	0.12	0.14
Sitting	25.35	41.19	50.77	20.10	11.98	14.35	27.29	40.74	41.33	41.04	37.50	30.78	34.14
Standing	7.95	9.31	9.15	12.20	11.32	10.10	10.00	9.79	11.01	10.40	12.36	15.65	14.01

The consistent midday trough in activity observed across both research and pet cat populations is a key finding with important practical implications for feline welfare and energy management. This pattern is fundamentally driven by the cat's innate bimodal activity rhythm, an evolutionary adaptation for aligning activity with the crepuscular hunting patterns of their ancestors and the activity of primary prey, such as small rodents (Konecny, 1987; Merčnik et al., 2023). This innate rest period is significantly reinforced by thermoregulatory needs, particularly during warmer seasons. Rather than a simple avoidance of ambient heat, cats reduce strenuous activity to prevent activity-induced overheating, as the metabolic heat generated from movement is more difficult to dissipate when external temperatures are high. Detailed analysis of weather variables in Chapter 4 revealed that general activity decreases with rising temperatures, an association most pronounced during long summer days, suggesting that cats dynamically adjust their behaviour to maintain thermal balance. Behaviours related to energy conservation, such as time spent lying down, correspondingly increase during these periods, highlighting that a cat's daily time budget is not static but is continuously modulated in response to immediate thermal challenges. This aligns with observations in feral cats, which shift towards nocturnal activity in summer to avoid midday heat (Izawa, 1983), and in pet cats, which show reduced activity during extreme heat events (Palestrini et al., 2022). The practical implication is that cats require access to cool, sheltered resting places to cope with heat, a need that becomes increasingly important as climate patterns shift towards more frequent extreme weather events.

This brings to light the apparent paradox of research cats being observed resting in the sun during these inactive periods (personal observation). This behaviour illustrates a key nuance in feline thermoregulation: the choice of where to rest is separate from the decision to be inactive. Sunbathing is a low-energy, passive behaviour that allows the cat to maintain a high core body temperature with minimal metabolic cost, consistent with their high thermoneutral zone (30–38°C; National Research Council, 2006). The expression of this behaviour varies significantly based on environmental context, reflecting individual variation. For feral or free-roaming cats, the midday lull is pronounced, driven by both the lack of prey activity and high temperatures (Konecny, 1987; Merčnik et al., 2023). In contrast, for owned cats with reliable access to food and shelter, the innate rhythm is often modulated by owner schedules and thermal comfort (Horn et al., 2011; Piccione et al., 2013). Their reduced need to forage allows greater flexibility in resting choices, such as prioritizing a warm sunspot over the marginal energy savings of deep shade. This demonstrates that while the bimodal pattern is a robust baseline, its manifestation is highly plastic and subject to both immediate environmental factors and individual variation, defining the "normal range of behaviour" as a wide spectrum rather than a single fixed pattern (Garcia & Chebly, 2024). Ultimately, the midday lull is not a simple response to a single stimulus but a complex, energy-efficient strategy that balances innate rhythms with immediate environmental opportunities and constraints.

6.1.2 Methodological considerations and limitations

The innovative approach of this thesis, combining accelerometry with machine learning (ML) to quantify feline behaviour, represents a significant advancement over traditional observational methods. However, a critical evaluation of the methodological framework is essential for the robust interpretation of the findings and for guiding future research in this emerging field. The primary considerations and limitations of this work revolve around the generalisability of the ML model, the constraints of the sample size, and the nature of the data collection protocol.

A principal limitation is the application of an ML model trained on research cats in a semi-outdoor colony to a population of privately-owned cats in more complex and variable home environments. The Random Forest model achieved a validated accuracy of approximately 73% within the controlled research setting. However, the domestic environment introduces novel behaviours (e.g., specific types of play, complex social interactions) and context-specific postures that the model was not trained to recognise. This challenge was powerfully illustrated by the attempt to retrain the classifier for 'eating' behaviour; despite using new data to better reflect postures in the home, the updated model performed poorly on the pet cat dataset, producing a biologically implausible prediction that cats spent 25% of their day eating. This issue of generalisability is compounded by the inherent limitations of both the behavioural ethogram and the accelerometer technology itself. The model was constrained by the behaviours observed during the limited data annotation phase. For instance, the 'Active' category, while functional, is broad and likely encompasses distinct behavioural functions such as exploration and play. However, a fundamental limitation of accelerometry is its inability to infer behavioural intent; the accelerometer signature for 'walking' remains the same whether the cat is exploring a new space or engaging in a form of play. The model can only classify the physical movement, not the underlying motivation. This means that while the model provides a robust characterisation of overall activity, conclusions about the environmental associations with specific, functionally diverse behaviours within this broad category must be interpreted with caution. Nevertheless, it is crucial to note that despite these limitations in classifying fine-grained, motivation-based behaviours, the model's ability to consistently and successfully identify the foundational bimodal activity pattern across all pet cat groups lends significant credibility to its overall validity. This suggests that while the model may struggle with the nuances of specific, ambiguous categories, it effectively captured genuine biological signals related to broad activity budgets and circadian rhythms.

The representativeness of the training data warrants consideration. The data used to train and internally validate the ML model were sourced from a single, continuous block of time (9 AM to 2 PM) on one day. While this period was selected because it captured the greatest diversity of behaviours in the research colony, it may not be fully representative of the cats' entire 24-hour repertoire, particularly crepuscular and nocturnal activities that are central to feline behaviour. This sampling strategy could have introduced a bias into the model, potentially affecting its performance on behaviours more common outside of this specific timeframe.

A further methodological consideration lies in the statistical approach chosen to analyse the proportional behavioural data in Chapters 4 and 5. This thesis predominantly employed Generalised Linear Mixed Models (GLMMs) to assess the impact of environmental variables on each behaviour individually. While this approach provides clear, interpretable results for specific actions, the alternative of using a Dirichlet regression, which models the entire activity budget as a single, compositional outcome, was carefully considered. A highly prevalent and stable behaviour such as 'lying' could theoretically serve as a suitable baseline category for a Dirichlet model. However, this approach introduces its own set of interpretational challenges, particularly concerning the infrequent but biologically significant behaviours that were of key interest in this research. In a Dirichlet model, the effect of covariates on all other behaviours is interpreted relative to this baseline. When the baseline accounts for a vast proportion of the time budget, the statistical power to detect meaningful changes in very low-proportion behaviours can be diminished. The effects on rare behaviours, such as 'littering' or 'scratching', can become statistically obscured or difficult to interpret when their variance is modelled against a behaviour that is orders of magnitude more frequent. Given that a primary aim was to identify the specific environmental drivers for each individual behaviour, including those that are rare, the GLMM approach was ultimately selected. This allowed for a direct and robust examination of the factors influencing each behaviour in isolation, free from the complexities of baseline selection and the potential masking of associations with infrequent actions. This represents a deliberate methodological choice: sacrificing a direct, holistic analysis of the entire activity budget in favour of gaining more precise and reliable inferences for the full spectrum of individual behaviours, from the most common to the rarest.

The study was also limited by its sample size and the profound influence of individual variation, which are common challenges in feline behaviour research. The final analysis of privately-owned cats was constrained to a small sample (n = 28) due to a notable participant dropout rate, which reduces statistical power, particularly when examining subgroups based on housing or social factors. This issue is compounded by known biases in recruiting research participants; the willingness of pet owners to participate in research trials often depends on their level of involvement with their pet, leading to a potential selection bias in the initial cohort. As demonstrated by (Herwijnen et al., 2018), this can result in a bias towards more involved owners, which was likely present in the sample for Chapter 5.

A critical finding across all analyses was that the individual cat often explained a larger portion of behavioural variance than the fixed environmental factors being tested. This high degree of inter-individual variation underscores that group-level averages can obscure significant individual differences in how cats respond to and cope with their environment. This represents a missed opportunity to fully explore the range of normal behavioural variation within the domestic cat population and highlights the need for an individual-based monitoring approach in future welfare assessments. To address these limitations, future research should develop robust approaches to improve recruitment and retention. Offering incentives, such as pet food or vouchers, has been shown to encourage participation from otherwise hesitant owners in similar controlled trials with dogs (Chia et al., 2018). By enhancing recruitment and retention, researchers can gather a more comprehensive and representative dataset, thereby increasing the robustness and applicability of behavioural findings across diverse cat populations.

In summary, these methodological considerations do not invalidate the study's findings but provide an essential framework for their interpretation. They highlight the complexities of applying ML to animal behaviour and underscore the necessity of context-specific model validation, robust ethogram design, and study protocols that account for high inter-individual variability. These limitations serve as a clear and constructive roadmap, identifying key directions for future research to build upon this work and develop more reliable and generalisable tools for the automated, objective study of animal behaviour.

6.1.3 Future directions

The findings and methodological limitations of this thesis lay a clear foundation for several promising avenues of future research. The work presented here pioneers the use of accelerometry and machine learning in a domestic feline context, but the refinement of these tools and their application to more complex behavioural and welfare questions remain a key objective. Future work should prioritise enhancing the accuracy and generalisability of the ML models, deepening the behavioural resolution through multi-sensor data fusion, and expanding the scope of research to address critical welfare and clinical questions.

First, the development of more robust and context-specific ML models is a critical next step. The challenges encountered when applying the research-cat model to the pet cat population highlight the necessity of training classifiers on data collected from the target environment. Future studies should focus on building larger, more diverse training datasets that include a wide range of breeds, ages, and lifestyles (e.g., indoor-only, free-roaming, multi-cat households) in their natural domestic settings. Furthermore, integrating a multi-sensor fusion approach, which combines accelerometer data with gyroscope and magnetometer data, could significantly enhance model accuracy. This would allow for a more nuanced characterisation of movement and posture, potentially enabling the model to better distinguish between behaviours with similar acceleration signatures, such as grooming and scratching, or different types of active states.

Second, to overcome the inherent limitation of accelerometers in determining behavioural intent, future research should integrate accelerometry with other bio-logging technologies. The broad 'Active' category, for example, could be dissected into functionally distinct behaviours by combining movement data with spatial information from GPS loggers. This would allow researchers to link accelerometer signatures to specific locations, helping to differentiate between exploratory behaviour in the garden, territorial patrols, or play within the home. The addition of animal-borne video cameras ('catcams') would provide the ultimate ground truth, allowing for the direct visual validation of complex behaviours and social interactions that are currently ambiguous from movement data alone. This integrated approach would move the field beyond classifying simple physical movements towards a more holistic understanding of the cat's behavioural repertoire in its natural environment.

Finally, with more refined and validated tools, research can expand to address pressing questions in feline welfare and veterinary medicine. Longitudinal studies across different climatic and cultural regions are needed to build upon the initial findings regarding seasonal and environmental modulation of behaviour. A particularly important area is the deeper investigation of social dynamics. For example, future work could explore how the quality of child-cat interactions, rather than just the presence of children, shapes feline behaviour, determining whether they serve as a source of enrichment or stress. Most significantly, this technology has immense potential as a non-invasive tool for health monitoring. Future studies should aim to identify the specific behavioural signatures associated with clinical conditions, such as the subtle changes in activity and grooming patterns that may signal the onset of osteoarthritis, chronic pain, or pruritic skin disease. The development of automated alerts for such changes could provide a powerful early-warning system for owners and veterinarians, enabling earlier diagnosis and intervention, and ultimately improving the welfare of millions of companion cats.

6.2 Conclusion

This thesis addressed a significant gap in feline behavioural science by moving beyond the constraints of traditional observational methods to quantitatively analyse the influence of environmental factors on domestic cat behaviour. By leveraging accelerometry and machine learning, this research developed and applied a non-invasive framework for the continuous, objective monitoring of cats, providing unprecedented insight into how their innate behaviours are shaped by the world they inhabit.

The research journey began with the development and validation of a robust machine learning model capable of classifying eight distinct behaviours from collar-mounted accelerometer data. This tool was then applied to two distinct populations, providing a multi-layered understanding of feline adaptation. In the semi-outdoor research colony, the study disentangled the complex associations season and weather and behaviour, demonstrating that while behaviours like activity and rest are adjusted in immediate response to meteorological conditions for thermoregulation, other behaviours, such as grooming, are entrained to deeper, photoperiod-driven biological rhythms like the biannual moulting cycle. The application of this model to pet cats further revealed the profound impact of the domestic environment, showing how housing conditions and social dynamics, including the presence of other cats and children, were significantly associated with their behaviour. Across both studies, a consistent bimodal activity rhythm was evident, confirming this foundational feline trait. However, the principal contribution of this thesis lies in quantifying how the expression of this rhythm is powerfully shaped by an interplay of seasonal, meteorological, and social pressures.

The fundamental contribution of this work is both methodological and scientific. Methodologically, it provides a validated blueprint for applying modern bio-logging and machine learning techniques to the study of domestic cats in their natural environments, marking an advancement from short-term, subjective observations to long-term, high-resolution monitoring. Scientifically, it provides the first comprehensive, quantitative evidence of how the daily life cats is a dynamic response to a range of environmental influences, from the overarching cycle of the seasons to the immediate social complexities of the home. These findings have significant practical implications for feline welfare, providing a foundation of evidence for veterinarians, welfare scientists, and cat owners to better understand and assess the well-being of a cat by considering its individual responses within its specific environmental context.

In conclusion, this thesis successfully demonstrates that the behaviour of the domestic cat, while rooted in innate biological rhythms, is remarkably plastic. By pioneering a technological approach to behavioural monitoring, this work paves the way for a new era of feline research, one that can lead to a deeper, more empathetic understanding of our feline companions and promote evidence-based stewardship to enhance their welfare in an increasingly human-dominated world.

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Image generated with Meta AI

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Chapter 6

Appendices

Image generated with Meta AI

Appendices

Appendix I – Chapter X

Due to unforeseen issues arising in the analyses of the samples crucial for this chapter resulted in an incomplete draft. A significant amount of my time went into conducting this trial and getting the data ready for final analysis. It was therefore decided that this chapter should be added as an appendix.

Accelerometry as a proxy for energy expenditure in domestic cats (*Felis catus*).

X.1 Introduction

Every living animal requires energy to meet their bodies energy requirements. To maintain a healthy bodyweight, energy expenditure needs to be balanced with intake. A negative energy balance can result in weight loss, while a positive energy balance can result in weight gain. In domestic cats (*Felis catus*), excess weight gain is one the biggest health risks, with a prevalence as high as 63% in New Zealand (Cave et al., 2012). In mammals, total energy expenditure (TEE) is determined by four components: (I) basal metabolic rate (BMR), (II) physical activity (PA), (III) diet-induced thermogenesis (DIT), and (IV) adaptive thermogenesis (AT; Case et al., 2011). Of these four components, PA is the most variable and can significantly influence daily energy requirements. Current techniques that have been used to determine energy requirements, and that form the basis for feeding guidelines, do not lend themselves daily variations in PA and how this can influence daily energy requirements.

Studies to determine daily energy requirements of domestic cats generally used one of three methods: (I) indirect calorimetry (IC), (II) doubly labelled water (DLW) or (III) feeding experiment (FE; Bermingham et al., 2010). Indirect calorimetry and DLW are both expensive methods, and for indirect calorimetry the animal generally has to be confined, limiting PA (Volp et al., 2011). A FE study needs to be conducted over a longer period of time to be able to determine whether bodyweight is stable or increases/decreases. In addition, energy expenditure trials have traditionally been done with colony-housed cats (Bermingham et al., 2010). The living conditions of colony-housed cats, which are often controlled and maintained at set levels, are different from pet cats, where living conditions are more variable

(Bermingham et al., 2010; Hill, 2006). Living conditions can influence the physical activity of domestic cats. A study comparing two different housing conditions, reported that cats with access to a larger area, both indoor and outdoor, showed higher levels of physical activity (Piccione et al., 2013).

Accelerometry is a promising method to estimate TEE, taking physical activity into account. Acceleration and energy expenditure are linked in vertebrates, as vertebrates move by contracting muscles, for which energy is needed, resulting in acceleration and deceleration (see Gleiss et al., 2011; Wilson et al., 2019 for more details). Accelerometers have successfully been used to estimate energy expenditure in a range of animal species, including a range of birds (Green et al., 2009; Halsey et al., 2009; Sutton et al., 2021), domestic dogs (Wrigglesworth et al., 2011), and polar bears (Pagano & Williams, 2019). Raw acceleration data is passed through a filter, or a smoothed average is used, to subtract the static component (i.e., the gravitational pull) and derive the dynamic body acceleration (DBA) for each of the three axes (Wilson et al., 2019). The DBA values are then summed into either overall dynamic body acceleration (ODBA) or the vectorial sum of dynamic body acceleration (VeDBA; Wilson et al., 2019). Whether to choose ODBA or VeDBA, depends on the orientation of axes of the device with respect to the animal's major body axes (Wilson et al., 2019). To calculate ODBA, the absolute values of the DBA for all three axes are summed (Wilson et al., 2006), treating each axis individually (Qasem et al., 2012). Acceleration, however, is a vectorial quantity, so mathematically, summing the axes DBA is not correct (Qasem et al., 2012; Wilson et al., 2019). Despite this, a study comparing ODBA and VeDBA, reported that ODBA accounted for slightly more variation in oxygen consumption than VeDBA in both humans and animals (Qasem et al., 2012). If the axes of the device can be aligned to the major body axes of the animal, then ODBA can be used. However, if the axes of the device cannot be aligned to the major body axes of the animal, or if device orientation cannot be guaranteed during deployment, then VeDBA is advised (Qasem et al., 2012).

The aim of the current study was to determine whether accelerometry, specifically DBA, could estimate energy expenditure of domestic cats using accelerometers attached to a harness. Using the doubly labelled water technique to determine energy expenditure, the current study aimed to determine whether both ODBA and VeDBA were correlated to energy expenditure in domestic cats. It was hypothesised that both ODBA and VeDBA were correlated to energy expenditure in domestic cats. Furthermore, the current study compared ODBA and VeDBA as proxies for energy expenditure to determine which of the two was a better proxy. Though PA can account for a large proportion of TEE, an earlier study conducted in the same colony, showed that cats were active for approximately 4% of their time (Smit et al., 2023). Physical activity was therefore not thought to be the major driver of TEE in domestic cats. Rather, the BMR, which generally accounts for 60% - 75% of energy expenditure, was thought to be the largest contributing factor to TEE in domestic cats (Case et al., 2011). Dynamic body acceleration, however, does not cover non-movement-based energy expenditure (Wilson et al., 2019). The main driver of BMR is the amount of metabolically active tissue in the body, for which fat free mass (FFM) is the closest approximation (Ravussin et al., 1982). The current study, therefore, added FFM to the ODBA and VeDBA models to determine if this increased the proportion of variance in energy expenditure as explained by the model. Because domestic cats are highly inactive, it was hypothesised that including the FFM improved the models.

X.2 Methods

The aim of this study was to determine whether accelerometry can be used as a predictor for energy expenditure in domestic cats. The study consisted of two phases: determination of (I) apparent nutrient digestibility (ADC) and (II) energy expenditure. The study took place at the Massey University Centre for Feline Nutrition, Palmerston North, New Zealand (latitude 40˚ 23′ S, longitude 175˚ 36′ E), and was approved by the Massey University Animal Ethics Committee (MUAEC 22/20).

X.2.1 Animals

A total of eight healthy desexed male (n = 4) and female (n = 4) domestic shorthair cats aged from xx to xx years (mean ± SD, kg) were included in the study. The cats were fed the same complete and balanced commercially available canned wet diet (Table x.1) throughout the study, fed *ad libitum*, unless otherwise stated. Cats had *ad libitum* access to water, unless otherwise stated.

Table x.1. Macronutrient profile on as fed basis of a canned feline diet.

Macronutrient	Amount
Gross energy (kcal/kg)	891.0
Metabolisable energy (kcal/kg)[1]	713.3
Moisture (g/kg)	841.3
Dry matter (g/kg)	155.4
Crude ash (g/kg)	22.5
Organic matter (g/kg)	80.7
Crude protein (g/kg)	47.4
Crude fat (g/kg)	2.24
Crude fibre (g/kg)	133.0
Nitrogen free extract (g/kg)	2.61

[1] Metabolisable energy = [(gross energy food – gross energy faeces) – ((gram protein consumed – gram protein faeces) × 0.86)] / amount food consumed × 1000 (AAFCO, 2021).
[2] Organic matter = dry matter – crude ash.
[3] Nitrogen free extract = 1000 – crude ash – crude protein – crude fat – crude fibre.

X.2.2 Phase I: Apparent nutrient digestibility

For the digestibility trial, cats were housed in individual metabolism cages (Figure x.1a) for a total of ten days, which consisted of a five-day adjustment period and a five-day collection period (Figure x.2). The cats had access to double litter trays (Figure x.1b) that allowed separate collection of urine and faeces. Cats were placed together in the play area for one hour per day under supervision. During the collection period, individual daily food intake was measured, daily diet samples were taken from two random cans, and total faecal output were collected. Diet samples and faeces were frozen at -20 °C, freeze dried and ground for analysis.

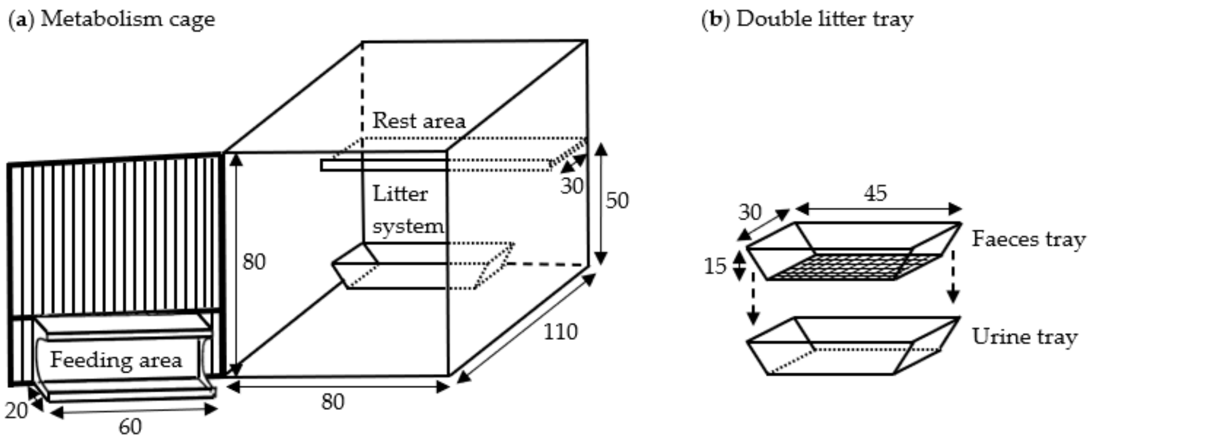

Figure X.1. (a) Individual metabolism cage measuring 80 × 80 × 110 cm and (b) double litter trays (right). Adapted from Hendriks et al. (1999).

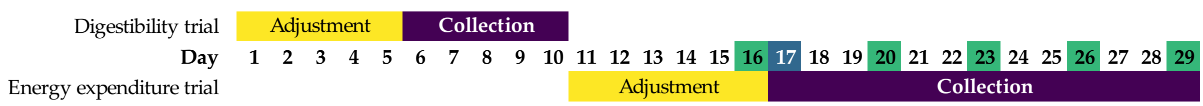

Figure X.2. Timeline of digestibility and energy expenditure trial. Green indicates blood sampling; blue indicates blood sampling + injection with doubly labelled water.

The diet and faeces were analysed for gross energy (bomb calorimeter), moisture (AOAC 925.10), crude ash (AOAC 920.153), crude protein (AOAC 968.06) and crude fibre (AOAC 962.09/978.10). Crude fat content of the diet was determined using the Mojonnier (AOAC 954.02) and crude fat diet of the faeces was determined using the Soxhlet (AOAC 2003.06) method. The carbohydrate content on a freeze-dried matter base was estimated by calculating the nitrogen-free extract (NFE) according to equation x.1.

x.1	$NFE\ \% = 100 - \ crude\ ash\ \% - crude\ protein\ \% - crude\ fat\ \% - crude\ fibre\ \%$

The contents of protein, fat and carbohydrate in the diet and faeces was then used to calculate the ADC for each individual cat according to equation x.2.

x.2	$ADC = (content\ in\ diet - content\ in\ faeces)/content\ in\ diet$

The food quotient (FQ) was calculated considering the total intake and ADC for protein (P), fat (F) and carbohydrates (C) according to equation x.3 (Black et al., 1986).

x.3	$FQ = \frac{(P_{intake}\ \times ADC_P \times 0.781) + (F_{intake} \times ADC_F \times 1.427) + (C_{intake} \times ADC_C \times 0.746)}{(P_{intake}\ \times ADC_P \times 0.966) + (F_{intake} \times ADC_F \times 2.019) + (C_{intake} \times ADC_C \times 0.746)}$

X.2.3 Phase II: Energy expenditure

X.2.3.1 Doubly labelled water injection

Following the digestibility trial, all eight cats were group-housed in a single semi-outdoor colony cage (Figure x.1). Cats were given six days following phase I to re-adjust to their colony cage and were re-habituated to wearing a harness. An isotonic DLW solution (^2H_2O, 0.7 g/kg BW at 99.9 atom%, Merck KGaA, Darmstadt, Germany; $H_2{}^{18}O$, 0.13 g/kg BW at 97.1 atom%, CortecNet, Les Ulis, France; NaCl, 0.9%) was injected into the cephalic vein using a catheter. The catheter was flushed with 1 mL of isotonic saline (NaCl, 0.9%) to ensure complete administration of the DLW solution, after which the catheter was removed. Local anaesthetic, Emla Cream (2.5% lignocaine and 2.5% prilocaine), was administered topically on both legs 30 minutes prior DLW injection. Food and water were withheld 12 hours prior to injection of the DLW solution and 4 hours after injection. Energy expenditure was estimated over a twelve-day period (Figure X.2) using the doubly labelled water (DLW) method.

Blood samples (1.5 mL) were taken by jugular venepuncture one day before the DLW injection (baseline sample), 4 hours after DLW injection (equilibrium sample) and 3, 6, 9 and 12 days after DLW injection. All five samples following DLW injection, were taken at a consistent time of day. Local anaesthetic, Emla Cream (2.5% lignocaine and 2.5% prilocaine), was administered topically on the neck 30 minutes prior to blood sampling. Blood samples were collected into EDTA vacutainers and plasma was separated by centrifuging for 15 minutes at 1,400 × g. Plasma samples were stored and frozen at -20 °C in crimp vials with a crimp cap containing a butyl rubber septum until analysis.

X.2.3.2 Isotope analysis

X.2.3.3 Calculations

Enrichment of the body water pool with of ^{2}H (N_d) or ^{18}O (N_o), was calculated according to equation x.4. The calculated pool size of ^{18}O was used for total body water (TBW) estimation (Ballevre et al., 1994). *One of the two equations would be selected based on the data provided by the lab.*

x.4	$N\,(mol) = \;(?\times 1000)/18.02$ $N(mol) = \frac{WA}{18.02a} \times \frac{(\delta_a - \delta_t)}{(\delta_s - \delta_p)}$

The elimination rates (k; per day) for ^{2}H (k_d) and ^{18}O (k_o) were calculated from the difference in normalised enrichment between the equilibrium sample ($X(t_1)$) and samples taken on days 3, 6, 9 and 12 ($X(t_i)$), according to equation x.5 (Schoeller et al., 1986). With ln as the natural logarithm.

x.5	$k(d^{-1}) = (ln[X(t_i)/X(t_1)])/(t_i - t_1)$

Using the estimated TBW (N_o) and the mean ratio of water to FFM, for which the reference factor is 0.732 (Ballevre et al., 1994), the FFM can be calculated according to equation 3.6. The fat mass (FM) was calculated by subtracting the FFM from total bodyweight.

x.6	$FFM(kg) = \frac{((18.02 \times N_o)/0.732))}{1000}$

The CO_2 production (rCO_2) was calculated as the difference in the disappearance rate of ^{18}O and ^{2}H according to equation 3.7 (Lifson & McClintock, 1966).

x.7	$rCO_2(mol/day) = (N_o/2.08)(k_o - k_d) - 0.015(N_o \times k_d)$

Energy expenditure (EE) was calculated according to equation 3.8, using rCO_2, corrected for the food quotient (FQ; Equation 3.3). Energy expenditure was expressed per kg BW and per kg FFM.

x.8	$EE(kcal/day) = rCO_2 \times (22.4 \times [(3.70/FQ) + 1.326])$

X.2.3.4 Activity monitor

Accelerometer data were collected using the harness attachment method and downloaded as described in Chapter 2. Cats wore the harness-mounted accelerometer continuously for a total of 12 days. The twelve-day collection period started directly after the equilibrium sample was taken and ended right before the final blood sample was taken. Acceleration data were sampled at a frequency of 30 Hz (raw acceleration data), with a dynamic range of ± 8 g.

Shepard et al. (2008), reported the importance of choosing the appropriate moving window to smooth acceleration data. Therefore, the static component of the raw acceleration data was calculated for each axis using running mean windows of 0.5, 1, 1.5, 2, 3, 4, 6, and 8 seconds. For each running mean window, the static component was subtracted from the raw acceleration value to obtain the dynamic component, i.e., dynamic body acceleration (DBA). The DBA was then used to calculate ODBA (Wilson et al., 2006) and VeDBA (McGregor et al., 2009) according to equations x.9 and x.10, respectively. Both ODBA and VeDBA were summed over 24-hour successive periods to obtain daily activity values.

x.9	$ODBA = \lvert DBA_x \rvert + \lvert DBA_y \rvert + \lvert DBA_z \rvert$
x.10	$VeDBA = \sqrt{(DBA_x^2 + DBA_y^2 + DBA_z^2)}$

X.2.3.4 Energy expenditure per behaviour

Accelerometer data were downloaded, and feature engineered as described in Chapter 2. Using the feature engineered data, the behaviour of the cats was classified using a ML model previously validated in Chapter 2. The model had an overall accuracy of ~73% and F1-score of ~68% and classified eight different behaviours: active (walking and trotting), eating, grooming, littering, lying, scratching, sitting, and standing. For each behaviour, the ODBA and VeDBA were determined.

