FROM MOVEMENT TO MEANING

BRIDGING COMPUTER VISION AND BEHAVIOUR RESEARCH TO INVESTIGATE ACTIVITY PATTERNS AND SOCIAL INTERACTIONS IN PIGS



Clémence A.E.M. Orsini

Propositions

1. The numerous options for quantifying behaviour offered by movement-tracking data make methodological choices challenging. *(this thesis)*

2. A complete picture of animal behaviour requires integrating individual, dyadic, group, and environmental data. *(this thesis)*

3. Success of interdisciplinary research projects is predicted by the betweenness centrality of the researchers involved.

4. Word limits imposed by scientific journals on the Discussion compromise the clarity of scientific publications.

5. Art and science are complementary ways of making sense of reality.

6. Given their role in forced migration, Western countries have the responsibility to support refugee integration.

7. Relief after a stressful experience gives a stronger perception of well-being than stable comfort.

Propositions belonging to the thesis, entitled

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From movement to meaning

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In memory of my brother, Félix
(1993-2021)

Table of contents

Chapter 1	General introduction	8
Chapter 2	Impact of proximity definitions and sampling rates on social networks in pigs based on tracking using computer vision	28
Chapter 3	Consistency of group-level activity patterns of growing-finishing pigs, obtained by a tracking-by-detection algorithm	60
Chapter 4	Activity and synchrony patterns obtained by a tracking-by-detection algorithm as potential predictors of tail biting at pen and individual level in pigs	88
Chapter 5	Who interacts with whom? Estimating individual and dyadic variation in proximity, tail biting, and ear biting in pigs using generalised linear mixed models	122
Chapter 6	Behaviour recognition of tail and ear biting in pigs using AI-based computer vision	152
Chapter 7	General discussion	182
Miscellaneous	References	218
	Summary	238
	Resumé	243
	Acknowledgements	249
	About the author	259
	Education and training certificate	260
	Publications	262

1

Chapter 1

Chapter 1

General Introduction

This thesis is part of a large collaborative project, the IMAGEN project, which involves academic and industry partners from the Netherlands, including ethologists, animal breeders, data scientists, and computer vision engineers. The overall aim of the project is to develop and apply computer vision algorithms for behavioural monitoring and improving pig welfare. This thesis focuses on spatial proximity and tail and ear biting in growing-finishing pigs using computer vision approaches.

The current chapter presents the background and significance of the research in this thesis. It starts by describing the transformation in pig production and then introduces the social nature of pigs. After this, the chapter focuses on two specific aspects of pig social interactions: social preferences and spatial proximity, and provides an overview of current knowledge on damaging behaviours. The chapter then addresses the current limitations and requirements for monitoring pig social interactions. Finally, it highlights the knowledge gaps and presents the aim and scope of the thesis.

1. Transformation of pig production

1.1. Intensification of pig production

Over the past decades, the demand for meat products has considerably increased in response to the growing world population. Pork accounts for approximately 33% of global meat production, making it the second most produced meat in the world after poultry, and the most produced in Europe (OECD/FAO, 2025). This increasing demand, combined with market pressure, has driven a shift in pig farms toward more intensive production systems. The intensification of pork production, which started initially after World War II, has continued to increase, leading to a decline in the number of pig farms and a rise in the number of pigs per farm. In the Netherlands, between 2015 and 2025, the number of small farms (less than 500 pigs per farm) has decreased by two-thirds, while the average number of pigs per farm has increased by nearly 50%, reaching about 5 000 pigs (CBS, 2025).

1.2. Societal concern and the concept of animal welfare

In parallel with the intensification of pork production, consumers have become increasingly interested in how their food is produced and in the conditions under which farm animals are raised (Lassen et al., 2006; Thorslund et al., 2017). This growing concern has created a need for production systems to transition toward systems that promote the quality of life of farm animals and ensure their welfare. Animal welfare is a complex concept whose definition

continues to evolve and remains subject to discussion. While multiple definitions exist, they often focus on three main aspects: the biological functioning, the emotional state, and the ability to express natural behaviours (Fraser et al., 1997). Behaviour is therefore an important component of welfare, as it reflects how animals interact with their environment and with each other. More specifically, social interactions have been described as a key component of welfare. Positive social interactions demonstrate the animals' capacity to engage in goal-directed, rewarding activities with conspecifics and contribute to welfare (Mellor et al., 2020). In contrast, restrictions of positive interactions with conspecifics or negative social interactions can induce stress and compromise welfare (Proudfoot and Habing, 2015). Therefore, given the importance of social interactions for welfare, it is essential to understand how pigs behave under natural conditions and how they interact with conspecifics under commercial conditions.

2. Pigs are social animals

2.1. Social interactions under natural conditions

Pigs are highly social animals that live in groups and develop social structures. Under natural conditions, a small number of sows form groups with their offspring (Graves, 1984; Gonyou, 2001). Groups can also sometimes split up into smaller groups and merge with other groups. Females leave the group a few days before farrowing to build a nest. They stay isolated with their piglets during the first days after farrowing. After birth, piglets compete by pushing and biting their littermates to access the most productive teats. These contests determine the teat position, which is maintained throughout lactation (Newberry and Wood-Gush, 1985). Piglets remain in the farrowing nest for the first week or two after birth. They start to socialise and interact with pigs outside their litter when they accompany the sow to forage and gradually integrate with the rest of the group (Jensen and Redbo, 1987; Petersen et al., 1989). They interact with other piglets through nose-to-nose contact and social play (Frädrich, 1974; Newberry and Wood-Gush, 1988). Aggressive behaviour can occur between littermates and non-littermates, but usually takes place as part of playful sequences, such as chasing and head knocking (Petersen et al., 1989). This type of play fighting is known to contribute to their social development and to the establishment of a hierarchy (Pellis and Pellis, 2017).

Around seven months of age, males leave their family and form other groups with two or three other males. As they mature, adult males become solitary and only join a group of sows during mating seasons (Graves, 1984; Gonyou, 2001). Under natural conditions, aggression

between pigs is generally limited, but can occasionally occur in the context of competition for resources (Frädrich, 1974; Stolba and Wood-Gush, 1989; Gabor et al., 1999) or more vigorously between adult males during the rutting season (Mendl, 1995). Groups of sows are stable and organised based on a linear dominance hierarchy, which is maintained through conflict avoidance by subordinate individuals (Jensen and Redbo, 1987; Mauget and Boissin, 1987; Gonyou, 2001). Typically, adult sows dominate younger sows and juveniles within the group, while adult boars are dominant over all other group members when they join the group during the mating season (Gonyou, 2001).

2.2. Social interactions under farming conditions

In commercial systems, domestic pigs develop social structures which are largely influenced by management practices and housing conditions. From birth to weaning, piglets typically remain with the sow and their littermates in a farrowing pen. Similar to the behaviour observed in the wild, piglets start developing a social hierarchy just after birth, with the establishment of a teat order among littermates by fighting for access to the teats (Ewbank, 1976). Piglets also develop social bonds with their littermates and engage in affiliative behaviours (e.g., social nosing, lying in proximity) and play behaviour.

At weaning, piglets are separated from the sow and grouped with unfamiliar pigs. They are kept in groups that differ significantly from those observed in the wild. In growing and finishing farms, group sizes generally range from 10 to 30 pigs of the same age per pen. However, farms are also moving toward larger groups, with some housing over 100 pigs per pen (Meyer-Hamme et al., 2016). Pigs are usually grouped according to their age, and sometimes to their body weight or sex, often without considering familiarity or kinship (Clouard-Mésange, 2025). The separation from familiar littermates and the mixing with unfamiliar pigs disrupt the existing bonds and lead to the establishment of a new social structure among pigs. The social structure of domestic pigs is based on a dominance hierarchy, which is established during a brief period of vigorous fighting after unfamiliar pigs are mixed (Ewbank, 1976). These fights usually occur between pairs of animals, and the outcome determines which animal dominates the other. In most groups, dominance hierarchies are non-linear, meaning that dominance relationships are not always transitive. For example, Pig A dominates Pig B, Pig B dominates Pig C, and Pig C dominates Pig A (Bolhuis et al., 2005). Throughout the growing and finishing periods, pigs may be regrouped multiple times to optimise growth performance and management, which destabilises hierarchies and thereby requires the establishment of a new social structure. Domestic pigs

are kept in very uniform groups with little variation in size or weight (Gonyou, 2001). Therefore, the establishment of dominance relationships leads to vigorous fights, as there is no clear difference in strength. Dominance relationships are typically established within the first 48 hours after mixing, after which the social structure is maintained through avoidance behaviours by subordinates (Jensen, 1982). In addition to agonistic behaviours, domesticated pigs engage in a large variety of social interactions with their pen mates, including affiliative behaviours (e.g., social nosing, lying in proximity and play behaviour) and damaging behaviours (e.g., ear biting, tail biting, and flank biting). As this thesis focuses on spatial proximity and tail and ear biting, these behaviours are described in more detail in the following sections.

3. Social preferences and spatial proximity

3.1. Social preferences

Wild pigs living in groups associate non-randomly and develop preferential affiliative relationships (McIlraith et al., 2025). This means that some individuals tend to associate and perform more bidirectional affiliative interactions with each other (i.e., grooming, spatial proximity during resting) compared to other group members (Silk et al., 2006; Kalbitz et al., 2016; Moscovice et al., 2017). These associations are shaped by both the environment, such as shared resources (Karczmarski et al., 2005; Peignier et al., 2019), habitat structure (Leu et al., 2016), predation risk (Groenewoud et al., 2016), and individual characteristics, such as sex, age (Rushmore et al., 2013; Rushmore et al., 2023), personality (Wolf and Krause, 2014) and reproductive status (Rushmore et al., 2013).

Also, on commercial farms, affiliative relationships may play an important role in maintaining the group's social cohesion and potentially have a positive impact on welfare. The presence of a preferred partner may have a buffering effect when exposed to a stressful event (Mason and Mendoza, 1998; Newberry and Swanson, 2008; Nagasawa and Kikusui, 2021). On the other hand, breaking social bonds can be associated with emotional distress and reduced animal welfare (Boissy and Le Neindre, 1997; Panksepp, 2011). Despite this potential importance, social preferences in pigs are still poorly understood. A few studies suggest that pigs can form preferential relationships under commercial conditions, through allogrooming, social nosing, and proximity while lying (e.g., Clouard et al., 2024). However, these relationships are generally weak, with only a few pigs forming stronger bonds (Durrell et al., 2004; Goumon et al., 2020; Camerlink et al., 2022; Clouard et al., 2024) and a limited

stability of bonds over time and across life phases (Durrell et al., 2004; Jowett and Amory, 2021).

Preferential associations and the social role of each individual can be investigated through social network analyses (SNA); see Text box 1. This approach has been widely applied in studies on wild animals to understand social dynamics, but remains limited in farm animal research.

3.2. Spatial proximity

In wild boars, social interactions are often approximated by measuring spatial proximity, i.e. physical closeness between animals, as interactions are likely to happen when animals are close (Bieber et al., 2019; Marin and Couderchet, 2024; McIlraith et al., 2025). This approach is based on the hypothesis that, in the wild, animals have sufficient space to choose whether to avoid or stay close to others. This may be particularly relevant in groups of pigs under natural conditions, where social hierarchies are often maintained through avoidance behaviours.

Under farming conditions, spatial proximity is often associated with affiliative behaviours, with the assumption that pigs spending time next to each other are not actively avoiding each other and may also engage in positive interactions, such as social nosing (Durrell et al., 2004; Goumon et al., 2020; Camerlink et al., 2022). However, in contrast to the wild, domestic pigs are kept in restricted space (i.e., according to EU legislation, between 0.15 m^2 for pigs weighing less than 10 kg and 1 m^2 per pig over 110 kg; EU, 2008). In such a limited space, the distinction between pigs physically close to one another and the rest of the group is particularly debatable, as the restricted space may limit their ability to isolate themselves or choose and avoid specific pen mates. Groups of growing and finishing pigs are also homogeneous, and therefore, pigs have a limited choice of partners compared with natural conditions. Therefore, it remains unclear if proximity indeed indicates affiliations or reflects preferences for locations. Importantly, proximity may not necessarily imply positive interactions and may also occur in the context of aggression or damaging behaviours (Li et al., 2018; Charles et al., 2024; Agha et al., 2025). For example, pigs engaging in tail or ear biting may lie near their victims, and spatial proximity could also reflect a preference for a specific victim.

Text box 1: Social Network Analyses

In behavioural studies, social network analysis (SNA) is a methodological approach to quantify the social structure of a group and identify the social roles of each individual within this group (Makagon et al., 2012; Buttner et al., 2015; Buttner et al., 2019; Sosa et al., 2021). Social networks are built by quantifying interactions across all the possible pairs of individuals. They are visualised as sociograms (Figure 1), where the individuals are represented as nodes (A, B, C,…, I; Figure 1) and are connected by edges (proportional to the strength of the interaction). The edges may have a direction, with a clear initiator and receiver (e.g., tail biting and ear biting, Figure 1a), or be non-directional (e.g., spatial proximity, Figure 1b).

Several network metrics can be calculated from the interaction data, each capturing different aspects of the network. Group-level network metrics provide information about the whole network structure and enable the comparison between different groups, whereas individual-level network metrics describe the position of each individual within the network. Metrics can reflect aspects of prominence, such as unequal interactions with the presence of key individuals, and cohesion, indicating the presence of subgroups or tightly connected individuals. Direct network metrics are calculated using only immediate interactions, whereas indirect network metrics consider more complex network structures and relationships.

(a) Directional network *(b) Non-directional network*

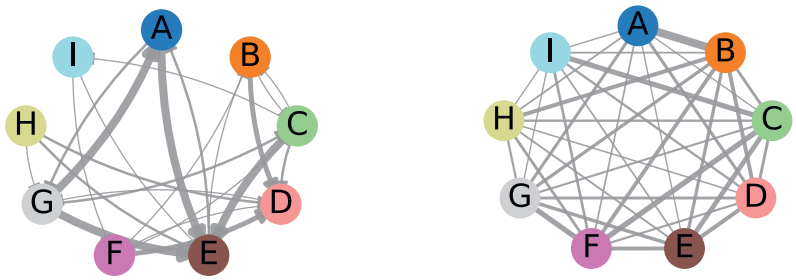


Figure 1. Example of the structure of (a) directional and (b) non-directional social networks. A, B, C, …, I are the nodes representing the individuals, and the connections between the nodes are the edges, proportional to the strength of the social interactions.

4. Damaging behaviours

4.1. Tail and ear biting and their consequences

Tail biting and ear biting are damaging behaviours whereby a pig uses its teeth to bite, chew or orally manipulate another pig's tail or ears (Schroder-Petersen and Simonsen, 2001). These two behaviours are the most common damaging behaviours in commercial farms. Previous studies reported a prevalence of 0.26 to 59.1% for tail damage (Smulders et al., 2008; Harley et al., 2012; Keeling et al., 2012; Scollo et al., 2016) and 3 to 14.9% for ear damage (Smulders et al., 2008; Van Staaveren et al., 2018). These behaviours can occur in isolated cases involving only a few pigs, or rapidly escalate within the group into an outbreak with several pigs involved (Taylor et al., 2010; Diana et al., 2019). Tail and ear biting seriously compromise the welfare of the victim by causing stress and pain (Munsterhjelm et al., 2013). Moreover, victims can easily become infected through the open wound, and these infections can then spread systemically throughout the body of the victim and may result in abscesses, paralysis, pyaemia and even death (Huey, 1996; Sihvo et al., 2012). At the same time, the biter's behaviour may also reflect underlying welfare problems, such as insufficient opportunities to express natural behaviours (e.g. rooting and foraging) or an unbalanced diet (Minussi et al., 2023), or a genetic predisposition (Breuer et al., 2003). The related economic repercussions are high for producers due to reduced weight gain (Wallgren and Lindahl, 1996; Sinisalo et al., 2012), the need for veterinary treatments, and carcass condemnation (Kritas and Morrison, 2007).

Two distinct stages around an outbreak of tail biting have been identified (Fraser, 1987). In the first "pre-injury" stage (i.e. before any wounding of tails occurs), a pig is rooting and chewing the tail of another pen mate lightly. This behaviour is usually tolerated by the receiver and may be performed while both animals are lying down. Tail chewing might result in a small bleeding wound and progress to the "injury stage". The bleeding tail often attracts other pigs and encourages further biters, leading to a drastic escalation, i.e. an outbreak. At the beginning of this injurious stage, the recipient reacts by avoiding the biter or by emitting vocalisations indicative of discomfort. In severe cases, the victim gradually stops resisting and escaping, becomes apathetic and spends most of the time lying down (Sambraus, 1985).

4.2. Environmental risk factors of tail and ear biting

Understanding the underlying causes of damaging behaviours like tail and ear biting is challenging, as they appear to have multifactorial origins. Tail biting has been widely studied and is known as a problem with many environmental risk factors, such as high stocking density (Schroder-Petersen and Simonsen, 2001), poor ventilation, suboptimal diet formulation and distribution (Fraser et al., 1991) or lack of substrates to explore (D'Eath et al., 2014). In contrast, little is known about ear biting, but it appears to share some environmental risk factors with tail biting (Brunberg et al., 2011; van der Meer et al., 2017). One key risk factor shared by both behaviours is the absence of sufficient manipulative materials, resulting in the redirection of pigs' natural need for foraging towards other pigs (Brunberg et al., 2011; Camerlink and Turner, 2013; van der Meer et al., 2017; van Staaveren et al., 2024). The pen materials, such as the floor, the drinking trough or the feeder, are often unsuitable for exploring and chewing (Feddes and Fraser, 1994), and pen mates can be chosen by the pigs as an alternative (Beattie et al., 1996). However, tail biting has also been recorded in outdoor-kept growing finishing pigs where they had greater access to substrates and space (Walker and Bilkei, 2006). This thus shows that the occurrence of tail biting, and potentially ear biting, is clearly multifactorial. It is also important to note that various forms of biting exist in terms of intensity, occurrence and persistence, and these differences in biting may also reveal different aetiologies of the problem (Taylor et al., 2010)

4.3. Individual risk factors of tail and ear biting

Besides environmental risk factors, individual pig risk factors have also been identified. Previous studies frequently reported that males are more likely to be bitten and less likely to bite than females (Penny et al., 1981; Sambraus, 1985; Hunter et al., 1999). However, Sinisalo et al. (2012) found no difference in the prevalence of victims between boars, barrows and females. Nevertheless, the risk may increase in all-female groups compared to all-male or mixed sex groups (Hunter et al., 2001; Zonderland et al., 2011b). Being the recipient of tail biting or the biter might also be related to genetic predispositions. The genetics of modern domestic pigs and their breeding history, which is based on individual performance, may have contributed to selecting individuals who are more likely to perform or receive damaging behaviours (Breuer et al., 2003). Ursinus et al. (2014b) found that high levels of tail biting were related to higher estimated breeding values for weight, growth, and litter size, which is in line with findings on genetic correlations between tail biting and production traits reported

by Breuer et al. (2003). A breed effect has also been reported by Breuer et al. (2003), with a higher tail biting incidence in Landrace compared with Large White. In this study, tail biting was also found to be heritable in Landrace (h^2=0.27), in contrast to Large White pigs. Furthermore, exploration and feed motivation are heritable in pigs (Lawrence and Terlouw, 1993; Breuer et al., 2003; Baumung et al., 2006; Renaudeau et al., 2006), suggesting that motivation to manipulate and bite tails may also may also have a heritable component.