X.2.4 Statistics

All data computation and statistical analyses were carried out using RStudio version 4.1.1 (RStudio Team, 2021).

X.3 Preliminary results

X.3.1 Apparent Nutrient digestibility

Using the digestibility coefficients of the macronutrients in the diet (Table x.2), the food quotient was calculated to be 0.75.

Table x.2. Average (± standard deviation) digestibility coefficients of the macronutrients in the canned diet

Macronutrient	Digestibility coefficient
Dry matter	0.77 ± 0.03
Crude ash	0.50 ± 0.05
Crude protein	0.85 ± 0.02
Crude fat	0.89 ± 0.06
Crude fibre	0.76 ± 0.10
Gross energy	0.80 ± 0.04

X.3.2 Energy Expenditure

X.3.2.1 Smoothing of data

Accelerometer data was smoothed using different running mean windows, ranging from 0.5 to 8 seconds, to determine which window would be best.

X.3.2.2 Approximating energy expenditure

X.3.2.3 Energy expenditure per behaviour

Not all behaviours cost the same amount of energy. Boxplots for the ODBA (Figure x.3) and VeDBA (Figure x.4) were generated to get a visual representation of the energetic cost of each of the eight behaviours. As expected, active behaviours have the highest ODBA and VeDBA, whereas inactive behaviours, such as lying and sitting, have the lowest. This is similar to findings reported in dingoes (*Canis dingo*), where lying and sitting had low ODBA values, whereas active behaviours, such as trotting and running, had the highest (Tatler et al., 2018). According to the plots, scratching is one of the behaviours with the highest energetic costs.

Scratching has been reported to result in high accelerometer readings (Andrews et al., 2015), so its energetic cost is likely overestimated. Research cats, on average, spent less than 1% of their time on scratching (Chapters 2, 3 and 4), so it is not likely that it greatly affects the approximation of energy expenditure using accelerometer data.

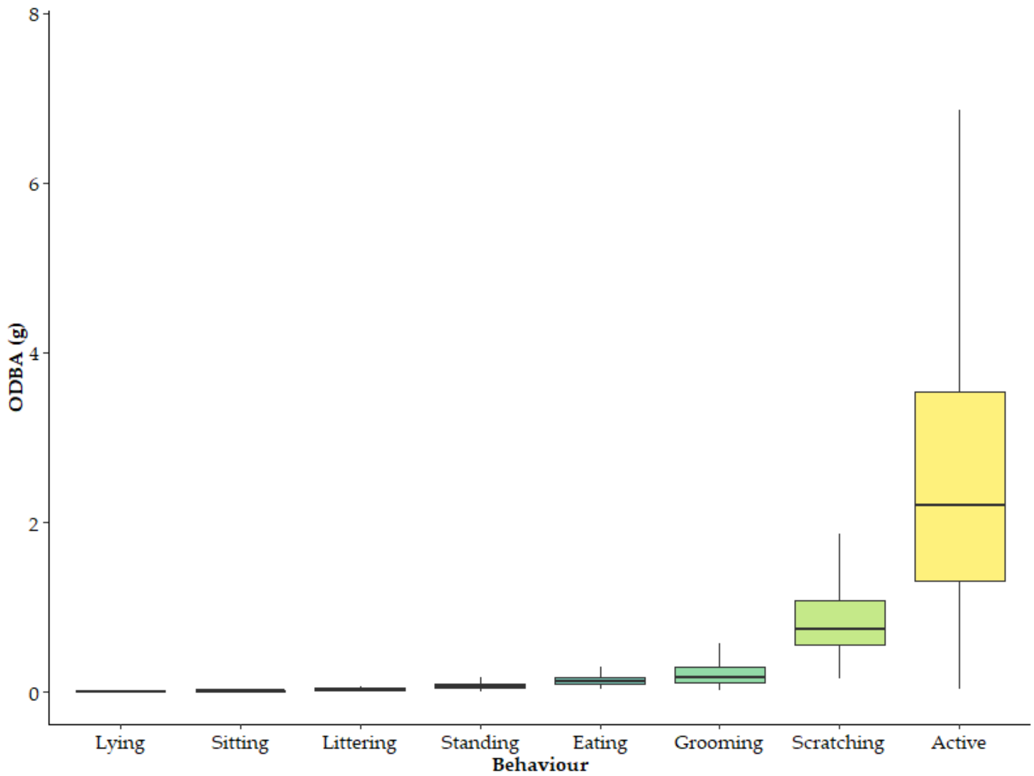

Figure x.3. Boxplots of the ODBA per behaviour.

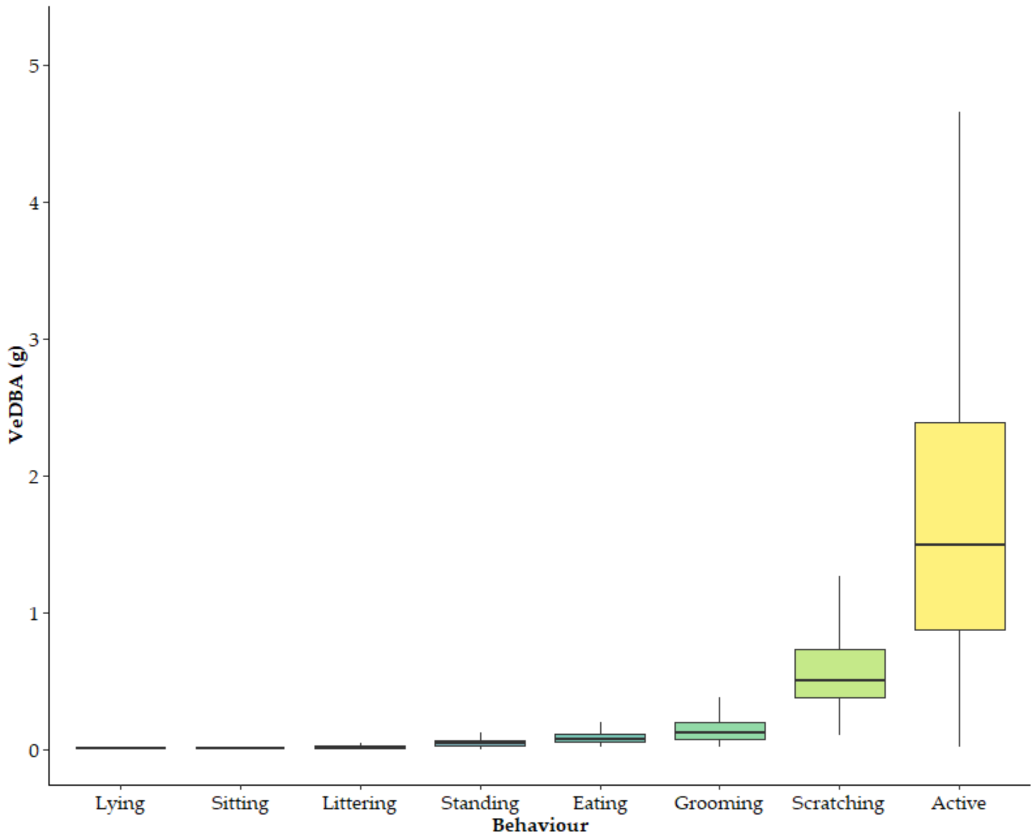

Figure x.4. Boxplots of the VeDBA per behaviour.

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Appendix II – Published paper Chapter 3

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Article

The Use of Triaxial Accelerometers and Machine Learning Algorithms for Behavioural Identification in Domestic Cats (*Felis catus*): A Validation Study

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Abstract: Animal behaviour can be an indicator of health and welfare. Monitoring behaviour through visual observation is labour-intensive and there is a risk of missing infrequent behaviours. Twelve healthy domestic shorthair cats were fitted with triaxial accelerometers mounted on a collar and harness. Over seven days, accelerometer and video footage were collected simultaneously. Identifier variables (n = 32) were calculated from the accelerometer data and summarized into 1 s epochs. Twenty-four behaviours were annotated from the video recordings and aligned with the summarised accelerometer data. Models were created using random forest (RF) and supervised self-organizing map (SOM) machine learning techniques for each mounting location. Multiple modelling rounds were run to select and merge behaviours based on performance values. All models were then tested on a validation accelerometer dataset from the same twelve cats to identify behaviours. The frequency of behaviours was calculated and compared using Dirichlet regression. Despite the SOM models having higher Kappa (>95%) and overall accuracy (>95%) compared with the RF models (64–76% and 70–86%, respectively), the RF models predicted behaviours more consistently between mounting locations. These results indicate that triaxial accelerometers can identify cat specific behaviours.

Keywords: domestic cat; accelerometer; random forest; self-organizing map; behaviour classification

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Citation: Smit, M.; Ikurior, S.J.; Corner-Thomas, R.A.; Andrews, C.J.; Draganova, I.; Thomas, D.G. The Use of Triaxial Accelerometers and Machine Learning Algorithms for Behavioural Identification in Domestic Cats (*Felis catus*): A Validation Study. *Sensors* **2023**, *23*, 7165. https://doi.org/10.3390/s23167165

Academic Editor: Benedicte Vanwanseele

Received: 30 June 2023
Revised: 10 August 2023
Accepted: 11 August 2023
Published: 14 August 2023

1. Introduction

Animal behaviour can provide a reliable and non-invasive indication of animal health and welfare. In domestic cats (*Felis catus*), behavioural changes can indicate the presence of illness, pain, or distress [1]. Behavioural monitoring of pet cats is often carried out by their owner(s). However, owner observation is subjective, and they cannot monitor their pets continuously, and they may therefore miss early and subtle signs of illness. This is exacerbated by the fact that changes in behaviour in response to illness and/or pain can often be subtle and well disguised by the cat [1]. In addition, any behavioural research trial using traditional methods, scoring behaviour manually either directly or from video recordings, is labour-intensive. Accelerometers are a promising tool to help continuously monitor the behaviour of animals, including domestic cats.

To date, few studies in domestic cats have used accelerometer data from non-commercial triaxial accelerometers to distinguish between or identify specific behaviours [2,3]. Accelerometers can measure body movement in terms of acceleration in one to three orthogonal planes: craniocaudal (surge; forwards/backwards), mediolateral (sway; left/right), and dorsoventral (up/down) [4]. Measuring these accelerations in multiple directions allows detection of both dynamic (motion) and static (gravity) accelerations [4,5]. Watanabe et al. [3] were able to successfully distinguish drinking (100% accuracy), eating (68% accuracy), trotting (78% accuracy), and galloping (71% accuracy) in a single domestic cat using only acceleration data along the craniocaudal plane (forwards/backwards). Galea et al. [2] successfully built two identifying models for twelve different behaviours from triaxial acceleration data from ten domestic cats, using random forest (RF) and self-organizing maps (SOM).

The location of the accelerometer on the animal is an important factor to consider. Aspects to consider when determining the attachment site include the animal species, potential effects of attachment site on behaviour, behaviours that are of interest in the study, and rigidity of the attachment of the accelerometer on a site [4,6]. For example, an accelerometer attached to the back of an animal is less likely to register fine-scale head movements involved in eating behaviour which may be detectable by a collar-mounted accelerometer [4]. In domestic cats, the most commonly used site of accelerometer attachment is a collar with the device positioned ventrally. Attachment to a collar, however, can result in rotation of the accelerometer and residual movement (i.e., movement of the device after the physical movement stops) which is dependent on the looseness of the collar, weight of the accelerometer, and the animal's behaviour [4,6]. A greater model accuracy was found in dogs for accelerometers attached to a harness than a collar [7]. It is therefore important to identify behaviours of interest before determining the accelerometer placement location.

To be able to identify behaviours using accelerometer data, machine learning (ML) techniques are often used to build classifier models. Depending on the dataset, some ML techniques might be a better fit than others. Nathan et al. [8] reported that the random forest (RF) ML technique had the highest accuracies for identifying behaviour of free ranging griffon vultures from accelerometer data. In that study, the accuracies of five frequently used supervised ML techniques were compared: linear discriminant analysis (LDA), support vector machines (SVM), classification and regression trees (CART), random forests (RF), and an artificial neural network (ANN) [8]. Galea et al. [2] compared SOM with RF and found that SOM had a higher overall accuracy than RF (99.6% vs. 98.9%, respectively) for behaviour classification of domestic cats wearing a harness-mounted accelerometer.

In the present study, commercially available accelerometers were attached to domestic cats on both a collar and a harness, to capture movement data needed to build behaviour identifier models. The aim of the current study was to compare model performance between the two sites of attachment, (collar and harness) and two machine learning techniques (RF and supervised SOM). It was hypothesised that both RF and SOM models of harness-mounted accelerometer data would have better overall performance, or ability to identify behaviour, when compared with models of the collar-mounted accelerometer, due to the greater rigidity of the harness-mounted accelerometer reducing the risk of individual and residual device movement. However, given that the collar-mounted accelerometer was expected to be more likely to detect finer-scale head movements, it was expected that the model of the collar-mounted accelerometer would have higher accuracy in detecting eating behaviour than harness-mounted accelerometer models. Furthermore, as the SOM model had higher overall performance compared with the RF model in the study by Galea et al. [2], it was also hypothesised that in the current study SOM models would have higher overall performance compared with the RF model.

2. Materials and Methods

The study was conducted at the Massey University Centre for Feline Nutrition, Palmerston North, New Zealand (latitude 40°23′ S, longitude 175°36′ E) between 30 June and 7 July 2021. This study was approved by the Massey University Animal Ethics Committee (MUAEC 21/23).

2.1. Animals and Design

The study comprised two phases: habituation and data collection. For the habituation phase, 16 healthy desexed male (n = 7) and entire female (n = 9) domestic shorthair cats aged from 2.3 to 4.4 years (mean $\pm$ SD, 2.64 $\pm$ 0.62 years) and weighing between 2.6 to 5.2 kg (3.93 $\pm$ 0.89 kg) were assessed for inclusion in the study. The habituation phase lasted for five weeks: four weeks for habituation to the cat harness and one week for habituation to the accelerometers attached to both a collar and harness. Cats were already accustomed to wearing collars and thus relatively little habituation was needed for accelerometer attachment. However, three cats did not habituate to the harness and one cat persisted in biting the harnesses of other cats, thus these animals were removed from the study. A subset of twelve desexed male (n = 5) and entire female (n = 7) cats aged from 2.3 to 4.4 years (mean ± SD, 2.75 ± 0.69 years) and weighing between 2.6 to 5.1 kg (3.85 ± 0.82 kg) who had successfully completed the habituation period were included in the data collection phase. During data collection, each cat wore two accelerometers, one attached to a collar and one to a harness, for seven consecutive days. During the same seven days, cats were under continuous video surveillance. Throughout both phases of the study, cats were housed in two semi-outdoor colony cages (Figure 1), fed a complete and balanced [9] commercial canned diet (Heinz Wattie's Ltd., Hastings, New Zealand), and had *ad libitum* access to water.

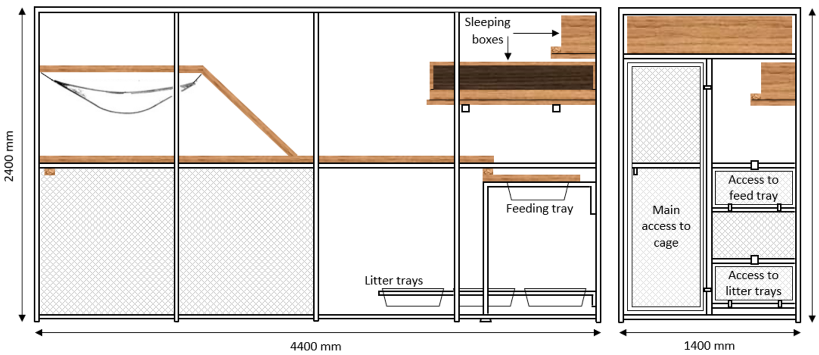

Figure 1. Colony cages as seen from the side (**left**) and front (**right**), measuring 1400 mm × 2400 mm × 4400 mm.

2.2. Data Collection

Cats were fitted with a collar and harness to which an ActiGraph wGTX-BT accelerometer (weighing 19 g and measuring 33 mm × 46 mm × 15 mm) was attached (ActiGraph, Pensacola, FL, USA). On the collar the accelerometer was positioned ventrally (Figure 2a), and on the harness it rested on the left shoulder blade (Figure 2b). The orientation of the accelerometers was uniform across all cats for each mounting location. For the collar-mounted accelerometer, the orientation of the X, Y, and Z axes were lateral, dorso-ventral, and cranio-caudal, respectively, whereas for the harness-mounted accelerometer the orientation of the X, Y, and Z axes were cranio-caudal, dorso-ventral, and lateral, respectively. Acceleration data were sampled at a frequency of 30 Hz (raw acceleration data), with a dynamic range of ±8 g. For each cat, a unique pattern of reflective tape was placed on the two accelerometers to allow cat identification under infrared light.

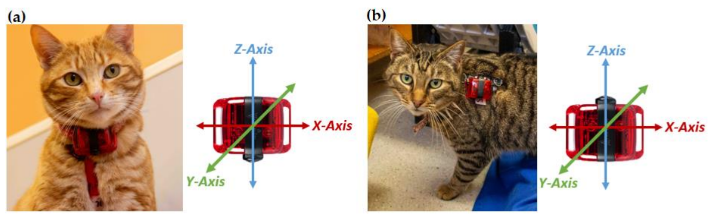

Figure 2. Placement and orientation of the ActiGraph wGT3X-BT accelerometer on a (**a**) collar and (**b**) harness.

Cats were filmed in real time using a 4K Swann® security camera system (Swann Communications USA, Santa Fe Springs, CA, USA) capable of automatically switching between natural and infrared light, enabling continuous observation under natural light and dark conditions. A selection of active (climbing, jumping, fighting, playing, rolling, rubbing, running, trotting, walking), inactive (lying, sitting, standing), maintenance (digging, drinking, eating, grooming, littering, scratching, shaking), and other (other, out of sight, allogrooming, human contact) behaviours were then retrospectively scored using BORIS [10] by a single scorer (Table 1). Behaviours were scored continuously and were then exported using a one-second (s) time interval. For all cats, behaviour was scored for the first day of data collection, between 09:00 AM and 02:00 PM, when cats were expected to show the largest range of behaviours because of the presence of staff and feeding within those hours.

Table 1. Ethogram including definitions for scored behaviours.

Behaviour	Description
Active	
Climbing [11]	Cat ascends and/or descends a vertical object or structure.
Jumping horizontal	Cat leaps from one point to another horizontally.
Jumping vertical	Cat leaps from one point to another vertically.
Fighting [12]	Cat engages in aggressive physical combat with another cat. Piloerection generally present of tail and back fur.
Playing [12]	Cat interacts with a (cat) toy or with another cat in a non-aggressive manner. Ears generally point forward, inverted U-shape of tail. Piloerection generally absent.
Rolling [11]	Cat rotates its body from side to side while lying on a horizontal surface. During the roll, when the cat is on its back, the belly is exposed, and all paws are in the air.
Rubbing	Cat rubs body against a surface or object.
Running [12,13]	Forward locomotion at a fast gait. Four-beat, asymmetric gait. Has a suspension phase. Fastest gait.
Trotting [12,13]	Forward locomotion at a swift gait performed. Two-beat, symmetric movement. Body is supported by two diagonal legs during contact with ground. Intermediate gate.
Walking [12,13]	Forward locomotion at a slow gait. Four-beat, symmetric movement with limbs moving sequentially. Includes slow walk (three or four feet contact ground during any one phase), fast walk (two or three feet contact ground during any one phase). Slowest gait.
Inactive	
Lying [11]	Body of the cat is in a horizontal position on a horizontal surface. Cat can be lying on its side, back, belly, or curled up.
Sitting [11]	Cat is in an upright position, with the hind legs flexed and under the body, and with front legs extended and straight at the front of the body.
Standing [11]	Cat is immobile and supporting the body with extended legs and all paws touching the surface.
Maintenance	
Digging [11]	Cat breaks up or moves substrate around with either one of its front paws.
Drinking [11]	Cat ingests water by lapping up with the tongue.
Eating [11]	Cat ingests food by chewing with the teeth and swallowing.
Grooming [11]	Cat cleans itself by either licking, scratching, biting, or chewing the fur on its body. Includes the licking of a front paw and wiping it over its own head.
Littering	Cat urinates or defecates.
Scratching [11]	Cat scratches its body using the claws of its hind paw.
Shaking [11]	Cat rotates its abdomen or head rapidly from side to side.
Other	
Other	Any behaviour that does not fit into one the behaviours included in this ethogram.
Out of sight	Cat is not visible to the observer.
Allogrooming [11]	Cat licks the fur on the head or body of another cat.
Human contact	Cat is having direct contact with a human, either being petted or being held/carried.

2.3. Model Classification

All data computation and statistical analyses were carried out using RStudio version 4.1.1 [14]. The R code, including R packages used, has been published in a GitHub repository [15].

2.3.1. Intra-Rater Reliability

To test the intra-rater reliability, a subset of five randomly selected 15 min video recordings were scored for behaviour for a second time, with a time interval of six months between the first and second behaviour scoring. Intra-rater reliability was tested using the Kappa coefficient (κ) with the R package 'irr' [16]. Results for the Kappa coefficient were interpreted according to Fleiss [17], where values > 0.75 indicated excellent agreement, 0.40 to 0.75 indicated fair to good agreement, and <0.40 indicated poor agreement.

2.3.2. Derivation Identifier Variables

Raw acceleration data for each axis were exported from the devices using ActiLife software (version 6.13.4; ActiGraph, Pensacola, FL, USA). Using RStudio v1.4.1 [14], a total of 32 identifier variables were derived from the raw accelerometer data and summarized into 1 s epochs (i.e., time interval): mean acceleration (X, Y, Z), sum acceleration (X, Y, Z), minimum (min) acceleration (X, Y, Z), maximum (max) acceleration (X, Y, Z), standard deviation (sd) of acceleration (X, Y, Z), skewness (X, Y, Z), kurtosis (X, Y, Z), correlation (XY, XZ, YZ), vector magnitude (VM; mean, sum, min, max, sd, skewness, kurtosis), and overall dynamic body acceleration (ODBA; see Table 2 for detailed description of each identifier variable).

Table 2. Description of identifier variables.

Identifier Variable	Description
Mean	Mean, calculated for every second using the raw acceleration data (30 measures per second).
Sum	Sum, calculated for every second using the raw acceleration data. $Sum_{(Axis)} = \sum_{i=1}^{N} Axis_i$
Minimum (min)	Minimum value of every 30 measures within each second.
Maximum (max)	Maximum value of every 30 measures within each second.
Standard deviation (sd)	Measures the spread of the data.
Skewness	Asymmetry of the distribution.
Kurtosis	Weight of the tails relative to a normal distribution.
Vector magnitude (VM)	$VM = \sqrt{X^2 + Y^2 + Z^2}$
Overall dynamic body acceleration (ODBA)	$ODBA = \sum_{i=1}^{N} \lvert DBA_X \rvert + \lvert DBA_Y \rvert + \lvert DBA_Z \rvert$
Dynamic body acceleration (DBA) [1]	$DBA = Sum_{axis} - moving\ average$

[1] Accelerometer data from each axis were individually smoothed using the moving average over 1 s. The DBA was not included as an identifier variable.

2.3.3. Building Behaviour Identifier Models

Before building the models, behaviours that were not observed and behaviours classified as "other" or "out of sight", were removed from the dataset. Two ML techniques were used to build identifier models to identify behaviours in domestic cats: (I) RF and (II) supervised SOM. RF is a ML technique that builds a multitude of decision trees and combines the output at the end [18]. SOM is a ML technique that produces two-dimensional maps, usually a grid of nodes, of multi-dimensional and complex data, where nodes that are similar are located close to each other [19]. A model was made with each modelling technique for each mounting location: RF for collar (CRF) and harness (HRF) and SOM for collar (CSOM) and harness (HSOM).

The RF models were built using the R packages 'caret' [20] and 'randomForest' [21]. The default settings for the number of trees (n = 500) and the number of variables randomly sampled as candidate at each split (n = $\sqrt{n_{variables}}$) were used. The SOM models were built using the R package 'Kohonen' (version 3.0.11) [22], with the number of times the dataset was presented to the network set to the default setting (n = 100). Each model was built using a subset (70%) of the complete dataset. The model was then used, and tested, to identify the behaviour using the identifier variables of the remaining 30% of the complete set. A confusion matrix was computed by comparing the identified behaviours with the observed behaviours.

2.3.4. Model Evaluation

Using the computed confusion matrix, behaviours for each model were labelled as true positive (TP) when the behaviour was correctly identified by the model, true negative (TN) when the behaviour was correctly identified by the model as not occurring, false negative (FN) when the behaviour was observed but not identified by the model, or false positive (FP) when the behaviour was identified by the model but was not observed. Using data from the confusion matrix, the accuracy (Equation (1)), precision (Equation (2)), sensitivity (Equation (3)), and specificity (Equation (4)) were calculated for each behaviour:

$$\text{Accuracy} = (\text{TP} + \text{TN})/(\text{TP} + \text{TN} + \text{FP} + \text{FN}), \tag{1}$$

$$\text{Precision} = \text{TP}/(\text{TP} + \text{FP}), \tag{2}$$

$$\text{Sensitivity} = \text{TP}/(\text{TP} + \text{FN}), \tag{3}$$

$$\text{Specificity} = \text{TN}/(\text{TN} + \text{FN}). \tag{4}$$

Overall model performance was determined by calculating the overall accuracy (Equation (5)) and Kappa coefficient (κ; Equation (6)) [23]. Results for the Kappa coefficient were interpreted according to Fleiss [17].

$$\text{Overallaccuracy} = (\text{TP} + \text{TN})/(\text{TP} + \text{TN} + \text{FP} + \text{FN}) \tag{5}$$

$$\hat{\kappa} = \left(N \times \sum_{i=1}^{k} x_{ii} - \sum_{i=1}^{k} (x_{i+} \times x_{+i})\right) / N^2 - \sum_{i=1}^{k} (x_{i+} \times x_{+i}) \tag{6}$$

Multiple identifier models were built for both the collar- and harness-mounted accelerometer. For each model, the overall accuracy and estimated Kappa coefficient were evaluated, and for each behaviour the sensitivity, specificity, precision, and accuracy were calculated. Behaviours with low values were clustered with the lbehaviour they were misclassified as in the model if the behaviour belonged to the same category (active, inactive, maintenance), or were removed if in a different category. The new model was then built, and the overall accuracy and estimated Kappa coefficient were compared with the previous model. This behavioural selection and clustering, hereafter referred to as the 'modelling round', continued until the overall accuracy and Kappa coefficient did not improve or until only three behavioural categories remained: active, inactive, and maintenance.

2.4. Daily Activity Budgets and Dirichlet Regression

For accelerometer data not used to build the models, the behaviour of the cats was determined using the final models. Daily activity budgets (proportion of time spent showing each behaviour) were calculated for each cat. Using the R package DirichletReg [24], a Dirichlet regression with log link was performed as a function of mounting location (collar and harness), modelling technique (RF and SOM), and the day of observation. A Dirichlet regression allows for statistical testing between proportions [25]. The Dirichlet regression was performed separately for each modelling round (MR).

3. Results

From the 7 days of video footage from the 12 cats, a total of 166,754 s (≈46 h and 20 min; 3 h and 50 min per individual) of recordings were scored for behaviours. Of the 24 behaviours (Table 1) scored in the video recordings, 4 behaviours ('rolling', 'running', 'drinking', and 'human contact') were not observed at any time and were therefore removed before model building (Appendix A). Similarly, 'fighting' (n = 10 s) and 'playing' (n = 1 s) were removed due to their low occurrence. 'Jumping horizontal' (n = 53 s) and 'jumping vertical' (n = 186 s) were grouped into a single category 'jumping' (Appendix A). Seconds (i.e., datapoints) where cats were identified as 'out of sight' (n = 38,395 s) and 'other' (n = 4116 s), were also removed from the dataset. These changes resulted in a total of 124,230 datapoints which consisted of 15 different behaviours. Four modelling rounds were conducted which resulted in a total of 16 different behavioural identification models (Appendix A).

3.1. Intra-Rater Reliability

The intra-rater reliability, comparing the agreement between the first and second rounds of behaviour scoring of video data by the scorer, was tested and found to be excellent ($\kappa = 0.93$, $p < 0.001$).

3.2. Model Performance

It was observed that the initial models were overfitted to behaviours with large numbers of datapoints (e.g., lying; Appendix A), therefore behaviours with large numbers of datapoints were limited to n = 7000. For this reason, the numbers of datapoints for inactive and maintenance were also limited to n = 5000 for the fourth and final round of modelling (Appendix A). Datapoints were limited by randomly selecting 7000 or 5000 datapoints for each behaviour using the sample function in R.

The first modelling round included 15 behaviours which included climbing, jumping, rubbing, trotting, walking, lying, sitting, standing, grooming, littering, digging, eating, scratching, shaking, and allogrooming. In the first modelling round, the confusion matrices showed that some behaviours were not identified by the models (true positive = 0), e.g., climbing, digging, and allogrooming using the CRF model (Supplementary Material Tables S1–S4). Climbing, jumping, rubbing, digging, shaking, and allogrooming were removed before the second modelling round because of their small sample size. Trotting was often misclassified as walking in both the CRF and HRF models of the first modelling round, and the two were therefore merged into "active" (Supplementary Material Tables S1 and S2). Scratching was often misclassified as grooming in both the CRF and HRF models of the second modelling round and was merged with grooming before the third modelling round (Supplementary Material Tables S5 and S6). The remaining models identified all of the included behaviours (Supplementary Material Tables S9–S16) with an accuracy ≥ 0.75 (Supplementary Material S2 Tables S17–S20). The precision with which the models identified each behaviour ranged from 0.25 to 1.00; however, precision could not be calculated for behaviours that were not identified by the models (Supplementary Material S3 Tables S21–S24). The sensitivity of the models that contained behaviours that could not be identified was 0.00 (Supplementary Material S4 Tables S25–S28). For behaviours that were identified by the models, sensitivity ranged from 0.02 to 1.00. Precision and sensitivity decreased as the number of false positives or false negatives, respectively, increased compared with the number of true positives. Model specificities for identified behaviours were ≥ 0.90, except for eating in the RF models in the third modelling round, where the specificity was 0.72 for the CRF model, and 0.76 for the HRF model (Supplementary Material S5 Tables S29–S32).

Irrespective of mounting location, the overall performance values of the SOM models were higher than those of the RF models, with both Kappa and overall accuracy values > 0.95 for the SOM models (Table 3). The RF models generally showed fair to good agreement (κ between 0.40 and 0.75) between the observed and identified behaviours. The harness HRF models showed excellent agreement ($\kappa > 0.75$) in the second and third modelling round (Table 3). For the RF models, both the Kappa and overall accuracy values were higher for the HRF models than the collar CRF models in modelling rounds 1–3 (Table 3). It was only in the fourth modelling round, containing only three behavioural categories, that the CRF models outperformed the HRF models (Table 3). The overall performance values for the CSOM and HSOM models were very similar, apart from modelling round three, where the overall performance values for the HSOM model were higher than those of the CSOM model (Table 3).

Table 3. Kappa and overall accuracy values for each modelling round, mounting location (collar and harness), and modelling technique (random forest (RF) and self-organizing map (SOM)).

Modelling Round	Kappa		Overall Accuracy	
	RF	SOM	RF	SOM
		Collar		
1	0.642	0.962	0.7	0.968
2	0.678	0.997	0.733	0.997
3	0.684	0.953	0.739	0.961
4	0.742	0.999	0.83	0.999
		Harness		
1	0.729	0.962	0.772	0.968
2	0.753	0.996	0.795	0.997
3	0.757	0.997	0.799	0.998
4	0.739	0.999	0.827	0.999

3.3. Daily Activity Budgets

Accelerometer data that were not used to build the models (a total of six days) were used to identify the behaviour of each cat using each model in each modelling round. For each model, the proportion of time spent showing each identified behaviour was compared using Dirichlet regression [25].

Models from the first modelling round had low precision and sensitivity for identifying behaviours due to very low or zero true positives (climbing, jumping, trotting, digging, shaking, allogrooming) due to either not being identified or their very low occurrence (Table 4). Behaviours with high values overall for performance, including walking, lying, sitting, standing, grooming, eating, had varying results, depending on the model. The most frequently identified behaviours were lying (28.20–52.69%) and sitting (18.74–28.93%; Table 4). Grooming ranged from as low as 6.99% to as high as 20.69% and eating ranged from 3.32% to 22.67% (Table 4). For the RF models, differences in mean daily percentages were found for lying (p < 0.001), littering (p = 0.017), and eating (p = 0.005) between the CRF and HRF models (Table 4). For SOM models, differences were found in walking, lying, sitting, standing, and grooming ($p \leq 0.001$ for all; Table 4) between the CSOM and HSOM models. Comparing the modelling techniques for the collar models (CRF and CSOM), the only behaviour that did not show a difference was rubbing (p = 0.104; Table 4). Comparing the modelling techniques for the harness models (HRF and HSOM), no differences were found for rubbing (p = 0.472) and walking (p = 0.737; Table 4). Most behaviours that showed no differences were behaviours with low precision and sensitivity (Supplementary Material S3 Tables S21–S24 and Supplementary Material S4 Tables S25–S28).

Despite the high results for performance of littering in both the CSOM and HSOM models and scratching in the HSOM model, these behaviours were not predicted at all in the second modelling round, but were identified by both the CRF and HRF models (Table 5). Lying (29.17–52.52%) and sitting (17.47–28.57%) remained the most commonly identified behaviours in the second modelling round (Table 5). Eating (3.22–22.15%) and grooming (7.15–18.91%) behaviours showed a wide range depending on the model used, which was similar to the first modelling round (Table 5). For the second modelling round, differences in mean daily percentages were found between the CRF and HRF models for lying (p < 0.001) and eating ($p = 0.030$; Table 5). The identified percentages of behaviours between the CSOM and HSOM were different ($p < 0.05$) for all behaviours that were identified by the models (Table 5). The CRF and CSOM models showed differences for active ($p = 0.041$), lying ($p > 0.001$), sitting ($p < 0.001$), standing ($p < 0.001$), grooming ($p = 0.019$), and eating ($p = 0.004$; Table 5). The HRF and HSOM models showed differences for active ($p = 0.025$), lying ($p < 0.001$), sitting ($p < 0.001$), grooming ($p = 0.003$), and eating ($p < 0.001$; Table 5).

Table 4. Differences in mean ± standard error daily percentages of identified behaviours between models for modelling round 1.

	CRF *		HRF *		CSOM *		HSOM *	
Climbing	-		0.03 ± 0.01		-		-	
Jumping	0.01 ± 0.00		0.03 ± 0.01		-		-	
Rubbing	0.07 ± 0.01		0.11 ± 0.04		1.89 ± 0.43		0.42 ± 0.15	
Trotting	-		-		-		-	
Walking †	2.51 ± 0.33	b	3.02 ± 0.38	b	0.45 ± 0.07	a	4.57 ± 0.58	b
Lying †	52.69 ± 2.21	d	47.54 ± 2.80	c	28.20 ± 2.27	a	33.76 ± 2.04	b
Sitting †	25.29 ± 2.45	c	28.93 ± 2.88	c	23.08 ± 2.79	b	18.74 ± 1.89	a
Standing †	8.08 ± 1.18	b	8.16 ± 0.87	b	7.70 ± 3.16	a	8.83 ± 1.08	c
Grooming †	6.99 ± 0.29	a	7.99 ± 0.31	a	15.92 ± 0.75	b	20.68 ± 1.50	c
Littering	0.06 ± 0.01	a	0.64 ± 0.25	b	-		-	
Digging	-		0.01 ± 0.00		-		-	
Eating †	4.08 ± 0.45	b	3.32 ± 0.30	a	22.67 ± 1.56	c	12.99 ± 1.30	c
Scratching	0.20 ± 0.03	b	0.21 ± 0.03	b	0.08 ± 0.02	a	-	
Shaking	0.02 ± 0.00		0.01 ± 0.00		-		-	
Allogrooming	-		0.01 ± 0.00		-		-	

a–d Different superscripts within a behaviour indicate a significant difference ($p < 0.05$). † Behaviour was significantly affected by day ($p < 0.05$). * CRF = Collar Random Forest, HRF = Harness Random Forest, CSOM = Collar Self-Organizing Map, HSOM = Harness Self-Organizing Map.

Table 5. Differences in mean ± standard error daily percentages of identified behaviours between models for modelling round 2.

	CRF *		HRF *		CSOM *		HSOM *	
Active †	2.71 ± 0.37	c	3.22 ± 0.41	c	0.09 ± 0.01	a	2.64 ± 0.27	b
Lying	52.52 ± 2.37	d	47.73 ± 2.92	c	29.17 ± 1.85	a	38.00 ± 2.39	b
Sitting †	25.35 ± 2.58	c	28.57 ± 3.01	c	24.46 ± 3.12	b	17.47 ± 1.96	a
Standing †	7.95 ± 1.25	b	8.37 ± 0.93	b	3.99 ± 2.85	a	11.81 ± 1.29	b
Grooming †	7.15 ± 0.31	a	8.07 ± 0.33	a	18.91 ± 0.89	b	16.14 ± 1.50	c
Littering	0.07 ± 0.02		0.62 ± 0.25		-		-	
Eating †	4.05 ± 0.47	b	3.22 ± 0.31	a	22.15 ± 1.68	d	13.95 ± 1.30	c
Scratching	0.19 ± 0.03		0.20 ± 0.03		1.24 ± 0.42		-	

a–d Different superscripts within a behaviour indicate a significant difference ($p < 0.05$). † Behaviour was significantly affected by day ($p < 0.05$). * CRF = Collar Random Forest, HRF = Harness Random Forest, CSOM = Collar Self-Organizing Map, HSOM = Harness Self-Organizing Map.

The most frequently identified behaviours in the third modelling round remained lying (27.82–53.21%) and sitting (20.66–28.04%), with grooming behaviour ranging from 7.59% to 13.91% (Table 6). As seen in the second modelling round, eating behaviour showed a large range (3.28% to 26.79%; Table 6). In the third modelling round, no differences in the mean percentages of identified behaviours were found between the CRF and HRF models ($p > 0.05$), whereas all behaviours differed between the CSOM and HSOM models (eating $p = 0.012$, all other behaviours $p < 0.001$; Table 6). Differences in mean daily percentages were found between the CRF and CSOM models for active, lying, sitting, standing, grooming (all $p < 0.001$), and eating ($p = 0.002$; Table 6). For the HRF and HSOM models, differences were found for active, lying, and sitting (all $p < 0.001$), and eating ($p = 0.011$; Table 6).

Table 6. Differences in mean ± standard error daily percentages of identified behaviours between models for modelling round 3.

	CRF *		HRF *		CSOM *		HSOM *	
Active †	2.70 ± 0.37	c	3.17 ± 0.40	c	0.10 ± 0.02	a	1.87 ± 0.21	b
Lying †	53.21 ± 2.34	c	49.82 ± 2.85	c	27.82 ± 2.98	a	39.58 ± 2.00	b
Sitting †	24.88 ± 2.58	b	27.35 ± 3.02	b	28.04 ± 3.40	c	20.66 ± 2.21	a
Standing †	7.64 ± 1.30	b	7.92 ± 0.97	b	3.33 ± 2.76	a	9.57 ± 1.00	c
Grooming †	7.59 ± 0.35	a	8.45 ± 0.35	a	13.91 ± 0.99	b	13.20 ± 1.55	a
Eating †	3.98 ± 0.47	a	3.28 ± 0.31	a	26.79 ± 2.91	c	14.11 ± 1.47	b

a–c Different superscripts within a behaviour indicate a significant difference ($p < 0.05$). † Behaviour was significantly affected by day ($p < 0.05$). * CRF = Collar Random Forest, HRF = Harness Random Forest, CSOM = Collar Self-Organizing Map, HSOM = Harness Self-Organizing Map.

For the fourth and final modelling round, the behaviours present in the third modelling round were merged into three main categories: active, inactive, and maintenance. Inactive behaviour was the most commonly identified behavioural category (51.16–84.46%), followed by maintenance (10.90–34.06%) and active (3.64–14.78%; Table 7). In the fourth modelling round, no differences were found in mean daily percentages of active ($p = 0.898$), inactive ($p = 0.574$), and maintenance ($p = 0.907$) behaviours between the CRF and HRF models (Table 7). For the SOM models, there was a difference in mean daily percentage between the CSOM and HSOM models for inactive behaviours ($p < 0.001$; Table 7). Differences in mean daily percentages were found between the CRF and CSOM for all three categories, which was also true between the HRF and HSOM (all $p < 0.001$; Table 7).

Table 7. Differences in mean ± standard error daily percentages of identified behaviours between models for modelling round 4.

	CRF *		HRF *		CSOM *		HSOM *	
Active	4.64 ± 0.49	a	5.20 ± 0.61	a	14.78 ± 2.09	b	10.81 ± 0.72	b
Inactive	84.46 ± 0.58	c	83.27 ± 0.57	c	51.16 ± 3.27	a	61.98 ± 2.30	b
Maintenance	10.90 ± 0.47	a	11.53 ± 0.46	a	34.06 ± 1.59	b	27.21 ± 2.35	b

a–c Different superscripts within a behaviour indicate a significant difference ($p < 0.05$). * CRF = Collar Random Forest, HRF = Harness Random Forest, CSOM = Collar Self-Organizing Map, HSOM = Harness Self-Organizing Map.

The effect of day was included in the Dirichlet regression and showed that, in the first modelling round, day influenced the proportion of walking ($p < 0.001$), lying ($p = 0.004$), sitting ($p < 0.001$), standing ($p < 0.001$), grooming ($p < 0.001$), and eating ($p < 0.001$) behaviour (Table 4). In the second modelling round, day influenced active ($p = 0.019$), sitting ($p < 0.001$), standing ($p = 0.020$), grooming ($p = 0.027$), and eating ($p = 0.019$; Table 5). In the third modelling round, day influenced active ($p = 0.017$), lying ($p = 0.025$), sitting ($p < 0.001$), standing ($p = 0.014$), grooming ($p = 0.004$), and eating ($p = 0.011$) behaviour (Table 6). In modelling round four, active ($p = 0.076$), inactive ($p = 0.766$), and maintenance ($p = 0.413$) were not influenced by day.

4. Discussion

The current study aimed to build a model to identify cat behaviour using accelerometer data. Generally, the more classes that were included in a model, the lower the accuracy of it. In the current study, the models for three behavioural classes (active, inactive, and maintenance) had the highest accuracy (Table 3). In the current study, similar behaviours that were often misclassified were merged (e.g., trotting and walking) or removed from the model (e.g., digging). This reduction of behaviour classes lowers the risk of misclassification, resulting in fewer false positives and false negatives, thereby increasing the accuracy. Similar results were found in a study on cheetahs (*Acinonyx jubatus*), where merging of similar behaviours resulted in models with higher accuracy [13]. Another study, modelling behaviour using accelerometer data of oystercatchers (*Haematopus ostralegus*), found that a model with three behaviour classes had a lower absolute cross-validation error than a model with eight behaviour classes [26]. These results show that there is a trade-off between a more representative model, including more behaviours, and accuracy. Despite decreasing accuracy with increasing classes, all models in the current study had an accuracy $\geq$0.70.

Two modelling techniques, RF and SOM, and two mounting locations, collar and harness, were compared. Early models (data not shown) were able to identify behaviours that had relatively large sample sizes (e.g., lying), but had difficulty with behaviours with a sample size lower than 500 (e.g., climbing). In order to balance the dataset from which the models were built, behaviours with a large sample size were limited to 7000 datapoints. Despite this limit, the models from the first round of modelling had difficulty identifying behaviours with a low sample size such as climbing (n = 32), jumping (n = 239), and trotting (n = 308). Galea et al. [2] reported that SOM models of behaviours with a sample size less than 2000 datapoints had lower accuracy, sensitivity, and precision compared with behaviours with a sample size larger than 2000. Low sample sizes were the result of a behaviour being displayed infrequently.

In the current study, most behaviours with low sensitivity and precision were those that consisted of swift movements and/or behaviours of short duration (<one second). This is in agreement with [27] who reported that models of data derived from collar-mounted accelerometers attached to captive dingoes (*Canis lupus dingo*) had more difficulty identifying active behaviours consisting of swift movements performed over a short period of time. Capturing swift and short duration movements is a challenge especially encountered in small animal species, as movements are generally quicker than in larger animals [4]. A study using data from accelerometers attached to chipmunks (*Tamias*), a small-bodied animal (<100 g), found the lowest sampling frequency that resulted in negligible decrease in accuracy was 20 Hz [28]. In the current study, jumping was often misidentified as walking, a behaviour that was often observed and identified immediately before and after the jump. In the current study, the shortest lasting behaviour (jumping) lasted for an average of 0.89 s (results not shown). Accelerometer data were collected at 30 Hz and summarised into one-second epochs, which could have led to the acceleration signature of very short-lasting behaviours being lost in the signature of the behaviour immediately before or after they occurred. Choosing an epoch length that resembled the length of these shorter behaviours might help in the ability of models to identify them more accurately. In addition, a shorter epoch could also increase the sample size of infrequent behaviours. While a smaller epoch length can increase the sample size, it will increase the computational time to train and test the models [27]. In the current study, the total number of observations (Appendix A) for each short-lasting behaviour was very close to the total amount of time it was observed in the video recordings. A one-second epoch is therefore thought to be small enough when considering the behaviours included in the current study.

It was hypothesised that the harness-mounted accelerometer would have better performance values compared with the collar. There was little difference in Kappa and overall accuracy between the CSOM and HSOM models within each modelling round. However, the majority of the RF models had higher performance values when data from devices attached to a harness were compared with the collar. These results are in agreement with a study with domestic dogs, where harness-mounted accelerometers resulted in models where accuracy was higher (87–91%) than collar-mounted accelerometers (69–76%) [7]. One of the reasons cited for the higher accuracy of harness-mounted accelerometers compared with collar-mounted ones was the firmer attachment the harness provided for the device [7]. Collar attachment, in contrast, resulted in changes in device orientation and residual movement [7]. For cats, it is challenging to obtain a firmer device attachment with a collar, as securing the collar tightly might result in discomfort or injury [29]. Despite the harness models generally having better performance compared with the collar models when considering the RF modelling technique, the collar and harness models identified similar percentages of each behaviour within each behavioural round (Tables 4–7).

In the current study, it was hypothesised that the models from the collar-mounted accelerometers would be better for identifying more subtle behaviours such as eating and drinking, as these behaviours are associated with head movement rather than body movement. While drinking and eating behaviours have been successfully distinguished using data from only one axis of an accelerometer attached to a collar on a single domestic cat [3], different attachment methods (harness vs. collar) have not been compared for these fine-scale behaviours in domestic cats. In the current study, the differences in performance values between the CSOM and HSOM models were very small, on average <1%. For the RF models, however, the performance values of the harness model for eating behaviour were always higher than those of the RF collar models. This could be the result of the design of the feeding area in the colony cages (Figure 1). Cats were often observed to place their front paws in the feeding tray, while their hind paws remained on the wooden walkway surrounding the feeding tray, resulting in a forward tilted posture where the head and shoulders were lower than their hips. This change in posture during eating is likely to have resulted in a greater change in the orientation of the harness-mounted accelerometer compared with the collar [7]. In a home situation it would be expected that food bowls would be on the ground or slightly elevated and thus will not result in the cat being tilted forward [30,31].

As hypothesised, in the current study the SOM models had higher Kappa and overall accuracy values compared with the RF models. These results are in agreement with previous findings reported on domestic cats by [2], where the SOM model had a mean accuracy of 99.6%, compared with the RF model of 98.9%. The mean accuracy of the RF model as reported by [2] was higher than the overall accuracy reported in the current study (70–83%). It should be noted, however, that mean accuracy and overall accuracy were calculated differently, and cannot therefore be directly compared.

In addition to Kappa and overall accuracy to determine model performance, the current study further evaluated the performance of the models. To date, rather than using models on a new dataset and then comparing the results, the ability of models to identify behaviours has been based on performance results, such as measures of accuracy [8,27]. In the current study, all models were used to identify the behaviour of the same 12 domestic cats, using accelerometer data that were not used in the training and testing of the model. The results showed that the identified behaviours, expressed as a percentage of total behaviour, were identified more consistently with the RF models between mounting locations and across modelling rounds than the SOM models.

A possible explanation for the seemingly poorer performance of the SOM models when presented with a new dataset is overfitting. Overfitting occurs when a model fits the training data so well, it memorises noise in the dataset, leading to a model that does not perform well on a new dataset [32]. There are different reasons why overfitting might occur, including a dataset that is too small and/or the presence of too many predictor variables, making the model overcomplicated [32,33]. Galea et al. [2] tested how the accuracy of the SOM changed with different sample sizes for the training dataset and reported that the accuracy of the SOM plateaued after 20,000 samples. With the exception of the fourth modelling round, the training dataset (70%) contained more than 20,000 samples, making the size of the dataset sufficient according to results reported by [2]. Since the sample size of the current study was probably sufficient, the most likely explanation for the overfitting of the SOM models is overcomplication of the models due to many predictor variables. Overfitting due to too many predictor variables can be avoided by either selecting fewer predictor variables, or by increasing the sample size [32]. The predictor variables included in the current study were based on the 26 predictor variables identified as most effective by [27] and the 31 used by [2]. The SOM models were simplified to as few as four predictor variables (mean for X, Y and Z, and ODBA), but this did not improve the results (results not shown).

A supervised SOM is a type of artificial neural network that consists of an input layer, a single hidden layer, and an output layer in the form of a grid map consisting of neurons [34].

There is a neighbourhood relationship between the neurons on the output grid map [34]. The neurons of the hidden layer are connected to the samples in the input layer through weights, and weights are updated with each iteration [35]. Due to the neighbourhood relationship between neurons, changes in the weight of one neuron will affect other neurons in its neighbourhood [34]. Allende et al. [36] reported that SOMs are sensitive to outliers because of how the changing weight of one neuron affects the neighbouring neurons. It is reasonable to expect outliers in behavioural datasets, as behaviour can be very dynamic. A cat sitting, for example, can sit completely stationary, but it might suddenly turn its head back when it hears a noise, triggering the accelerometer due to the movement. In both cases, the cat is identified simply as sitting but will result in different accelerometer traces where one might be identified as an outlier. It is possible that the outliers of the dataset not used to build the model included outliers that were different than those contained in the training dataset. This could have led to the SOM being able to identify behaviours in the training dataset with high accuracy but having problems with identifying behaviours in a novel dataset. The SOM models could possibly be improved by distinguishing more subtle differences in behaviour and posture, e.g., separately annotating sitting completely stationary and moving the head around while sitting. It was decided not to re-watch the video recordings to separately identify more subtle differences within a single behaviour, as scoring behaviour is very labour-intensive, and the results show that the RF models identify behaviours consistently across mounting locations and are the best fit for the dataset generated in this study.

Literature on the activity budget of domestic cats is limited and results cannot be compared directly due to differences in housing conditions, behaviours, and sampling method. Despite these differences, the time domestic cats spent on eating behaviours was surprisingly consistent, with daily time spent eating being approximately 2–3% [37–40]. The RF models showed that in the current study cats spent between ~3% and ~4% of their time eating, whereas this ranged between ~13% and ~28% when identified with the SOM models. Not only did the RF models identify behaviour more consistently between mounting locations, but they also identified eating behaviour with a similar percentage as reported in the literature. This further supports the choice of RF models for the dataset generated in the current study.

The present study provided an insight into the activity budgets of colony-housed cats. Irrespective of modelling technique used or mounting location, cats spent the majority of their time inactive. The RF models identified that inactive behaviours accounted for between ~83% and ~86% of all behaviours. This was greater than the ~62% observed in farm cats [40], but comparable to that observed in privately owned cats (~84%) [39]. The difference in the percentage of inactive behaviours between these studies is probably due to the farm cats having the ability to roam around the farm and hunt for prey, whereas the cats in the current study had limited opportunity to roam and had a consistent *ad libitum* food source. Panaman [40] reported that four of the five farm cats were active hunters, which resulted in active behaviours (hunting and travelling) being observed for ~18% of their day, whereas the colony-housed cats were active (walking, trotting) for only ~3–5% of their time when the RF models were used.

5. Conclusions

The current study successfully produced identification models using accelerometer data to identify cat behaviour, paving the way to make behavioural studies in domestic cats less labour-intensive in the future. A trade-off was found between the number of behaviours included in the model and accuracy; however, the accuracy for all models, including the models with 15 behaviours, was $\geq$0.70. Despite the higher performance values of the SOM models, the RF models appear to predict cat behaviour more consistently. No differences in performance values between the collar and harness were found. Performance values, especially sensitivity and precision, of less frequent behaviours can be improved by increasing the sample size in future studies. The current study also provided valuable information about activity budgets of colony-housed cats which spent most of their time inactive. More research is advised to examine the potential for accelerometers and machine learning to monitor behavioural changes in cats to allow health monitoring.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/s23167165/s1, Supplementary Material S1: Confusion matrices of identification models; Supplementary Material S2: Accuracies of identification models; Supplementary Material S3: Precisions of identification models; Supplementary Material S4: Sensitivities of identification models; Supplementary Material S5: Specificities of identification models.

Author Contributions: Conceptualization, M.S., R.A.C.-T., C.J.A., I.D. and D.G.T.; methodology, M.S. and S.J.I.; software, M.S. and S.J.I.; validation, M.S.; formal analysis, M.S. and S.J.I.; investigation, R.A.C.-T., C.J.A., I.D. and D.G.T.; resources, R.A.C.-T., C.J.A. and D.G.T.; data curation, M.S. and S.J.I.; writing—original draft preparation, M.S.; writing—review and editing, S.J.I., R.A.C.-T., C.J.A., I.D. and D.G.T.; visualization, M.S.; supervision, R.A.C.-T., C.J.A., I.D. and D.G.T.; project administration, M.S.; funding acquisition, D.G.T. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: The animal study protocol was approved by the Animal Ethics Committee of Massey University (MUAEC 21/23).

Informed Consent Statement: Not applicable.

Data Availability Statement: R-dataframes of the data presented in this study are openly available in FigShare at https://doi.org/10.6084/m9.figshare.23605842 (accessed on 30 June 2023) [41]. Raw datafiles are available on request from the corresponding author due to the large size. R-scripts are openly available through GitHub [18].

Acknowledgments: We wish to thank Karin Weidgraaf, Margreet Hekman, and Rachael Richardson for their help in training the cats to wear harnesses and the accelerometers.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

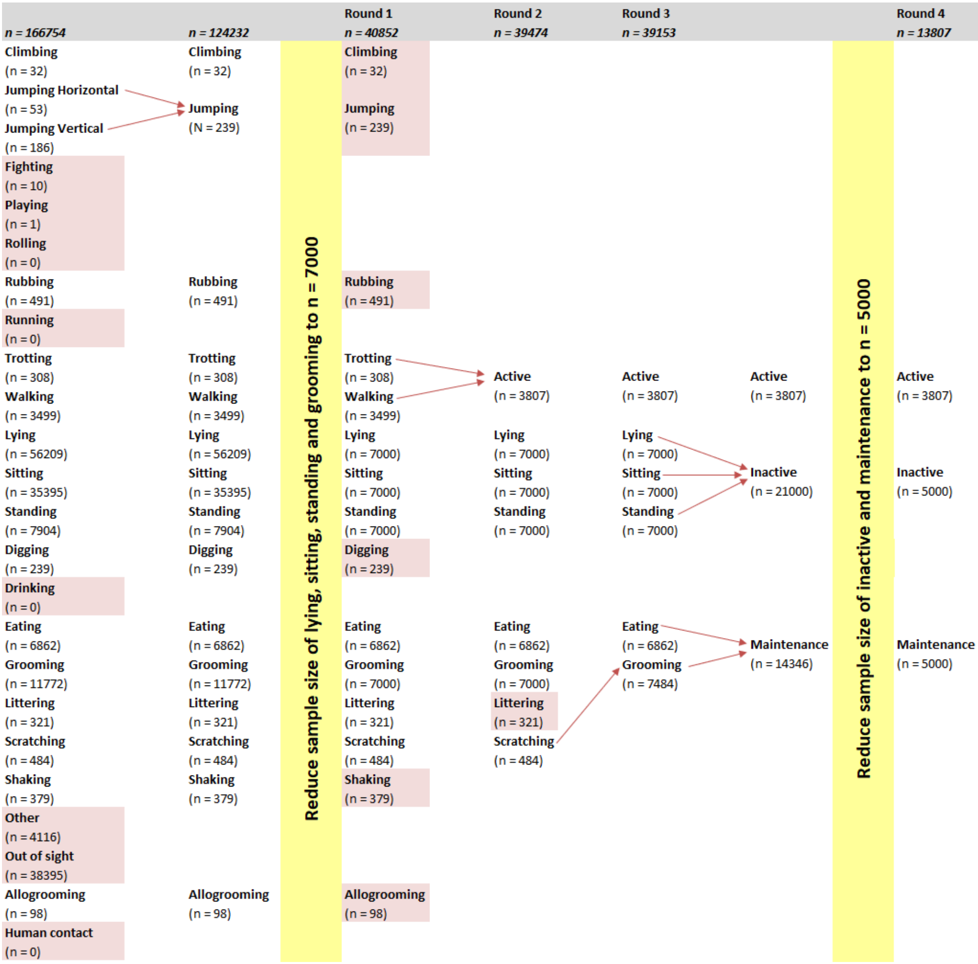

Figure A1. Process of behavioural selection before and between modelling building rounds. Behaviours marked in red were removed. Red arrows indicate the combining of behaviours into new or existing categories. The first two columns show the deletion and merging of behaviours before the first modelling round. The number of observations per behaviour is stated in brackets under the behaviour (n in seconds), and the total number (in seconds) of all behavioural observations is at the top of each column.

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Appendix III – Confusion matrices of classification models

Modelling round 1

Numbers along the diagonal represent the true positive (TP) value. Pred = identified behaviour, Ob = observed behaviour.

Table A1. Confusion matrix for modelling round 1 of the collar-mounted data using a Random Forest model.

Pred \ Ob	Climbing	Jumping	Rubbing	Trotting	Walking	Lying	Sitting	Standing	Grooming	Littering	Digging	Eating	Scratching	Shaking	Allogrooming
Climbing	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Jumping	0	4	0	0	1	0	0	0	0	0	0	0	0	0	0
Rubbing	0	0	20	0	1	0	0	0	0	0	0	0	1	2	0
Trotting	0	0	0	2	1	0	1	0	0	0	0	0	0	0	0
Walking	2	33	23	40	533	0	20	213	43	2	8	41	19	31	1
Lying	0	0	5	0	9	1855	203	98	39	10	0	8	2	6	1
Sitting	0	3	3	5	30	139	1536	161	70	26	0	9	2	5	1
Standing	3	17	17	28	226	80	233	1231	152	18	4	86	25	28	3
Grooming	4	6	46	14	156	12	77	212	1526	4	17	137	26	29	19
Littering	0	0	0	0	0	2	3	2	0	34	0	0	0	0	0
Digging	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Eating	0	6	33	3	81	12	23	174	269	2	42	1776	3	4	4
Scratching	0	1	0	0	7	0	4	2	1	0	0	1	67	2	0
Shaking	0	1	0	0	4	0	0	7	0	0	0	0	0	6	0
Allogrooming	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table A2. Confusion matrix for modelling round 1 of the harness-mounted data using a Random Forest model.