Although there is evidence of individual variation between pigs in biting and being bitten, little is known about the consistency of being a biter or a victim across time. Ursinus et al. (2014) found that tail biters tend to change across production phases, whereas victims remain more consistent in the role of victim. In addition, two studies have investigated whether biters preferentially target specific pen mates, but have addressed this question at different levels. Zonderland et al. (2011a) found no evidence that pigs have a preference to bite specific pen mates. Li et al. (2018) reported that pigs are more likely to bite litter mates than other pen mates. SNA may help to better understand how tail and ear biting develops over time and identify key individuals and their characteristics (see Text box 1).

4.4. Prevention of damaging behaviours

Tail docking (i.e. amputating the distal part of the tail, usually without anaesthesia or analgesia) is a common procedure, adopted by farmers, to prevent tail biting. This measure has demonstrated its effectiveness in considerably reducing a pig's chances of being bitten (Hunter et al., 2001) which might be explained by the decreased accessibility due to the short length (Thodberg et al., 2018). Simonsen et al. (1991) also hypothesise that the risk might be reduced because tail-docked pigs are more sensitive to pain and react more vigorously to manipulation on their tails. However, tail docking is a controversial intervention associated with physical pain and behavioural distress (Morrison and Hemsworth, 2020). Despite its prohibition as a routine measure by the EU Council Directive 2008/120/EC, this procedure is still widely used in many EU member states, and there is an urgent need to develop alternative and non-aversive solutions to prevent and control tail biting. Many studies suggest that environmental enrichment reduces the chance of damaging behaviours (Bøe, 1993; Petersen et al., 1995; Ursinus et al., 2014c). Since January 2003, the provision of "appropriate environmental enrichment" to pigs of all ages is mandatory in the EU. However, this directive leaves considerable room for choosing the type of material, and the amount and frequency with which this material is provided, whereas these factors influence the effect of enrichment.

For example, Zonderland et al. (2008) found that straw was more effective in preventing tail biting than a chain or a rubber hose.

4.5. Detection of damaging behaviours and interventions

Providing permanent access to litter materials that are effective to prevent tail biting (such as straw), may be costly, associated with extra labour and cannot be used in housing systems with slatted floors due to the difficulties of evacuating the manure. Another approach to preventing tail biting could be to intervene only when early signs of damaging behaviours are detected. Zonderland et al. (2008) found that providing a small amount of straw twice a day and removing the biter when at least one pig was observed with a fresh tail wound was effective to stop the spread of tail biting within the pen. Chou et al. (2019) were able to control 80% of tail biting outbreaks within 18.4 ± 1.7 days on average using one or multiple intervention strategies (removing biters, victims or adding 3 ropes). To limit the negative effects and their spread within the group, damaging behaviours should be diagnosed at an early stage. However, tail biting is typically only detected by the farmer at a severe injury stage when the tail is wounded and bleeding. Therefore, there is a need for continuous monitoring of damaging behaviours and identifying early warning signals to timely intervene before the escalation in the pen and major damage occurs.

5. Current limitations and future requirements for monitoring pig social behaviour

A better understanding of social interactions, such as ear and tail biting, and spatial proximity, may help to improve welfare by guiding management practices and identifying (social) traits that can be integrated into breeding programs. For these applications, social interactions must be monitored continuously to obtain high-quality data that are both accurate and representative (e.g., reflecting actual interactions without overlooking or overemphasising specific ones), ideally at the individual level. However, so far, most studies have relied on manual annotations, which have clear limitations.

5.1. Complexity of monitoring social interactions

Several factors may influence the behaviour observations, and thereby affect the quality of the data. Social interactions are often complex behaviours, making observations challenging for observers. For example, the differentiation between play fighting and aggression is often reported as a particularly challenging behaviour to observe, especially in young pigs (Cordoni

et al., 2022). Ear and tail biting are usually short lasting behaviours, and it may be difficult for observers to distinguish between nosing and real biting. Recording proximity also poses significant challenges of which a key challenge is that there is no gold standard for when animals are close in proximity. Different studies have applied different thresholds to define "close proximity", including 50% of one pig's body in contact with another (Li et al., 2018), 30 cm between pigs (Goumon et al., 2020), or 1 m in sows (Jowett and Amory, 2021). Another challenge is that these thresholds may be challenging for observers to identify reliably, both in live observations and video recordings.

Furthermore, observers may also be biased by the experimental setting. For example, when scoring behaviours in different housing conditions, observers may be influenced to record more positive behaviours and fewer negative behaviours in enriched than in barren environments. Although approaches such as using blind observers are applied to reduce these potential biases, it is not always possible to hide the experimental conditions (Tuyttens et al., 2014).

Therefore, there is a need for monitoring behavioural interactions objectively and reducing the potential bias between observers. This will also allow a better comparison between studies.

5.2. Need for continuous monitoring

In research, behaviours are typically observed over limited time periods using manual observations, which is highly time-consuming and therefore limits sampling duration. Brief social interactions, such as tail and ear biting, are often sporadic and brief, and may be missed if observations are restricted to a few hours per day or rely on scan sampling. Missing tail biting events reduces the accuracy of network metrics (Wilder et al., 2022). Also, for longer-term interactions, such as time spent in proximity, large quantities of data across all interacting individuals are necessary to build a reliable representation of the social structure (Davis et al., 2018). Insufficient sampling might result in missed connections between individuals and potentially have significant implications for social network structure.

Behaviours are typically also incorporated into farm welfare assessments by recording the presence or absence of specific behaviours, or by determining whether a behaviour is performed for a certain duration during the observation period, e.g., Welfare Quality (Dalmau et al., 2009). Continuous monitoring of the behaviour of individual pigs would also enable

the derivation of continuous variables with biological relevance. For example, a disruption of the circadian rhythm has been suggested as a potential indicator of welfare issues (Gorka et al., 1996; Wagner et al., 2021; Bus et al., 2023) and is associated with mood disorders and reduced well-being in humans (Lyall et al., 2018). Therefore, continuous monitoring of pig behaviour may enable the development of new indicators of welfare based on continuous variables.

5.3. Need for individual-level measures

Behavioural data at the individual level are essential for advancing our understanding of social interactions, as they make it possible to identify the roles of individuals within interactions. Some individuals may play key roles, such as contributing to group cohesion, or be consistently involved in damaging behaviours as biters or victims. In research, identifying the role of each individual would enable investigation of how inter-individual differences (e.g. personality and coping styles) are associated with specific social roles, whether pigs develop social preferences, and how these roles and preferences change over time. Furthermore, in breeding programmes, selection for desirable behavioural traits requires individual-level data from large numbers of pigs. In farm management, early identification of biters and victims may provide valuable information for preventing the escalation of outbreaks, for example by removing biters and victims from the pen (Schroder-Petersen and Simonsen, 2001; Zonderland et al., 2008) or treating victims (Arey, 1991). Furthermore, individual pigs may differ in baseline behaviours that are associated with later damaging behaviours. Therefore, individual-level monitoring is required to establish behavioural baselines and detect meaningful changes over time, which may otherwise be hidden in group-level data.

6. Automated approaches to study social interactions

In contrast to manual observations, automated monitoring of behaviour, through the use of sensors or video-based algorithms, offers continuous, objective and potentially individual-level data.

6.1. Monitoring individual behaviours

Tracking enables the identification of individual animals while also providing detailed information about their activity, proximity to others, and location over time. Previous studies have investigated tracking farm animals with location sensors such as GPS (Chopra et al.,

2020; Ozella et al., 2020) or RFID (Voulodimos et al., 2010; Floyd, 2015). These systems typically rely on an antenna and an electronic chip, often integrated into the ear tag of each animal. They have the advantage of producing individual location data that can be used for further analysis. In commercial farms, RFID is commonly used at feeding stations to identify individual pigs and monitor their feeding behaviours. However, these devices present limitations in monitoring individual movements. They are expensive, require regular maintenance, and require frequent replacement. In addition, those systems can be highly sensitive to environmental noise, and their accuracy may limit their application to provide the correct location of animals housed in small areas (Ozella et al., 2020).

Other studies have therefore moved toward alternative methods to track farm animals, such as video-based approaches. One example is a video-based tracking-by-detection algorithm, which identifies individuals and tracks their movements over time by detecting animals in each frame and linking these detections across frames to build individual trajectories. Animal detection can be done using bounding boxes, which provide a simple rectangle around each animal, instant segmentation, which provides the exact pixels belonging to each animal, and key point detection, which identifies important points on the animal. The development of these algorithms is facilitated by the existence of open-source codes and pre-trained models that can then be fine-tuned for specific environments and objects using extra annotations. For example, You Look Only Once (YOLO) is a popular object detection model (Redmon and Farhadi, 2018) that was first released in 2016 and has quickly evolved to others versions, such as YOLOv10 released in 2024 (Wang et al., 2024) with improvements in accuracy, speed, and flexibility (Hussain, 2023). These models have been successfully applied to detect objects with different features, for example, humans in the context of video surveillance (Caputo et al., 2021). However, maintaining the identity of individuals over time remains particularly challenging, especially for individuals with similar appearances housed in groups with limited space allowance. As a result, the performance of tracking algorithms in farm animals is often limited and often leads to the loss of the identity of individuals and identity switches (Guo et al., 2015; Guo et al., 2023; Huo et al., 2023). Solutions have been proposed to improve tracking of farm animals, for example, by combining tracking-by-detection with RFID from feeders (Mora et al., 2024), or with the detection of distinct individual signs, such as individually-coloured ear tags (Schmidt et al., 2022) or ARUCO markers (van Putten et al., 2025).

6.2. Monitoring spatial proximity

Tracking-by-detection algorithms provide the location of each individual across time. This information can be used to measure proximity to pen mates by calculating the distance between animals. Location sensors, such as GPS, have been widely used in wild animals to assess spatial proximity (Nathan et al., 2022) and are particularly well adapted to study the proximity patterns of animals kept in large outdoor areas. GPS has also been used to study spatial proximity between farm animals kept in relatively large areas, such as cows housed in an indoor barn of ~0.2 ha (Chopra et al., 2020) and sheep grazing outdoors on pastures of ~1-2 ha (Ozella et al., 2020). However, similarly to the limitation described above for identifying individual animals, the application of these sensors in dense groups of farm animals kept in relatively small areas is challenging, as the quality of the data collected is limited by the resolution of the sensor (Ozella et al., 2020), which might be insufficient to provide accurate distance between animals.

As an alternative to GPS and RFID-based methods, video-based tracking-by-detection algorithms, by detecting the pig's location in each frame, also give the opportunity to calculate proximity between pen mates. However, to our knowledge, the use of such an algorithm to study spatial proximity has been limited to mice (Shemesh et al., 2013) and *Drosophila* (Schneider et al., 2012) and has not been explored in farm animals.

6.3. Detecting damaging behaviours

Recent studies have explored the use of computer-vision approaches to detect social interactions between pigs, with most research focusing on aggression (Oczak et al., 2014; Viazzi et al., 2014; Lee et al., 2016; Chen et al., 2019), mounting (Nasirahmadi et al., 2016), and play behaviour (Gan et al., 2021; Larsen et al., 2023). These interactions are characterised by close proximity between pigs and rapid movements, features that facilitate their detection by computer vision. In contrast, only a few studies have attempted to identify tail and ear biting or other damaging behaviours using computer vision (Liu et al., 2020; Hakansson and Jensen, 2023; Odo et al., 2023; Odo et al., 2024). Detecting these interactions remains technically challenging as they are subtle and often characterised by minimal movements and short duration, and can occur in different postures. In addition, tail and ear biting are rare and sporadic, making it difficult to collect sufficient data to train algorithms. Therefore, the development of the models is often based on limited and relatively homogeneous datasets

and/or on detection of specific, most easily detectable forms of damaging behaviour only. Hence, there is a need to develop more generalised models that also capture more subtle forms of damaging behaviours.

6.4. Detecting early signs of damaging behaviours

Because tail and ear biting are technically challenging to detect and measure, previous studies have also focused on automatically detecting indirect indicators associated with the development of damaging behaviours. Apart from the increase in tail and ear biting itself on the days preceding tail damage outbreaks, there is evidence in the literature that pigs may also change other behaviours. These changes include an increase in activity and signs of restlessness (Statham et al., 2009; Ursinus et al., 2014a), an increase in object-directed behaviours, changes in feeding and drinking patterns (Wallenbeck and Keeling, 2013; Viitasaari et al., 2015), and lowered tail postures (Lahrmann et al., 2018; Wedin et al., 2018). Several studies have attempted to identify those indicators with automated methods (see references below).

Automated methods have been developed to measure activity in pigs, either by measuring the distance moved from a tracking-by-detection algorithm (van der Zande et al., 2021) or detecting specific postures, such as lying, standing and sitting (Nasirahmadi et al., 2015; Kim et al., 2017; Sivamani et al., 2020; Scaillierez et al., 2024). While these automated methods show promising results for quantifying activity, it remains unclear to what extent activity-based metrics derived from these approaches can reliably indicate changes preceding outbreaks of damaging behaviours. To date, their potential for automatically detecting change in activity before outbreaks has not been explored.

Various methods have been developed to detect pigs' exploration of enrichment materials, which could also be used in the context of damaging behaviours. These approaches include adding sensors directly to the enrichments, such as mechanical counters (Bracke and Ettema, 2014), UHF-RFID devices like the Bite-o-Mat (Eisermann et al., 2022; Eisermann et al., 2025), passive infrared detectors, accelerometers, and recognising object-oriented behaviours with computer vision (Veldkamp et al., 2023). These approaches offer promising tools to monitor object-oriented behaviours and potentially predict damaging behaviours, although further validation is needed.

Additionally, data from electronic feeding stations can indicate a reduction in the feeding behaviours linked with tail biting (Wallenbeck and Keeling, 2013; Munsterhjelm et al., 2015). Feeding and drinking are relatively easy to measure automatically with sensors; however, these measures are not specific (Larsen et al., 2019b) and do not always predict tail damage (Bus et al., 2024).

Tail posture, especially low and tucked tails, has also been proposed as an indicator of tail biting (Zonderland et al., 2009; Lahrmann et al., 2018; Larsen et al., 2018). Tail posture can be automatically detected with 3D cameras, but this approach requires costly cameras (D'Eath et al., 2018; D'Eath et al., 2021). In addition, tail postures have many nuances, and although a tucked tail is mainly associated with tail biting, pigs may also change tail posture due to other causes (Camerlink and Ursinus, 2020; Reimert et al., 2025).

Overall, several early indicators of damaging behaviours have been identified in the literature and may be suitable for automated monitoring. However, further work is needed to validate these indicators across different settings and types of tail biting, and to move toward decision-support systems.

Conclusion and knowledge gaps

In commercial systems, domestic pigs are kept in groups and develop social structures that are influenced by management practices and housing conditions. Pigs are highly social animals, and understanding their social interactions is important, as these interactions are a key component of welfare. Positive social interactions, such as lying in close proximity, can promote welfare, whereas negative interactions, such as ear and tail biting, can severely compromise it.

In large commercial farms, identifying social structures and ear and tail biting is nearly impossible by human observation, particularly at a large scale. Computer vision provides new opportunities to overcome these limitations by enabling continuous, automated monitoring of pig behaviour at the individual level over extended periods.

However, to date, research on automated behaviour monitoring has focused predominantly on developing and validating computer vision systems. In contrast, limited attention has been given to translating the behavioural data generated by these systems into biologically meaningful measures and applying advanced analyses to uncover complex behavioural patterns. In particular, it remains unclear how computer vision systems can be used to

characterise social structures, quantify individual and group-level variation, and identify early behavioural indicators of welfare problems, such as ear and tail biting. Bridging this gap between technological development and biological application is essential to fully realise the potential of automated monitoring systems, which could further advance our understanding of pig behaviour and inform management practices to improve pig welfare.

Aim and scope of the thesis

The overall aim of this thesis is to explore the potential of using computer vision for monitoring social interactions and activity patterns in pigs, with the overarching goal of improving pig welfare. The initial focus of the thesis was on social interactions, specifically investigating tail biting and other social behaviours through automated individual behaviour recognition. However, due to technical challenges encountered during the development and implementation of the algorithms, obtaining behaviour recognition data from these algorithms suitable for research was not feasible within the timeframe of the project. Consequently, this thesis focuses on social interactions quantified through proximity measures derived from tracking-by-detection algorithms and manual annotations of ear and tail biting, while extending the scope to include activity patterns. An overview of the different chapters of this thesis is presented in Figure 2.

Chapter 2 explores how a tracking-by-detection algorithm can be used to investigate social networks in pigs based on spatial proximity, and whether methodological choices regarding proximity definitions and sampling rates affect social networks of inactive pigs. **Chapter 3** examines the long-term consistency of group-level activity patterns, also derived from a tracking-by-detection algorithm, while accounting for environmental fluctuations. After characterising group-level activity patterns and their variation over time, **Chapter 4** investigates whether group-level activity patterns can predict tail wounds and whether individual activity is associated with performing or receiving tail biting. **Chapter 5** explores whether individual pigs differ in their proximity to pen mates and in performing and receiving ear and tail biting, and whether, beyond individual variation, specific pairs of pigs spend on average more time in proximity or engage in biting more frequently than others. It introduces a novel modelling approach for analysing social interactions and assessing individual differences and social preferences simultaneously, by partitioning variation in social interactions into individual and dyadic random effects. **Chapter 6** describes a video-based behaviour recognition algorithm developed to identify ear and tail biting behaviours. Finally, these chapters are integrated and discussed in the General Discussion (**Chapter 7**).

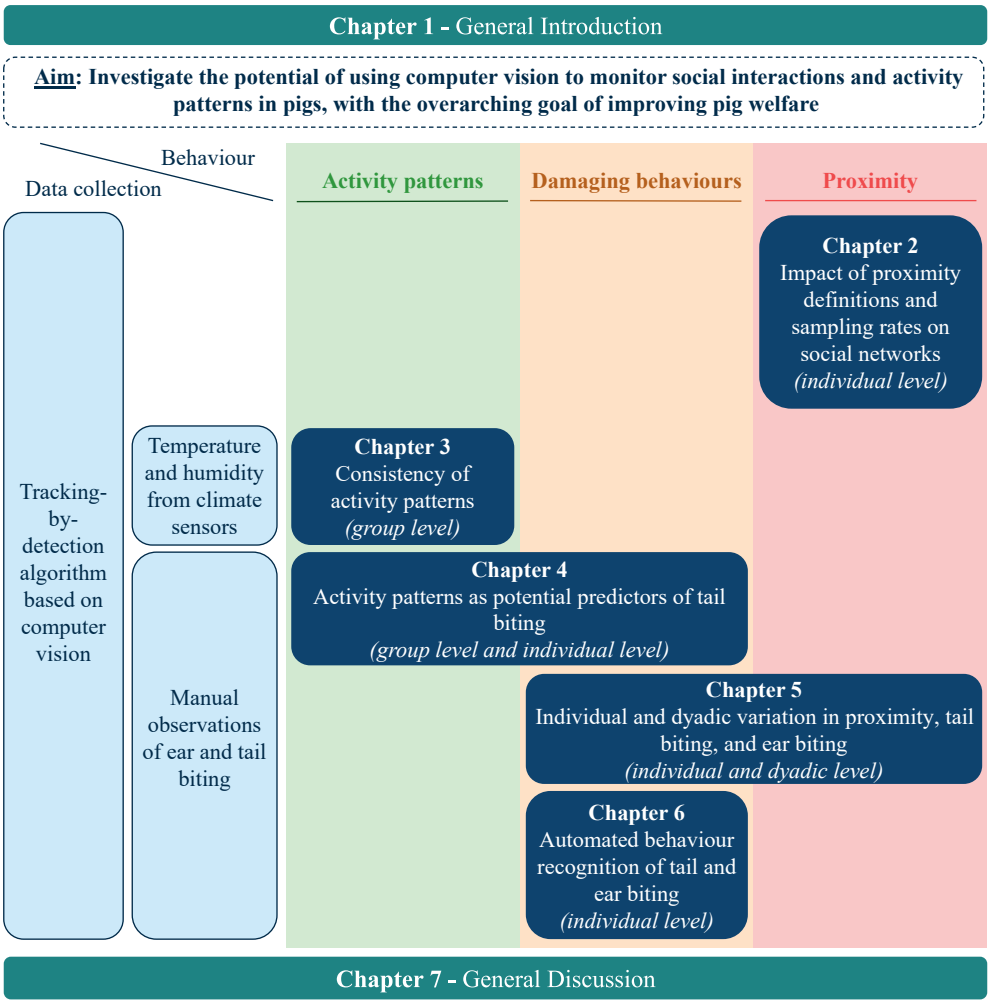


Figure 2. Overview summarising the different chapters of this thesis.



2



Chapter 2

Chapter 2

Impact of proximity definitions and sampling rates on social networks in pigs based on tracking using computer vision

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Abstract

In farm animals, social network analysis has become a popular approach to explore preferential associations. This study investigated how different spatial proximity definitions and sampling rates affect social networks based on proximity using computer vision. Video data collected over three days in 21 pens (6 pigs/pen), either enriched or barren, were analysed using a tracking-by-detection method based on bounding boxes. Networks were constructed with five different definitions of proximity: (1) distance between centroids of bounding boxes <50cm, (2) occurrence of overlap of surfaces of bounding boxes, (3) surface overlap of bounding boxes >20%, (4) a combination of (1) and (3), and (5) the harmonic mean of the distance between the two individuals. For each proximity definition, networks built with downsampled data were compared to a network built with 0.5 frames per second. The network metric degree centrality was less affected by proximity definitions compared to eigenvector centrality and clustering coefficient. To maintain high correlations with the complete network ($r>0.90$), downsampling should not go beyond 1 frame every 6 min. This work shows how computer vision data can be used for social network analysis in livestock with limited space and choice of social environment, and how metrics depend on proximity definitions and sampling rates.

1. Introduction

Social network analysis (SNA) is a powerful method to quantify inter-individual interactions and identify the social roles of each individual within a group (Makagon et al., 2012). The use of this method has become popular for studying the social dynamics within animal groups or populations and its application has increased considerably in recent years (e.g., Buttner et al., 2019; Makagon et al., 2012; Sosa et al., 2021). Previous studies on wild animals have, for example, shown the potential of SNA to detect temporal behaviour changes (Davis et al., 2018) and to identify key individuals whose removal or introduction strongly impacts the dynamics of the group (Kulahci et al., 2018; Makagon et al., 2012; Modlmeier et al., 2014). In addition, in zoo-housed populations, SNA can help to develop effective conservation strategies (Lewton and Rose, 2021) and improve welfare by reducing social stress (Rose and Croft, 2015). In a social network, the individual animals are represented as nodes and are connected by edges. The edges can be direct when there is a clear initiator or receiver (e.g., in aggressive interactions), or indirect (e.g., during communal resting) (Farine and Whitehead, 2015). Centrality metrics (e.g., degree, betweenness, eigenvector or clustering coefficient) describe the position of each individual within the network, representing different facets of behaviour such as connectivity or influence roles (Makagon et al., 2012). General network metrics (e.g., density, fragmentation, or radius) provide information about the overall network structure, such as the cohesion or the brokerage, and enable the comparison between different groups of similar sizes (Adelman et al., 2015; Aplin et al., 2015).

Besides its application on wild and zoo animals, SNA is a promising method to gain knowledge about social interactions in farm animals, such as pigs (*Sus scrofa domesticus*), and to positively impact their welfare. A better comprehension of social interactions in pigs may open doors to new management or breeding strategies to improve their group functioning (Finkemeier et al., 2018). Changes in measures of centrality and cohesion could be used to predict the escalation of abnormal behaviours within groups of pigs. These changes could also help in decision-making to remove key individuals involved in the spread of these behaviours (Makagon et al., 2012; McCowan et al., 2008). In addition, when pigs are transferred between production stages, they are subjected to repeated changes in group composition, which often destabilise the social structure and result in aggression (Coutellier et al., 2007). SNA can guide management practices to reduce social stress and minimise the destabilising of the social structure. For example, removing pigs with a high centrality from poorly interconnected groups is likely to have a negative impact by destabilising the group,

compared with removing animals from more cohesive groups (Makagon et al., 2012). SNA can also help to identify preferential affiliations and their drivers (e.g., sex, age, relatedness, dominance status) (Chopra et al., 2020; Clouard et al., 2024b; Vázquez-Diosdado et al., 2023) and manage groups to keep preferred affiliative partners together, as they may provide social buffering against stressful events (Reimert et al., 2014). Previous studies revealed that domestic pigs are highly social animals and may develop social preferences, expressed especially by close spatial proximity during rest (Durrell et al., 2004; Goumon et al., 2020; Stookey and Gonyou, 1998). The choice of lying partners has, therefore, been suggested as a potential indicator of affiliative preferences.

When performing SNA, researchers have to make a multitude of choices for data collection and analysis. Behavioural data can be collected in a variety of ways, including differences in the sampling method, the period of study, and the definition of the connections between individuals (i.e. edge definitions) (Davis et al., 2018). Depending on the research question being addressed, the edges can be defined based on specific behavioural interactions (e.g., grooming, agonistic behaviours) or on spatial proximity. However, in the literature, there is no consensus on how spatial proximity is defined. In the context of lying, for example, Durrell et al. (2004) defined spatial proximity as two growing pigs spending time in physical contact or in very close parallel contact , whereas Li et al. (2018) specified a threshold for proximity of 50% of the pig's body in contact with the other pig. Goumon et al. (2020) considered growing pigs as lying in spatial proximity when they were within 30 cm of each other , while Jowett and Amory (2021) used a threshold of 1 m in sows. The definition of these thresholds may depend also on the size of the animals, on the environment in which they are housed, on the stocking density, and on the behaviour that is considered (for example lying in close proximity, versus exploring in close proximity; Goumon et al., 2020).

Different spatial proximity definitions might significantly affect the network metrics, and the choice of a definition has therefore important implications for the conclusions that can be drawn from the network (Farine and Whitehead, 2015). For example, using a smaller distance threshold to capture spatial proximity may result in a lower frequency of individuals captured as in close proximity, and, thus, a lower individual average degree and lower network density (Davis et al., 2018). A few studies have tested the impact of different protocols on social networks, including the effect of the sampling methods (Davis et al., 2018; Wilder et al., 2022), or different social interactions and proximity techniques (Castles et al., 2014; Chopra et al., 2020). These studies demonstrated that using different methods significantly influences

the results of the SNA. However, to our knowledge, the impact of different proximity definitions on proximity networks in pigs has not been investigated so far.

Apart from proximity definitions, sampling rates vary widely across SNA studies in pigs, with data collection periods ranging from one day (Agha et al., 2022; Foister et al., 2018) to a few hours across several days (Agha et al., 2020; Buttner et al., 2015; Li et al., 2018). For SNA-based proximity in pigs, some studies used instantaneous scan sampling, where observations are made by scanning videos at fixed time points (e.g., every 10 min; Charles et al., 2024; Li et al., 2018), while others record proximity continuously over a defined observation window (e.g., 30 min; Clouard et al., 2024a). Most of the SNA studies are based on manual observations which are highly time-consuming and therefore limit sampling duration. However, large quantities of data across all possible interacting individuals are necessary to build a robust and accurate representation of the social network (Davis et al., 2018). Insufficient sampling might result in missed connections between individuals and can have significant implications on social network structure (Farine and Whitehead, 2015).

Recent advances in sensing technologies provide the opportunity to considerably increase the sampling rate of the data collection for SNA. Using such technologies, spatial positions of pigs may be investigated continuously at an individual level and over a long period. Location sensors, such as Global Positioning Systems (GPS), have been widely used in wild animals to assess contact patterns and study social networks based on spatial proximity (Nathan et al., 2022). These sensors are particularly well adapted to study behaviours of animals kept in large outdoor areas compared with cameras, which have only a limited field of view. In farm animals, previous studies investigated the structure of the network of animals raised in relatively large areas (outdoor, free stall barn) with location sensors such as GPS (Chopra et al., 2020; Ozella et al., 2020). However, the application of these sensors in dense groups of farm animals kept in relatively small areas is challenging, as the quality of the data collected is limited by the accuracy of the sensor (Chopra et al., 2020; Ozella et al., 2020), which might be insufficient to provide the correct distance between animals when all distances are relatively short (e.g., within 30 cm, as the threshold used in Goumon et al., 2020). In addition, such sensors are associated with high costs and often require regular maintenance and therefore are not optimal for applications in large-scale commercial farms (Nathan et al., 2022).

As an alternative to GPS, the use of computer vision algorithms is a non-invasive and relatively low-cost method that allows the collection of data at high sampling rates by providing the accurate location of individuals in each frame. Previous studies showed promising results of computer vision algorithms to track individual farm animals, such as cows (Mar et al., 2023), laying hens (van Putten et al., 2025), and pigs (Guo et al., 2023; van der Zande et al., 2021b) in various environments. In pigs, these algorithms have been applied to measure individual activity (van der Zande et al., 2022b). By detecting the pig's location in each frame, they also give the opportunity to calculate proximity to pen mates and location preferences. In previous studies, social interactions between animals have been extracted from computer vision tracking algorithms in different ways, such as identifying individuals that simultaneously occupy the same region of interest (Shemesh et al., 2013) or using a combination of thresholds on close distance, orientation of the head and proximity duration (Schneider et al., 2012). However, the use of computer vision tracking algorithms to study social proximity has been limited and predominantly focused on small animals, such as mice and *Drosophila*. In addition, multiple options are also available here to define proximity, and therefore decisions need to be made on how to build the social networks. Furthermore, by giving information at the frame level, these algorithms generate a very large amount of data and may require a long computing time. Therefore, downsampling of camera frames is necessary to study social networks based on tracking algorithms, in order to reduce computing time and to make outputs accessible efficiently to researchers, breeders, or farmers.

Thus, computer vision algorithms allow for many proximity definitions and sampling rates. However, to the best of our knowledge, no research has investigated the effect of different proximity definitions and sampling rates on the social networks of livestock, including pigs, based on computer vision tracking. Therefore, this study aims to explore how different proximity definitions and sampling rates affect proximity social networks in inactive pigs based on tracking data using computer vision in two different housing conditions. We expect that both proximity definition and sampling rate crucially impact the structure of the network resulting in notable changes in the network metrics.

2. Material and Methods

All methods complied with the European Directive 2010/63/EU and Dutch law on the protection of animals used for scientific purposes. The Animal Care and Use Committee of

Wageningen University approved the experiment (AVD1040020186245). All methods applied in the study were performed in accordance with the ARRIVE guidelines and regulations (du Sert et al., 2020). No anesthesia was performed during the experiment and the pigs were not euthanised after use.

2.1. Animals and housing

The pigs used in this study were the same as those described in van der Zande et al. (2021a) and Parois et al. (2022). The aim of these studies was to study resilience in pigs housed in different housing conditions. Hereto pigs were subjected to several challenges between nine and 21 weeks of age. Pigs were 15 weeks of age when they were used for the current study. Three weeks before that, they had been exposed to a 2-h transport challenge with their pen mates (Parois et al., 2022). Briefly, the experiment was carried out on 126 crossbred boars and gilts, equally divided into 3 different batches, and housed at CARUS research facility of Wageningen University and Research (Wageningen, the Netherlands) from 9 weeks of age. The pigs were grouped into 21 pens (n = 6 pigs per pen, balanced in sex) and kept in two different housing systems: 9 barren pens and 12 enriched pens. The unequal distribution of the pens across the two housing systems was due to technical issues with the cameras in the barren pens. In the barren system, the pigs were housed in pens with a partly slatted floor (1.2 x 4.7m). The enriched pens were double in size (2.4 x 4.7m) and the floor was covered with sawdust, straw, and peat, as bedding material, and several types of objects (toys, jute bags, rope, egg boxes) or substrate (hay, or alfalfa) were provided according to an alternating schedule. The temperature within the pens was recorded via temperature sensors during the three days of data collection. The temperature reached 23°C during the first two days and 22°C during the third day. Artificial light was provided between 07:00 and 19:00h.

2.2. Data collection and computer vision algorithm

All pens were equipped with an RGB camera (Velleman: 1lux/f2.0) mounted above the pen (top-down view) and plugged into electrics. Videos were recorded with a frame rate of 25 frames per second (FPS) and a resolution of 352 by 288 pixels. Videos were collected and analysed on three consecutive days at 15 weeks of age using the computer vision algorithm for object detection and tracking described by van der Zande et al. (2021b). This algorithm was trained on 4,000 annotated images spread across different days and pens. The algorithm You Only Look Once version 3 (Redmon and Farhadi, 2018), combined with Simple Online

Realtime Tracking (Bewley et al., 2016) was used to detect and track the location of each pig by a bounding box. The tracking data was cleaned manually by removing false positive detections (detections of more than six individuals per pen) and the sequential bounding box ID was connected to the real ID of the animal. More details about false positive detections can be found in van der Zande et al. (2021b).

2.3. Calculation and inactivity definition

To calculate proximity definitions during inactivity, we first needed to define when the pigs were inactive. Hereto, the distance moved by each pig in the three days was calculated by comparing the centroid of the bounding boxes of the same individual in two consecutive frames sampled at one frame per minute. Equation (1) from the Pythagorean theorem was used, where x_t and y_t are the coordinates of the centroid of the bounding boxes at frame t, and x_{t+1} and y_{t+1} are the corresponding coordinates at frame $t + 1$. An individual was considered inactive when the $distance\ moved$ between frame t and frame $t + 1$ was below 20 cm. This simple threshold was selected based on preliminary examinations of frames to capture instances when pigs were changing lying positions, such as transitioning between lateral and ventral lying while filtering out pigs in locomotion.

$$distance\ moved = \sqrt{(x_{t+1} - x_t)^2 + (y_{t+1} - y_t)^2} \quad \text{(Equation 1)}$$

2.4. Calculations of proximity definitions

The proximity between two pigs was only calculated when they were simultaneously inactive.

Distance between individuals

For each pair of pigs, the distance between the two individuals was calculated from the centroids of their bounding boxes within the same frame. The centroid of the bounding box corresponds to the point of intersection of its two diagonals. Equation (2) was used, where x_{id_1} and y_{id_1} are the coordinates of the centroid of the bounding box of pig id_1, and x_{id_2} and y_{id_2}, the corresponding measure for pig id_2.

$$distance_{id_1 id_2} = \sqrt{\left(x_{id_1} - x_{id_2}\right)^2 + \left(y_{id_1} - y_{id_2}\right)^2} \quad \text{(Equation 2)}$$

Surface of overlap of the bounding boxes

The surface of overlap of two bounding boxes within the same frame (S) was calculated from the coordinates of the bounding boxes (Supplementary Figure S1). The percentage of the overlap of the surface (surface overlap) was calculated as the surface of overlap divided by the sum of the areas of the two bounding boxes using Equation (3).

$$surface\ overlap = \frac{S}{S_1+S_2} \times 100\% \quad \text{(Equation 3)}$$

Proximity definitions

Five different definitions of proximity were used to build the social networks (Table 1); four binary definitions based on the distance between the centroids and/or surface overlap of the bounding boxes, and a weighted proximity, being the inverse of the harmonic mean of the distances between two individuals. This approach was chosen, as it assigns more significance to differences in distance when pigs are in close proximity compared to when they are further apart. For instance, if there are three distance records for two pigs (0.5m, 1m, and 1.5m), the mean distance is 1m. However, the mean proximity is calculated as (1/0.5 + 1/1 + 1/1.5)/3, resulting in a value of 0.82. This value is smaller than the reciprocal of the mean distance (1/1 = 1), indicating that shorter distances (such as 0.5m) have a more pronounced impact than longer distances (like 1.5m). P_{weig}, the weighted proximity (cm) was calculated using Equation (4), where $distance_{id_1id_2}(k)$ is the distance between the centroid of the bounding box of pig id_1 and pig id_2 (calculated similarly to Equation (2)) in the frame *k*, and *n* is the total number of frames in which the two individuals were simultaneously inactive. The thresholds of 20% and 50cm were chosen by combining insights from existing literature (50cm corresponding to the 30cm as used in Goumon et al. (2020), with an additional 20cm to account for the centroid of the bounding box, rather than the edge of the pig) and through preliminary examination of frames (Figure 3).

$$P_{weig} = \frac{1}{n}\sum_{k=1}^{n}\frac{1}{distance_{id_1id_2}(k)} \quad \text{(Equation 4)}$$

Table 1. Proximity definitions used to construct the five different social networks.