Ob / Pred	Climbing	Jumping	Rubbing	Trotting	Walking	Lying	Sitting	Standing	Grooming	Littering	Digging	Eating	Scratching	Shaking	Allogrooming
Climbing	1	0	0	0	2	0	0	1	0	0	0	0	0	0	0
Jumping	1	4	0	0	4	0	0	1	0	0	0	2	0	2	0
Rubbing	0	1	70	2	13	1	1	25	11	0	3	2	1	3	0
Trotting	0	0	0	2	1	0	1	0	0	0	0	0	0	0	0
Walking	6	38	17	38	680	2	11	266	25	6	16	23	26	36	1
Lying	0	0	7	0	4	1989	27	73	9	6	0	10	0	4	0
Sitting	0	5	2	7	33	13	1711	138	91	10	0	0	0	9	5
Standing	0	7	12	37	187	64	232	1226	137	35	9	64	18	27	6
Grooming	1	9	27	6	90	21	107	254	1761	2	6	35	34	23	13
Littering	0	0	0	0	0	0	3	5	0	34	0	0	0	0	0
Digging	0	0	0	0	0	0	0	0	1	1	10	2	0	0	0
Eating	0	7	12	0	32	10	4	110	65	2	27	1920	1	4	2
Scratching	0	0	0	0	3	0	3	1	0	0	0	0	65	2	0
Shaking	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0
Allogrooming	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2

Table A3. Confusion matrix for modelling round 1 of the collar-mounted data using a Self-Organising Map model.

Ob / Pred	Climbing	Jumping	Rubbing	Trotting	Walking	Lying	Sitting	Standing	Grooming	Littering	Digging	Eating	Scratching	Shaking	Allogrooming
Climbing	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Jumping	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Rubbing	3	17	90	16	0	0	0	0	0	11	43	0	0	12	6
Trotting	2	29	36	65	0	0	0	0	0	2	25	0	28	40	15
Walking	0	3	1	1	1049	0	5	11	2	0	0	1	1	17	0
Lying	0	0	0	0	0	2100	0	0	0	0	0	0	0	0	0
Sitting	0	0	0	0	0	0	2095	0	0	0	0	0	0	0	0
Standing	1	0	1	0	0	0	0	2089	0	0	0	0	0	0	0
Grooming	1	2	3	0	0	0	0	0	2098	0	0	0	1	0	0
Littering	0	0	0	0	0	0	0	0	0	83	0	0	0	0	0
Digging	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Eating	0	0	0	0	0	0	0	0	0	0	0	2057	0	0	0
Scratching	0	0	0	0	0	0	0	0	0	0	0	0	115	0	0
Shaking	2	20	16	10	0	0	0	0	0	0	3	0	0	44	8
Allogrooming	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table A4. Confusion matrix for modelling round 1 of the harness-mounted data using a Self-Organising Map model.

Ob / Pred	Climbing	Jumping	Rubbing	Trotting	Walking	Lying	Sitting	Standing	Grooming	Littering	Digging	Eating	Scratching	Shaking	Allogrooming
Climbing	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Jumping	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Rubbing	0	0	145	0	0	0	0	0	0	0	0	0	0	0	0
Trotting	0	9	0	40	0	0	1	0	0	14	0	0	14	9	1
Walking	0	0	0	1	1039	0	2	16	1	0	0	1	1	11	0
Lying	0	0	1	0	1	2100	0	0	0	0	0	0	0	0	0
Sitting	0	0	0	1	0	0	2097	0	0	0	0	0	0	0	0
Standing	0	0	0	2	9	0	0	2084	1	0	0	1	2	5	0
Grooming	0	0	0	0	0	0	0	0	2098	0	0	0	5	0	0
Littering	0	4	0	4	0	0	0	0	0	52	1	0	30	16	25
Digging	0	0	0	0	0	0	0	0	0	0	68	0	0	0	0
Eating	0	3	0	1	0	0	0	0	0	0	0	2055	0	3	0
Scratching	9	19	1	24	0	0	0	0	0	23	2	1	76	37	1
Shaking	0	36	0	19	0	0	0	0	0	7	0	0	17	32	2
Allogrooming	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Modelling round 2

Numbers along the diagonal represent the true positive (TP) value. Pred = identified behaviour, Ob = observed behaviour.

Table A5. Confusion matrix for modelling round 2 of the collar data using a Random Forest model.

Pred \ Ob	Active	Lying	Sitting	Standing	Grooming	Littering	Eating	Scratching
Active	596	2	12	231	45	4	38	20
Lying	13	1861	187	106	41	8	8	3
Sitting	36	125	1554	159	75	19	5	3
Standing	220	85	235	1226	122	18	83	19
Grooming	164	11	84	220	1573	3	140	34
Littering	0	1	3	3	0	36	0	0
Eating	107	15	24	152	272	8	1784	1
Scratching	6	0	1	3	1	0	0	65

Table A6. Confusion matrix for modelling round 2 of the harness data using a Random Forest model.

Pred \ Ob	Active	Lying	Sitting	Standing	Grooming	Littering	Eating	Scratching
Active	730	3	21	339	35	9	26	29
Lying	20	2007	25	54	10	7	17	1
Sitting	32	12	1690	112	76	11	0	1
Standing	229	59	241	1228	159	22	76	17
Grooming	99	15	117	265	1784	6	46	38
Littering	0	1	3	6	0	40	0	0
Eating	29	3	3	96	61	1	1893	0
Scratching	3	0	0	0	4	0	0	59

Table A7. Confusion matrix for modelling round 2 of the collar data using a Self-Organising Map model.

Pred \ Ob	Active	Lying	Sitting	Standing	Grooming	Littering	Eating	Scratching
Active	1142	0	3	13	2	1	0	4
Lying	0	2100	0	0	0	0	0	3
Sitting	0	0	2097	0	0	0	0	2
Standing	0	0	0	2087	0	0	0	2
Grooming	0	0	0	0	2127	0	0	3
Littering	0	0	0	0	0	94	0	0
Eating	0	0	0	0	0	1	2058	0
Scratching	0	0	0	0	0	0	0	131

Table A8. Confusion matrix for modelling round 2 of the harness data using a Self-Organising Map model.

Pred \ Ob	Active	Lying	Sitting	Standing	Grooming	Littering	Eating	Scratching
Active	1128	0	0	11	0	0	2	1
Lying	0	2100	0	0	0	0	0	0
Sitting	0	0	2099	0	0	0	0	1
Standing	14	0	1	2089	1	0	0	0
Grooming	0	0	0	0	2128	0	0	7
Littering	0	0	0	0	0	96	0	0
Eating	0	0	0	0	0	0	2056	0
Scratching	0	0	0	0	0	0	0	136

Modelling round 3

Numbers along the diagonal represent the true positive (TP) value. Pred = identified behaviour, Ob = observed behaviour.

Table A9. Confusion matrix for modelling round 3 of the collar data using a Random Forest model.

Pred \ Ob	Active	Lying	Sitting	Standing	Grooming	Eating
Active	615	1	17	240	66	45
Lying	17	1870	223	112	44	10
Sitting	44	110	1543	174	64	9
Standing	205	91	234	1175	151	79
Grooming	191	12	66	241	1709	129
Eating	70	16	17	158	240	1786

Table A10. Confusion matrix for modelling round 3 of the harness data using a Random Forest model.

Pred \ Ob	Active	Lying	Sitting	Standing	Grooming	Eating
Active	745	2	21	328	50	26
Lying	9	1997	33	70	14	10
Sitting	32	17	1648	127	75	0
Standing	214	59	274	1209	173	79
Grooming	103	20	120	252	1898	37
Eating	39	5	4	114	64	1906

Table A11. Confusion matrix for modelling round 3 of the collar data using a Self-Organising Map model.

Pred \ Ob	Active	Lying	Sitting	Standing	Grooming	Eating
Active	1006	1	4	15	2	0
Lying	0	1964	0	0	0	0
Sitting	0	0	2093	0	0	0
Standing	0	1	0	2077	0	0
Grooming	0	0	0	0	2118	0
Eating	136	134	3	8	154	2058

Table A12. Confusion matrix for modelling round 3 of the harness data using a Self-Organizing Map model.

Pred \ Ob	Active	Lying	Sitting	Standing	Grooming	Eating
Active	1137	0	3	17	1	0
Lying	0	2100	0	0	0	0
Sitting	1	0	2097	0	0	0
Standing	0	0	0	2081	0	0
Grooming	0	0	0	0	2273	0
Eating	4	0	0	2	0	2058

Modelling round 4

Numbers along the diagonal represent the true positive (TP) value. Pred = identified behaviour, Ob = observed behaviour.

Table A13. Confusion matrix for modelling round 3 of the collar data using a Random Forest model.

Pred \ Ob	Active	Inactive	Maintenance
Active	905	147	69
Inactive	125	1211	111
Maintenance	112	142	1320

Table A14. Confusion matrix for modelling round 3 of the harness data using a Random Forest model.

Pred \ Ob	Active	Inactive	Maintenance
Active	901	158	85
Inactive	112	1196	86
Maintenance	129	146	1329

Table A15. Confusion matrix for modelling round 3 of the collar data using a Self-Organising Map model.

Pred \ Ob	Active	Inactive	Maintenance
Active	1142	1	2
Inactive	0	1499	0
Maintenance	0	0	1498

Table A16. Confusion matrix for modelling round 3 of the harness data using a Self-Organising Map model.

Pred \ Ob	Active	Inactive	Maintenance
Active	1142	2	1
Inactive	0	1497	0
Maintenance	0	1	1499

Appendix IV – Accuracy of classification models per behavioural class

CRF = Collar Random Forest, HRF = Harness Random Forest, CSOM = Collar Self-Organising Map, HSOM = Harness Self-Organising Map.

Table A17. Accuracy for modelling round 1.

	CRF	HRF	CSOM	HSOM
Climbing	0.999	0.999	0.999	0.999
Jumping	0.994	0.994	0.994	0.994
Rubbing	0.989	0.989	0.987	1.000
Trotting	0.992	0.992	0.983	0.992
Walking	0.919	0.928	0.997	0.996
Lying	0.949	0.980	1.000	1.000
Sitting	0.917	0.943	1.000	1.000
Standing	0.854	0.861	0.999	0.997
Grooming	0.891	0.921	0.999	0.999
Littering	0.994	0.994	0.999	0.990
Digging	0.994	0.995	0.994	1.000
Eating	0.923	0.966	1.000	0.999
Scratching	0.992	0.993	0.998	0.985
Shaking	0.990	0.991	0.990	0.987
Allogrooming	0.998	0.998	0.998	0.998
Average	0.960	0.970	0.996	0.996

Table A18. Accuracy for modelling round 2.

	CRF	HRF	CSOM	HSOM
Active	0.924	0.926	0.998	0.998
Lying	0.949	0.981	1.000	1.000
Sitting	0.918	0.945	1.000	1.000
Standing	0.860	0.859	0.999	0.998
Grooming	0.898	0.922	1.000	0.999
Littering	0.994	0.994	1.000	1.000
Eating	0.928	0.970	1.000	1.000
Scratching	0.992	0.992	0.999	0.999
Average	0.933	0.949	0.999	0.999

Table A19. Accuracy for modelling round 3.

	CRF	HRF	CSOM	HSOM
Active	0.924	0.930	0.987	0.998
Lying	0.946	0.980	0.988	1.000
Sitting	0.919	0.940	0.999	1.000
Standing	0.857	0.856	0.998	0.998
Grooming	0.903	0.948	0.987	1.000
Eating	0.746	0.790	0.963	0.999
Average	0.882	0.907	0.987	0.999

Table A20. Accuracy for modelling round 4.

	CRF	HRF	CSOM	HSOM
Active	0.891	0.883	0.999	0.999
Inactive	0.873	0.879	1.000	0.999
Maintenance	0.895	0.892	1.000	1.000
Average	0.886	0.885	1.000	0.999

Appendix V – Precision of classification models per behavioural class

CRF = Collar Random Forest, HRF = Harness Random Forest, CSOM = Collar Self-Organising Map, HSOM = Harness Self-Organising Map.

Table A21. Precision for modelling round 1.

	CRF	HRF	CSOM	HSOM
Climbing	N/A	0.250	N/A	N/A
Jumping	0.800	0.286	N/A	N/A
Rubbing	0.833	0.526	0.455	1.000
Trotting	0.500	0.500	0.269	0.455
Walking	0.528	0.571	0.962	0.969
Lying	0.830	0.934	1.000	0.999
Sitting	0.772	0.845	1.000	1.000
Standing	0.572	0.595	0.999	0.990
Grooming	0.668	0.737	0.997	0.998
Littering	0.829	0.810	1.000	0.394
Digging	N/A	0.714	N/A	1.000
Eating	0.730	0.874	1.000	0.997
Scratching	0.788	0.878	1.000	0.394
Shaking	0.333	1.000	0.427	0.283
Allogrooming	N/A	1.000	N/A	N/A
Average	0.682	0.701	0.828	0.790

Table A22. Precision for modelling round 2.

	CRF	HRF	CSOM	HSOM
Active	0.629	0.612	0.980	0.988
Lying	0.836	0.937	0.999	1.000
Sitting	0.786	0.874	0.999	1.000
Standing	0.611	0.605	0.999	0.992
Grooming	0.706	0.753	0.999	0.997
Littering	0.837	0.800	1.000	1.000
Eating	0.755	0.907	1.000	1.000
Scratching	0.855	0.894	1.000	1.000
Average	0.752	0.798	0.997	0.997

Table A23. Precision for modelling round 3.

	CRF	HRF	CSOM	HSOM
Active	0.625	0.636	0.979	0.982
Lying	0.822	0.936	1.000	1.000
Sitting	0.794	0.868	1.000	1.000
Standing	0.607	0.602	1.000	1.000
Grooming	0.747	0.890	1.000	1.000
Eating	0.397	0.451	0.826	0.997
Average	0.665	0.731	0.967	0.996

Table A24. Precision for modelling round 4.

	CRF	HRF	CSOM	HSOM
Active	0.807	0.788	0.997	0.997
Inactive	0.837	0.858	1.000	1.000
Maintenance	0.839	0.829	1.000	0.999
Average	0.828	0.825	0.999	0.999

Appendix VI – Recall of classification models per behavioural class

CRF = Collar Random Forest, HRF = Harness Random Forest, CSOM = Collar Self-Organising Map, HSOM = Harness Self-Organising Map.

Table A25. Recall for modelling round 1.

	CRF	HRF	CSOM	HSOM
Climbing	0.000	0.111	0.000	0.000
Jumping	0.056	0.056	0.000	0.000
Rubbing	0.136	0.476	0.612	0.986
Trotting	0.022	0.022	0.707	0.435
Walking	0.508	0.648	1.000	0.990
Lying	0.883	0.947	1.000	1.000
Sitting	0.731	0.815	0.998	0.999
Standing	0.586	0.584	0.995	0.992
Grooming	0.727	0.839	0.999	0.999
Littering	0.354	0.354	0.865	0.542
Digging	0.000	0.141	0.000	0.958
Eating	0.863	0.933	1.000	0.999
Scratching	0.462	0.448	0.793	0.524
Shaking	0.053	0.027	0.389	0.283
Allogrooming	0.000	0.069	0.000	0.000
Average	0.359	0.431	0.624	0.647

Table A26. Recall for modelling round 2.

	CRF	HRF	CSOM	HSOM
Active	0.522	0.639	1.000	0.988
Lying	0.886	0.956	1.000	1.000
Sitting	0.740	0.805	0.999	1.000
Standing	0.584	0.585	0.994	0.995
Grooming	0.739	0.838	0.999	1.000
Littering	0.375	0.417	0.979	1.000
Eating	0.867	0.920	1.000	0.999
Scratching	0.448	0.407	0.903	0.938
Average	0.645	0.696	0.984	0.990

Table A27. Recall for modelling round 3.

	CRF	HRF	CSOM	HSOM
Active	0.539	0.652	0.881	0.996
Lying	0.890	0.951	0.935	1.000
Sitting	0.735	0.785	0.997	0.999
Standing	0.560	0.576	0.989	0.991
Grooming	0.752	0.835	0.931	1.000
Eating	0.868	0.926	1.000	1.000
Average	0.724	0.787	0.956	0.997

Table A28. Recall for modelling round 4.

	CRF	HRF	CSOM	HSOM
Active	0.792	0.789	1.000	1.000
Inactive	0.807	0.797	0.999	0.998
Maintenance	0.880	0.886	0.999	0.999
Average	0.827	0.824	0.999	0.999

Appendix VII – Specificity of classification modes per behavioural class

CRF = Collar Random Forest, HRF = Harness Random Forest, CSOM = Collar Self-Organising Map, HSOM = Harness Self-Organising Map.

Table A29. Specificity for modelling round 1.

	CRF	HRF	CSOM	HSOM
Climbing	1.000	1.000	1.000	1.000
Jumping	1.000	0.999	1.000	1.000
Rubbing	1.000	0.995	0.991	1.000
Trotting	1.000	1.000	0.985	0.996
Walking	0.958	0.954	0.996	0.997
Lying	0.962	0.986	1.000	1.000
Sitting	0.955	0.969	1.000	1.000
Standing	0.909	0.918	1.000	0.998
Grooming	0.925	0.938	0.999	1.000
Littering	0.999	0.999	1.000	0.993
Digging	1.000	1.000	1.000	1.000
Eating	0.936	0.973	1.000	0.999
Scratching	0.999	0.999	1.000	0.990
Shaking	0.999	1.000	0.995	0.993
Allogrooming	1.000	1.000	1.000	1.000
Average	0.976	0.982	0.998	0.998

Table A30. Specificity for modelling round 2.

	CRF	HRF	CSOM	HSOM
Active	0.967	0.957	0.998	0.999
Lying	0.963	0.986	1.000	1.000
Sitting	0.957	0.975	1.000	1.000
Standing	0.920	0.918	1.000	0.998
Grooming	0.933	0.940	1.000	0.999
Littering	0.999	0.999	1.000	1.000
Eating	0.941	0.980	1.000	1.000
Scratching	0.999	0.999	1.000	1.000
Average	0.960	0.969	1.000	1.000

Table A31. Specificity for modelling round 3.

	CRF	HRF	CSOM	HSOM
Active	0.965	0.960	0.998	0.998
Lying	0.958	0.986	1.000	1.000
Sitting	0.959	0.974	1.000	1.000
Standing	0.921	0.917	1.000	1.000
Grooming	0.939	0.975	1.000	1.000
Eating	0.720	0.761	0.955	0.999
Average	0.910	0.929	0.992	1.000

Table A32. Specificity for modelling round 4.

	CRF	HRF	CSOM	HSOM
Active	0.928	0.919	0.999	0.999
Inactive	0.911	0.925	1.000	1.000
Maintenance	0.904	0.896	1.000	1.000
Average	0.914	0.913	1.000	1.000

Appendix VIII – F1-score of classification models per behavioural class

CRF = Collar Random Forest, HRF = Harness Random Forest, CSOM = Collar Self-Organising Map, HSOM = Harness Self-Organising Map.

Table A33. F1-score for modelling round 1.

	CRF	HRF	CSOM	HSOM
Climbing	N/A	0.154	N/A	N/A
Jumping	0.105	0.094	N/A	N/A
Rubbing	0.234	0.500	0.522	0.993
Trotting	0.042	0.042	0.389	0.444
Walking	0.518	0.607	0.980	0.980
Lying	0.856	0.941	1.000	1.000
Sitting	0.751	0.830	0.999	0.999
Standing	0.579	0.589	0.997	0.991
Grooming	0.696	0.785	0.998	0.998
Littering	0.496	0.493	0.927	0.456
Digging	N/A	0.235	N/A	N/A
Eating	0.791	0.903	1.000	0.998
Scratching	0.583	0.594	0.885	0.450
Shaking	0.092	0.052	0.407	0.283
Allogrooming	N/A	0.129	N/A	N/A
Average	0.479	0.463	0.828	0.781

Table A34. F1-score for modelling round 2.

	CRF	HRF	CSOM	HSOM
Active	0.570	0.626	0.990	0.988
Lying	0.860	0.946	0.999	1.000
Sitting	0.763	0.838	0.999	1.000
Standing	0.597	0.595	0.996	0.994
Grooming	0.722	0.793	0.999	0.998
Littering	0.518	0.548	0.989	1.000
Eating	0.807	0.914	1.000	1.000
Scratching	0.588	0.559	0.949	0.968
Average	0.678	0.727	0.990	0.993

Table A35. F1-score for modelling round 3.

	CRF	HRF	CSOM	HSOM
Active	0.579	0.644	0.927	0.997
Lying	0.855	0.944	0.967	1.000
Sitting	0.763	0.824	0.998	0.999
Standing	0.582	0.589	0.994	0.995
Grooming	0.749	0.862	0.964	1.000
Eating	0.544	0.607	0.904	1.000
Average	0.679	0.745	0.959	0.998

Table A36. F1-score for modelling round 4.

	CRF	HRF	CSOM	HSOM
Active	0.800	0.788	0.999	0.999
Inactive	0.822	0.827	1.000	1.000
Maintenance	0.859	0.856	0.999	1.000
Average	0.827	0.824	0.999	1.000

Appendix IX – Published paper Chapter 4

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STATEMENT OF CONTRIBUTION
DOCTORATE WITH PUBLICATIONS/MANUSCRIPTS

We, the student and the student's main supervisor, certify that all co-authors have consented to their work being included in the thesis and they have accepted the student's contribution as indicated below in the Statement of Originality.

Student name:	Michelle Smit
Name and title of main supervisor:	Assoc. Prof. D.G. Thomas
In which chapter is the manuscript/published work?	Chapter 3

Describe the contribution that the student and members of the supervisory team have made to the manuscript/published work:[1]
Conceptualization, M.S., R.A.C.-T., I.D., C.J.A., and D.G.T.; methodology, M.S.; software, M.S.; validation, M.S.; formal analysis, M.S.; investigation, M.S.; data curation, M.S.; writing—original draft, M.S.; writing—review and editing, R.A.C.-T., I.D., C.J.A., and D.G.T.; visualization, M.S.; supervision, R.A.C.-T., I.D., C.J.A., and D.G.T.; project administration, M.S., R.A.C.-T., I.D., C.J.A., and D.G.T.; funding acquisition, D.G.T. All authors have read and agreed to the published version of the manuscript.

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Article

Longitudinal Study on the Effect of Season and Weather on the Behaviour of Domestic Cats (*Felis catus*)

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Simple Summary: This study explored how seasonal and weather variations influence domestic cat behaviours. Using accelerometer data and a validated machine learning model, eight behaviours—active, eating, grooming, littering, lying, scratching, sitting, and standing—were tracked in seven research cats over 13 weeks throughout the year, alongside concurrent weather data collection. Generalised linear mixed models revealed seasonal differences for eating, grooming, littering, lying, scratching, and sitting but not for active behaviours or standing. A higher temperature humidity wind index and longer daylength increased time spent eating, lying, and standing while reducing time spent active, grooming, littering, and sitting. More rain led to less time grooming and scratching. These findings highlight seasonality in cat behaviours, influenced by weather conditions, and can aid in providing guidance to cat facility managers as to when additional resources could be beneficial, such as brushing cats in times when grooming and scratching are increased.

Abstract: To date, little is known about seasonal changes in specific cat behaviours, and how these are affected by weather patterns. Using accelerometer data and a validated machine learning model, behaviours including being active, eating, grooming, littering, lying, scratching, sitting, and standing were quantified for seven research cats for a total of 13 weeks spread over one year, with weather data being collected simultaneously. Generalised linear mixed models were used to statistically test for seasonal differences in proportional behavioural data and how behaviour was affected by weather variables. Seasonal differences were found for time spent eating ($p < 0.001$), grooming ($p < 0.001$), littering ($p = 0.037$), lying ($p < 0.001$), scratching ($p < 0.001$), and sitting ($p < 0.001$) but not for active behaviours and standing ($p > 0.05$). A positive interaction effect of the temperature humidity wind index and daylength was found for time spent eating, lying, and standing (all $p < 0.001$), while it was negative for active ($p < 0.001$), grooming ($p < 0.001$), littering ($p = 0.004$), and sitting ($p < 0.001$). Rainfall negatively affected grooming ($p = 0.023$) and scratching ($p = 0.037$). These findings highlight seasonality in cat behaviours, influenced by weather conditions.

Keywords: feline; domestic cat; research cat; seasonal behaviour; weather

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Received: 22 January 2025
Revised: 14 February 2025
Accepted: 21 February 2025
Published: 22 February 2025

Citation: Smit, M.; Andrews, C.J.; Draganova, I.; Corner-Thomas, R.A.; Thomas, D.G. Longitudinal Study on the Effect of Season and Weather on the Behaviour of Domestic Cats (*Felis catus*). *Animals* **2025**, *15*, 637. https://doi.org/10.3390/ani15050637

1. Introduction

Any living individual displays at least one behaviour at any given time, which is a response to either internal or external stimuli, or a combination of both [1]. Domestic cats can be exposed to a range of external stimuli that differ based on how they are housed. A recent large-scale study across Europe, North America, Australia and, New Zealand reported that approximately 59% of pet cats had access to the outdoors [2]. In New Zealand, an estimated 83% (~1 million) of pet cats have outdoor access [3], where they are exposed to seasonal and meteorological changes (i.e., weather patterns). To date, little is known about how these changes might affect the behaviour of domestic cats.

Seasons are characterised by differences in daylength and weather. The natural light–dark cycle plays a key role in the timing of peak activity of organisms [4,5], including domestic cats [6–8]. Daylength also plays a role in seasonal activity, with [9] reporting that indoor research cats, housed under natural light conditions and constant temperature and relative humidity, travelled greater distances in both spring and autumn than in winter. Other studies also reported differences in activity between seasons, although this differed between housing conditions. Free-roaming cats have been shown to be more active in spring and summer than in autumn and winter [10–12]. These studies, however, did not distinguish between pet, stray, or feral cats, and did not attempt to identify specific behaviours. Horn et al. [13] compared the activity of unowned free-roaming cats to that of free-roaming pet cats and found contrasting results. Unowned cats were most active in autumn and winter, while pet cats were more active in spring and autumn. They attributed these differences to higher energy demands during the colder months in the unowned cats, while pet cats appeared to prioritise comfort, avoiding extreme hot and cold conditions. While seasonal data can provide valuable insights, utilised alone it does not specifically indicate which weather variable might play a role in behavioural changes.

In free-roaming cats, activity has been reported to be positively and negatively correlated with temperature and rain, respectively [10–12]. Konecny et al. [14] reported the lowest activity in feral cats was around midday when the ambient temperature was at its highest. While Izawa [15] also reported a negative correlation between temperature and activity during the day, this correlation was positive during the night. A questionnaire-based study, including both indoor-only and free-roaming pet cats, found that extreme weather events affected specific behaviours of pet cats [16]. Sudden decreases in temperature were associated with an increase in eating behaviour, whereas intake decreased in hot weather (temperature not specified). There was, however, a lack of detail on what constituted excessively hot temperatures, and owner-reported data are subjective [16].

Current knowledge of the effects of season and weather changes on cat behaviour have primarily come from activity studies using visual observation, radio tracking, Global Positioning Systems (GPS), or accelerometers. While these studies can provide valuable insights into activity patterns, they do not capture the full range of behaviours that cats display. Traditionally, for behavioural studies, researchers have relied on direct observation of the animal(s) and manual recording of behaviours using an ethogram [17,18]. Though effective, direct observation is labour intensive, limited by the ability of the observer to continuously monitor animals for long periods or in challenging environments, and is subjective [17,18]. The emergence of video recording devices has allowed more detailed behaviour capture and analysis to occur, with the ability to pause and review footage multiple times, thereby limiting the effect of observer fatigue [18]. In addition, video recording, when operated from a distance or remotely, can limit the potential effect of the presence of an observer on animal behaviour [18]. Scoring behaviour from video recordings, however, remains labour intensive. In addition, several studies have reported high interindividual variation in activity among domestic cats, despite being housed under the same conditions [19–21]. The use of high-frequency accelerometer data in combination with machine learning (ML) has emerged as an alternative, less labour-intensive tool to classify animal behaviours.

Several studies have now validated ML models to continuously and objectively classify domestic cat behaviour from acceleration data, providing more comprehensive data than traditional observation methods [22–25]. Accelerometers and ML offer great potential in studying behavioural responses to external stimuli, such as seasonal and weather-related changes. A previous study examined the effects of season and housing conditions on eight behaviours of pet cats, with behaviour being classified using accelerometers and machine learning (ML) [26]. In this study, pet cats with outdoor access showed lower levels of active behaviours (walking and trotting) in winter than summer, whereas no seasonal differences were observed among indoor-only pet cats. The remaining seven behaviours (eating, grooming, littering, lying, scratching, sitting, and standing) were not affected by season or housing but were influenced by other environmental factors, including the presence of children and other cats. Previously validated ML models have been used successfully in other animal species for behavioural studies, for example, chipmunks (*Tamias* spp.) [27], oystercatchers (*Haematopus ostralegus*) [28], and pumas (*Puma concolor*) [29]. While these studies did not specifically examine the effects of environmental factors such as temperature, humidity, and rainfall on animal behaviour, they illustrated the power of accelerometery and machine learning for studying animal behaviour. The current study aimed to investigate seasonal domestic cat behavioural patterns, quantified using accelerometer data and a model previously validated by the same authors [24], and the influence of weather patterns on them, in a controlled environment.

2. Materials and Methods

This study was conducted at the Massey University Centre for Feline Nutrition, Palmerston North, New Zealand (latitude 40°23′ S, longitude 175°36′ E). The study was approved by the Massey University Animal Ethics Committee (MUAEC 22/23).

2.1. Animals and Housing

Eight healthy, desexed male (n = 4) and desexed female (n = 4) domestic shorthair cats were group housed in a single semi-outdoor colony cage for a year (Figure 1). At the start of the trial, the average ± SD age of the cats was 4.2 ± 0.8 years, and bodyweight was 4.2 ± 0.9 kg. The bodyweight of every cat was measured on a weekly basis throughout the trial. Cats were fed a complete and balanced [30] commercial canned diet (Heinz Wattie's Ltd., Hastings, New Zealand), and had ad libitum access to water for the duration of the study.