Network name	Type of definition	Proximity definition
DIST	binary	Distance between the centroids of the bounding boxes of pig id_1 and pig id_2 is within 50 cm.
OVER	binary	Presence (yes or no) of overlap between the bounding boxes of pig id_1 and pig id_2.
SURF	binary	Percentage of overlap of the surface of the bounding boxes of pig id_1 and pig id_2 is above 20%.
DIST_SURF	binary	Distance between the centroids of the bounding boxes of pig id_1 and pig id_2 is within 50 cm and percentage of overlap of the surface of their bounding boxes is above 20%.
WEIG	quantitative	Harmonic mean of the distance between the centroids of the bounding boxes of pig id_1 and pig id_2.

2.5. Agreement between proximity definitions

The percentage of agreement was calculated for each pair of the binary proximity definitions and each pair of bounding boxes across time using Equation (5). $Agreement$ refers to the instances where pairs of bounding boxes were classified similarly by the two proximity definitions (either both in close proximity or both not in close proximity). $Disagreement$ refers to the instances where one proximity definition categorised the bounding boxes as in close proximity while the other did not.

$$\%\ of\ agreement = \frac{Agreement}{Agreement + Disagreement} \times 100 \quad \text{(Equation 5)}$$

2.6. Social network analysis

Construction of matrices for social network analysis

A matrix of proximity was generated for each pen and proximity definition. We filtered this matrix to keep only the associations when the individuals were simultaneously inactive and in close proximity (according to each definition). The edges of each network (for the four binary definitions) were built with a half weighted index (HWI) (Cairns and Schwager, 1987) using Equation (6), where $T_{prox_{id_1 id_2}}$ is the total time during which pig id_1 and pig id_2 were simultaneously inactive and in close proximity according to one of the definitions, T_{id_1} the total time pig id_1 spent inactive, and T_{id_2} the total time pig id_2 spent inactive. This correction was necessary to account for variation in activity between pigs from the same pen. Otherwise, more active pigs might have appeared more central in a network simply due to their increased activity level, rather than their actual social preferences.

$$HWI = \frac{T_{prox_{id_1 id_2}}}{(T_{id_1}+T_{id_2})/2} \quad \text{(Equation 6)}$$

Similarly, we calculated the HWI for the quantitative proximity definition (WEIG) using Equation (7), where $T_{id_1 id_2}$ is the total time during which pig id_1 and pig id_2 were simultaneously inactive.

$$HWI = \frac{P_{weig} \times T_{id_1 id_2}}{(T_{id_1}+T_{id_2})/2} \quad \text{(Equation 7)}$$

The HWI in Equation (6) represents the proportion of time that two pigs were simultaneously inactive and in close proximity, adjusted for their individual inactivity durations. Similarly in Equation (7), the HWI represents the proportion of time that two pigs were simultaneously inactive, adjusted for both individual inactivity duration and the proximity, defined as the average distance between the two pigs.

Construction of the complete and reduced networks

To estimate the effect of sampling rate on social networks, we compared a complete network to networks built with different sampling rates. For each proximity definition, the complete network was built using a frame rate of 0.5 FPS (corresponding to one frame every two seconds) to reduce potential noise due to micro-movements of the bounding boxes (van der

Zande et al., 2022a). For each proximity definition, networks were built using different sampling rates, by using different sampling intervals (i.e. the interval between frames) ranging from one frame per 10s to one frame per hour. From here on, we will refer to these networks as reduced networks, to distinguish them from the complete network (with one frame per 2s).

Network visualisation

Undirected social networks were visualised with R (version 4.1.2, R Foundation, Vienna, Austria), using the package "igraph" (Csárdi et al., 2025) where nodes represent individuals, and edges the HWI.

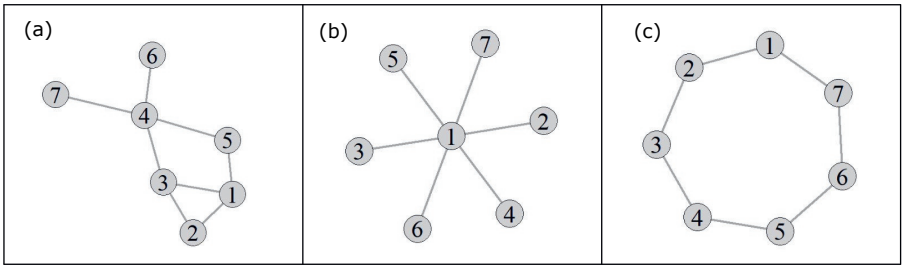
Network metrics

For each network, we calculated four different network metrics (Table 2 and Figure 1) that measure different aspects of the network, both at individual and group level, based on direct and indirect connections. These metrics were selected based on their widespread use and established biological relevance (Makagon et al., 2012). They measure different aspects of the network and were therefore used as a representative case to illustrate the impact of proximity definitions and sampling rates on the network. Their characteristics are summarised in Table 2, and examples are given in Figure 1. Direct/indirect relates to whether a metric measures properties using only immediate relationships (direct) or considers more complex network structures or relationships (indirect). Local/global, on the other hand, refers to whether a metric provides information about the network as a whole structure (global) or about the micro-structure of the network (local). Degree and eigenvector centrality reflect the prominence of a node, the degree centrality serving as an indicator of animals that are well connected with others and the eigenvector centrality as an indicator of influential animals (Cheney et al., 2016). In the context of the study, a pig with a high degree centrality is lying in proximity to many of its pen mates, whereas a pig with a high eigenvector centrality is lying in proximity to other pigs that are themselves lying in proximity to many of their pen mates. Clustering coefficient and radius evaluate the cohesiveness and the strength of bonds in a group (Adelman et al., 2015; Aplin et al., 2015). The clustering coefficient evaluates the cohesiveness between the neighbours of a specific node (pen mates it lies close to) and the radius between all group members. A pig with a high clustering coefficient is part of a closely connected group, where its neighbours frequently lie in proximity to each other. A low radius value indicates that most of the pigs are lying in proximity to most of their pen mates.

Table 2. Description of the network metrics.

Metric	Level	Direct/ Indirect	Local/ Global	Measure	Description
Degree centrality	Individual	Direct	Local	Prominence	Weighted number (sum of the half-weighted degree) of direct connections the focal node has to other nodes in the network.
Eigenvector centrality	Individual	Indirect	Global	Prominence	Influence of a node based on its neighbours' connections. A node is more central when connected to highly connected nodes.
Clustering coefficient	Individual	Indirect	Local	Cohesion	Tendency of the neighbours of a node to be interconnected.
Radius	Group	Direct	Global	Cohesion	Minimum distance between any pair of nodes in the network, considering the longest path lengths.

Definitions are adapted from Makagon et al. (2012) and McKee and Dallas (2024).



At the individual level							
Network (a)	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Degree centrality	3	2	3	4	2	1	1
Eigenvector centrality	0.94	0.74	1	0.93	0.71	0.36	0.36
Clustering coefficient	0.33	1	0.33	0	0	-	-

At the network level			
	a	**b**	**c**
Radius	2	1	3

high

low

Figure 1. Examples of networks (a, b and c) and their metrics. Individual-level metrics are shown only for network a.

2.7. Comparison of social network metrics

A Mann-Whitney U test was used to assess whether the metric of the enriched pens (n=12) differed significantly from the metric of the barren pens (n=9) within each proximity definition. This non-parametric statistical test was used because the data were not normally distributed.

A bivariate linear model was fitted in ASReml 4.2 (Butler et al., 2023) to estimate the correlation between the same metric for pairs of proximity definitions or pairs of sampling rates (Equation 8),

$$\begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \begin{bmatrix} X_1 & 0 \\ 0 & X_2 \end{bmatrix} \begin{bmatrix} \beta_1 \\ \beta_2 \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \end{bmatrix} \quad \text{(Equation 8)}$$

where $\mathbf{y}_1$ and $\mathbf{y}_2$ are the response vectors for the first and second trait, respectively, X_1 and X_2 are the design matrices for the vectors of fixed effects β_1 and β_2, and ε_1 and ε_2 are the vectors of residuals. Traits 1 and 2 were either the metrics of a pair of proximity definitions, or the metrics of a pair of sampling rates. When analysing sampling rates, trait 1 was always the metric of the complete network and trait 2 the metric of the reduced network. The fixed effects included housing and sex for the individual-level metrics, and housing for the pen-level metric (radius). The normality of the residuals was assessed for each univariate model by visual inspections (histograms and QQ-plots) and a Shapiro-Wilk test. A log transformation was applied to the radius, as the residuals of the models built with radius and

DIST and DIST_SURF were not normally distributed. Residuals follow a bivariate normal distribution with (co)variance matrix:

$$var\begin{bmatrix}\boldsymbol{\varepsilon}_1\\ \boldsymbol{\varepsilon}_2\end{bmatrix} = \begin{bmatrix}\sigma^2_{\varepsilon_1} & \rho_{12}\sigma_{\varepsilon_1}\sigma_{\varepsilon_2}\\ \rho_{12}\sigma_{\varepsilon_1}\sigma_{\varepsilon_2} & \sigma^2_{\varepsilon_2}\end{bmatrix} \otimes \mathbf{I}$$

where $\otimes$ denotes the Kronecker product of two matrices and **I** is an identity matrix. The ρ_{12} is the parameter of interest, *i.e.*, the correlation between the metrics for trait 1 and trait 2. Hence, correlations were estimated after the correction of response variables for the fixed effects.

To assess the significance of the correlations, we calculated the Z-score by dividing the correlation coefficient by the standard error.

3. Results

3.1. Data description

Distribution of the distance and surface overlap of bounding boxes

Figure 2a shows the distribution of the distance between the centroids of bounding boxes among all possible pairs of individuals when both were inactive. In enriched pens, the average distance between bounding box centroids was 202.9±96.6 cm (mean ± standard error), whereas, in barren pens, it was 129.9±88.4 cm. Note that the enriched pens were twice as large as the barren pens. In enriched pens, the distribution was right-skewed without clear peaks (Figure 2a). In barren pens, the distribution was more complex, with three local maxima. In addition, in the enriched pens, 2.3% of the pairs of bounding boxes were in close proximity based on their distance (<50cm), whereas in the barren pens, this was 11.3 % (Figure 2a).

Figure 2b shows the distribution of the percentage of overlap, between pairs of bounding boxes with more than 0% overlap. In total, 15.9% of the pairs of bounding boxes overlapped in enriched pens and 32.3% in barren pens (Figure 2b). For both housing conditions, the distribution followed a right-skewed decreasing trend, with a higher probability for a small overlap than a large overlap. The probability of an overlap greater than ~60% was almost zero. Within the pairs that showed overlap, the percentage of overlap was smaller in enriched pens than in barren pens. In addition, in the enriched pens, 5.2% of the pairs of bounding

boxes were in close proximity based on their overlap (>20%), whereas in the barren pens this was 14.4% (Figure 2b).

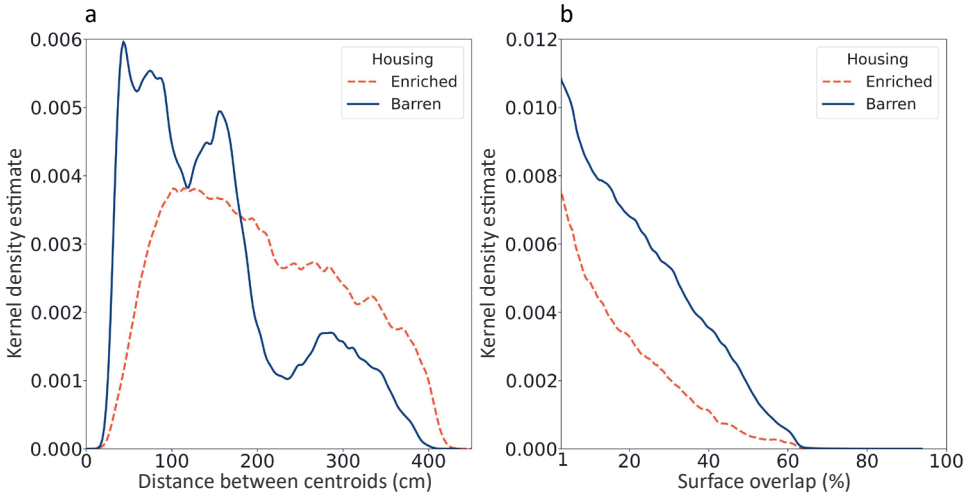


Figure 2. Distributions of the distance between the centroids of pairs of bounding boxes (a) and the percentage of overlap of the surfaces of pairs of overlapping bounding boxes (b), separate for enriched and barren housing conditions. These distributions are based on n=21 pens (12 enriched, 9 barren), each pen containing 15 pairs of bounding boxes (for 6 individuals) at each time point (FPS=0.5) and over 3 days. Note that panel b starts at values greater than 0% to focus on cases where bounding boxes overlap.

Agreement between proximity definitions

Table 3 shows the percentage of agreement of the four binary proximity definitions. The agreement varied from 81.9% between DIST_SURF and OVER to 98.9% between DIST and DIST_SURF (Table 3). The lowest agreements were found between OVER and the other definitions, and the highest between DIST_SURF and the two definitions DIST and SURF (Table 3).

Figure 3 shows four cropped frames with the bounding boxes of two pigs, illustrating agreement (Figure 3a) and disagreement between the binary proximity definitions (Figure 3b-d). As an example, we concentrate our result description on DIST and DIST_SURF. In Figure 3b, the two pigs adopted a parallel ventral position, resulting in a short distance between the centroids of their bounding boxes (DIST criterion for proximity satisfied) but a limited surface overlap (SURF proximity criterion rejected). In Figure 3c-d, only the SURF criterion was met and not DIST. This occurred, for example, when the two pigs faced each

other, with a portion of their body aligned in parallel (Figure 3c), or when the two pigs lay at an angle (Figure 3d).

Table 3. Percentage of agreement between the four binary proximity definitions.

Proximity definition	DIST	SURF	DIST_SURF	OVER
DIST	100	-	-	-
SURF	94.8	100	-	-
DIST_SURF	98.9	95.9	100	-
OVER	82.9	86.1	81.9	100

The percentages of agreement are calculated based on the tracking data with a sampling rate of 0.5 FPS. DIST: Distance between centroids of bounding boxes <50 cm, SURF: Overlap of bounding boxes >20%, DIST_SURF: Combination of DIST and SURF, OVER: Presence of overlap between bounding boxes.

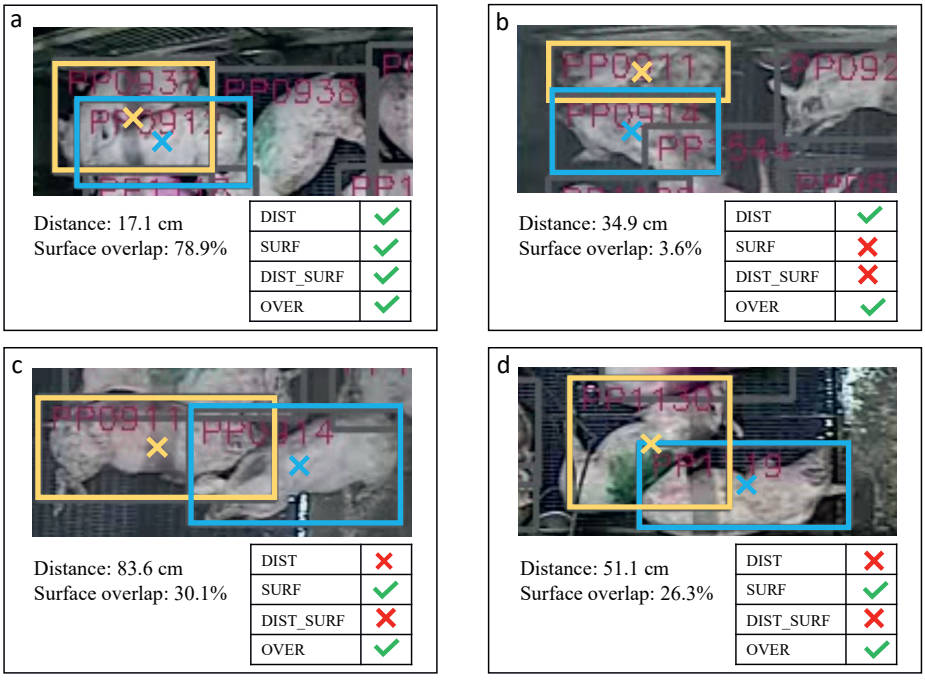


Figure 3. Examples of cropped frames showing detected pairs of pigs with bounding boxes (a-d). In blue and yellow, the bounding boxes and their respective centroids are highlighted. Below the frames, the distance between the centroids of the bounding boxes and the surface overlap of the bounding boxes are given. The table indicates whether the pigs fulfil each proximity definition (marked by a green check) or not (indicated by a red cross). DIST: Distance between centroids of bounding boxes <50 cm, SURF: Overlap of bounding boxes >20%, DIST_SURF: Combination of DIST and SURF, OVER: Presence of overlap between bounding boxes.

3.2. Consequences of the proximity definitions for the network

The results reveal significant differences between enriched and barren pens for some of the network metrics (Table 4). Within the same proximity definition, barren pens exhibited a higher degree centrality, clustering coefficient and radius compared to the enriched pens (Table 4). This result indicates denser connectivity within the network of the barren pens, in line with the distribution of the distance and surface overlap (Figure 2).

Table 4. Comparison of four network metrics (mean ± standard deviation) per housing condition (Barren vs. Enriched) built with different proximity definitions.

Proximity definition	Housing	Degree centrality	Clustering coefficient	Eigenvector centrality	Radius
DIST	Barren	50.8±6.4	0.42±0.02	0.40±0.04	10.1±3.7
	Enriched	8.7±1.4	0.30±0.02	0.39±0.04	1.2±0.5
		***	***		***
DIST_SURF	Barren	40.4±5.2	0.41±0.02	0.39±0.04	7.8±3.5
	Enriched	7.6±1.3	0.30±0.02	0.39±0.04	0.96±0.5
		***	***		***
SURF	Barren	64.5±5.5	0.45±0.02	0.39±0.03	13.2±3.6
	Enriched	22.4±2.5	0.40±0.02	0.40±0.03	4.1±1.6
		***	***		***
OVER	Barren	**144.7**±5.8	0.59±0.01	**0.41**±0.01	**31.7**±5.8
	Enriched	**68.4**±3.9	0.55±0.01	**0.41**±0.01	**14.5**±2.4
		***	***		***
WEIG	Barren	4.0±0.2	**0.73**±0.01	**0.41**±0.01	0.03±0.01
	Enriched	2.5±0.1	**0.76**±0.01	**0.41**±0.01	0.02±0.01
		***	*		**

The 10 networks were built with a sampling rate of 0.5 FPS (complete networks). Proximity between two pigs is defined with DIST: Distance between centroids of bounding boxes <50 cm, SURF: Overlap of bounding boxes >20%, DIST_SURF: Combination of DIST and SURF, OVER: Presence of overlap between bounding boxes, WEIG: harmonic mean of the distance between the centroids of the bounding boxes. Differences between housing conditions were tested with a Mann-Whitney U test for each metric and proximity definition and are indicated below, $*P < 0.05$, $**P < 0.01$, $***P < 0.001$. Values in bold indicate the highest value per metric. Note that the enriched pen is twice the size of the barren pen.

Figure 4 shows the correlations, estimated by a bivariate model, of the complete networks built with the five different proximity definitions for each of the four metrics studied. All correlations were highly significant ($Z>3.29$, $p<0.001$), indicating strong associations for the same network metric across different proximity definitions. Overall, positive correlations were observed but the strength of these correlations varied largely. Strong correlation coefficients were observed for the direct metric degree centrality, ranging from 0.66 to 0.99 (Figure 4). However, these correlations were lower for indirect metrics with values decreasing to 0.39 for eigenvector centrality and 0.35 for clustering coefficient. For the indirect metrics, the correlations were found to be weaker for the local metric clustering coefficient than the global metric eigenvector centrality. At the network level, the radius metric showed both weak and strong correlations, ranging from 0.52 to 0.96 (Figure 4).

Among the binary proximity definitions, there was a trend to stronger correlations between the metrics when the proximity definition was built using the same geometric measure (Figure 4). For instance, there were higher correlations between the metrics, when proximity was based on bounding box centroid distance (DIST and DIST_SURF) or between the ones based on surface overlap (SURF and OVER). On the other hand, correlations tended to be lower when comparing different geometric measures; particularly between DIST_SURF and OVER (correlation coefficients <0.66).(Interestingly, the correlations between the proximity definition WEIG and the other four definitions differed largely depending on which metric was considered. The correlations between a metric of a pair of proximity definitions were particularly high with degree centrality and lower with the other metrics (Figure 4).

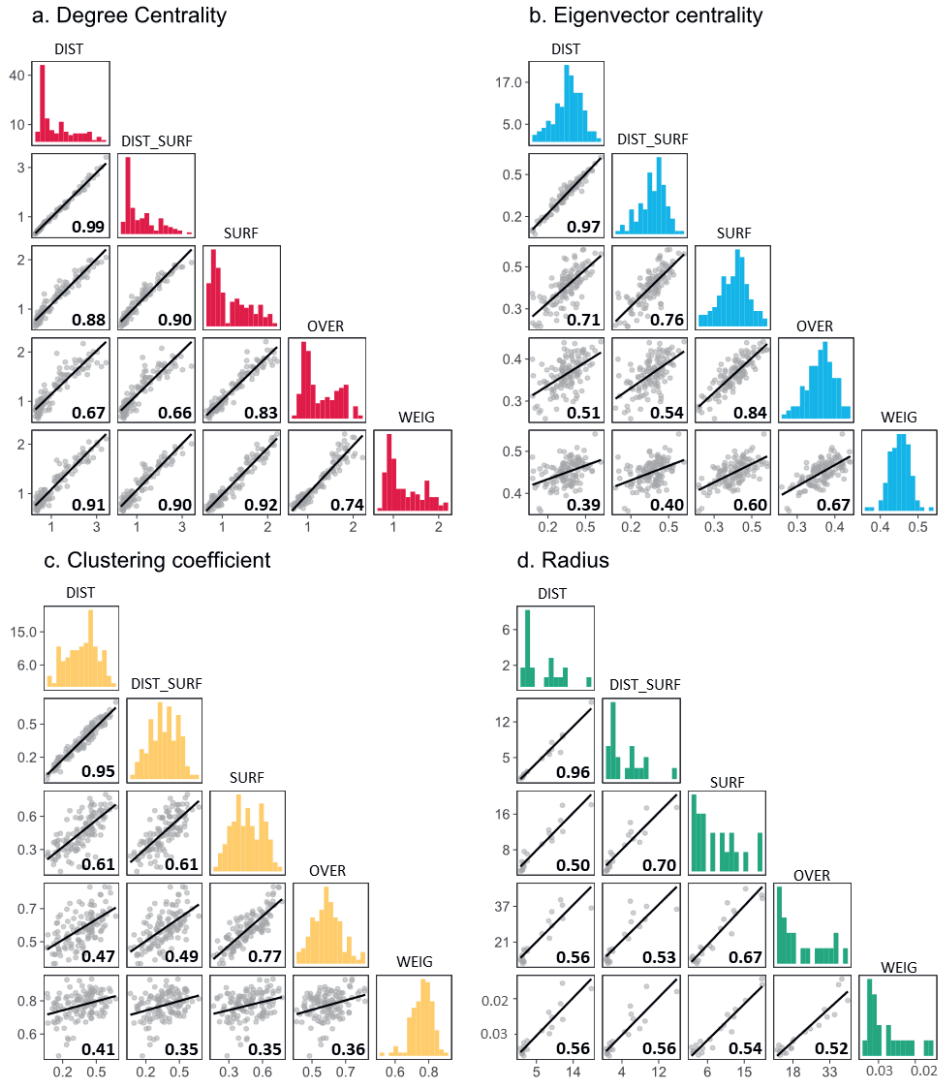


Figure 4. Comparison of network metrics built with different proximity definitions. (a) Degree centrality, (b) Eigenvector centrality, (c) Clustering coefficient, (d) Radius. The network metrics are calculated based on the tracking data with a sampling rate of 0.5 FPS. The lower off-diagonal shows scatter plots with the linear fit in black and the correlation coefficients calculated from the bivariate model. All the correlations were significant ($p<0.001$). The correlations coefficients for the radius were estimated with a log-transformation, due to the non-normal distribution of the residuals. The scatter plot and distribution of the radius values are plotted with the original data. Proximity between two pigs is defined with DIST: Distance between centroids of bounding boxes <50 cm, SURF: Overlap of bounding boxes >20%, DIST_SURF: Combination of DIST and SURF, OVER: Presence of overlap between bounding boxes, WEIG: harmonic mean of the distance between the centroids of the bounding boxes.

3.3. A case study of an enriched pen

To illustrate the influence of the choice of a proximity definition on the network, a case study of an enriched pen is presented in Figure 5. The DIST, DIST_SURF, and SURF networks show variations in edge strengths between different nodes within the network. These variations suggest that certain pairs of individuals spent more time in close proximity compared to other pairs (Figure 5). In contrast, in the OVER and WEIG networks, all individuals appeared to be nearly equally connected within the network, suggesting a more uniform distribution of proximity across the group. This contrast between the networks is also reflected by the network metrics, with higher variations between the metrics values for different nodes in DIST, DIST_SURF, and SURF than in OVER and WEIG. The high connectivity between all pairs of individuals in OVER and WEIG is reflected by the higher clustering coefficient for both OVER and WEIG compared with DIST, DIST_SURF, and SURF (Figure 5).

Furthermore, certain edges (e.g., 4-6 and 1-5) exhibited consistent strength levels across all networks, whereas others displayed varying strength between the five different networks (Figure 5). For example, edge 3-4 was characterised by weak strength in OVER, SURF, and WEIG, but high strength in DIST and DIST-SURF (Figure 5). As a result, we observed that pigs were ranked differently across networks, according to the network metrics. For example, in DIST and DIST_SURF, Pig 3 exhibited a noticeably high centrality (according to average degree and eigenvector) whereas Pig 1 had a low centrality (Figure 5). This position was, however, not consistent across the five network definitions.

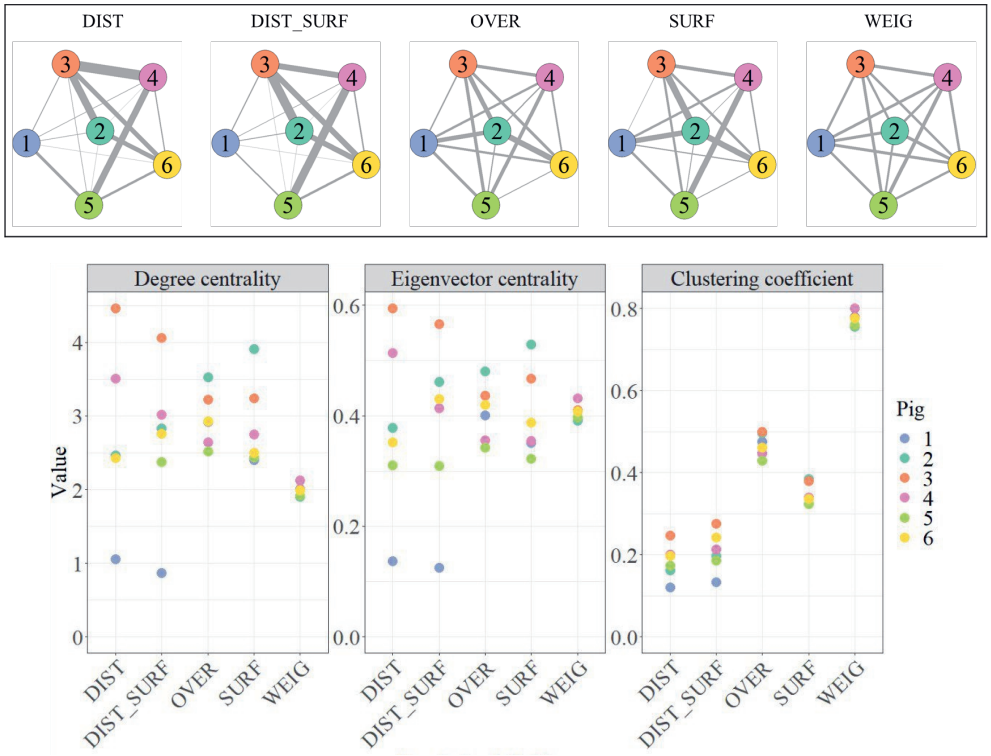


Figure 5. An example of the structure of the networks for an enriched pen based on the different proximity definitions. The network metrics are calculated based on the tracking data with a sampling rate of 0.5 FPS. The width of the edge is proportional to the strength of the proximity. The degree centrality shown in this plot has been normalised by dividing the value by the average degree centrality of each proximity definition. The normalisation was applied to the degree centrality to facilitate the comparison across different networks. In contrast, normalisation was not necessary for eigenvector centrality and clustering coefficient, as these metrics are already bounded between 0 and 1. Proximity between two pigs is defined with DIST: Distance between centroids of bounding boxes <50 cm, SURF: Overlap of bounding boxes >20%, DIST_SURF: Combination of DIST and SURF, OVER: Presence of overlap between bounding boxes, WEIG: harmonic mean of the distance between the centroids of the bounding boxes.

3.4. Consequences of downsampling for each network metric and proximity definition.

The impact of downsampling the tracking data for the two housing conditions combined is shown in Figure 6 and presented separately for enriched and barred pens in Supplementary Figure S2. The impact of downsampling varied across network metrics (Figure 6). Overall, the degree, eigenvector centrality, and radius were minimally impacted by downsampling. Especially for the degree centrality, the correlations with the complete network (1 frame every 2s) remained high (>0.90) even after reducing the sampling rate to 1 frame every hour (Figure 6). Lower correlations between the reduced networks and the complete network were found for the clustering coefficient. To maintain high correlations for all the network metrics (>0.90) without considering the housing conditions, the downsampling should not go beyond 1 frame every 6min (Figure 6). However, in barren pens, a larger sampling rate (1 frame every 25min) would be sufficient to maintain high correlations for all network metrics, whereas in enriched pens, the downsampling should not go beyond 1 frame every 6min (Supplementary Figure S2).

The impact of downsampling on the network metrics varied across proximity definitions. For the networks built with WEIG, the metrics of the reduced networks maintained strong correlations with the complete network (ranging from 0.86 for clustering coefficient to 0.98 for degree centrality at a 1 frame per hour sampling rate, Figure 6). For degree centrality and radius, the choice of a binary proximity definition seems to have less impact on the effect of downsampling on the correlations. For degree centrality, for example, the maximum difference between the lowest and highest correlations for different proximity definitions was 0.05 (observed at a sampling rate of 1 frame per 45min). In contrast, the choice of a binary proximity definition has a clear impact on the effect of downsampling on the clustering coefficient. For the clustering coefficient, the maximum difference between the lowest and highest correlations for different proximity definitions was 0.55 (achieved with 1 frame per hour, Figure 6). The clustering coefficient of the networks DIST and DIST_SURF were more sensitive to downsampling than the clustering coefficient of OVER and SURF.

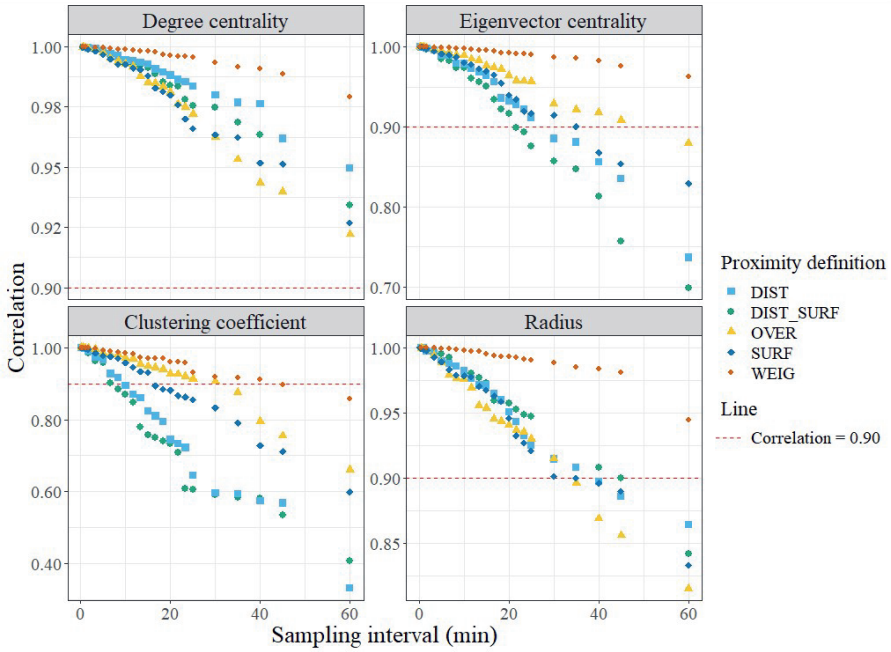


Figure 6. Correlations between the metrics of the reduced network (built with different sampling intervals) and the metrics of the complete network (2s sampling interval), for the degree centrality, eigenvector centrality, clustering coefficient, and radius. Note that the y-axis scale differs between panels. These plots show the results for both enriched and barren environments combined.

4. Discussion

This study aimed to explore how different proximity definitions and sampling rates affect social network metrics of inactive pigs. Clear differences between networks, at both the individual and the network level, were revealed when using different proximity definitions. Network metrics differed in their sensitivity to downsampling, and this sensitivity was also affected by the chosen proximity definition.

In previous studies on spatial proximity in pigs with manual observation, lying in spatial proximity was defined in different ways (Durrell et al., 2004; Goumon et al., 2020; Jowett and Amory, 2021; Li et al., 2018). The definition seems to depend on the interpretation of the observer whether two pigs are in proximity or not. Given the absence of one unique proximity definition, the goal of this study was not to identify the best definition for validating the detection of proximity. However, observers likely agree that pigs are in close proximity when there is full-body contact (as captured by DIST definition, see Figure 3. a,b.). In contrast, part-body contact (captured by definition based on the overlap of bounding boxes,

i.e. SURF and OVER, see Figure 3. c,d.) is more likely to result in interobserver discrepancies, for example in the case when pigs are tail-to-tail.

The downside of DIST, SURF and DIST_SURF, the latter definition combining distance and overlap, is that the experimenter needs to decide on a minimal threshold that distinguishes whether pigs are in close proximity or not. The decision on this threshold might be arbitrary, as the 'ideal' distance is currently unknown (Bartlett et al., 2022). This threshold needs to be decided carefully as a larger threshold, for example, may include more pairs of individuals considered as in close spatial proximity, resulting in a higher degree centrality (Davis et al., 2018). The dependency of the results on the definition of the threshold also hampers comparisons of studies. In this study, we set thresholds for two definitions: DIST with a threshold of 50cm distance between the centroids of two bounding boxes, and SURF with a threshold of 20% overlap of the surface of bounding boxes. DIST depends on the size of the animal, and the threshold should therefore be higher with larger pigs. SURF already takes into account the size of the animal, which makes it possible to use the same threshold for older pigs. An alternative to defining the threshold by an experimenter may utilise the size of the bounding box for the threshold.