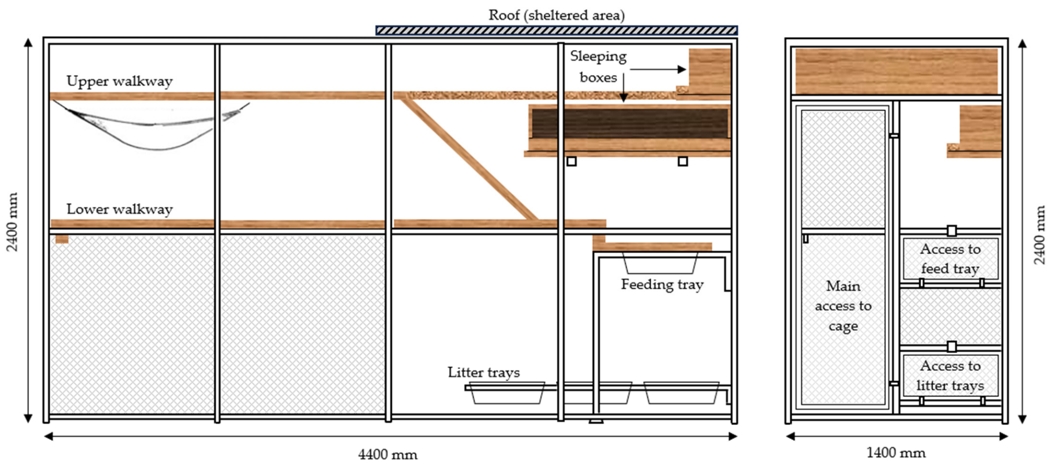

Figure 1. Colony cages as seen from the side (**left**) and front (**right**), measuring 1400 × 2400 × 4400 mm. (Figure first published in [24]).

2.2. Accelerometer Data Collection

ActiGraph™ wGTX-BT accelerometers (weighing 19 g and measuring 33 mm × 46 mm × 15; dynamic range ± 8 g; ActiGraph® Pensacola, FL, USA) were positioned ventrally on a collar (Figure 2a), with the orientation of the x-, y-, and z-axes laterally, dorso-ventrally, and cranio-caudally, respectively (Figure 2b). Acceleration data were sampled at a frequency of 30 Hz (defined as the raw acceleration data) and then downloaded and exported into csv files using ActiLife software (version 6.13.4; ActiGraph™, Pensacola, FL, USA). Raw acceleration data were feature engineered to and summarised into 1 s epochs to obtain the 32 variables required by the behaviour classification model as previously described in [24]. Using the feature-engineered data, the behaviour of the cats was classified using a collar-based model previously validated by [24]. The model classifies behaviour for every 1 s datapoint and had an overall accuracy of ~73% and F1-score of ~68% and classified eight different behaviours: active (walking and trotting), eating, grooming, littering, lying, scratching, sitting, and standing (see Table 1 for behaviour descriptions). This combination of behaviours was selected due to their performance in the ML model and potential medical relevance (e.g., scratching for dermatological problems) as described in [24]. Accelerometer data were collected for seven consecutive days, every four weeks for a year, starting in March 2023, and ending in February 2024 (Figure 3), capturing a total of 91 days of accelerometer data per cat. Events that deviated from normal were noted, such as a social disturbance resulting from a new individual being introduced to a pen, or groups of students visiting for practical classes.

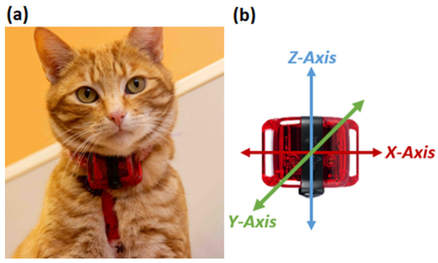

Figure 2. (**a**) Placement and (**b**) orientation of the ActiGraph™ wGT3X-BT accelerometer on a collar. (Figure first published in [24]).

Table 1. Description of behaviours as identified by the machine learning model. (Definitions first described in [24] and adapted from [31], unless otherwise stated).

Behaviour	Description
Active (walking and trotting)	Walking: forward locomotion at a slow, four-beat and symmetric gait with limbs moving sequentially. Includes slow walk (three or four feet in contact with the ground at any time) and fast walk (two or three feet in contact with the ground at any time). Slowest gait. Trotting: Forward locomotion with a swift, two-beat and symmetric gait. Body is supported by two diagonal legs during contact with ground. Intermediate gait [32,33].
Eating	Cat ingests food (or other edible substances) by means of chewing with the teeth and swallowing.
Grooming	Cat cleans itself by licking, scratching, biting, or chewing the fur on its body. May also include licking of a front paw and wiping it over the head.
Littering	Cat urinates or defecates.
Lying	Cat's body is in contact with the ground in a horizontal position, including on its side, back, belly, or curled in a circular formation.

Table 1. *Cont.*

Behaviour	Description
Scratching	Cat scratches its body using the claws of its hind feet.
Sitting	Cat is in an upright position, with the hind legs flexed and resting on the ground, while front legs are extended and straight.
Standing	Cat is in an upright position and immobile, with all four paws on the ground and legs extended, supporting the body.

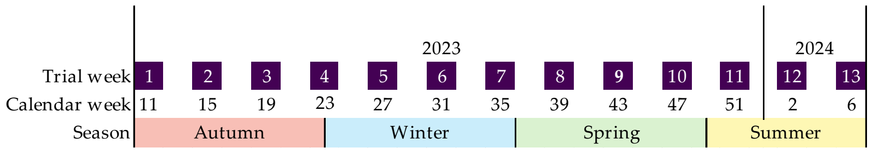

Figure 3. Timeline of data collection, including calendar year and week, trial week, and the season (red = autumn, blue = winter, green = spring, yellow = summer).

2.3. Weather Data Collection

A Vantage Pro2™ ISS weather station (Davis Instruments, Hayward, CA, USA) located at the Centre for Feline Nutrition (−40.390344, 175.615829) collected hourly weather data continuously from 1 March 2023 till 29 February 2024. The weather station was connected to a solar panelled gateway EnviroMonitor System (Davis Instruments, Hayward CA, USA), which sent hourly weather data via cellular connection to https://www.weatherlink.com/, from which the hourly weather data were downloaded. Seven weather variables were selected: average temperature (°C), minimum and maximum temperature (°C), average relative humidity (%), average temperature, humidity and windchill index (THW, °C), average wind speed (m/s), and total rainfall (mm; Table 2). Four seasons were recognised: autumn (March–May), winter (June–August), spring (September–November), and summer (December–February).

Table 2. Units and definitions of selected weather variables.

Weather Variable	Unit	Definition [34]
Temperature	°C	Average temperature over the 60 min period.
Minimum temperature	°C	Minimum temperature recorded over the 60 min period.
Maximum temperature	°C	Maximum temperature recorded over the 60 min period.
Relative humidity	%	Average saturation of the air with water at its current temperature over the 60 min period.
THW index	°C	Average calculated temperature per 60 min period that takes temperature, humidity, the heating effects of sunshine, and cooling effects of the wind (wind chill) into account to determine what it feels like in the shade. [1]
Rainfall	mm	The total rainfall recorded during the 60 min period
Wind speed	m/s	The average wind speed recorded during the 60 min period.

[1] THW index = heat index − (1.072 × wind speed) [35], with heat index determined based on [36,37].

The R package 'suncalc' [38] was used to obtain daily data on the exact times of light phases based on the longitude and latitude coordinates of the weather station (−40.390344, 175.615829). With these data, daylength was determined.

2.4. Statistical Analyses

All data computation and statistical analyses were carried out using RStudio version 4.1.1 [39]. Statistical significance was defined as $p \leq 0.05$, with a trend being 0.05 > p < 0.10. All results are presented as the mean ± standard error of the mean (SEM).

2.4.1. Seasonal Differences

Following behaviour classification, the data were cleaned by removing acceleration data from the times each cat was not wearing the collar. Seasons were assigned to the individual datapoints in the dataset based on the calendar date. For each season, the proportion of time each cat was classified as exhibiting each behaviour was determined. Outliers were identified using boxplots and were removed if they occurred during a noted event or disturbance. Generalised linear mixed models (GLMMs), using the R package 'glmmTMB' [40], with a beta distribution and logit link to account for the proportional nature of the data, were used to statistically test the proportional behavioural data. Three GLMMs were created for each behaviour: (1) a simple model with no predictors, (2) an intermediate model with only cat as a random effect, and (3) a full model that included cat as a random effect and the season as a fixed effect as in Equation (1):

$$logit(\mu_{ij}) = \beta_0 + \beta_1 X_{ij} + u_j \quad (1)$$

where μ_{ij} is the expected proportion of time cat j spends on the behaviour in observation i, β_0 is the intercept, β_1 is the fixed effect of season, X_{ij} is the categorical variable indication season for observation i for cat j, and $u_j \sim \mathcal{N}(0, \sigma^2)$ is the random intercept for cat j to account for individual differences.

The three models were compared with an ANOVA to determine which factors improved the model, and the marginal and conditional R^2 of the full models were determined. The marginal R^2 value is the variance explained by only the fixed effect, whereas the conditional R^2 value is the variance explained by both the random and fixed effects. Bodyweights were averaged over the seasons for each cat and analysed using a linear mixed-effects model to determine seasonal differences. To determine differences between the seasons, pairwise comparisons of estimated marginal means were conducted for each behaviour and cat bodyweight using the R package 'emmeans' [41]. A Tukey adjustment was used to correct for multiple pairwise comparisons.

2.4.2. Effect of Weather Variables on Behaviour

Daily proportions for each behaviour were calculated using the cleaned dataset, and daily averages for temperature (including minimum and maximum), relative humidity, THW index, and wind speed, and the sum of rainfall were calculated. These daily averages were merged with daily behavioural proportions based on date, and the effect of weather conditions were statistically tested using a GLMM with a beta distribution and logit link. Similar to the GLMM testing above, three GLMMs were performed, with the same simple and middle models. The full model included cat as a random effect and weather conditions as fixed effects. The full model followed the same mathematical formulation and assumptions as in Equation (1) but with the fixed effects being weather variables.

The marginal and conditional R^2 values for each model were determined. The inclusion of weather conditions as fixed effects was determined based on their correlation coefficients, which were interpreted as defined by [42]. Weather data were scaled using the scale function in R prior to statistical modelling.

3. Results

Data collection originally scheduled for calendar week 43 (trial week 9) was postponed by a week until week 44 due to illness of the researcher. One of the cats was humanely euthanised due to an illness unrelated to the study; therefore, only data from seven cats were included in the data analyses. One week of data was not collected for two cats, one in trial week 9 and one in trial week 12, due to animal illness.

A small number of outliers were identified in the dataset (Figure 4). Most identified outliers for grooming and scratching were found to belong to one cat: Cho. She was diagnosed with seasonal allergies, and therefore, her grooming and scratching data were excluded from the data analyses. Large variations in many behaviours were observed among all cats in trial week 5 when compared to other trial weeks (Supplementary Material S1). In that week, one cat was placed back into an incorrect pen, which appeared to impact both its behaviour and that of the other cats in the study. For this reason, the behavioural data of trial week 5 were removed from the dataset for all cats and excluded from data analyses. The previously mentioned outliers were removed as they could have introduced confounding effects. Large variations in behaviour were observed for Nimbus in trial week 10, but no events or disturbances were reported for that week, and, therefore, these data were not removed (Supplementary Material S1 Figure S6). Table 3 shows the seasonal and total amount of data included per cat in the final data analyses, following the removal of when cats were not wearing the collar and outliers as defined previously.

Table 3. Seasonal and total amount of days, hours, minutes, and seconds included per cat in the final data analyses.

	Autumn	Winter	Spring	Summer	Total
Cho [1]	20 days 00:41:13	19 days 00:24:24	20 days 00:07:44	17 days 00:01:42	77 days 00:15:03
George	23 days 00:00:00	20 days 00:43:59	21 days 00:00:00	18 days 00:14:59	82 days 00:58:58
Hagrid	23 days 00:00:00	20 days 00:00:00	21 days 00:00:00	17 days 00:17:59	83 days 00:17:59
Merry	23 days 00:00:00	20 days 00:00:00	21 days 00:00:00	17 days 00:44:59	82 days 00:44:59
Mrs. Norris	23 days 00:00:00	20 days 00:00:00	14 days 00:00:00	18 days 00:00:00	76 days 00:00:00
Nimbus	23 days 00:00:00	20 days 00:00:00	20 days 00:34:59	18 days 00:00:00	83 days 00:34:59
Scabbers	23 days 00:00:00	13 days 00:00:00	21 days 00:00:00	18 days 00:00:00	76 days 00:00:00

[1] Seconds identified as grooming or scratching behaviour were removed before calculating total days, hours, minutes, and seconds of data included in data analyses.

3.1. Seasonal Differences

3.1.1. Bodyweight

Cats were weighed weekly (Figure 5), and their weights averaged per season of the year. Six cats were included in the analysis due to weight loss in one cat (Mrs. Norris). No significant differences in average bodyweight were identified among seasons (4.2 ± 0.4 kg; $p > 0.05$).

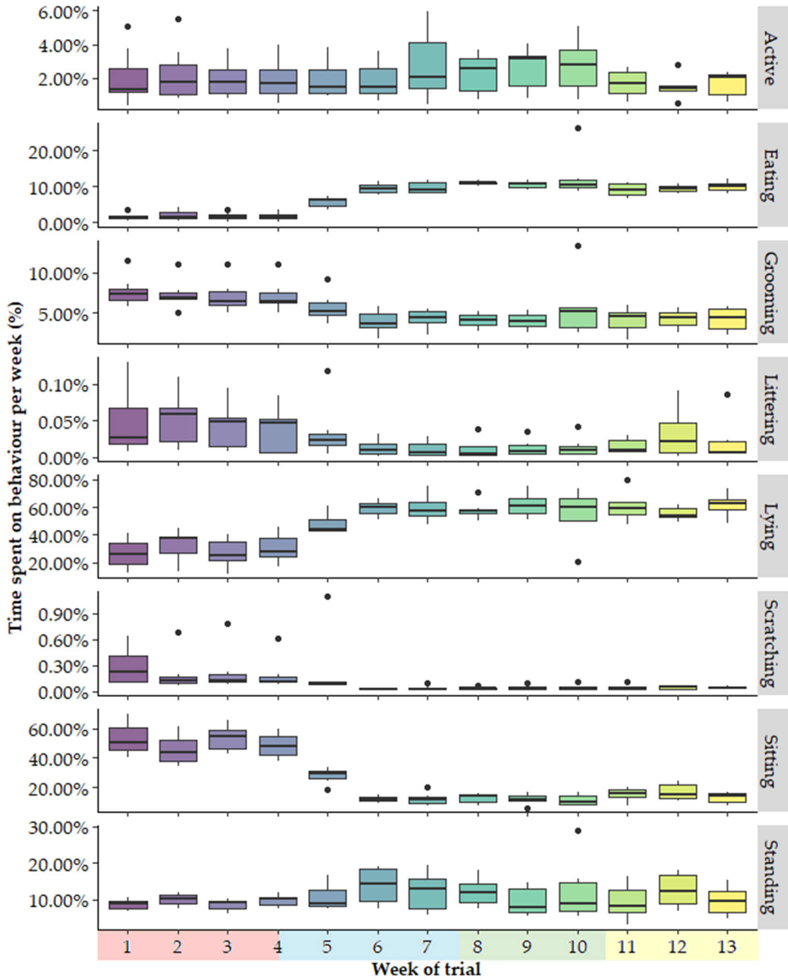

Figure 4. Boxplots of weekly proportional behaviour data. • indicate outliers and seasons are indicated along the x-axis by colours: red = autumn, blue = winter, green = spring, yellow = summer.

3.1.2. Behaviours

Inclusion of cat as a random effect improved the active behaviours GLMM (p = 0.003) but not the GLMM of eating, grooming, littering, lying, scratching, sitting, and standing ($p > 0.05$; Table 4). Inclusion of season as a fixed effect improved the GLMM model for eating ($p < 0.001$), grooming ($p < 0.001$), littering (p = 0.037), lying ($p < 0.001$), scratching ($p < 0.001$), and sitting ($p < 0.001$) but not for active behaviours and standing ($p > 0.05$; Table 4).

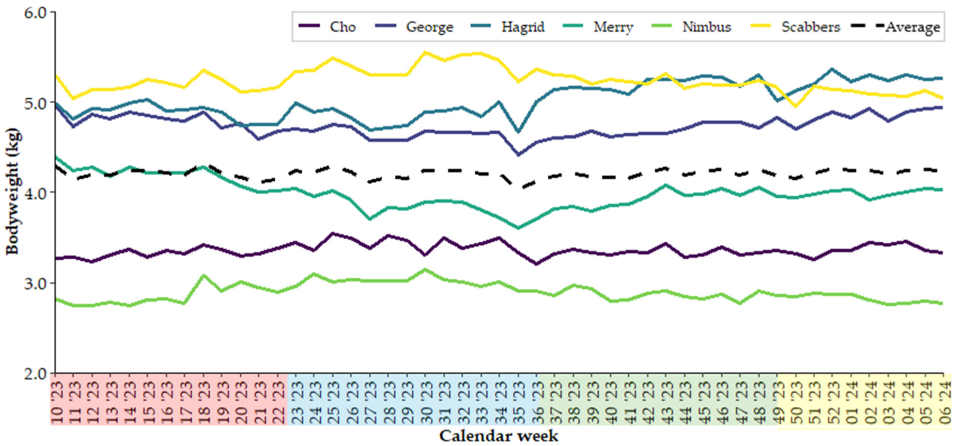

Figure 5. Weekly bodyweight (kg), expressed per calendar week, of all individual cats included in the study. Seasons are indicated along the x-axis by colours: red = autumn, blue = winter, green = spring, yellow = summer.

Table 4. Marginal and conditional R-squared (R^2) values for each behaviour.

Behaviour	R^2	
	Marginal [1]	Conditional [1]
Active	0.08	0.66 *
Eating	0.95 *	0.95
Grooming	0.41 *	0.81
Littering	0.25 *	0.38
Lying	0.88 *	0.93
Scratching	0.60 *	0.93
Sitting	0.94 *	0.94
Standing	0.13	0.50

[1] Marginal R^2 = variance explained by the fixed effects; conditional variance = variance explained by both the fixed and random effects [43]. * Indicates significant improvement of the model ($p < 0.001$).

Cats were observed to spend the most time eating in spring (11.34 ± 0.48%), followed by summer (9.52 ± 0.48%) and winter (7.73 ± 0.83%), and the least in autumn (1.73 ± 0.42%; Figure 6a). Time spent eating was lower in autumn compared to the three other seasons ($p < 0.001$) and was lower in winter than in both spring ($p < 0.001$) and summer ($p = 0.035$). A trend was found for the difference between spring and summer ($p = 0.057$).

Cats groomed most in autumn (6.83 ± 0.47%), followed by winter (4.57 ± 0.70%), spring (4.46 ± 0.56%), and summer (4.04 ± 0.47%; Figure 6b). Time spent on grooming was higher in autumn compared to all the other three seasons ($p < 0.001$). A trend was found for higher levels in winter compared to summer ($p = 0.083$) and no differences were found between spring and either winter or summer ($p > 0.05$).

Cats littered most in autumn (0.046 ± 0.012%), followed by summer (0.022 ± 0.004%), winter (0.017 ± 0.004%), and spring (0.013 ± 0.009%; Figure 6c). Time spent littering was higher in autumn compared to winter ($p = 0.022$), spring ($p = 0.002$), and summer ($p = 0.021$). No differences were found between winter, spring, and summer ($p > 0.05$).

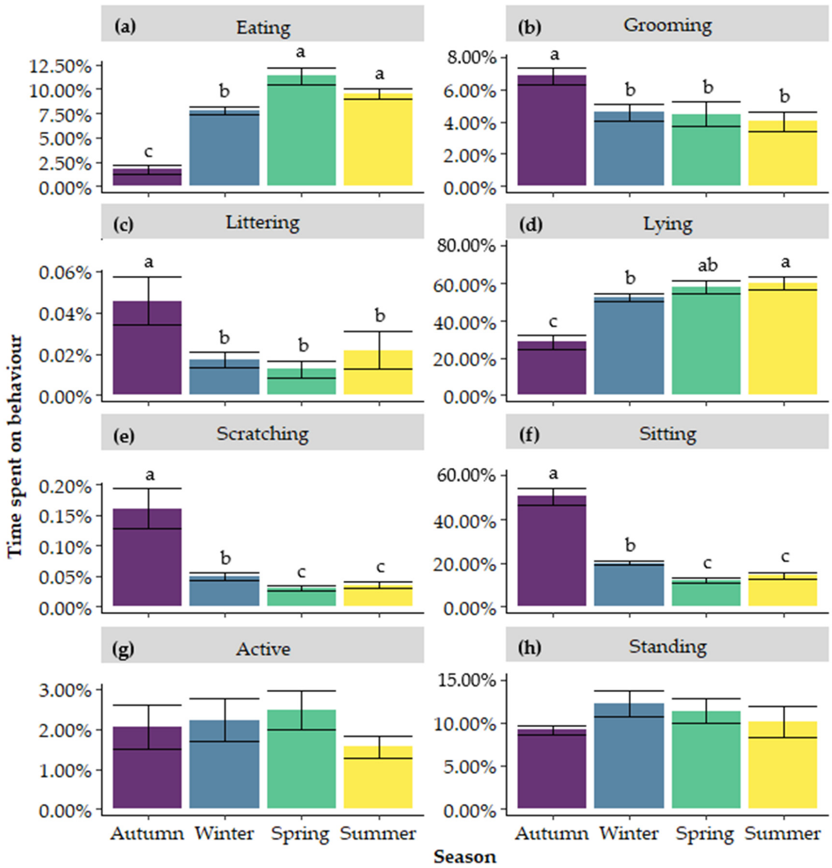

Figure 6. Average time spent (**a**) eating, (**b**) grooming, (**c**) littering, (**d**) lying, (**e**) scratching, (**f**) sitting, (**g**) active, and (**h**) standing in autumn, winter, spring, and summer. [a–c] Different superscripts indicate significant differences ($p \leq 0.05$).

Cats spent most time lying in summer (60.33 ± 3.92%), followed by spring (58.29 ± 3.37%), winter (52.88 ± 3.52%), and autumn (28.68 ± 3.93%; Figure 6d). Time spent on lying was lowest in autumn compared to all other seasons ($p < 0.001$). A trend was found for the difference between winter and summer ($p = 0.076$), and no difference was found between spring and summer ($p > 0.05$).

Cats scratched most in autumn (0.16 ± 0.03%), followed by winter (0.05 ± 0.00%), summer (0.04 ± 0.02%), and spring (0.03 ± 0.01%; Figure 6e). Cats spent the most time scratching in autumn compared to the other three seasons ($p < 0.001$). Scratching was higher in winter compared to both spring ($p = 0.008$) and summer ($p = 0.014$). No difference was found between spring and summer ($p > 0.05$).

Cats sat most in autumn (50.77 ± 3.73%), followed by winter (20.10 ± 1.14%), summer (14.35 ± 0.97%), and spring (11.98 ± 1.61%; Figure 6f). Cats spent more time sitting in autumn compared to the other three seasons ($p < 0.001$). Cats spent more time sitting in winter compared to both spring ($p < 0.001$) and summer ($p = 0.013$) and no difference was found between spring and summer ($p > 0.05$).

Despite not being significantly different, cats were observed to display active behaviours (walking and trotting) between 1.56 ± 0.54% (in summer) and 2.47 ± 0.27% (in spring; Figure 6g) of their time, and cats stood between 9.15 ± 0.53% (in autumn) and 12.20 ± 1.38% (in winter) of their time (Figure 6h).

3.2. Effect of Weather Variables on Behaviours

Data on weather variations can be found in Supplementary Material S2. Correlation coefficients between weather conditions and daylength are presented in Table 5. A very high correlation was found between the THW index and temperature (0.99), and a high correlation was found between temperature and relative humidity (−0.71). Moderate correlations were found between the THW index and relative humidity (−0.64), daylength and temperature (0.51), and daylength and the THW index (0.50). A low correlation was found between wind speed and relative humidity (−0.46). All other correlations were negligible. Due to the moderate correlation between daylength and the THW index, these were included in the model as an interaction. Thus, 'THW × daylength' and rainfall were included in the GLMM.

Table 5. Correlation matrix with correlation coefficients of weather conditions and daylength.

	Temperature	Relative Humidity	Wind Speed	THW Index	Rainfall	Daylength
Temperature	1.00					
Relative humidity	−0.71	1.00				
Wind speed	0.27	−0.46	1.00			
THW index	0.99	−0.64	0.15	1.00		
Rainfall	−0.04	0.16	0.08	−0.05	1.00	
Daylength	0.51	−0.36	0.13	0.50	−0.04	1.00

For all behaviours, the inclusion of 'THW index × daylength' and rainfall as fixed factors significantly improved the model ($p < 0.001$; Table 6). Inclusion of cat as a random effect improved the model for all behaviours ($p < 0.001$), except for sitting ($p > 0.05$; Table 6). The variance explained by the model differed between behaviours, with the most variance explained for lying ($R^2_{conditional} = 0.68$), sitting ($R^2_{conditional} = 0.61$), and eating ($R^2_{conditional} = 0.57$; Table 6). The model explained < 0.50 of the variance for each of the other behaviours. The 'THW index × daylength' interaction had a significant effect on all behaviours ($p < 0.05$; Table 6). Both THW index and daylength were negatively correlated with the time spent in active behaviours, grooming, littering, scratching, and sitting but positively correlated with eating, lying, and standing. Rainfall negatively affected time spent grooming ($p = 0.023$) and scratching ($p = 0.037$), and a negative trend was found for littering ($p = 0.053$; Table 6).

Table 6. R-squared (R^2), estimates, and p-values for the effect of the THW index, daylength, and rainfall on cat behaviour.

Behaviour	R-Squared		THW Index × Daylength		Rainfall	
	Marginal [1]	Conditional [1]	Estimate [2]	*p*-Value	Estimate [2]	*p*-Value
Active	0.03 *	0.46 †	−0.079	<0.001	−0.018	0.418
Eating	0.52 *	0.57 †	0.264	<0.001	0.001	0.959
Grooming	0.16 *	0.44 †	−0.087	<0.001	−0.043	0.023

Table 6. *Cont.*

Behaviour	R-Squared		THW Index × Daylength		Rainfall	
	Marginal [1]	Conditional [1]	Estimate [2]	*p*-Value	Estimate [2]	*p*-Value
Littering	0.05 *	0.16 †	−0.110	0.004	−0.079	0.053
Lying	0.58 *	0.68 †	0.227	<0.001	−0.034	0.225
Scratching	0.21 *	0.25 †	−0.173	<0.001	−0.082	0.037
Sitting	0.60 *	0.61	−0.290	<0.001	−0.032	0.345
Standing	0.06 *	0.30 †	0.097	<0.001	0.010	0.598

[1] Marginal R^2 = variance explained by the fixed effects; conditional = variance explained by both the fixed and random effects [43]. [2] Estimate based on the log odds ratio scale. * Indicates inclusion of fixed effects significantly improved the model ($p < 0.001$). † Indicates inclusion of the random cat effect significantly improved the model ($p < 0.001$).

4. Discussion

Longitudinal studies of animal behaviour have traditionally been challenging due to their labour-intensive observational methods. Developing ML models to classify cat behaviours from acceleration data has significantly reduced this and allowed for detailed longitudinal behavioural studies. The semi-outdoor living conditions of the cats at the Massey University Centre for Feline Nutrition, which exposes them to natural light and weather conditions, provided an opportunity for a longitudinal study into the effects of season and weather on cat behaviour.

In healthy individuals, changes in bodyweight are the result of an imbalance in energy requirements and energy intake [44]. In this study, no seasonal differences in bodyweight were observed, suggesting there was a balance between energy intake and requirements throughout the year. By contrast, Bermingham et al. [45] observed a seasonal change in bodyweight among cats housed in the same research facility, with bodyweight increasing in the months leading up to winter and decreasing in spring.

Data on seasonal changes in the energy requirements of domestic cats are scarce and contradictory. Kappen et al. [46] reported that indoor-housed research cats required a lower energy intake during short-day (winter) compared to long-day conditions (summer) to maintain their bodyweight. Similarly, Bermingham et al. [47] reported lower energy requirements per kg of bodyweight in winter than in summer for older semi-outdoor-housed research cats (~10 years) but not in younger cats (~3 years) housed either indoors or semi-outdoors. When energy requirements were expressed per kilogram of lean body mass, which closely reflects the amount of metabolically active tissue [44], seasonal differences in the energy requirements were no longer observed in the older cats [47]. Among cats fed ad libitum, bodyweight did not differ between winter and summer, regardless of age and housing condition [47], suggesting energy requirements did not differ seasonally. Conversely, Serisier et al. [48] reported that energy intake in research cats, housed both indoors only and indoors/outdoors and fed ad libitum, was highest in in late autumn and winter. Bodyweight, however, did not change significantly throughout the seasons, suggesting a change in energy requirement with the seasons was driven by maintaining body temperature or changes in physical activity (PA).

Kappen et al. [46] observed a lower PA (measured with an accelerometer) during short-day conditions than long-day conditions, which could have contributed to the lower energy requirements observed during the short-day conditions. Similarly, in the current study, no differences in the amount of time spent on active behaviours were observed between the seasons for cats fed ad libitum, which could explain their stable bodyweights throughout the year. Neither [47] nor [48] measured PA, although [48] argued that the PA of cats in their study remained constant throughout the study, as the housing conditions and periods for free and play activity remained constant. Differences in housing that could have resulted in different energy requirements could be an explanation for the differences in seasonal bodyweight change between the current study and those observed by [45], but this is unlikely as they were housed similarly.