Two of our definitions, OVER and WEIG, did not rely on a threshold set by the experimenter. OVER, i.e. the presence of overlap between two bounding boxes, might have included pigs that did not have any kind of contact. This definition can be relevant for a large population in a large area, but it may not be so suitable for pigs kept in relatively small pens. WEIG, the quantitative definition of proximity, was defined as the harmonic mean proximity between pigs and calculated as the average of the reciprocals of their distances. This definition assigns more significance to differences in distance when pigs are in close proximity compared to when they are further apart. As this approach includes all the distances, we expect it to be more powerful in distinguishing between certain pairs of individuals, for example, in distinguishing one pair that does not meet a binary definition of proximity but is often slightly above the threshold to another pair that consistently remains far apart.

At the individual level, changes in proximity definition had a minor effect on the direct metric degree centrality, whereas the indirect metrics (eigenvector centrality and clustering coefficients) were considerably affected. Degree centrality only considers a node's immediate connections, making it less sensitive to changes in the network (Davis et al., 2018) induced by different proximity definitions, compared with indirect metrics which consider the

importance of a node based not only on its own connections but also on the connections of its neighbours (Makagon et al., 2012). A different proximity definition could result in changes in the weight of the edge and neighbouring nodes, potentially causing a cascading effect throughout the entire network structure and leading to significant shifts in the values of the indirect metric. In line with this result, Castles et al. (2014), who compared baboon networks based on three different proximity definitions (distance rule, chain rule, and nearest neighbour) also observed that the direct metrics degree and closeness were less affected by the chosen proximity definition than the indirect metric betweenness (another indirect metric that quantifies the extent to which a node serves as an intermediary between other nodes in a network).

The local metric clustering coefficient was more affected by the choice of proximity definition than the global metric eigenvector centrality. The clustering coefficient is based on micro-level patterns within the network, whereas eigenvector centrality takes into account a node's influence on the entire network and captures larger network patterns that may remain more consistent across proximity definitions. This could explain the lower correlation coefficients found between clustering coefficient metrics based on different proximity definitions and suggests that the networks based on the five different proximity definitions share more common information at a global network level, but may not align as closely at a local level.

Degree centrality, eigenvector centrality, and radius were also less impacted by downsampling than the clustering coefficient. For most of the proximity definitions (except DIST and DIST_SURF), downsampled tracking data still provided robust information (i.e. correlations between the yielded metrics and complete network remained > 0.90) on the positions of individuals within the network. These results agree with Davis et al. (2018), who found that low levels of sampling (10 samples/individual) can provide the same information as high levels of sampling (>64 samples/individual in the same period) for social networks based on proximity in baboons. Furthermore, downsampling had a negligible impact on the WEIG networks across various network metrics, compared with the binary definitions. This distinction lies in the nature of the proximity definition: WEIG integrates proximity between individuals in each frame, whereas the binary definitions consider individuals in proximity in a given frame only if they meet the specific condition. Downsampling increases the probability of missing a frame where this specific condition is met. Within the binary definitions, DIST and DIST_SURF were particularly affected by downsampling, given their

restrictive condition occurring less frequently than OVER and SURF. Networks built with DIST and DIST_SURF require therefore a higher sampling rate to produce networks that reflect the social patterns on the complete period.

To produce networks that reflect similar social patterns as a high sampling rate, while reducing the data processing time, the downsampling should not go beyond 1 frame every 6 minutes in inactive pigs. A larger sampling interval may be sufficient when studying animals in limited space. In comparison, Larsen et al. (2023) recommended a sampling interval of 1 frame every 30s for assessing feeding duration in pigs. When investigating social networks based on proximity, longer sampling intervals remain reliable, given the higher frequency of proximity occurrences compared to feeding events and the focus on network metrics and not directly on duration.

The different values of the metrics across networks might also be a consequence of different types of proximity captured by the definitions. Although we found a high percentage of agreement between the binary proximity definitions, especially between DIST, SURF, and DIST_SURF, when examining specific frames, these definitions appear to relate to distinct types of proximity. DIST seems to capture spatial proximity in cases where both individuals engaged in full-body contact, while SURF seems to capture situations where individuals were in part-body contact. In addition, OVER seems to capture both full-body and part-body contacts, including very small body contacts and even the absence of body contact.

It is unknown why a pig decides to be in full-body contact (as captured by DIST) or in part-body contact (as captured by SURF) with another pig, and which of these choices more accurately represents having a social preference for that other pig. The preference for full-body contact may be partially attributed to the pig's thermoregulatory needs (Camerlink et al., 2022; Spoolder et al., 2012). However, in our study, the temperature was within the thermoneutral zone (22°C and 23°C), which reduced the likelihood of associations being driven by thermoregulation (Huynh et al., 2005). In addition, lying together for thermoregulation is more prevalent among newborns than among older pigs as used in this study (Camerlink et al., 2022; Villanueva-García et al., 2021). In contrast, part-body contact, such as head-to-head, might mean being engaged in more specific social behaviours (e.g., nosing). In this study, no differentiation could be made between various body parts and information regarding the orientation of the pigs could not be considered. SURF might have captured part-body contact with all parts of the pig's body, including head-to-head or tail-to-

tail contact, each potentially being driven by completely different motivations. Including the detection of specific key body points in the computer vision algorithm, for example, by detecting the head and the tail, could help to identify the direction of the pigs and to make the distinction between lying in close proximity head-to-head vs. tail-to-tail. In a previous study, Wutke et al. (2021) showed the potential of using key point detection to build networks based on specific contacts (head-to-head and head-to-tail).

In our study, we examined proximity during inactive periods, defined as instances where the distance moved between two frames one minute apart was less than 20cm. We assumed that when inactive, pigs were predominantly in a lying posture, taking into account that fattening pigs spend the major part of their time lying (Ekkel et al., 2003). However, our method could not distinguish between lying and standing pigs, therefore inactive defined pigs may have also included pigs that were standing still in the same location, for instance, when pigs in enriched environments were exploring straw. This method is therefore not suitable to assess welfare based on activity, as behaviours that are beneficial to pigs' welfare, such as exploration of straw (Beattie et al., 2000; Bolhuis et al., 2005; Luo et al., 2020; Van de Weerd et al., 2005), are misclassified as inactivity. Additionally, our definition might have excluded pigs that were moving while lying, for example changing from lateral to sternal postures. We intentionally opted for a simple definition, as the main focus of our paper was on defining proximity and not on inactivity. Nevertheless, for research focused on networks based on spatial proximity during lying periods, more sophisticated criteria (such as analysing consecutive active frames) or using alternative algorithms to differentiate between postures, could be investigated.

We observed a greater number of pairs of individuals with smaller distances and with larger overlapping values of their bounding box surfaces in barren pens compared to enriched pens. This suggests that when more space is given to the pigs, they do not choose to stay as close as in smaller environments. This questions the biological relevance of using spatial proximity to investigate social preferences in pigs kept under intensive housing conditions. Limited space allowance may inhibit the ability to express social preferences and maintain individual relationships reflected by spatial proximity (Durrell et al., 2004; Li et al., 2018). In contrast, it has been shown that pigs with access to outdoor areas, generally characterised by more space, exhibited non-random social preferences in their lying behaviour (Goumon et al., 2020). Therefore, specific pro-social behaviours, such as play or social nosing contacts might be more relevant when investigating social preferences in restricted space (Camerlink and

Turner, 2013; Portele et al., 2019). Gan et al. (2021) developed an algorithm based on convolutional neural networks to identify social behaviours between piglets (snout-snout, snout-body and play behaviour). However, data collection methods to study SNA based on an algorithm for such specific social behaviours and how the choice of one method affects the network metrics still have to be investigated.

In conclusion, computer vision algorithms based on tracking allow for the collection of data on location of individuals at a high sampling rate and are therefore useful to characterise social networks based on proximity. However, our results demonstrate that social network characteristics are influenced by both proximity definition and sampling rate and that their impact varies for different network metrics. Moreover, the effect of the sampling rate on network structure and the position of individuals within the network depends on the proximity definition chosen. This means that proximity definitions and sampling rates need to be selected carefully when using computer vision algorithms for social network analysis.

Supplementary material

Figure S1 shows how the surface of overlap was calculated for the two proximity definitions SURF and OVER. The surface of overlap of two bounding boxes in the same frame (S) was calculated from the coordinates of the bounding boxes, using the formula below, where min(a,b) is the minimum between a and b, and max(a,b) the maximum between a and b, $x_{r\_id_1}$ and $x_{r\_id_2}$ are the x-coordinates of the right boundary of the bounding box containing pig id_1 and pig id_2 respectively, $x_{l\_id_1}$ and $x_{l\_id_2}$, the x-coordinates of the left boundary of the bounding box containing pig id_1 and pig id_2 respectively, $y_{b\_id_1}$ and $y_{b\_id_2}$ the y-coordinates of the bottom boundary of the bounding box containing pig id_1 and pig id_2 respectively, and $y_{t\_id_1}$ and $y_{t\_id_2}$, the y-coordinates of the top boundary of the bounding box containing pig id_1 and pig id_2 respectively.

$$S = [\min(x_{r\_id_1}, x_{r\_id_2}) - max(x_{l\_id_1}, x_{l\_id_2})] \times [min(y_{b\_id_1}, y_{b\_id_2}) - max(y_{t\_id_1}, y_{t\_id_2})]$$

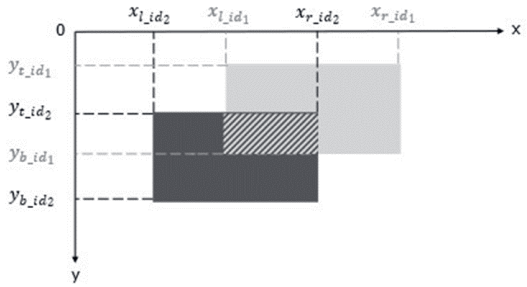


Figure S1. Coordinates of two bounding boxes used to calculate the overlap of their surface.

The correlations between the metrics of the reduced network (built with different sampling intervals) and the metrics of the complete network (2s sampling interval, corresponding to 0.5 FPS) are presented separately for barren and enriched pens in Figure S2, The impact of downsampling varied between both housing systems and network metrics (Figure S2). In barren pens, all the network metrics were reliably estimated (correlation coefficients with the complete network >0.90) up to a 25min sampling interval (Figure S1a), whereas in enriched pens, metrics were reliably estimated only up to a 6min interval (Figure S1b). In both housing conditions, the clustering coefficient was the network metric most strongly impacted by downsampling. In contrast, degree centrality was the least affected by downsampling (estimated reliably up to one frame every hour in barren pens and every 40min in enriched pens). Eigenvector centrality and radius were only slightly impacted in barren pens but were more strongly affected in enriched pens.

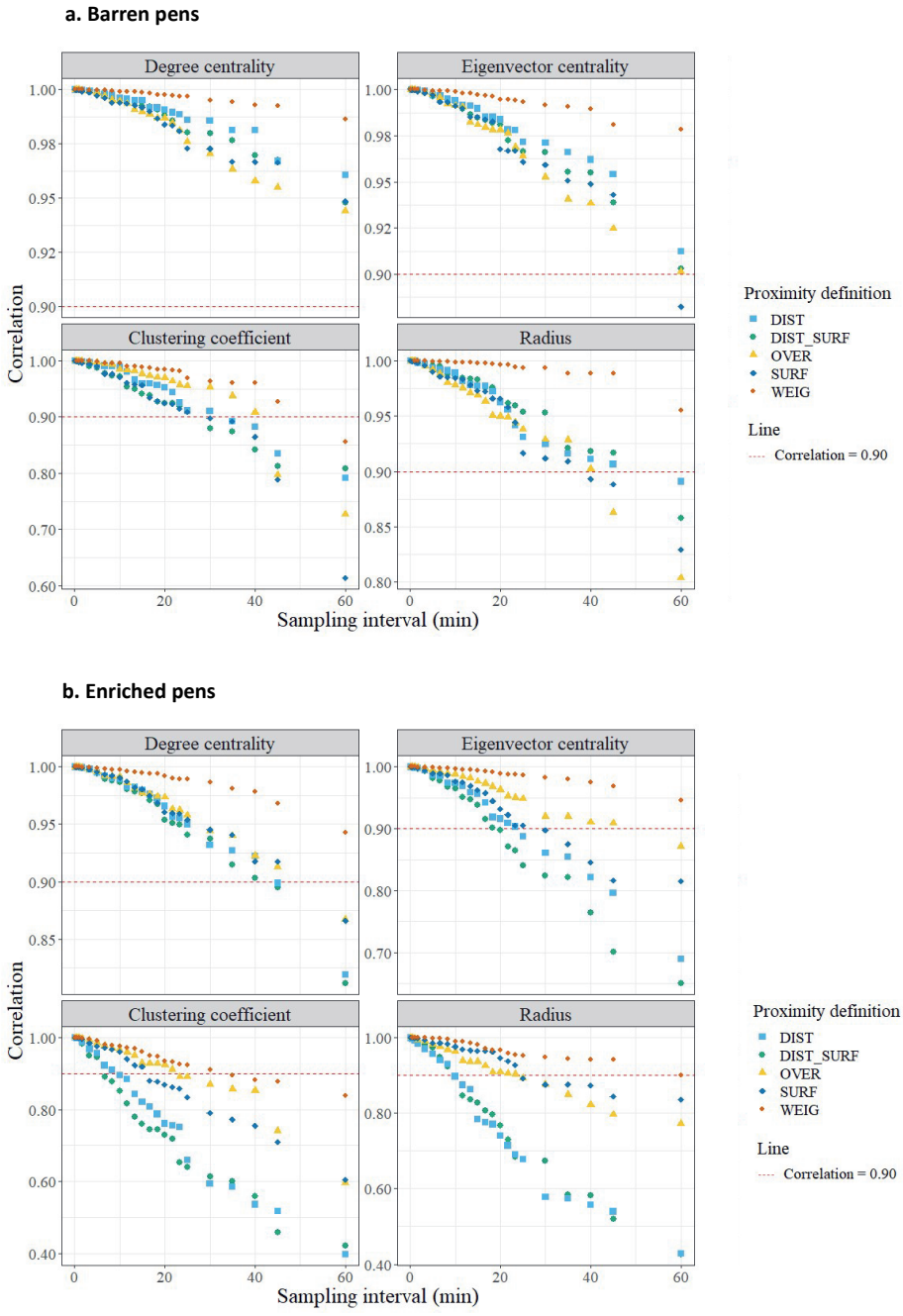


Figure S2. Correlations between the metrics of the reduced network (built with different sampling intervals) and the metrics of the complete network (2s sampling interval), for the degree centrality, eigenvector centrality, clustering coefficient, and radius for (a) Barren pens and (b) Enriched pens. Note that the y-axis scale differs between panels.

Chapter 3

Chapter 3

Consistency of group-level activity patterns of growing-finishing pigs, obtained by a tracking-by-detection algorithm

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Abstract

With recent advances in technology, it is possible to continuously monitor group-level activity in commercial pig farms. This activity can be used to identify behavioural deviations associated with health and welfare issues. However, before such deviations can be reliably identified, it is essential to first characterise basal activity patterns to distinguish normal fluctuations from changes associated with health or welfare issues. This study aimed to investigate the consistency of group-level activity patterns over time, obtained from video recordings through a tracking-by-detection algorithm. We followed two batches of growing-finishing pigs, with 8 pens per batch. Batch A was characterised by a relatively stable, low temperature-humidity index (THI), whereas batch B was characterised by a higher THI, particularly during the final two weeks. A tracking-by-detection algorithm was run over 12 weeks of the growing-finishing period, sampling two days per week every two weeks. From the tracking output, three pen-level activity metrics were derived: average activity, relative amplitude, and intra-daily variability, the latter reflecting fragmentation of activity patterns. Associations between these activity metrics and week, weekday, and THI were analysed. Overall, we found a strong association between week and all activity metrics, indicating clear changes over time, though differing between batches. In batch B, we observed a clear transition from monophasic to biphasic activity patterns, accompanied by a decrease in average activity and relative amplitude, and an increase in intra-daily variability. In contrast, batch A showed no clear transition to a biphasic pattern, with activity metrics fluctuating across weeks without a consistent directional trend. Average activity was relatively consistent across pens over time, indicating that pens with higher activity in one week tended to remain higher in the other weeks. In contrast, the more complex metrics relative amplitude and intra-daily variability showed lower consistency across weeks. Furthermore, in batch A, where THI variation between weekdays was limited, differences in activity metrics were minimal between weekdays. Conversely, batch B showed stronger and more variable associations between weekday and activity metrics across weeks and THI. In conclusion, this study shows the potential of using the output of a tracking algorithm to characterise group-level activity patterns in growing-finishing pigs. However, our results also highlight that interpreting such patterns to detect deviations requires careful consideration, as activity is influenced by both age and THI and may fluctuate between weekdays.

1. Introduction

Monitoring the activity of pigs provides valuable information, as changes in activity can indicate health and welfare issues. For example, environmental stressors such as heat stress, high humidity and ammonia levels, that negatively impact pig welfare (Jones et al., 2001; Spoolder et al., 2012; Bus et al., 2025), have been associated with a decrease in activity (Huynh et al., 2005; Kim et al., 2008). In addition, several studies have shown that activity at the group level increases on the days preceding a tail-biting outbreak (Statham et al., 2009; Larsen et al., 2019; Larsen et al., 2020), although findings are not entirely consistent, as Orsini et al. (2025) reported that group-level activity could not predict tail damage. It has been suggested that welfare issues may not only affect the overall activity level, but also disrupt the circadian activity pattern in activity (Gorka et al., 1996; Meerlo et al., 1999; Bunney and Bunney, 2000; Rutherford et al., 2006). Hence, monitoring activity patterns at the group level may help to detect environmental stress or behavioural issues, such as tail-biting, enabling timely interventions.

To use behavioural changes as reliable indicators of problems, it is important to first establish basal activity levels and circadian activity patterns in pigs, so that normal fluctuations can be distinguished from changes associated with health or welfare issues (Bus et al., 2021). Previous studies have reported that pigs on commercial farms spend approximately 70% of their time inactive (Fraser, 1985; Bolhuis et al., 2005) and that their activity fluctuates throughout the day, following a diurnal circadian activity pattern (Orsini et al., 2025; Ocepek, 2026), which is also reflected in a circadian pattern in feed intake (Haer and Merks, 2010; Bus et al., 2023). However, activity levels are influenced by several factors. For example, the presence of enrichment materials in the pen (Beattie et al., 2000; Bolhuis et al., 2005, 2006; Luo et al., 2020), access to outdoor areas (Blumetto et al., 2013), longer daylight periods and moderate temperatures (Huynh et al., 2005; Kim et al., 2008) have been associated with increased activity. In contrast, high-fibre diets (Brouns et al., 1994; Bolhuis et al., 2010) and increased feeding space per pig can reduce activity (Spoolder et al., 1999). Activity level and circadian patterns also change with age. Overall activity decreases with age (Bolhuis et al., 2005; Luo et al., 2020), and the daily activity rhythm shifts from a single activity peak in younger pigs to two distinct activity peaks in older pigs, one in the late morning and another in the late afternoon (Schouten, 1986; Bus et al., 2023; Yang et al., 2024a; Orsini et al., 2025). However, the age at which this shift occurs varies between studies, with week 6 (Schouten, 1986) and week 22 (Orsini et al., 2025) reported in the literature. In addition, the extent to

which a circadian rhythm is expressed may differ strongly between individuals (Ocepek, 2026).

Previous studies have largely focused on measuring activity over short observation periods, as manually annotating activity, for example, through scoring postures (lying, standing, or sitting), is labour-intensive. Most research has focused on overall activity levels, whereas the potential of changes in circadian activity patterns as indicators of health and welfare issues has been indicated in some studies (van der Zande et al., 2020; van der Zande et al., 2022; van Dixhoorn et al., 2024) but remains largely unexplored. Therefore, more research is needed to increase our understanding of normal activity patterns and circadian rhythms in pigs. Identifying changes in activity and circadian patterns requires monitoring activity continuously over long periods, which is only feasible with automated methods. In recent years, computer vision approaches have shown promising results in monitoring activity, from video recordings, continuously over long periods. In particular, activity can be quantified by measuring the distance moved from a tracking-by-detection algorithm (van der Zande et al., 2022; Hollifield et al., 2024; Yang et al., 2024a; Orsini et al., 2025). Tracking individuals over long periods to monitor activity at the individual level remains challenging due to identity switches in tracking-by-detection algorithms (van der Zande et al., 2021; Guo et al., 2023; Yang et al., 2024b). However, measuring the distance moved from a tracking-by-detection algorithm is a straightforward approach to estimate group-level activity, as identity switches have little impact on pen-level activity (Orsini et al., 2025). Tracking-by-detection algorithms generate data at the frame level, resulting in very large datasets and high computing time. Consequently, recording continuous activity data every day in multiple pens over several months of fattening is not realistic in practice. Therefore, down-sampling the data is necessary, meaning that a choice needs to be made about which specific days to record. However, these specific days may not be representative of the overall activity and daily activity patterns, potentially affecting the conclusions drawn from the data. Understanding how consistent activity level and circadian activity patterns are over time is essential to reliably distinguish typical fluctuations from meaningful changes and to determine optimal recording periods.

Therefore, this study aimed to investigate the consistency of group-level activity patterns over time. For this purpose, a tracking-by-detection algorithm was run on a total of 178 days from 16 pens, sampling two days per week every two weeks of these two batches. Three activity metrics were derived from the tracking output. The consistency of these three activity

metrics across weeks and days of the week was investigated, while accounting for the influence of the Temperature-Humidity Index (THI) on these days.

2. Methods

2.1. Animals and housing

This study was conducted at a Topigs Norsvin (pig breeding company, 's-Hertogenbosch, the Netherlands) commercial farm in Germany. Sixteen pens were included in the study, equally divided between two batches: batch A (September to December 2021) and batch B (May to September 2022). Pigs arrived at 10 weeks of age and were housed for approximately 14 weeks until slaughter. Each pen contained only barrows, with 11 pigs per pen and a space allowance of 1.03 m² per pig. The pens were distributed across five rooms. Each fully slatted pen was equipped with two drinking nipples providing *ad libitum* water, and one electronic feeding station providing *ad libitum* access to a commercial dry feed (more details in Bus et al., 2023a). Enrichment materials were provided in compliance with European Union and German animal welfare legislation and consisted of a chain with plastic rings or a wooden block, and an extra feeder from which pigs could obtain chopped straw mixed with straw pellets by manipulating a chain. Pigs received natural lighting through windows and a night light to enable camera visibility during darkness. Pigs were identified by a coloured symbol that was sprayed on their backs twice per week on Tuesdays and Fridays.

2.2. Selection of the days for analyses

The analyses were performed on a subset of days from the fattening period due to limitations in computation time. Initially, 192 days were selected for analysis, representing two days per week (Wednesday and Saturday) for the 16 pens over six weeks (weeks 2, 4, 6, 8, 10, 12) following the pigs' arrival. These two days were chosen to be sufficiently spaced within the week, while avoiding human presence for marking and data collection in the pens on Tuesday and Friday. However, due to missing hours of videos, 14 Saturdays were discarded from the analyses, leaving 178 days available for analysis (Table 1). For all six weeks and 16 pens, all recordings on Wednesdays were available.

Table 1. Summary of the 178 days available for the analyses and the 14 missing days.

Week	2		4		6		8		10		12	
Batch/Day	Wed	Sat	Wed	Sat	Wed	Sat	Wed	Sat	Wed	Sat	Wed	Sat
A	8	8	8	8	8	7	8	8	8	8	8	8
B	8	4	8	0	8	8	8	7	8	8	8	8

The colour is based on the number of days available, varying from red (minimum number) to green (maximum number).

2.3. Activity data

A camera (Lorex, 4KSDAI168, Canada) was installed on the wall above each pen at a slight angle. Videos were recorded at 15 frames per second with a resolution of 1280 × 720 pixels and stored remotely in the cloud on an hourly basis.

Tracking algorithm and measure of the distance moved

Group-level activity data was derived from a tracking algorithm run on the 178 selected days. This tracking algorithm, described in Huo et al. (2023) and used in Orsini et al. (2025), was based on bounding-box multi-object detection and developed with an Enhanced Cascaded Association Flow (ECAF). During the algorithm's development and testing, it achieved a performance of 98–99% for Multiple-Object Tracking Accuracy (MOTA) and Identity F1 score (IDF1), along with a 0.56 score for Identity Switch (IDSW). The output of the tracking algorithm was down-sampled to 0.5 frames per second to reduce potential noise due to micro-movements of the bounding boxes (van der Zande et al., 2022).

The activity metrics were calculated based on the distance moved, measured with this tracking algorithm. Similar to Orsini et al. (2025), the distance moved of each bounding box was calculated by comparing the centroid of the same bounding box in two consecutive frames sampled at 0.5 frames per second. Equation 1 from the Pythagorean theorem was used, where x_f and y_f are the coordinates of the centroid of the bounding boxes at frame f, and x_{f+1} and y_{f+1} are the corresponding coordinates at frame $f+1$.

$$Distance\ moved = \sqrt{\left(x_{f+1} - x_f\right)^2 + \left(y_{f+1} - y_f\right)^2} \quad \text{(Equation 1)}$$

Calculations of activity metrics

To estimate the consistency of activity at the pen-level, three activity metrics, average activity, relative amplitude and the intra-daily variability, were derived from the tracking algorithm. Two examples of circadian activity patterns and their activity metrics are presented in Figure 1.

Average activity

The group-level average activity was calculated using Equation 2, as the average activity per bounding box, by summing the distance moved between consecutive frames at time t for each bounding box i and dividing it by N, the number of pigs in the group. The average distance moved was then smoothed by calculating a rolling mean (i.e., averaging over a moving window) with a 3h window, defined as optimal in Orsini et al. (2025).

$$Average\ activity\ = \frac{1}{N}\sum_{i=1}^{N} distance\ moved_{i,t} \quad \text{(Equation 2)}$$

Relative amplitude

The relative amplitude quantifies the difference between the most active periods and the least active periods within a day. This measure has been widely used in human research, including studies on circadian rhythm disruptions associated with Alzheimer's disease (Witting et al., 1990; Van Someren et al., 1999). The group-level relative amplitude was calculated based on the hourly average activity smoothed with the 3h window rolling mean, using Equation 3. Peak of activity (M10) was defined as the average activity during the 10 consecutive most active hours of the day, and low activity (L5) as the average activity during the least active 5 consecutive hours (Figure 1). The 10h and 5h windows were chosen based on the standard windows used to calculate intra-daily variability in human research and applied here to pigs as a practical choice.

$$Relative\ amplitude\ = M10 - L5 \quad \text{(Equation 3)}$$

Intra-daily variability

Intra-daily variability quantifies the fragmentation of activity within a day by measuring the frequency of transitions between activity and rest across the day. This activity metric reflects how frequently activity levels fluctuate between high and low activity periods, with higher intra-daily variability indicating more fragmented activity patterns. This measure has been

widely used in human research; for example, increased intra-daily variability of activity has been associated with a higher risk of Alzheimer's dementia (Witting et al., 1990; Van Someren et al., 1999; Li et al., 2020) and increased fragmentation of play has been associated with depression in children (Lous et al., 2002). For each day, the intra-daily variability was computed as the ratio of the mean squared difference between consecutive hourly activity values to the overall variance of the day's activity. The group-level intra-daily variability was calculated from the hourly activity data smoothed with the 3h rolling mean, using Equation 4, where A_i and A_{i-1} are the smoothed mean activity in hours i and $i-1$, and $\bar{A}$, the average activity.

$$Intra-daily\ variability = \frac{24\sum_{i=2}^{24}(A_i - A_{i-1})^2}{23\sum_{i=1}^{24}(A_i - \bar{A})^2} \quad \text{(Equation 4)}$$

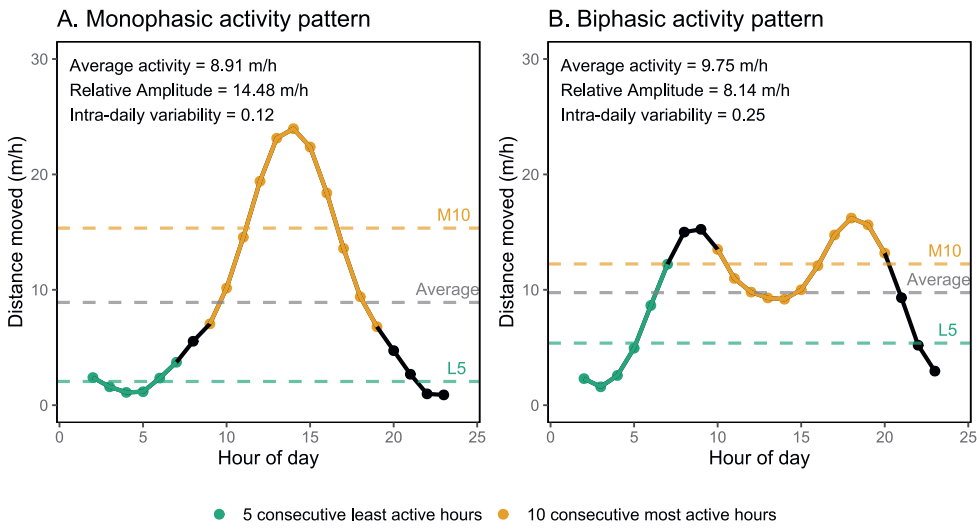


Figure 1. Example of a monophasic (A) and biphasic (B) activity pattern and their average activity, relative amplitude, and intra-daily variability.

2.4. Temperature-Humidity Index

Ambient temperature and relative humidity were measured by electro-chemical sensors DOL114 (see technical user guide for more details: https://www.dol-sensors.com/products/sensors/dol-114-humidity-and-temperature-sensor#tech-info), located in each room above the pen wall at a height of approximately 1.8 m. These sensors estimated the ambient temperature (°C) and relative humidity (%) every 15 min. The

measures of temperature and humidity were aggregated into a daily measure, using the mean. The daily measures of ambient temperature (T) and relative humidity (RH) were used to calculate the THI (Dikmen and Hansen, 2009) using Equation (5). The daily averages of THI for the two batches of pigs (A and B) are shown in Figure 2.

$$THI = (1.8T + 32) - (0.55 - 0.0055\,RH)(1.8T - 26) \text{ (Equation 5)}$$

The Temperature–Humidity Index (THI) was included in our analysis to account for fluctuations in temperature and humidity, potentially affecting the consistency of activity. Other environmental variables, including daylight, ammonia, and CO_2, were also recorded. However, due to high correlations among these variables (Supplementary Figure 1) and the well-documented influence of THI on activity, only THI was retained in the final analysis.

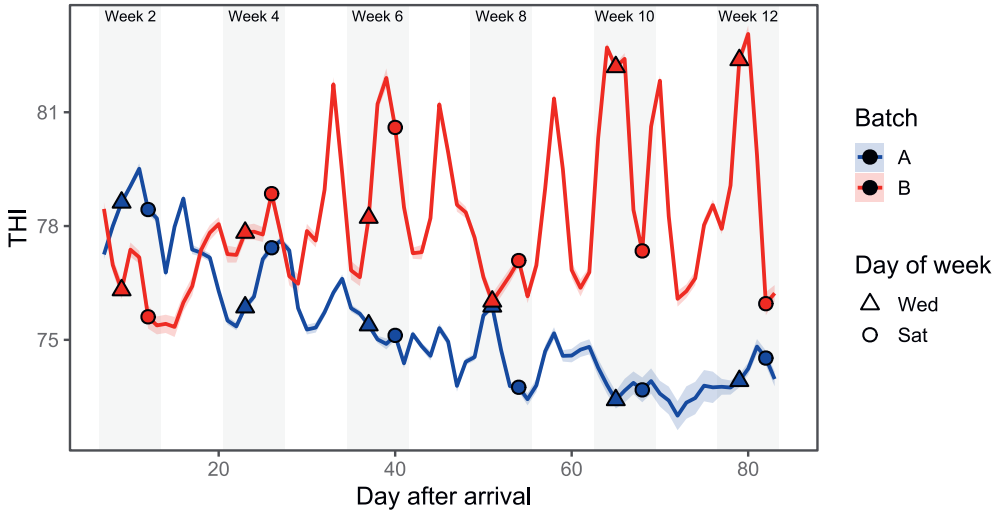


Figure 2. Daily mean of THI across time for the two batches of pigs.

2.5. Statistical analyses

All statistical analyses were performed in RStudio (version 2024.04.2) using R (version 4.2.2). Univariate linear mixed models were built using the *lmer* function from the *lme4* package version 1.1-31 (Bates et al., 2024) and bivariate linear mixed models were fitted in *ASReml-R* version 4.2.49 (Butler et al., 2023). The best fit of the model and the assumptions were assessed using the *DHARMa* package version 0.4.7 (Hartig, 2017), including visual inspection of residual versus fitted values, and tests for normality and uniformity of the

residuals, and overdispersion. Post-hoc pairwise comparisons were performed using the *emmeans* package version 1.8.5 (Lenth et al., 2019).

Data analysis was conducted separately for each batch, consistent with the approach of Bus et al. (2025). This approach was chosen because the batches differed in baseline THI and its fluctuation over time (Figure 2), as the two batches took place during different periods of the year with opposite variation of the daylight duration and temperature, which may have influenced the activity as described in the introduction.

The data analysis was performed in two steps. First, the consistency of the activity metrics across weeks was investigated using a dataset including only Wednesdays. Saturdays were excluded from this analysis to avoid confounding due to the variation in THI between Wednesdays and Saturdays (Figure 2) and unbalanced sampling due to an incomplete dataset on Saturdays (Table 1). Second, consistency of the activity metrics between days of the week was explored using the full dataset, including both days: Wednesday (n=96, Table 1) and Saturday (n=82).

Consistency of activity metrics between weeks

For each batch, three separate linear mixed models were built, one for each activity metric Y_{ij} (average activity, relative amplitude and intra-daily variability) as the response variable (Equation 6). All activity metrics were first log-transformed to normalise the residuals. Fixed effects included week ($week_j$) as a categorical variable to allow each week to have an independent mean effect, without assuming a linear trend, and a spline-transformed THI ($f(THI_{ij})$) to account for its non-linear association with the activity metrics. A random intercept for pen (pen_i) was included in the model to account for repeated measures within pens (Equation 6). The model initially also included the interaction between week and the spline-transformed THI to account for potential variation in the association between THI and the activity metrics across weeks. However, this interaction was not statistically significant ($P > 0.05$), and did not improve the model fit based on the Akaike Information Criterion (AIC). In addition, given the limited number of pens per batch, including the interaction would have risked over-parameterisation and reduced statistical power. Therefore, it was removed from the final model. Models were fitted using maximum likelihood, and the significance of the fixed effects (week and THI) was evaluated using likelihood ratio tests. Post-hoc pairwise comparisons between weeks were performed using Tukey-adjusted tests.

$$\log(Y_{ij}) = \beta_0 + \beta_1 week_{ij} + \beta_2 f(THI_{ij}) + pen_i + \varepsilon_{ij} \quad \text{(Equation 6)}$$

Bivariate linear models were built to estimate correlations of the same activity metric between pairs of weeks (Equation 7), where Y_k and Y_l are the same activity metrics measured on weeks k and l respectively. In each model, a week-specific intercept β_{0k} and β_{0l} and spline-transformed THI, $\beta_{1k}f(THI_k)$ and $\beta_{1l}f(THI_l)$ were fitted.

$$\begin{bmatrix} Y_k \\ Y_l \end{bmatrix} = \begin{bmatrix} \beta_{0k} + \beta_{1k}f(THI_k) \\ \beta_{0l} + \beta_{1l}f(THI_l) \end{bmatrix} + \begin{bmatrix} \varepsilon_k \\ \varepsilon_l \end{bmatrix} \text{ (Equation 7)}$$

The residuals follow a bivariate normal distribution with the variance-covariance matrix presented in Equation 8.

$$\begin{bmatrix} \varepsilon_k \\ \varepsilon_l \end{bmatrix} \sim N(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma^2_{\varepsilon_k} & \sigma_{\varepsilon_k,\varepsilon_l} \\ \sigma_{\varepsilon_k,\varepsilon_l} & \sigma^2_{\varepsilon_l} \end{bmatrix}) \text{ (Equation 8)}$$

Where $\sigma_{\varepsilon_k,\varepsilon_l}$ is the covariance of the activity metrics between the weeks k and l, and was used to estimate the residual correlations of the activity metrics between weeks. The estimated correlations reflect the consistency of the ranking of pens in activity across weeks, i.e., whether pens that are relatively more (or less) active in one week tend to remain relatively more (or less) active in another week, after adjusting for THI.