Another factor that can contribute to changes in energy requirements is thermoregulation. Energy requirements increase with decreasing ambient temperatures in order for animals to maintain their body temperature [44]. In evolutionary terms, increasing food intake in anticipation of colder weather would be advantageous for survival, helping to build energy reserves for times when food is scarce. Serisier et al. [48] found that ambient temperature and daylength impacted food intake. In autumn, cats also grow a denser fur coat in anticipation of colder weather, driven by a decrease in daylength and ambient temperatures [49–51]; this requires additional energy expenditure. The discrepancies reported for seasonal bodyweight changes in domestic cats could be due to different climatic conditions across studies, or individual cat variability. When averaged, no seasonal trends in bodyweight were apparent, but some individuals followed the pattern observed by [45], whereas the opposite was seen for others. Reasons for the differences between individuals in the present study are unknown but could be due to differences in individual activity levels or their position in the hierarchy (in a colony setting) and therefore access to food. Hierarchy was not determined in this study, and given the contradictory results and limited data, more research into seasonal fluctuations in energy requirements and bodyweight is warranted.

The weather conditions in the current study, particularly the interaction of the THW index and daylength, affected cat behaviour. Similar correlations between temperature, rainfall, and daylength and domestic cat activity have been reported, with rainfall shown to reduce cat activity [10,11,15,52]; however, rainfall had no effect on the time cats spent on active behaviours in the current study. This difference in results may be due to the cats' living conditions, given that this study utilised research cats that had limited space to roam, whereas other published studies focused on free-roaming domestic cats. A previous study in the same colony as the current study also found a negative relationship between rain and PA measured with an accelerometer and expressed as counts [53]. It is likely this negative relationship was the result of a decrease in grooming and scratching behaviour, both of which were negatively affected by rainfall in the current study, as those have been reported to lead to high activity counts by triggering the accelerometer [19].

While the present study found a negative relationship between the interaction of the THW index and daylength on time spent on active behaviours, others have reported a positive relationship [10,11]. Several factors could explain this difference. Izawa [15], for example, reported that the relationship between cat activity and temperature was positive at night but negative during the day. Environmental factors (time of day, temperature, relative humidity, and rain) have been reported to account for more variance in overall activity in a population with a larger proportion of feral cats (32.6%) compared to free-roaming pet cats (14.9%), suggesting that feral cats are more sensitive to environmental conditions [11]. In the current study, the fixed effects of THW index $\times$ daylength and rainfall explained only ~3% of the variation in time spent showing active behaviours, but this increased to ~46% when individual differences between cats were accounted for. These results suggest there is a complex relationship between activity, the weather, and living conditions, which may vary between individual cats. Additionally, weather conditions can change rapidly, even within an hour. These short-term fluctuations, however, were not captured in the current study, as data were aggregated daily rather than hourly. Future research could explore the relationship between domestic cat behaviour and weather conditions at an hourly resolution to uncover the fine-scale dynamics.

5. Conclusions

This study showed that ML models paired with accelerometer data are powerful tools for conducting detailed, longitudinal studies on cat behaviour. Weather conditions, particularly the interaction between the THW index and daylength, significantly affected cat behaviour, although individual differences between cats also accounted for a large proportion of the variance. Seasonal shifts in grooming and scratching appeared to be linked to seasonal hair growth cycles rather than environmental factors such as rainfall. In addition, this study provided valuable insights into how disruptions, such as the reintroduction of an absent cat, can disrupt behaviour patterns. Further research is needed into the relationship between energy intake, weather conditions, and activity in domestic cats. This study also showed the importance of refining the criteria for identifying outliers and understanding their causes, which will increase the reliability of behavioural studies.

These findings underline the importance of considering both environmental and individual factors when studying domestic cat behaviour, and although this study looked at the effect of weather variables, other environmental factors should be considered, such as different housing and social conditions. Future studies can apply the method to classify domestic cat behaviour in other settings.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/ani15050637/s1, Figure S1: Boxplots of daily proportional behaviour data for Cho; Figure S2: Boxplots of daily proportional behaviour data for George; Figure S3: Boxplots of daily proportional behaviour data for Hagrid; Figure S4: Boxplots of daily proportional behaviour data for Merry; Figure S5: Boxplots of daily proportional behaviour data for Mrs Norris; Figure S6: Boxplots of daily proportional behaviour data for Nimbus; Figure S7: Boxplots of daily proportional behaviour data for Scabbers; Figure S8: Change in daylength and monthly averages for total rainfall, temperature ($\pm$ minimum and maximum), THW index, relative humidity ($\pm$ minimum and maximum) and wind speed (+ maximum) from March 2023 till February 2024.

Author Contributions: Conceptualization, M.S., R.A.C.-T., I.D., C.J.A., and D.G.T.; methodology, M.S.; software, M.S.; validation, M.S.; formal analysis, M.S.; investigation, M.S.; data curation, M.S.; writing—original draft, M.S.; writing—review and editing, R.A.C.-T., I.D., C.J.A., and D.G.T.; visualization, M.S.; supervision, R.A.C.-T., I.D., C.J.A., and D.G.T.; project administration, M.S., R.A.C.-T., I.D., C.J.A., and D.G.T.; funding acquisition, D.G.T. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: The animal study protocol was approved by the Massey University Animal Ethics Committee (MUAEC 22/23).

Informed Consent Statement: Not applicable.

Data Availability Statement: The datasets presented in this article are not readily available because the dataset is too large. Requests to access the datasets should be directed to m.smit@massey.ac.nz.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

GLMM	Generalised linear mixed model
GPS	Global Positioning Systems
ML	Machine learning
PA	Physical activity
SD	Standard deviation

SEM	Standard error of the mean
THW	Temperature humidity windchill

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Appendix X – Trial week boxplot with identified outliers

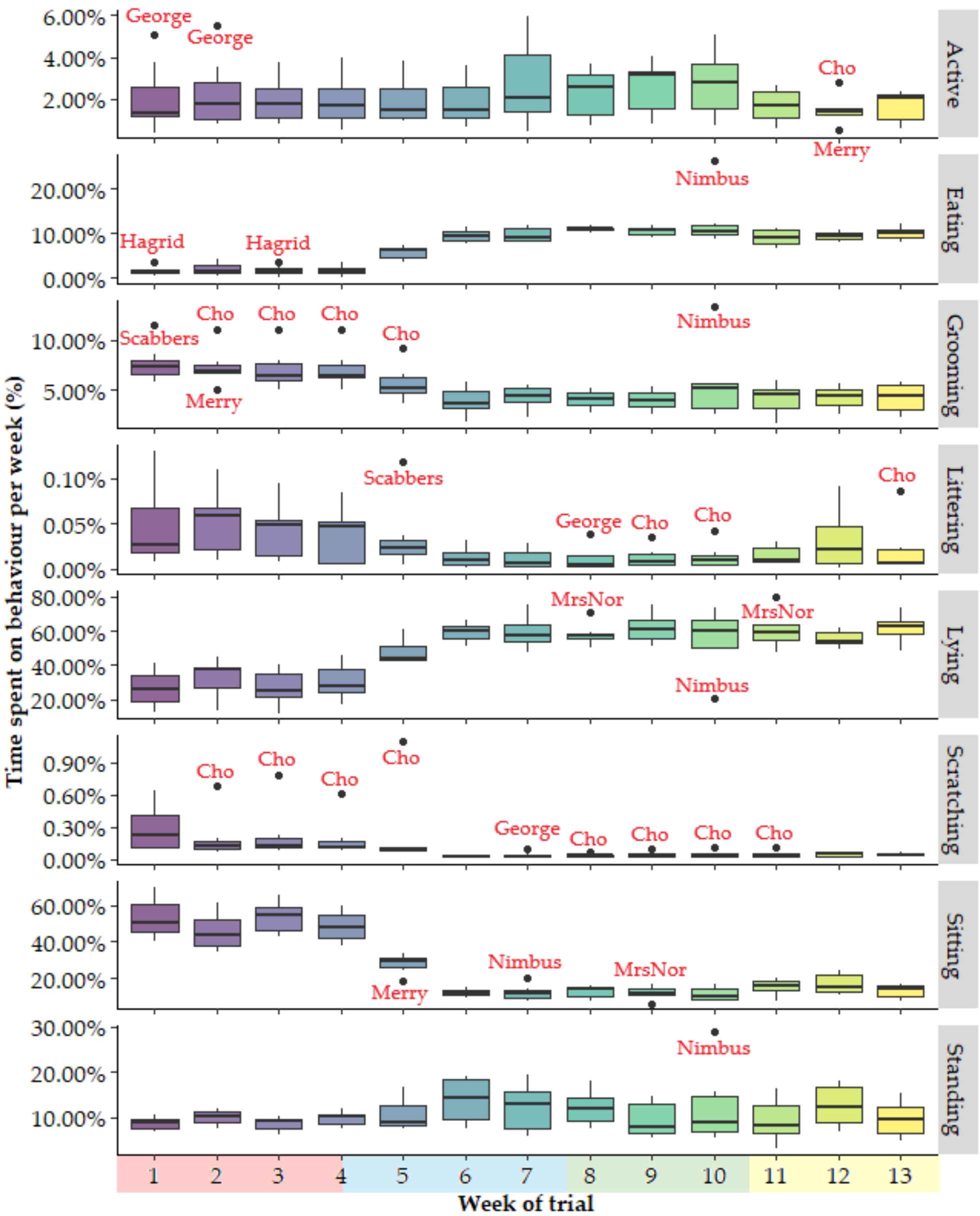

Figure A1. Behavioural boxplots using weekly proportional data. Seasons are indicated along the x-axis by colours: red = autumn, blue = winter, green = spring, yellow = summer.

Appendix XI – Boxplots of individual cats

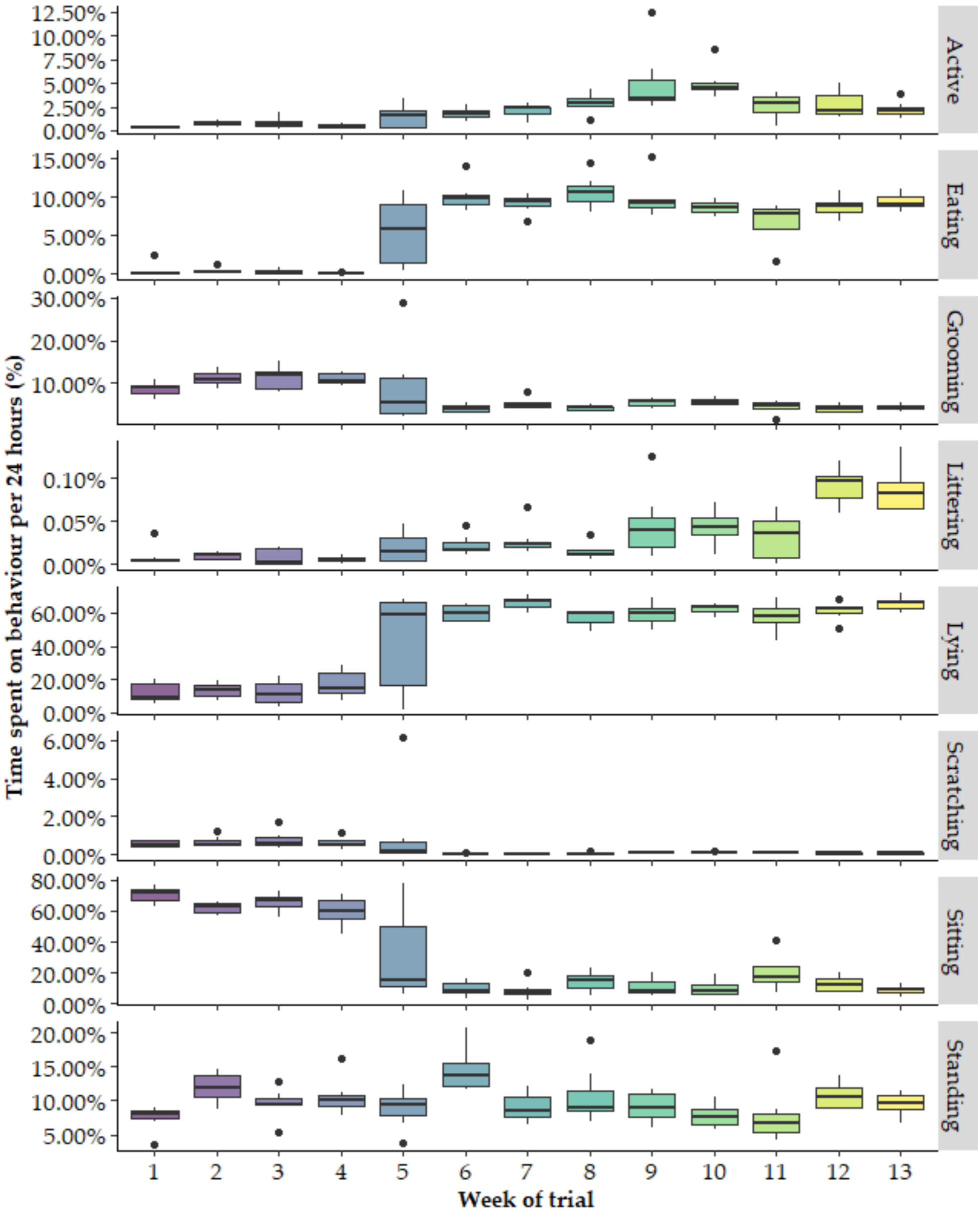

Figure A2. Boxplots of daily proportional behaviour data for Cho.

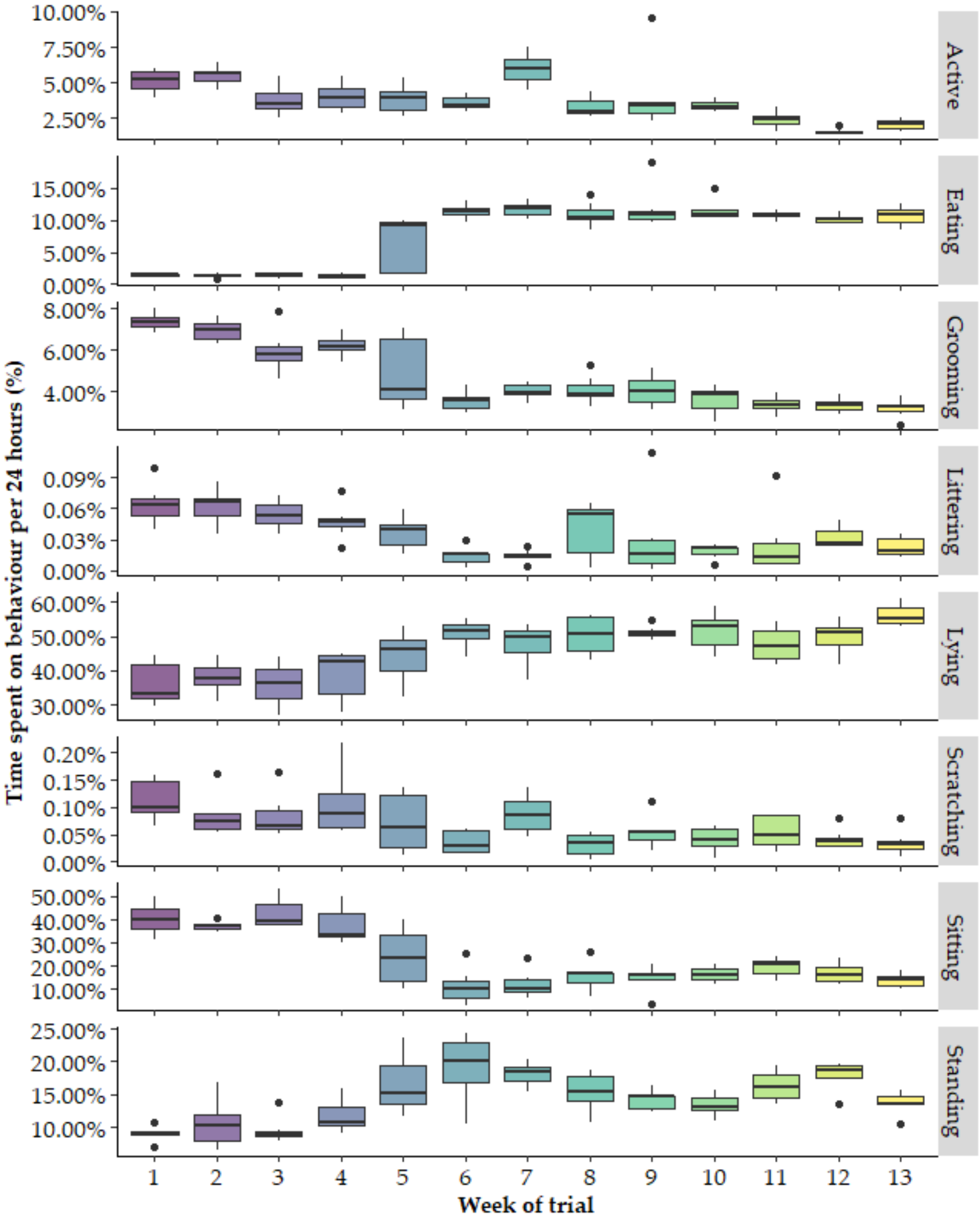

Figure A3. Boxplots of daily proportional behaviour data for George.

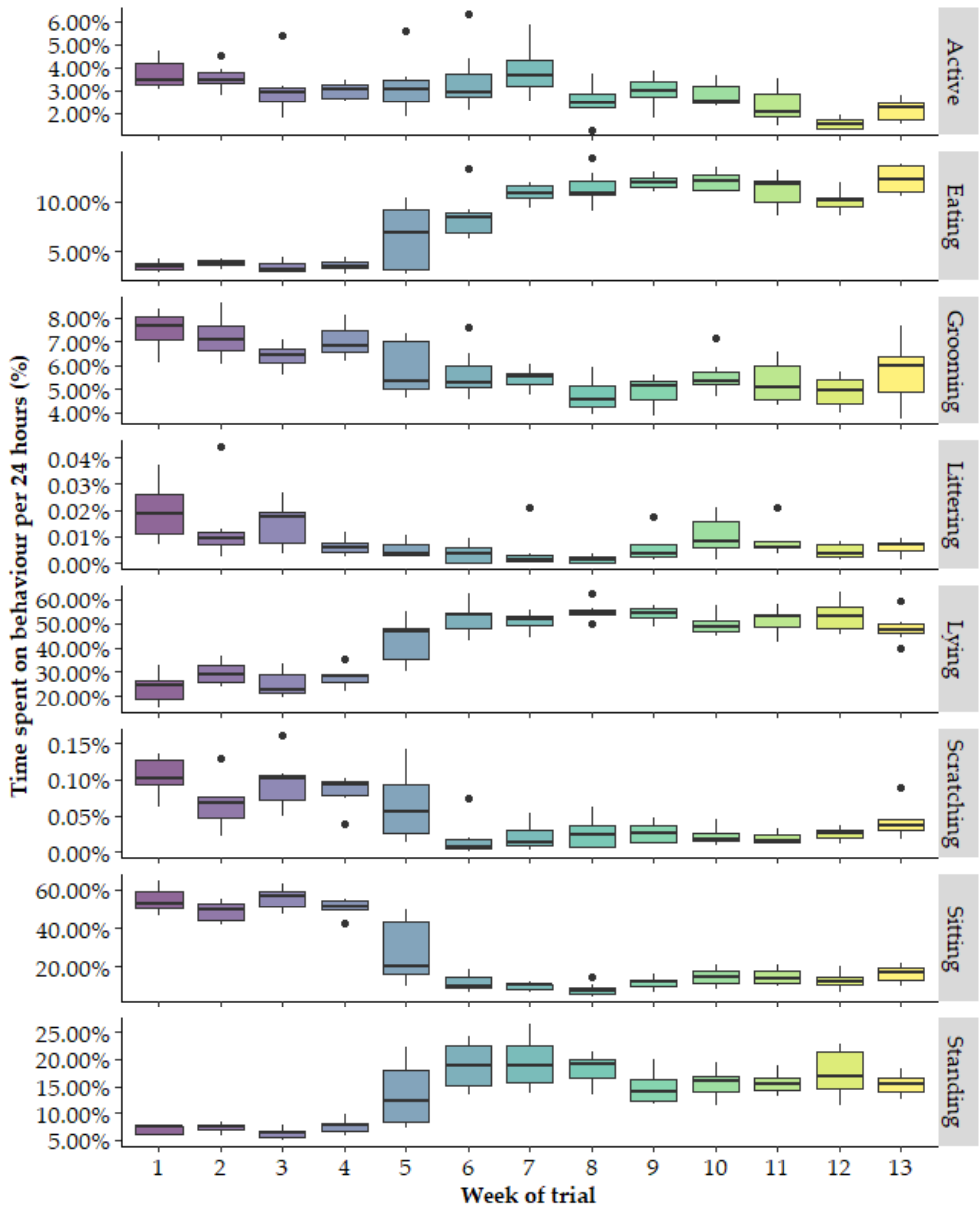

Figure A4. Boxplots of daily proportional behaviour data for Hagrid.

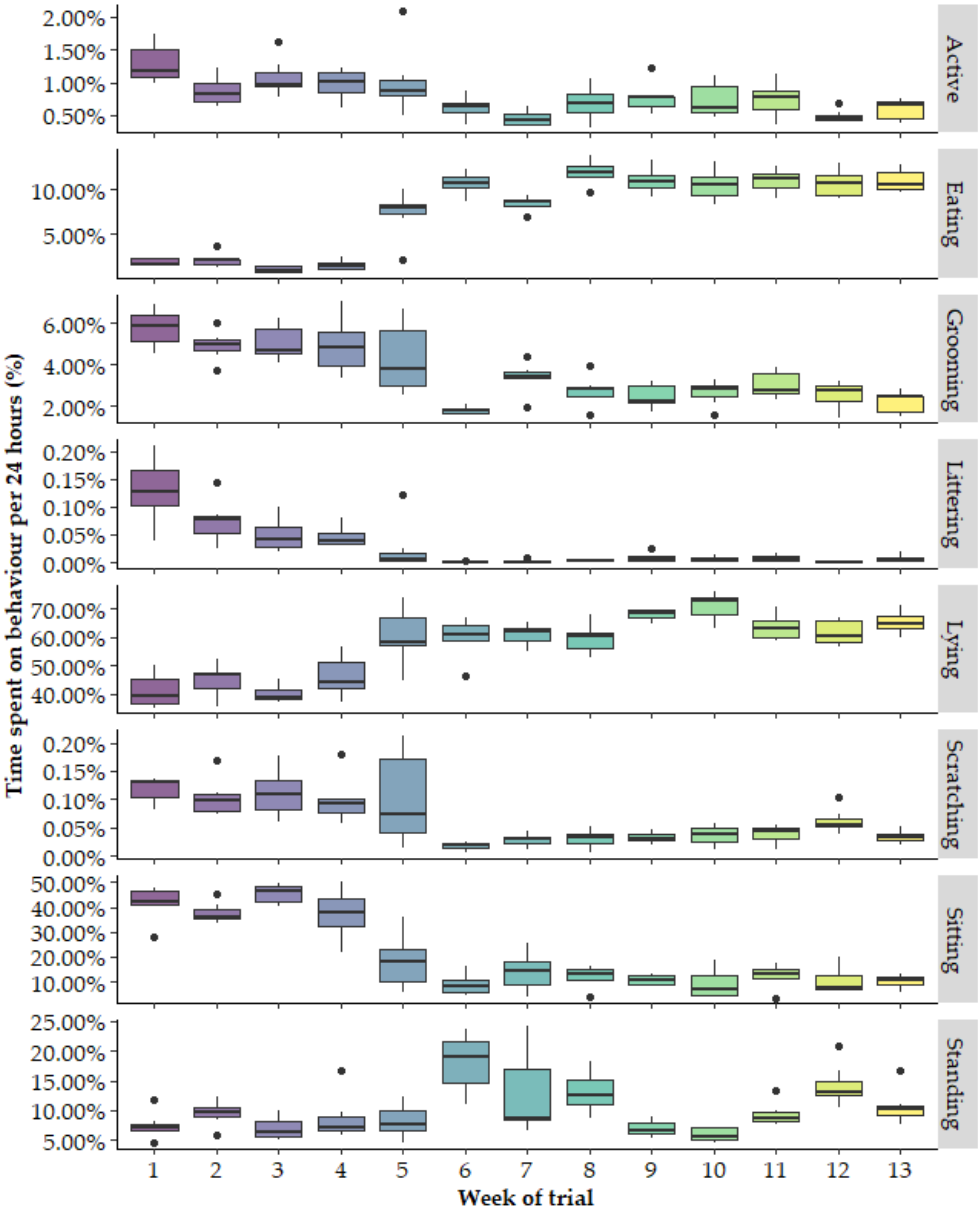

Figure A5. Boxplots of daily proportional behaviour data for Merry.

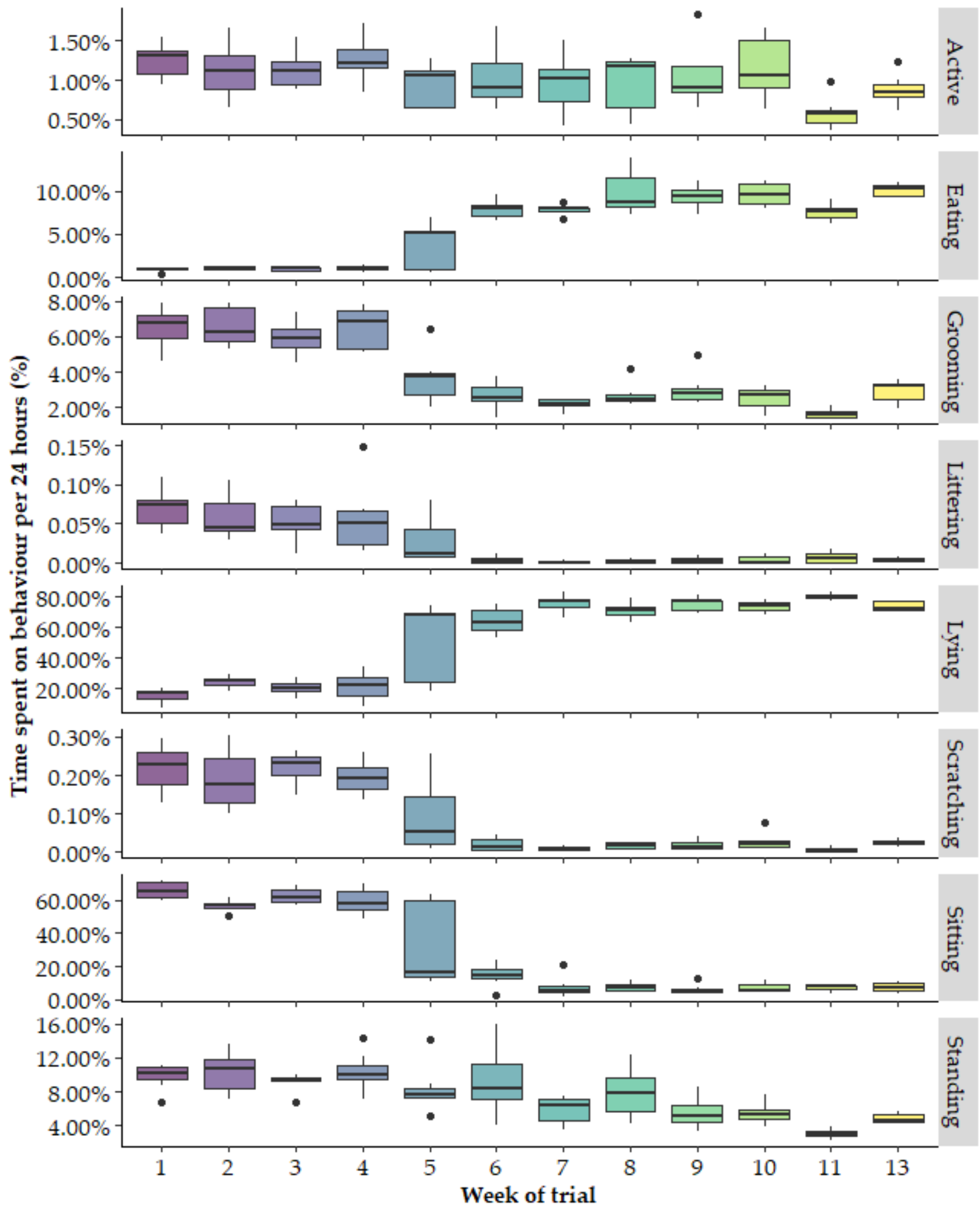

Figure A6. Boxplots of daily proportional behaviour data for Mrs Norris. Data for trial week 12 was removed due to illness.

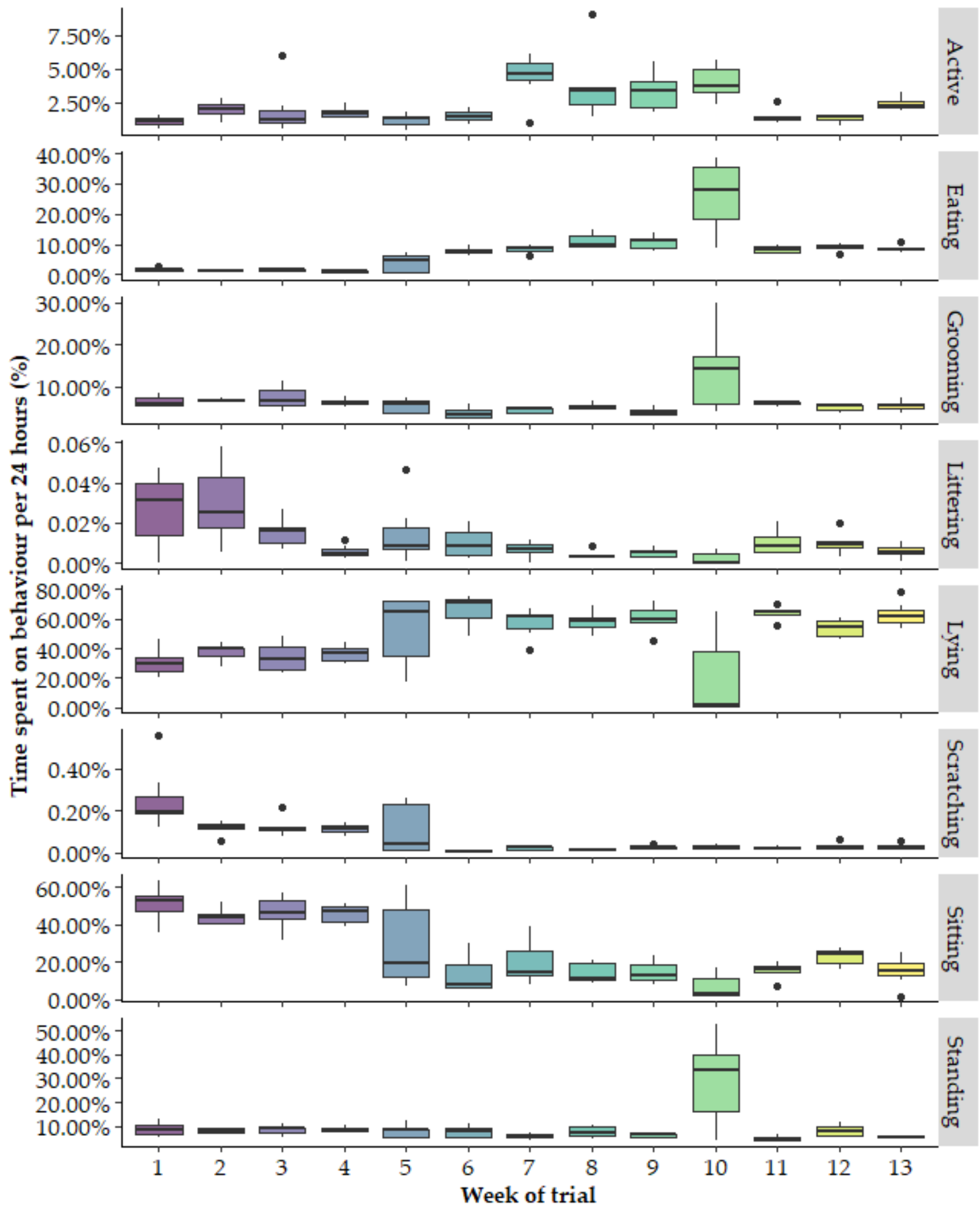

Figure A7. Boxplots of daily proportional behaviour data for Nimbus.

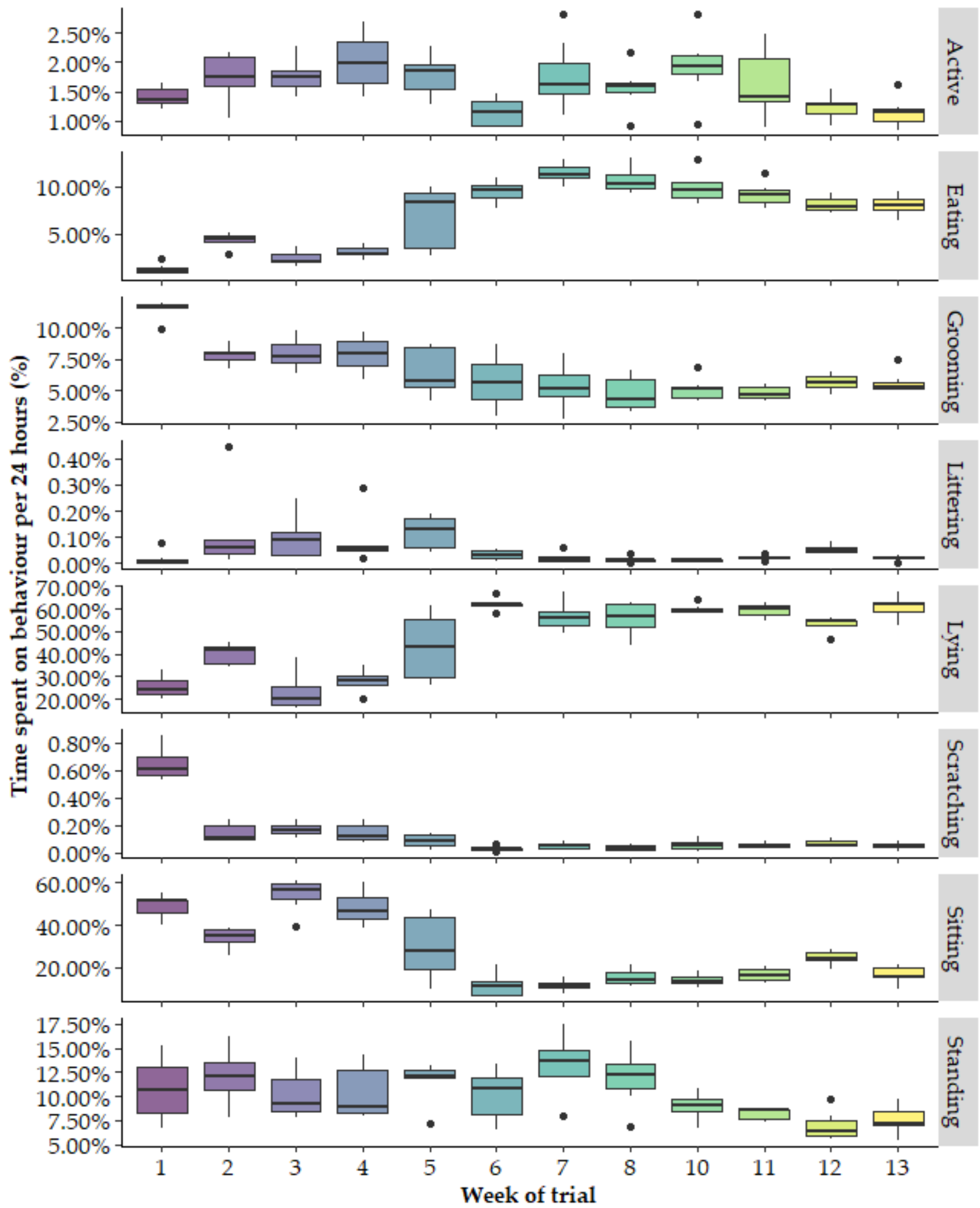

Figure A8. Boxplots of daily proportional behaviour data for Scabbers. Data for trial week 9 was removed due to illness.

Appendix XII – Published paper Chapter 5

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GRADUATE RESEARCH SCHOOL

STATEMENT OF CONTRIBUTION
DOCTORATE WITH PUBLICATIONS/MANUSCRIPTS

We, the student and the student's main supervisor, certify that all co-authors have consented to their work being included in the thesis and they have accepted the student's contribution as indicated below in the Statement of Originality.

Student name:	Michelle Smit
Name and title of main supervisor:	Assoc. Prof. D.G. Thomas
In which chapter is the manuscript/published work?	Chapter 5

Describe the contribution that the student and members of the supervisory team have made to the manuscript/published work:[1]

Conceptualization, M.S., R.A.C.-T., I.D., C.J.A. and D.G.T.; Methodology, M.S.; Software, M.S.; Validation, M.S.; Formal analysis, M.S.; Investigation, M.S.; Data curation, M.S.; Writing—original draft, M.S.; Writing—review & editing, R.A.C.-T., I.D., C.J.A. and D.G.T.; Visualization, M.S.; Supervision, R.A.C.-T., I.D., C.J.A. and D.G.T.; Project administration, M.S., R.A.C.-T., I.D., C.J.A. and D.G.T.; Funding acquisition, D.G.T.

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Smit, M., Corner-Thomas, R. A., Draganova, I., Andrews, C. J., & Thomas, D. G. (2024). How Lazy Are Pet Cats Really? Using Machine Learning and Accelerometry to Get a Glimpse into the Behaviour of Privately Owned Cats in Different Households. Sensors (Basel, Switzerland), 24(8), 2623. https://doi.org/10.3390/

○ **The manuscript is currently under review for publication**

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Student's signature:	Michelle Smit — Digitally signed by Michelle Smit Date: 2024.11.15 17:35:20 +13'00'	Main supervisor's signature:	David Thomas — Digitally signed by David Thomas DN: cn=David Thomas, c=NZ, o=Massey University, ou=School of Agriculture & Environment, email=d.g.thomas@massey.ac.nz Reason: I am approving this document Date: 2024.11.17 17:24:10 +13'00'

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How Lazy Are Pet Cats Really? Using Machine Learning and Accelerometry to Get a Glimpse into the Behaviour of Privately Owned Cats in Different Households

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Abstract: Surprisingly little is known about how the home environment influences the behaviour of pet cats. This study aimed to determine how factors in the home environment (e.g., with or without outdoor access, urban vs. rural, presence of a child) and the season influences the daily behaviour of cats. Using accelerometer data and a validated machine learning model, behaviours including being active, eating, grooming, littering, lying, scratching, sitting, and standing were quantified for 28 pet cats. Generalized estimating equation models were used to determine the effects of different environmental conditions. Increasing cat age was negatively correlated with time spent active ($p < 0.05$). Cats with outdoor access ($n = 18$) were less active in winter than in summer ($p < 0.05$), but no differences were observed between seasons for indoor-only ($n = 10$) cats. Cats living in rural areas ($n = 7$) spent more time eating than cats in urban areas ($n = 21$; $p < 0.05$). Cats living in single-cat households ($n = 12$) spent more time lying but less time sitting than cats living in multi-cat households ($n = 16$; $p < 0.05$). Cats in households with at least one child ($n = 20$) spent more time standing in winter ($p < 0.05$), and more time lying but less time sitting in summer compared to cats in households with no children ($n = 8$; $p < 0.05$). This study clearly shows that the home environment has a major impact on cat behaviour.

Keywords: domestic cat; feline; behaviour; home environment; accelerometry; machine learning

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Citation: Smit, M.; Corner-Thomas, R.A.; Draganova, I.; Andrews, C.J.; Thomas, D.G. How Lazy Are Pet Cats Really? Using Machine Learning and Accelerometry to Get a Glimpse into the Behaviour of Privately Owned Cats in Different Households. *Sensors* **2024**, *24*, 2623. https://doi.org/10.3390/s24082623

Academic Editor: Christoph M. Friedrich

Received: 18 December 2023
Revised: 17 April 2024
Accepted: 17 April 2024
Published: 19 April 2024

1. Introduction

The domestic cat (*Felis catus*) is one of most popular pets worldwide. In New Zealand, there are over 1.2 million pet cats, of which 74% are considered to be family members by their owners [1]. As every household is unique, the living conditions of pet cats can differ markedly. New Zealand households, for example, often have more than one cat (38%), dogs (10%), and/or children present [1]. In addition to this, cats are kept indoors only (11%), outdoors only (5%), or have both indoor and outdoor access (83%) [1]. The environment a cat is exposed to can therefore be composed of many different conditions that can affect the animal's welfare [2,3].

The welfare of an animal has been defined as the state of the animal as it attempts to cope with its environment [4]. In New Zealand, animal welfare is assessed using the five domains model, which considers the domains of (1) nutrition, (2) environment, (3) health, (4) behaviour, and (5) mental state [5]. One way to assess the welfare state of an animal is by observing its behaviour. Behaviour has been defined as "the internally coordinated response (actions or inactions) of whole living organisms (individuals or groups) to internal and/or external stimuli" [6]. Thus, behavioural observations can provide valuable information on an animal's welfare through the over- or under-expression of specific behaviours. To be able to use behavioural observations as an indicator for welfare, however, behaviours need to be measured accurately to understand how they are affected by different stimuli.

Despite humans living with cats for approximately 9500 years [7], little is known about how the home environment influences the welfare and behaviour of pet cats. Having access to the outdoors is generally accepted as beneficial to the cat's welfare. Indeed, some studies have found that cats kept exclusively indoors show more behaviours that are unacceptable to the owner (i.e., problem behaviours), with twice as much house soiling behaviour reported by the owners [8,9]. A study has reported that cats were more sociable when living in small families without children and had a higher quality of life score, based on care, behaviour, and physical examination, when living with conspecifics [10]. Thus, it is quite clear that many environmental variables have the potential to influence behaviour. However, it is unknown which factors influence which behaviours and how.

A recent review identified that the majority of previous studies focussed on only one variable to ensure that any differences between treatments or groups were most likely the result of that variable [2]. While studies focussing on one variable can be beneficial to identify variables in the environment that might influence the behaviour and welfare of cats, it does not resemble the in-home situation, where the environment is multi-variate. The review also noted that the majority of studies were completed outside the home setting, such as shelters, catteries, or laboratories [2]. A shelter, cattery, or laboratory are unlikely to resemble a home situation, and, therefore, results from these studies are not necessarily transferrable.

It is not surprising that little is known about the effects of a complex environment on cat behaviour. Behavioural studies are very labour-intensive and have traditionally been conducted using observational methods by either scoring the behaviour in real time or from video recordings [11]. When continuously scoring the behaviour of an animal, behaviours can easily be missed, and only one animal per observer can be scored at a time. There is also the risk of observer fatigue if behavioural scoring sessions are long. The majority of studies reviewed by Foreman-Worsley and Farnworth [2] scored behaviour using scan (i.e., instantaneous) sampling, which involves the observer recording the behaviour of an individual animals at predetermined time intervals [12]. With this method, there remains a risk of missing infrequent and/or short-lasting behaviours.

Accelerometers have been shown to have the potential to identify animal behaviour when combined with machine learning techniques (see review by [13]). Watanabe et al. [14] were the first to use accelerometer data from a cat to identify four behaviours with an accuracy > 65%. To date, three other studies have published validated machine learning techniques which identify cat behaviours from accelerometer data. These studies created a machine learning (ML) model with feral cats [15], with pet cats [16], and with colony cats [17]. The model created by [14] used data from only one cat, and the models created by [16] were created from data from a harness-mounted accelerometer. Few pet cats are accustomed to wearing a harness, thus Smit et al. [17] created models for both a collar- and a harness-mounted accelerometer. Creating a model to identify animal behaviour using ML techniques from accelerometer data is labour-intensive, although once a good working model has been created, identifying behaviours is quick and requires little labour.

This study aimed to examine the effects of several environmental conditions (e.g., indoor vs. outdoor, dry vs. mixed diet, and the presence of other cats, dogs, and/or children) and cat-specific conditions (e.g., age group and sex of the cat) on the behaviour of cats. Behaviours were quantified using a previously validated ML model with an overall accuracy of 73% [17]. This study also aimed to examine behavioural differences between summer and winter, and to determine whether the combination of season and environment affected the cats' different behaviours.

2. Materials and Methods

The study was conducted in the Manawatū-Whanganui region, New Zealand. The study was approved by both the Massey University Human Ethics (MUHEC 4000025773) and Animal Ethics Committees (MUAEC 22/24).

2.1. Owner and Cat Recruitment

Voluntary response sampling was used to recruit participants and their cat(s) by distributing flyers to local veterinary clinics and throughout Massey University in Palmerston North (Supplementary Materials S1). The flyer referred participants to a questionnaire that included questions about demographics, housing of the cat, and some general information about the cat(s) (Supplementary Materials S2).

A total of 61 cat owners completed the questionnaire, which captured information on 89 cats. Cats were excluded from participation if the questionnaire was incomplete (n = 15), if they lived outside the Manawatū-Whanganui region (n = 13), or if cats fell outside the age range of 1 to 10 years (n = 6). As some health conditions are known to affect behaviour, cats were also excluded if they suffered from a mobility related illness (e.g., osteoarthritis), a urinary tract and/or kidney disease, diabetes, and/or hyperthyroidism (n = 4). After excluding cats that did not meet the inclusion criteria (n = 29), a total of 60 eligible cats remained. The owners of these 60 cats were invited to participate in the trial. Participation was voluntary, and owners were able to withdraw their cat(s) at any time.

2.2. Data Collection

Data were collected over two periods: summer (1 December 2022–28 February 2023) and winter (1 June 2023–31 August 2023). An appointment was organised with each participant, during which their cat(s) were weighed and assigned a body condition score (BCS; 9-point scale) [18] by the same researcher for the whole study. Owners were also asked whether they fed their cats a wet diet, dry diet, or a mix of a wet and dry diet. Participating cats were fitted with a quick release collar, to which an ActiGraph™ wGT3X-BT (ActiGraph™, Pensacola, FL, USA) accelerometer was attached (weighing 19 g and measuring 33 mm × 46 mm × 15 mm). During each sampling period, owners habituated their cats to wearing the collar with the accelerometer over a six-day period (Table 1), followed by seven consecutive days of data collection. At the end of the data collection period, collars and accelerometers were retrieved and raw triaxial acceleration data were downloaded. If a cat lost its collar during the first or second collection period, their data were not included in the analysis.

Table 1. Training schedule for owners to habituate their cat(s) to wearing the collar with accelerometer, followed by seven days of data collection.

Training Day						
1	2	3	4	5	6	Day 7–14 data collection
2 h	4 h	6 h	8 h	24 h	Off	

Accelerometers were positioned ventrally on a collar (Figure 1a), with the orientation of the X, Y, and X axis lateral, dorso-ventral, and cranio-caudal, respectively (Figure 1b). Owners were given instructions on the orientation of the device, to ensure uniform attachment across all participating cats. The ActiGraph™ wGT3X-BT has a dynamic range of ±8 g. Acceleration data were sampled at a frequency of 30 Hz (raw acceleration data), downloaded, and exported into csv files using the ActiLife software (version 6.13.4; ActiGraph ™, Pensacola, FL, USA).

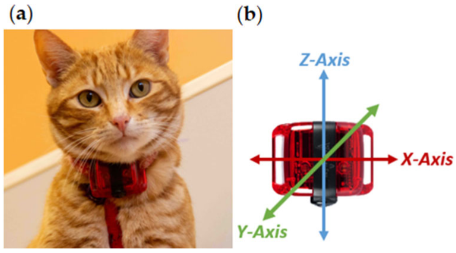

Figure 1. (**a**) Placement and (**b**) orientation of the ActiGraph™ wGT3X-BT accelerometer on a collar.

2.3. Statistical Analysis

Cat bodyweight and BCS were tested for differences between seasons (summer and winter) using a paired *t*-test and Wilcoxon signed-rank test, respectively, using RStudio v1.4.1 [19]. RStudio was also used to identify the behaviour of cats using the previously validated random forest model which identified eight behaviours: active, lying, sitting, standing, grooming, littering, eating, and scratching [17]. The random forest model required 32 identifier variables to be calculated in order to identify cat behaviours. These identifier variables were derived from the raw acceleration data (30 Hz) and summarized into 1 s epochs (Appendix A). Using the identifier variables and the previously validated random forest model, the behaviours of the cats were identified for each second of the day. For each cat, hourly and weekly proportions of all behaviours were calculated to visualise patterns in behaviour throughout the day.

The frequency of each behaviour was summed on a weekly basis for each cat and merged with data from the questionnaire. The weekly summed frequency of behaviours with variables obtained from the questionnaire was then exported into SPSS (version 29.0.0.0). The effects of different variables and their interactions on the assessed behaviours were tested using generalized estimating equation (GEE) models. GEE models were performed on the total weekly accelerometer count data (seconds) for each behaviour, with individual cats being defined as the subject variable, and season defined as the within-subject variable. It was assumed that the amount of each behaviour displayed by the cat in summer did not affect the amount displayed in winter, and, therefore, the structure of the working correlation matrix was set to independent. As count data were used for the GEE models, a Poisson distribution with log as the link function was selected.

A total of nine variables were included in the analysis: season, sex of the cat, age group, diet, housing, rural vs. urban, multi-cat vs. single-cat household, presence of at least one dog, and the presence of at least one child (<18 years; Table 2). The main effect of all nine variables on each of the eight behaviours were tested (main effects GEE models). A backwards stepwise procedure was followed, removing variables with a p-value > 0.10, until only variables remained with p-values $\leq$ 0.10. Given that data were collected for each cat in both summer and winter, the effects of the interaction of season with each of the remaining eight variables for each behaviour were also tested (individual GEE models). For each behaviour, interactions with a p-value $\leq$ 0.10 from the individual GEE models were combined into a multi-interaction GEE model. The same backwards stepwise procedure, as previously used for the main effects GEE, was then followed. For each behaviour, variables that were retained following the backwards stepwise procedure for both the main effects GEE model and multi-interaction GEE model were combined into multivariate GEE models. Another backwards stepwise procedure was followed until only significant variables remained ($p < 0.05$).

Table 2. Variables extracted from the questionnaire, or collected during an appointment, and their categories.

Variable	Categories
Season	Summer (December–February) Winter (June–August)
Sex of cat	Entire female Entire male Neutered female Neutered male
Age group [20,21]	Kitten (0–6 months) Junior (7 months–2 years) Prime (3–6 years) Mature (7–10 years) Senior (11–14 years) Geriatric ($\geq$15 years)
Diet	Dry Wet (e.g., canned, pouched, or raw) Mix (mix of dry and wet foods)
Housing	Exclusively indoors Indoors with limited outdoor access (e.g., harnessed walks, catio, or garden access) Indoors with unlimited outdoor access Exclusively outdoors Other
Rural vs. urban	Rural Urban
Multi-cat vs. single-cat household	Multi Single
Presence of at least one dog	No (absent; no dog(s) in household) Yes (present; at least one dog in household)
Presence of at least one child (<18 years)	No (absent; no child(ren) in household) Yes (present; at least one child in household)

3. Results

Of the 60 eligible cats identified from the questionnaire, owners of 18 cats did not respond to the invitation to participate in the study, resulting in a total of 42 cats that participated in the first collection period (summer). Of those 42, 5 lost their collars and 2 did not adapt to wearing the monitor and were thus excluded from the trial. In addition, one cat was euthanized due to reasons unrelated to this study between the first and second collection period, one cat was withdrawn from the study by the owner, and two cats were not booked in for the second collection period by the owner. The second collection period therefore included 33 cats, of which 5 cats lost their collar, resulting in a final sample size of 28 cats. Only data from these 28 cats were included in the data analysis.

Cats weighed less in summer (4.6 $\pm$ 0.15 kg) than winter (4.8 $\pm$ 0.17 kg; p = 0.015); however, no difference was found in BCS (median = 6; $p > 0.05$). All cats that participated in the study were desexed; therefore, hereafter they will be referred to as female and male. The cats were fed either a dry diet or a combination of dry and wet diets (e.g., canned or pouched). Of the eligible cats, cats were either housed indoors with unlimited outdoor access (hereafter considered outdoor), or indoors with limited outdoor access (hereafter considered indoor). In one household with two cats participating in the study, a child was born between the first and second collection, which transitioned these cats from a child-free household to a household with a child. In one of the households, a second cat was introduced between the first and second collection period, resulting in a change in classification from a single-cat to a multi-cat household (Table 3).

Table 3. Number of cats for each variable for the summer and winter study periods.

		Season				Season	
		Summer	Winter			Summer	Winter
Sex				**Housing**			
	Female	17	17		Indoor [2]	10	10
	Male	11	11		Outdoor [2]	18	18
Age group				**Number of cats in household**			
	Junior [1]	10	10		One	12	11
	Prime [1]	12	12		Two	9	10
	Mature [1]	6	6		Three	7	7
Coat length				**Dogs**			
	Long	5	5		Absent	19	19
	Short	23	23		Present	9	9
Environment				**Children (<18 years)**			
	Rural	7	7		Absent	20	18
	Urban	21	21		Present	8	10

[1] Junior = 1–2 years, prime = 3 to <7 years, mature = 7 to <11 years. [2] Indoor = cats with indoor only access, Outdoor = cats having both indoor and outdoor access.

For each behaviour, the main (Table 4) and interaction effects (Table 5) were modelled, and a backwards stepwise procedure was followed. The main effects and interactions with a p-value $\leq$ 0.10 that were retained following the backwards stepwise procedure were combined into multivariate GEE models, for which the results are shown. Percentages of time spent exhibiting every behaviour are presented as mean $\pm$ standard error (SE).

Table 4. p-values of the interactions from the individual GEE models following a backwards stepwise procedure. Only p-values < 0.10 are presented.

	Behaviour							
	Active	Eating	Grooming	Littering	Lying	Scratching	Sitting	Standing
Season × Sex of the cat	NS	NS	0.023	NS	NS	0.079	NS	NS
Season × Age group	<0.001	NS	NS	0.030	NS	NS	NS	0.002
Season × Diet	NS	NS	NS	0.063	NS	NS	0.055	NS
Season × Rural vs. urban	NS	<0.001	NS	NS	NS	0.013	NS	NS
Season × Housing	<0.001	NS	NS	NS	NS	NS	NS	NS
Season × Multi- vs. single-cat household	NS	NS	NS	NS	0.064	NS	NS	NS
Season × Dog(s) in household	NS	NS	NS	NS	NS	NS	NS	NS
Season × Child(ren) in household	NS	NS	NS	NS	0.006	NS	0.0016	<0.001

NS = not significant.

Table 5. p-values of the variables from the main effects GEE models following a backwards stepwise procedure. Only p-values < 0.10 are presented.

	Behaviour							
	Active	Eating	Grooming	Littering	Lying	Scratching	Sitting	Standing
Season	0.006	NS	0.046	NS	NS	NS	NS	0.082
Sex of the cat	NS	0.017	NS	NS	0.049	NS	0.090	NS
Age group	<0.001	0.066	0.057	NS	NS	NS	NS	NS
Diet	NS	0.017	NS	NS	0.015	NS	<0.001	NS
Rural vs. urban	NS	<0.001	NS	NS	0.092	NS	0.027	NS
Housing	<0.001	NS	NS	NS	NS	NS	NS	NS
Multi- vs. single-cat household	NS	NS	NS	NS	0.032	NS	0.006	NS
Dog(s) in household	NS	NS	NS	NS	NS	NS	NS	NS
Child(ren) in household	NS	0.051	0.090	NS	0.005	NS	0.002	0.001

NS = not significant.

3.1. Active

Overall, cats were active for 2.8 $\pm$ 0.25% of their time. There was an interaction of season $\times$ age (p < 0.001; Figure 2a) and season $\times$ housing (p < 0.001; Figure 2b) for active behaviour. In summer, junior cats spent more time being active (4.2 $\pm$ 0.58%) compared to prime (2.7 ± 0.37%; $p = 0.008$), but not mature cats (2.5 ± 0.73%), while in winter junior cats spent more time being active (3.5 ± 0.41%) than both prime (1.9 ± 0.27%; $p < 0.001$) and mature cats (2.1 ± 0.24%; $p = 0.002$). No seasonal differences were found within age groups ($p > 0.05$).

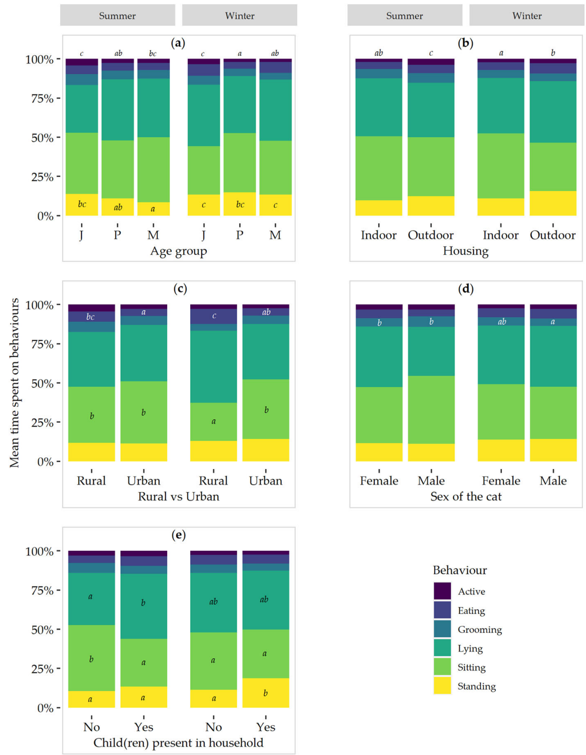

Figure 2. Effect of interaction on the different domestic cat behaviours: (**a**) season × age group with J = Junior, P = Prime, M = Mature; (**b**) season × housing; (**c**) season × 'rural vs. urban'; (**d**) season × sex of the cat; (**e**) season × child(ren) in household. $^{a–c}$ Within a behaviour, bars with different superscripts differ significantly ($p < 0.05$). Superscripts above the columns in (**a**,**b**) are for active behaviour.

Cats with outdoor access spent more time active in both summer ($p < 0.001$) and winter ($p < 0.047$) than indoor cats (3.9 ± 0.39% vs. 2.0 ± 0.36% and 2.7 ± 0.33% vs. 2.2 ± 0.23%, respectively). While cats with outdoor access were less active in winter than in summer ($p = 0.003$), there were no seasonal differences in the time spent active for indoor cats ($p > 0.05$).

3.2. Eating

Overall, cats spent 5.5 ± 0.46% of their time eating. There was an interaction of season × 'rural vs. urban' ($p < 0.001$; Figure 2c), whereby cats living in a rural environment spent more time eating in both summer ($p < 0.038$) and winter ($p < 0.001$) than urban cats (6.4 ± 0.71% vs. 4.6 ± 0.58% and 9.6 ± 1.20% vs. 4.7 ± 0.93%, respectively). Rural cats spent more time eating in winter than summer ($p < 0.001$), but urban cats showed no seasonal differences ($p > 0.05$).

3.3. Grooming

Overall, cats spent 5.5 ± 0.30% of their time grooming. There was an effect from age group, with junior cats grooming more than mature cats (6.3 ± 0.49% vs. 5.0 ± 0.38%; $p = 0.018$). A trend was found for the effect of children on the time spent grooming ($p = 0.096$), with cats spending more time grooming in households without children (5.8 ± 0.37%) than those with at least one child (4.6 ± 0.39%).

An interaction effect of season × sex of the cat was found on grooming behaviour ($p = 0.019$; Figure 2d), with male cats spending less time grooming in winter (4.7 ± 0.43%) than summer (6.8 ± 0.86%; $p = 0.006$). No difference was observed between winter and summer for female cats (5.4 ± 0.42% vs. 5.2 ± 0.50%; $p > 0.05$). In addition, within each season, there was no difference in the time spent grooming between male and female cats ($p > 0.05$).

3.4. Littering

Overall, cats spent little time littering (0.04 ± 0.01%). There was an interaction of season × age ($p < 0.001$) whereby mature cats spent more time littering in winter (0.06 ± 0.01%) than in summer (0.03 ± 0.01%; $p = 0.039$), and mature cats spent more time littering than junior cats (0.02 ± 0.00%) in winter ($p < 0.001$). No differences in time spent littering were found between summer and winter for junior (0.04 ± 0.02% vs. 0.02 ± 0.00%) and prime cats (0.02 ± 0.01% vs. 0.02 ± 0.00%; $p > 0.05$).

3.5. Lying

Overall, cats spent 36.7 ± 1.47% of their time lying. Female cats spent more time lying than male cats (37.9 ± 1.96% vs. 34.9 ± 2.19%; $p = 0.046$). Cats on a dry diet spent less time lying than cats on a mixed diet (34.9 ± 2.50% vs. 38.5 ± 1.49%; $p = 0.013$). Cats in multi-cat households spent less time lying (35.1 ± 1.41%) than cats in single-cat households (39.6 ± 2.82%; $p = 0.050$). A trend was found for 'rural vs. urban' on time spent lying ($p = 0.096$), with cats living rurally spending more time lying (40.4 ± 2.76%) than cats living in an urban area (35.5 ± 1.68%).

There was an interaction effect of season × child(ren) in the household ($p = 0.011$; Figure 2e), whereby cats in households where at least one child was present spent more time lying (41.4 ± 1.93%) than cats in households without children (33.2 ± 2.35%; $p = 0.002$) in summer but not winter (38.0 ± 3.25 vs. 37.5 ± 3.71; $p > 0.05$). In addition, no differences in time spent lying were found between seasons for cats in households with or without children ($p > 0.05$).

3.6. Scratching

Overall, cats spent very little time scratching themselves (0.12 ± 0.01%). There was an interaction effect of season × 'rural vs. urban' ($p = 0.001$), whereby cats that lived rurally spent more time scratching in summer than in winter (0.16 ± 0.04% vs. 0.07 ± 0.02%; $p = 0.003$). In winter, rural cats also spent more time scratching than urban cats (0.07 ± 0.02% vs. 0.12 ± 0.02%; $p = 0.031$). No seasonal differences in time spent scratching were found for cats living in an urban area (summer: 0.13 ± 0.02%, winter: 0.12 ± 0.02%; $p > 0.05$).

3.7. Sitting

Overall, cats spent 36.6 ± 2.04% of their time sitting. Cats fed a dry diet spent more time sitting (39.0 ± 3.59%) than cats on a mixed diet (34.2 ± 1.89%; $p < 0.001$). Cats in a multi-cat household spent more time sitting (39.2 ± 2.38%) than cats in a single-cat household (32.4 ± 3.22%; $p = 0.005$). While female cats sat less (35.5 ± 2.90%) than male cats (38.2 ± 2.74%), this was only a trend ($p = 0.092$).

There was an interaction of season × 'rural vs. urban' ($p = 0.048$; Figure 2c). Cats living in a rural area spent more time sitting in summer (35.6 ± 3.06%) than in winter (24.3 ± 4.92%; $p = 0.042$). No seasonal difference was found for urban cats (summer: 39.7 ± 2.89%; winter:

38.0 ± 3.97%; $p > 0.05$). In winter, cats living rurally spent less time sitting than cats living in an urban area ($p = 0.008$).

There was also an interaction of season × child(ren) in the household ($p = 0.006$; Figure 2e) whereby cats living in a household without children spent more time sitting in summer (41.9 ± 2.73%) than in winter (36.5 ± 4.34%; $p = 0.041$). No seasonal difference was found for sitting behaviour in households where there was at least one child present (summer: 30.5 ± 2.71%, winter: 31.0 ± 5.45%; $p > 0.05$). In summer, cats in a household without children spent more time sitting than cats in a household with a child(ren) ($p < 0.001$).

3.8. Standing

Overall, cats spent 12.7 ± 0.76% of their time standing. There was an interaction of season × age ($p = 0.002$; Figure 2a) whereby in summer, junior cats spent more time standing (13.8 ± 1.84%) than mature cats (8.6 ± 0.64%; $p < 0.001$) and showed a trend of standing more than prime cats (10.9 ± 0.80%; $p = 0.066$). In addition, mature cats spent less time standing in summer than in winter (8.6 ± 0.64% vs. 13.4 ± 1.84%; $p = 0.001$), but there were no differences among the other age groups.

There was also an interaction of season × child(ren) in the household ($p < 0.001$; Figure 2e), whereby cats in households with at least one child spent less time standing in summer (13.4 ± 2.04%) than in winter (18.7 ± 2.59%; $p = 0.005$). However, there was no seasonal difference for households without children (summer: 10.7 ± 0.78%, winter: 11.4 ± 0.74%; $p > 0.05$). In winter, cats in households without children spent less time standing than cats in households with at least one child ($p < 0.001$), but in summer the difference was only a trend ($p = 0.075$).

3.9. Daily Pattern of Behaviour

In both summer and winter, there was a bimodal pattern of behaviour which was driven by active and eating behaviours (Figure 3). In summer, peaks in active and eating behaviours were observed between 05:00–09:00 and 20:00–23:00, while in winter these peaks were between 06:00–08:00 and 16:00–19:00. In summer, between 1 December 2022 and 28 February 2023, the sun rose on 05:21 and 06:57, respectively, and set on 20:50 and 20:02, respectively [22]. In winter, between 1 June 2023 and 31 August 2023, the sun rose on 07:30 and 06:44, respectively, and set on 16:59 and 17:52, respectively [22].

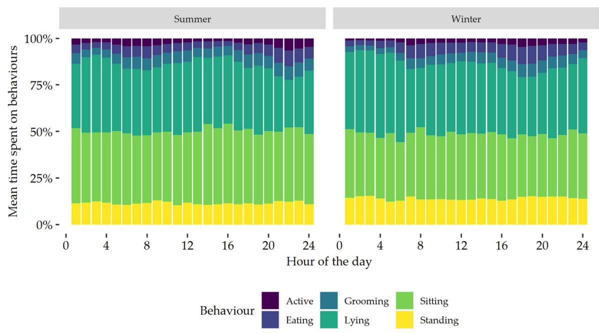

Figure 3. Daily behaviour patterns, expressed per hour, of all the domestic cats in summer and winter.

Cats which had both indoor and outdoor access showed a clear bimodal pattern of behaviour in both summer and winter; however, the bimodal pattern was less prominent in the summer for cats living indoors (Figure 4). Cats living in rural areas also showed a more pronounced bimodal pattern of behaviour, particularly time spent active and eating, than cats living in urban areas (Figure 5).

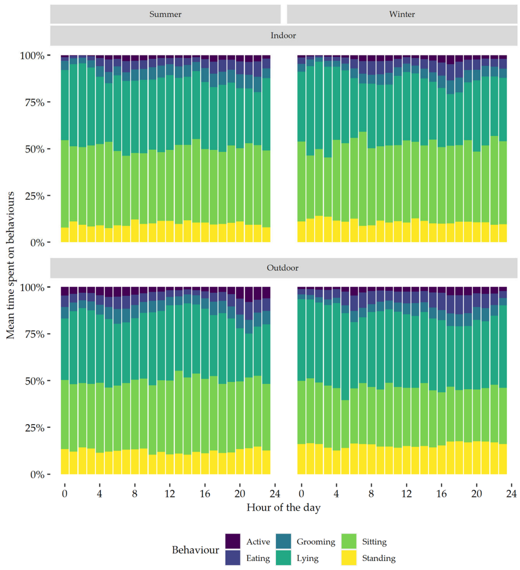

Figure 4. Daily behaviour patterns, expressed per hour, of all the domestic cats in summer and winter living either indoors or having both indoor and outdoor access (outdoor).

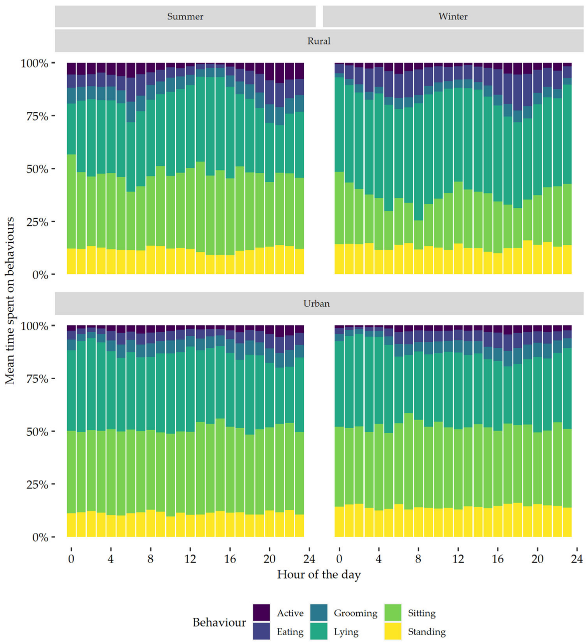

Figure 5. Daily behaviour patterns, expressed per hour, of all the domestic cats in summer and winter living either in rural or urban areas.

4. Discussion

The aim of this study was to investigate the behaviour of privately-owned domestic cats and determine how environmental conditions influence their behaviour. Foreman-Worsley and Farnworth [2] identified substantial gaps in our knowledge of how cats respond and interact with their multifactorial home environment. By quantifying cat behaviours, it is possible to determine which behaviours are affected by the home environment and what impact different aspects of this environment have on cats.

Studies on behavioural budgets in domestic cats are limited, and the studies available differ in the methods used to collect behavioural data, the season(s) in which data were collected, and housing conditions. In the current study, housing (indoors only vs. or indoor with outdoor access) showed a significant interaction with the season for active behaviour. As expected, time spent exhibiting active behaviour for indoor cats did not differ between seasons, whereas cats with outdoor access were more active in summer (3.9%) than in winter (2.7%). Two previous studies, both of outdoor colony housed cats, reported an effect of environmental temperature and relative humidity on physical activity [23,24]. Cats in the present study were more active in summer, when temperatures are generally higher than in winter. This was contrary to findings of the outdoor colony housed cats where physical activity declined with increasing temperatures [23,24]. Studies on the effect of weather on cat behaviour are scarce. Cats have a relatively high thermoneutral zone (30–38 °C; [25]), so cats may spend more time indoors in winter, possibly in front of a heat source, where it is warmer. Indoor cats are likely less affected by outdoor weather, as factors such as temperature and relative humidity are less likely to fluctuate indoors. However, a study assessing cat behaviour in response to extreme weather events, that included both indoor only cats (53%) and cats with outdoor access (47%), reported that 75% of cat owners perceived a decline in the level of activity during extreme hot weather events, while 66% of cat owners reported a decline in the level of activity during extreme cold weather events [26]. Not all owners reported an effect of extreme heat or cold on the behaviour of their cat during the study, which could be due to the effect of isolation and the presence or absence of heating and/or cooling sources in the house, affecting temperature fluctuations. It should be noted that owner-based assessment is subjective. Another possible explanation for the higher amount of time spent on active behaviours in summer than in winter by cats with outdoor access is an increase in hunting behaviour in summer. Several studies have shown that cats bring home more prey in summer than in winter [27–29], suggesting a higher activity in summer than winter. However, no data on hunting behaviour were collected during this study, so no further conclusions can be drawn. Galea et al. [16], however, successfully identified specific hunting behaviours in domestic cats using accelerometry and hunting behaviours. Thus, accelerometry and machine learning could prove a useful tool for future studies regarding the hunting behaviour of domestic cats.

In the current study, indoor cats were significantly less active than cats with outdoor access in both summer and winter. Berteselli et al. [30] reported that five indoor cats from the same household were twice as active than cats in the current study. It should be noted, however, that an observer was present in the house for behavioural observations in the study by [30], which could have influenced the behaviour of the cats. Smit et al. [24] reported higher physical activity levels when caretakers were present than when they were absent. In addition to this, maintenance behaviours, such as eating and grooming, were included as 'active' behaviours by [30], while these were considered separately in the current study. If time spent active, eating and grooming were summed in the current study, cats spent more than twice as much time being "active" than what was reported by [30]. A factor that may contribute to the difference in activity between housing conditions is the area that the cats have access to. It is likely that cats with outdoor access have access to larger areas than cats confined indoors. A study compared activity using accelerometers of cats with access to either 80–100 m^2 indoors and a 40–80 m^2 garden (group A), or 200–250 m^2 indoors and a 2000–2500 m^2 garden (group B) [31]. In that study, cats from group B were significantly more active than cats from group A. It should be noted, however, that cats in group A were also limited to only one hour per day of garden access, while the cats in group B had free access to the indoors and the garden but were kept in the garden for 11 h during the night [31]. The difference in activity was therefore likely due to a combination of access area and indoor/outdoor access management.

Age has been found to negatively affect overall physical activity in domestic cats [24,32], although it is unclear which behaviours contribute to this decline. Smit et al. [24] reported that cats in the kitten (≤6 months) and junior (>6 months and <3 years) age groups were more active than cats in the prime, mature, and senior age groups (≥3 and <15 years). In the current study, junior cats (≥1 and <3 years) were more active than both prime and mature cats (≥3 and <11 years). The difference between junior and mature cats was not significant in summer, but this was likely due to the large amount of variation observed for mature cats. Grooming and scratching behaviours have been reported to result in high activity counts when measured with accelerometers [33,34]. Indeed, an interaction of season and age on grooming behaviour was found in the present study. Cats in the mature age group spent less time grooming compared to junior cats. When owners were asked about behavioural changes in their older cats (≥11 years of age) compared to when they were younger, they reported a decline in grooming behaviour [35]. The current study suggests that the decrease in overall activity with increasing age reported by [24,32] was likely the result of a decrease in both active and grooming behaviour(s) with increasing age.

The current study found that the absence or presence of a child(ren) and other cats in the household affected some behaviours of cats; however, there was no effect from dogs in the household. Assuming that sitting and standing behaviours are indicative for a greater level of alertness than lying (which also included sleeping), it could be hypothesized that cats in households with at least one other cat or child were more alert. Cats in households have been reported to be less affectionate towards children than adults, especially towards children aged 3–5 years of age [36]. Parents also reported that children were generally the ones seeking an affectionate relationship with the cats, not the other way around [36]. In the current study, cats in multi-cat households spent less time lying and more time sitting than cats in single-cat households, which may also indicate a greater level of alertness. The results were less conclusive for the effect of children in the household. In the winter, cats in households with at least one child spent more time standing than cats in households without children, while in summer, cats in households with at least one child spent more time lying and less time sitting than cats in households without children. In the current study, all cats in households where there was at least one child present had outdoor access. It is therefore possible that in summer, cats spent more time outside, where they were at a lower risk of being disturbed by a child, whereas they may have been indoors more in winter. However, more research is needed to confirm this hypothesis.

When the time spent on each behaviour was plotted on an hourly basis, a bimodal behaviour pattern was observed which consisted of two daily peaks. Based on visual assessment, the bimodal pattern appears to be mainly driven by changes in active and grooming behaviours. A bimodal pattern in activity has previously been reported in domestic cats [24,37,38]. Parker et al. [38] investigated the circadian rhythm of active and eating behaviours of indoor housed cats, using a combination of accelerometry, Ultra-Wide Band tags, and automatic feeding scales, and found a bimodal pattern for both. The peaks in both behaviours predominantly occurred before sunrise and food renewal in the morning, and before sunset in the evening [38]. In the current study, peaks in time spent active and eating also coincided with sunrise and sunset. In the study by [38], ambient humidity and temperature were kept constant, while they were exposed to natural photoperiods through windows. Kappen et al. [37] reported that, under constant temperature, cats exposed to a 16 h photoperiod had a higher activity count than cats exposed to an 8 h photoperiod. Season, temperature, and photoperiod are correlated [39], and it is likely they all affect the behaviour of cats. It should also be noted that pet cats are also exposed to artificial light indoors, especially during the winter when day lengths are shorter. More research is warranted to determine the effects of these factors on feline behaviour.

In the current study, active behaviour was affected by the interaction of season and housing. When visually assessing active behaviour, the bimodal pattern was apparent during both summer and winter for cats with outdoor access, whereas indoor cats showed a bimodal pattern in winter but not summer. It could be hypothesised that the lack of a bimodal pattern of active behaviour of indoor cats in summer may be due to the occurrence of school holidays during this period, which may have resulted in owners and/or family members being home more often. Unfortunately, no data were collected on when owners were at home. Human presence has been shown to affect activity patterns in domestic cats [24,31]. In colony housed cats, ref. [24] reported higher levels of physical activity during hours when staff were present. Similarly, ref. [31] reported that cats with little outdoor garden access (group A) were more active when their owners were at home. Thus, the effect of owner presence on the behaviour of cats warrants further investigation, and recording owner presence should be considered in future studies.

The circadian rhythm of behaviours was also plotted for season × 'rural vs. urban'. The bimodal pattern, driven by active and grooming behaviours, was visually more pronounced in rural cats than it was in urban cats. Studies comparing the home range of rural and urban cats found that rural cats had much larger home ranges, which could be up to 14.4 times as large [40,41]. A larger home range would likely result in a higher physical activity and more pronounced peaks in activity. The current study, however, did not find an effect of season × 'rural vs. urban' on active behaviours. Cats with a larger home range might therefore not be necessarily more active than cats with a smaller home range. The current study did find an interaction of season with 'rural vs. urban' on time spent eating, with rural cats spending more time eating than urban cats. This could possibly have contributed to the more pronounced bimodal pattern seen in the rural cats. It is also worth noting that, apart from one cat, all rural cats had outdoor access, whereas the urban cats were composed of both indoor-only cats and cats with outdoor access. The combination of the interaction effect of season × 'rural vs. urban' on time spent eating, and the interaction of season × housing on time spent active, could have resulted in the more pronounced bimodal pattern that was visible in the rural cats.

5. Conclusions

This study showed that the previously validated machine learning model can be applied to cats in a home situation and that it can be used to determine the effects of environmental variables on cat behaviours. Overall, cats in the current study spent the majority of their time displaying inactive behaviours (lying, sitting, standing: 86%). Cats with both indoor and outdoor access spent more time displaying active behaviours compared to indoor only cats, and were more likely to be affected by weather conditions than indoor-only cats. More research is needed to determine the effect of weather on cat behaviour. The current study further supported the negative relationship between aging and physical activity and found that the decrease in physical activity is most likely driven by a decrease in both active and grooming behaviours. The current study also supported earlier findings of the bimodal pattern of behaviour of cats which appeared to be affected by housing and whether cats lived in a rural or urban areas. More research is warranted in this area, as studies on this topic are currently scarce.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/s24082623/s1, Supplementary Materials S1: Flyer distributed for owner and cat recruitment; Supplementary Materials S2: Questionnaire.

Author Contributions: Conceptualization, M.S., R.A.C.-T., I.D., C.J.A. and D.G.T.; Methodology, M.S.; Software, M.S.; Validation, M.S.; Formal analysis, M.S.; Investigation, M.S.; Data curation, M.S.; Writing—original draft, M.S.; Writing—review & editing, R.A.C.-T., I.D., C.J.A. and D.G.T.; Visualization, M.S.; Supervision, R.A.C.-T., I.D., C.J.A. and D.G.T.; Project administration, M.S., R.A.C.-T., I.D., C.J.A. and D.G.T.; Funding acquisition, D.G.T. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: The animal study protocol was approved by the Animal Ethics Committee of Massey University (MUAEC 22/24). The human study protocol has been evaluated by peer review and judged to be low risk. Consequently, it has not been reviewed by one of Massey University's Human Ethics Committees (MUHEC 4000025773).

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: A dataset including the weekly behavioural counts and percentages is available on FigShare at https://doi.org/10.6084/m9.figshare.24848292 (accessed on 18 December 2023) [42].

Acknowledgments: We wish to thank all cats and their owners for participating in this study.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

The random forest model used to identify the behaviours using acceleration data, requires a total of 32 identifier variables. These identifier variables were derived from the raw acceleration data (30 Hz) and summarized into 1 s epochs (i.e., time interval): mean acceleration (X, Y, Z), sum acceleration (X, Y, Z), minimum (min) acceleration (X, Y, Z), maximum (max) acceleration (X, Y, Z), standard deviation (sd) of acceleration (X, Y, Z), skewness (X, Y, Z), kurtosis (X, Y, Z), correlation (XY, XZ, YZ), vector magnitude (VM; mean, sum, min, max, sd, skewness, kurtosis), and overall dynamic body acceleration (ODBA; see Table A1 for detailed description of each identifier variable).

Table A1. Description and calculation of identifier variables. Table from [17].

Predictor Variable	Description
Mean	Mean, calculated for every second using the raw acceleration data (30 measures per second)
Sum	Sum, calculated for every second using the raw acceleration data $Sum_{(Axis)} \sum_{i=1}^{N} Axis_i$
Minimum (min)	Minimum value of every 30 measures within each second
Maximum (max)	Maximum value of every 30 measures within each second
Standard deviation (sd)	Measures the spread of the data
Skewness	Asymmetry of the distribution
Kurtosis	Weight of the tails relative to a normal distribution
Vector magnitude (VM)	$VM = \sqrt{X^2 + Y^2 + Z^2}$
Overall dynamic body acceleration (ODBA)	$ODBA = \sum_{i=1}^{N} \lvert DBA_X \rvert + \lvert DBA_Y \rvert + \lvert DBA_Z \rvert$
Dynamic body acceleration (DBA) [1]	$DBA = Sum_{axis} - moving\ average$

[1] Accelerometer data from each axis were individually smoothed using the moving average over 1 s.

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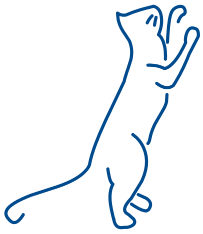
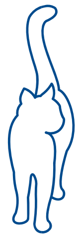
Appendix XIII – Flyer pet owner recruitment



CATS WANTED



Curious about what your cat does all day?

Enrol your cat in this study and receive a behaviour profile.

Using activity monitors, your cat's behaviour will be monitored for a week in summer and winter. We will be comparing your cat's behaviour between seasons and to other cats living in different housing conditions.

Main criteria

- Housed indoors
- Housed indoors with outdoor access
- Housed outdoors

Other criteria

- Aged between 1 and 10 years
- Used or trainable to wearing a collar or harness
- Available for 1 week in summer and winter

Scan the QR code for more information and to sign up or ask your vet for the information leaflet

Email: m.smit@massey.ac.nz

Email: m.smit@massey.ac.nz
Email: m.smit@massey.ac.nz
Email: m.smit@massey.ac.nz
Email: m.smit@massey.ac.nz
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Appendix XIV – Screening questionnaire

You are being invited to take part in a research study part of a doctoral study. This research will study the behaviour and physical activity of domestic cats in a home environment. To participate in this study, you will need to fill out this questionnaire.

More information on this study can be found in the information leaflet.
The questionnaire will take approximately 5-10 minutes.
*Required

I have read the provided information and agree that research data gathered for this study may be published or made available provided my name or other identifying information is not used *

☐ I agree

I understand that I am free to withdraw from this study at any time *

☐ I agree

Contact information

First and last name *

E-Mail Address *

Phone number *

How would you prefer to be contacted? *
Select one answer

☐ E-mail
☐ Phone

Household information

What is your age category? *
Select one answer

- [ ] < 18 years
- [ ] 18 – 24 years
- [ ] 25 – 34 years
- [ ] 35 – 44 years
- [ ] 45 – 54 years
- [ ] 55 – 64 years
- [ ] > 65 years

How many adults (18 years or older) are present in the household? *
Select one answer

- [ ] 0
- [ ] 1
- [ ] 2
- [ ] 3 or more

How many children (< 18 years) are present in the household? *
Select one answer

- [ ] 0
- [ ] 1
- [ ] 2
- [ ] 3 or more

Please specify the age category or categories of the child(ren) present in the household?
More than one answer possible

- [ ] Baby (up to 1 year)
- [ ] Toddler (1 – 3 years)
- [ ] Preschooler (3 – 5 years)
- [ ] School age (6 – 12 years)
- [ ] Teenager (13 – 18 years)

How many cats are present in the household? *

Select one answer

- ☐ 0
- ☐ 1
- ☐ 2
- ☐ 3
- ☐ 4
- ☐ 5 or more

Are there one or more dogs present in the household? *

Select one answer

- ☐ Yes
- ☐ No

General questions about your cat(s)

If more than one cat is present in your household, please only answer the questions for the cat(s) with who you want to participate in this study. It is possible to fill out part of the following questions for up to 4 cats.

Select the age category for your cat(s) *

Select one answer for each cat

	Kitten (0 - 6 months)	Junior (7 months - 2 years)	Prime (3 - 6 years)	Mature (7 - 10 years)	Senior (11 - 14 years)	Geriatric (15 years or older)
Cat 1	○	○	○	○	○	○
Cat 2	○	○	○	○	○	○
Cat 3	○	○	○	○	○	○
Cat 4	○	○	○	○	○	○

Select the gender for your cat(s) *
Select one answer for each cat

	Entire male	Neutered male	Entire female	Neutered female
Cat 1				
Cat 2				
Cat 3				
Cat 4				

Is your cat known with any of the following illnesses? *
Please select the illness(es) that apply to your cat(s)

	Mobility-related illness (e.g. osteoarthritis, fractures)	Urinary tract/kidney disease	Diabetes	Hyperthyroid
Cat 1				
Cat 2				
Cat 3				
Cat 4				

Select the living condition of your cat(s) *
Select one answer for each cat

	Exclusively indoors	Indoors with outdoor access	Exclusively outdoors	Other
Cat 1				
Cat 2				
Cat 3				
Cat 4				

If you answered "Other" in the previous question, please describe the living condition of your cat(s)

Is your cat used to wearing a collar and/or harness? *
Select one answer for each cat

	Collar	Harness	Collar & harness	Neither
Cat 1				
Cat 2				
Cat 3				
Cat 4				

Cat safety collar

To ensure the safety of your cat throughout the study, a cat quick release collar is required while your cat wears the activity monitor. Quick release collars have a type of clasp that pops open easily when force is applied. Below you can see the difference between a quick release collar and traditional collar.

Quick release collar

Traditional collar

Do you own a cat quick release collar? *
Select one answer

☐ Yes
☐ No

If you do not own a cat quick release collar, one will be provided during the study.

End of questionnaire

You have reached the end of the questionnaire. Thank you for your interest in this study and for completing this questionnaire. Depending on how many people are interested in participating in this study, a selection might be made. You will be informed if you are selected to participate in the study no later than mid November 2022.

Appendix XV – GLMM tables for eating, littering and lying behaviour

Below you can find the GLMM tables that contain the β_1 estimates, 95% confidence intervals and *p*-values for the univariate GLMM of time spent on eating (Table A37), littering (Table A38) and lying (Table A39).

Table A37. Results of GLMMs examining household and social variables associated with eating behaviour, as classified with the model. Presented are the estimates (β_1), 95% confidence interval (CI), *p*-values and reference category. Estimates are presented on the logit scale.

Variable	Estimate	95% CI	*p*-value	Reference category
		Univariate GLMMs		
Season	0.04	[-0.34, 0.41]	0.819	Winter
Age group (linear)	-0.05	[-0.43, 0.30]	0.772	Junior
Age group (quadratic)	0.26	[-0.06, 0.60]	0.106	Junior
Sex	-0.05	[-0.46, 0.36]	0.820	Neutered male
Housing	0.08	[-0.33, 0.52]	0.707	Free-roaming
Children	0.16	[-0.27, 0.60]	0.469	Present
Number of cats in household (linear)	-0.31	[-0.68, 0.03]	0.072	One
Number of cats in household (quadratic)	0.05	[-0.28, 0.40]	0.778	One
Dogs in household	0.21	[-0.21, 0.63]	0.302	Present

Table A38. Results of GLMMs examining household and social variables associated with littering behaviour, as classified with the model. Presented are the estimates (β_1), 95% confidence interval (CI), *p*-values and reference category. Estimates are presented on the logit scale.

Variable	Estimate	95% CI	*p*-value	Reference category
		Univariate GLMMs		
Season	0.03	[-0.42, 0.48]	0.896	Winter
Age group (linear)	0.23	[-0.20, 0.63]	0.274	Junior
Age group (quadratic)	0.34	[-0.04, 0.72]	0.076	Junior
Sex	-0.07	[-0.55, 0.38]	0.762	Neutered male
Housing	-0.18	[-0.63, 0.31]	0.453	Free-roaming
Children	-0.18	[-0.70, 0.29]	0.460	Present
Number of cats in household (linear)	-0.11	[-0.52, 0.29]	0.604	One
Number of cats in household (quadratic)	0.19	[-0.20, 0.60]	0.355	One
Dogs in household	0.11	[-0.39, 0.57]	0.660	Present

Table A39. Results of GLMMs examining household and social variables associated with lying behaviour, as classified with the model. Presented are the estimates (β_1), 95% confidence interval (CI), *p*-values and reference category. Estimates are presented on the logit scale.

Variable	Estimate	95% CI	*p*-value	Reference category
		Univariate GLMMs		
Season	0.08	[-0.19, 0.34]	0.562	Winter
Age group (linear)	0.11	[-0.15, 0.36]	0.387	Junior
Age group (quadratic)	-0.02	[-0.24, 0.20]	0.833	Junior
Sex	-0.11	[-0.38, 0.16]	0.434	Neutered male
Housing	0.02	[-0.26, 0.30]	0.904	Free-roaming
Children	0.16	[-0.12, 0.44]	0.256	Present
Number of cats in household (linear)	-0.19	[-0.43, 0.04]	0.099	One
Number of cats in household (quadratic)	0.01	[-0.22, 0.24]	0.935	One
Dogs in household	0.13	[-0.15, 0.41]	0.339	Present