Consistency of the activity metrics between days of the week

All activity metrics (Y_{ij}) were first log-transformed to normalise the residuals. For each batch, three separate linear mixed models were built, one for each activity metric Y_{ij} (average activity, relative amplitude and intra-daily variability) as the response variable (Equation 9). Fixed effects included week ($week_j$) as a categorical variable, the day of the week ($weekday_j$), and a spline-transformed THI ($f(THI_{ij})$) and their two-way interactions. The three-way interaction was initially tested, but was then removed from the models as it was non-significant for all three activity metrics ($P > 0.05$). The three two-way interactions were retained in all six models, as the likelihood ratio tests indicated the significance of these interactions and a reduction in AIC in at least one of the models. A random intercept for pen (pen_i) was included in the model to account for repeated measures within pens (Equation 9). Models were fitted using maximum likelihood, and the significance of the fixed effects (week, weekday and THI) was evaluated using likelihood ratio tests.

$$\log(Y_{ij}) = \beta_0 + \beta_1 week_j + \beta_2 weekday_j + \beta_3 f(THI_{ij}) + \beta_4(weekday_j \times week_j) + \beta_5\left(week_j \times f(THI_{ij})\right) + \beta_6\left(weekday_j \times f(THI_{ij})\right) + pen_i + \varepsilon_{ij} \text{ (Equation 9)}$$

3. Results

3.1. Consistency of activity patterns across weeks

Figure 3 presents the mean activity pattern and its standard error across weeks for the two batches. Visually, batch B, with higher THI values and greater THI fluctuations compared to batch A (Figure 2), showed a clear shift from a single late-afternoon peak to a biphasic pattern, with one peak in the late morning and another in the late afternoon. This biphasic pattern became pronounced from week 8 onward. It appeared relatively consistent across pens in batch B, as indicated by the low standard error of the mean. In contrast, the transition from a monophasic to a biphasic activity pattern was less pronounced in batch A, where THI was relatively stable (Figure 2). Across all weeks, the main activity peak in batch A remained in the late afternoon, although smaller secondary peaks in the late afternoon were also visible during weeks 2, 8, 10, and 12. The larger standard error of the mean observed in batch A suggests that some pens may also have displayed biphasic activity patterns from week 8 onward, but this pattern was not present in all pens, which is visually supported when investigating the activity pattern of each pen (Supplementary Figure 2).

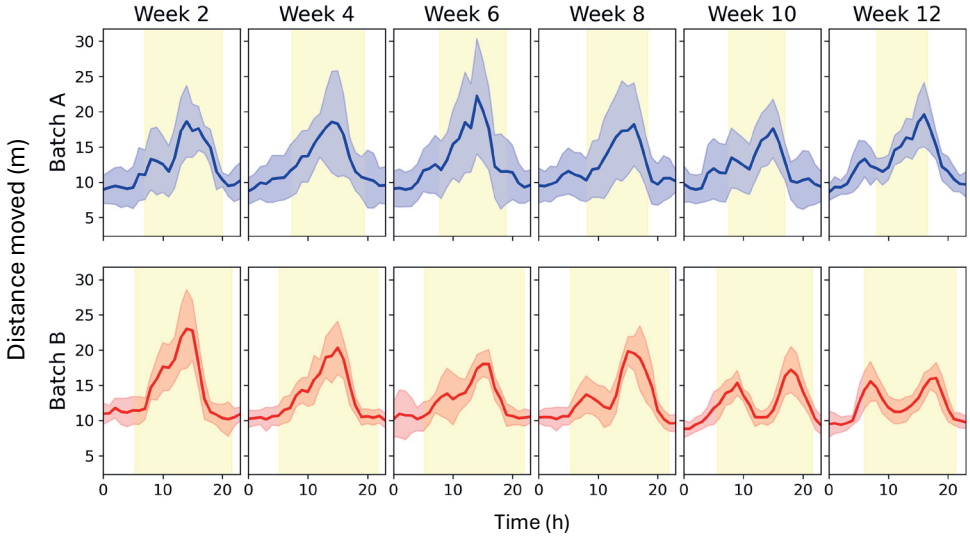


Figure 3. Activity patterns over the day for each week; (B) Average activity, relative amplitude, and intra-daily variability (± standard error) across weeks for the two batches. Different letters indicate statistically significant differences between weeks based on post-hoc pairwise comparisons using Tukey tests. Note: the Y-axis does not start at 0.

Table 2 presents the results of the likelihood ratio tests for the fixed effects for the three activity metrics, and Figure 4 shows the observed average activity, relative amplitude and intra-daily variability per week and the results of the Tukey tests. Week significantly influenced the three activity metrics in both batches, with all χ^2 ranging from 11.86 to 46.9, and most $P < 0.001$ (Table 2). For batch B, there was a clear trend for the average activity and relative amplitude to decrease, and for the intra-daily variability to increase with week (Figure 4). Between weeks 2 and 12, the average activity decreased by about 15%, the relative amplitude decreased by 30%, and the intra-daily variability increased by 40%. In contrast, for batch A, the three activity metrics fluctuated more across weeks, without a clear direction for the entire growing-finishing period. Both average activity and relative amplitude showed a peak at week 6. For average activity, week 6 was significantly higher than weeks 10 and 12, while no differences were observed between week 6 and weeks 2, 4, or 8. For relative amplitude, week 6 was significantly higher than weeks 8, 10, and 12, with no differences compared to weeks 2 and 4. Intra-daily variability showed only a single significant difference, between week 6 and week 12. Associations between THI and the activity metrics were limited. A significant effect of THI was only observed for the average activity in batch B ($\chi^2 = 9.94$, $P < 0.01$, Table 2), where higher THI was associated with lower average activity (Figure 5B).

Table 2. Results of the likelihood ratio tests for the fixed effects (week and THI) on the three activity metrics (AA: average activity, RA: relative amplitude and IV: intra-daily variability) for the two batches.

Batch	Activity metric	Week		THI	
		χ^2	*P*	χ^2	*P*
A	AA	11.9	**0.04**	0.02	0.89
A	RA	29.3	**<0.001**	0.02	0.87
A	IV	22.6	**<0.001**	1.14	0.28
B	AA	46.9	**<0.001**	9.94	**<0.01**
B	RA	38.0	**<0.001**	0.01	0.89
B	IV	29.9	**<0.001**	1.92	0.17

This analysis was performed on the dataset including only Wednesday. Week was included as a categorical variable, and THI as a continuous variable. Models were fitted separately for each batch. Significant values ($P < 0.05$) are indicated in bold.

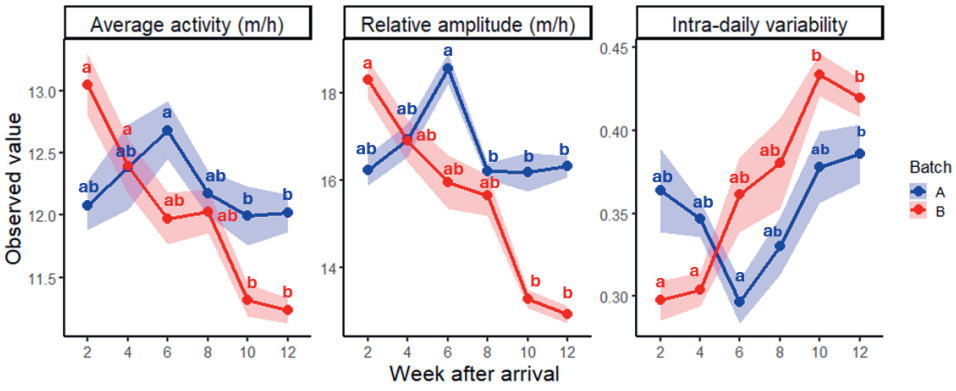


Figure 4. Average activity, relative amplitude, and intra-daily variability (± standard error) across weeks for the two batches. Different letters indicate statistically significant differences between weeks based on post-hoc pairwise comparisons using Tukey tests. Note: the Y axis does not start at 0.

Figure 5 shows the estimates of the residual correlations of the average activity, relative amplitude and intra-daily variability between weeks, after adjusting for the THI. These correlations indicate the consistency of the ranking of the pens over time, i.e., whether pens that show higher values (or lower) for a given activity metric in one week also tend to remain higher (or lower) compared to other pens in the other week. Overall, average activity showed stronger between-week correlations than the other two activity metrics, with significant correlation coefficients ranging from 0.82 to 0.98 in batch A and from 0.71 to 0.95 in batch B (Figure 5). In contrast, relative amplitude and intra-daily variability were less consistent across weeks, and most correlations were not statistically significant. For relative amplitude, batch A showed only one significant negative correlation (r = -0.80) between weeks 8 and 10 (Figure 5), indicating a switch between these two weeks in the ranking of the pens with high and low relative amplitude. In batch B, correlations of the relative amplitude between weeks were positive but generally weak to moderate, ranging from 0.10 to 0.87. Similarly, intra-daily variability showed generally weak to moderate correlations between weeks in both batches, with values ranging from -0.10 to 0.77 in batch A and from -0.54 to 0.81 in batch B (Figure 5), and only a small number of correlations were statistically significant.

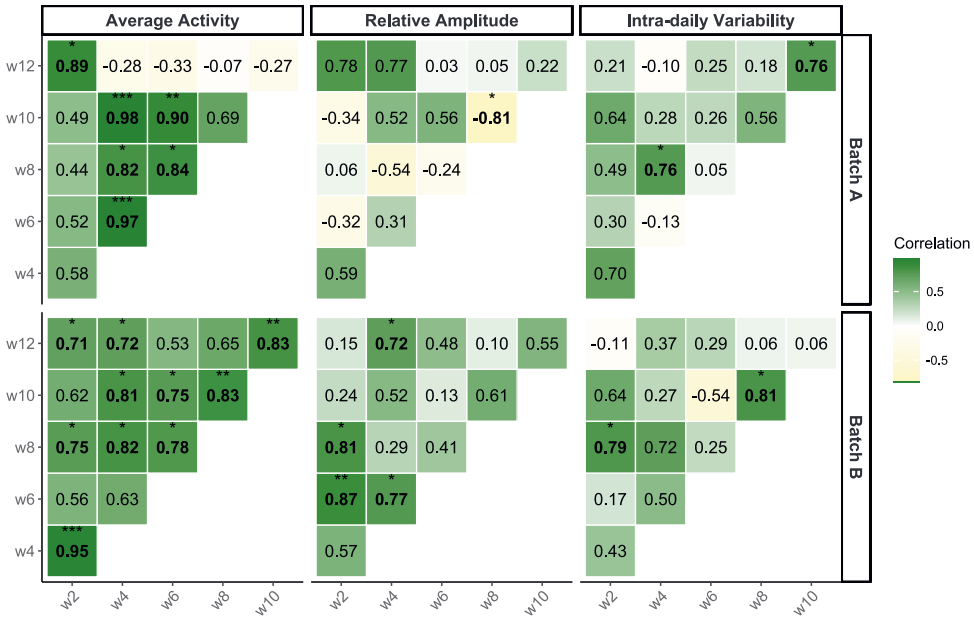


Figure 5. Estimates of the residual correlations between weeks for the three activity metrics (average activity, relative amplitude and intra-daily variability).

3.2. Consistency of activity patterns across days of the week

The observed mean activity, relative amplitude, and intra-daily variability for the two weekdays are shown in Figure 6 across weeks, and in Figure 7 across THI. Table 3 presents the results of likelihood ratio tests for the fixed effects of week, weekday, THI, and their interactions on the three activity metrics. In batch A, for average activity, no significant main effect of weekday, nor significant interactions with weekday, were observed (all $P > 0.10$, Table 3). This result suggests that average activity did not differ between Saturday and Wednesday on average across the weeks. Similar results were also observed for relative amplitude, although a tendency was found for the interaction between week and weekday ($\chi^2 = 10.9$, $P = 0.05$), indicating that the effect of weekday on relative amplitude varied across weeks. In contrast, intra-daily variability showed significant interactions between week and weekday ($\chi^2 = 16.9$, $P < 0.01$, Table 3) and week and THI ($\chi^2 = 28.51$, $P = 0.01$), indicating that both the effect of weekday and the effect of THI on intra-daily variability varied across weeks.

Unlike for batch A, several significant interactions were observed across all activity metrics for batch B. Significant interactions were found between week and weekday for all three

metrics, suggesting that activity patterns varied across weeks and differed between weekdays. Average activity was lower on Wednesday compared with Saturday in week 2, showed little difference in weeks 6 and 8, and was higher on Wednesday in weeks 10 and 12 (Figure 6). A similar pattern was observed for relative amplitude, which was lower on Saturday in weeks 2 and 6, but higher on Saturday in week 12 (Figure 6). No clear weekday differences in intra-daily variability were observed, except in weeks 10 and 12, where Wednesday values were lower than Saturday values (Figure 6).

A significant interaction was also found between weekday and THI for relative amplitude ($\chi^2 = 13.7$, $P < 0.01$, Table 3) and intra-daily variability ($\chi^2 = 11.0$, $P = 0.01$, Table 3), indicating that the association between THI and these metrics differed between Wednesday and Saturday. However, THI values were not evenly distributed across weekdays, with higher values observed on Wednesday, particularly in weeks 10 and 12 (Figure 2), which may have contributed to this interaction. For example, THI values above 81 occurred on Wednesday and coincided with lower relative amplitude and higher intra-daily variability, whereas such THI values were not observed on Saturday (Figure 7).

Overall, these results suggest that associations between weekday, week, and THI were not consistent across activity metrics. In batch A, where THI variation between weekdays was limited (Figure 2), weekday differences in activity metrics were minimal. In contrast, batch B showed stronger and more variable associations across weeks and THI.

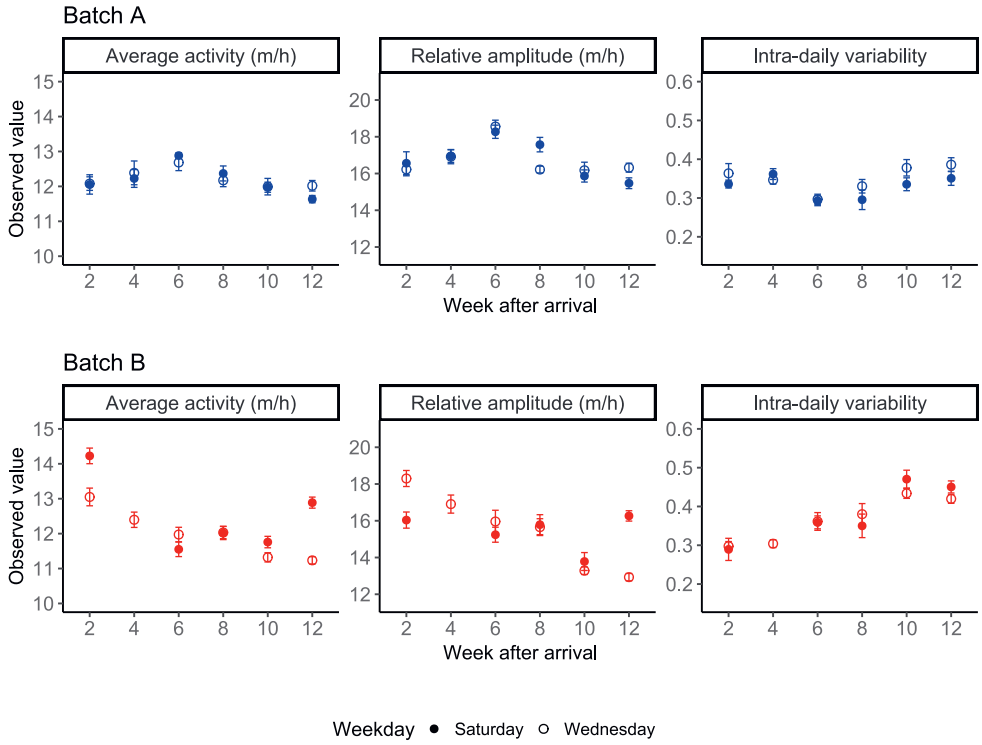


Figure 6. Mean average activity, relative amplitude, and intra-daily variability (± standard error) across weeks for the two days for the two weekdays. These plots were based on a dataset including Wednesday (n=96) and Saturday (n=82). Each point shows the mean activity metric, and the error bars show the standard error of the mean.

Table 3. Results of the likelihood ratio tests for the fixed effects (weekday, week, THI and their interactions) on the three activity metrics (AA: average activity, RA: relative amplitude and IV: intra-daily variability) for the two batches.

Batch	Metric	Week		Weekday		THI		Week x Weekday		Week x THI		Weekday x THI	
		χ^2	*P*	χ^2	*P*	χ^2	*P*	χ^2	*P*	χ^2	*P*	χ^2	*P*
A	AA	5.70	0.34	1.87	0.17	2.97	0.40	8.68	0.12	11.10	0.68	4.78	0.19
A	RA	7.42	0.19	0.62	0.43	4.81	0.19	10.9	**0.05**	11.08	0.68	4.78	0.19
A	IV	21.2	**<0.01**	3.11	**0.08**	5.03	0.17	16.9	**<0.01**	28.51	**0.01**	3.60	0.31
B	AA	7.08	0.21	0.55	0.46	9.78	**0.02**	24.7	**<0.001**	25.82	**0.04**	3.46	0.33
B	RA	25.0	**<0.001**	1.73	0.19	3.46	0.33	11.2	**0.02**	51.02	**<0.001**	13.7	**<0.01**
B	IV	19.2	**<0.01**	3.01	**0.08**	4.42	0.22	14.4	**<0.01**	83.09	**<0.001**	11.0	**0.01**

Weekday and week were included as categorical variables, and THI as a continuous variable. Models were fitted separately for each batch. Tendency ($P < 0.1$) and significant values ($P < 0.05$) are indicated in bold.

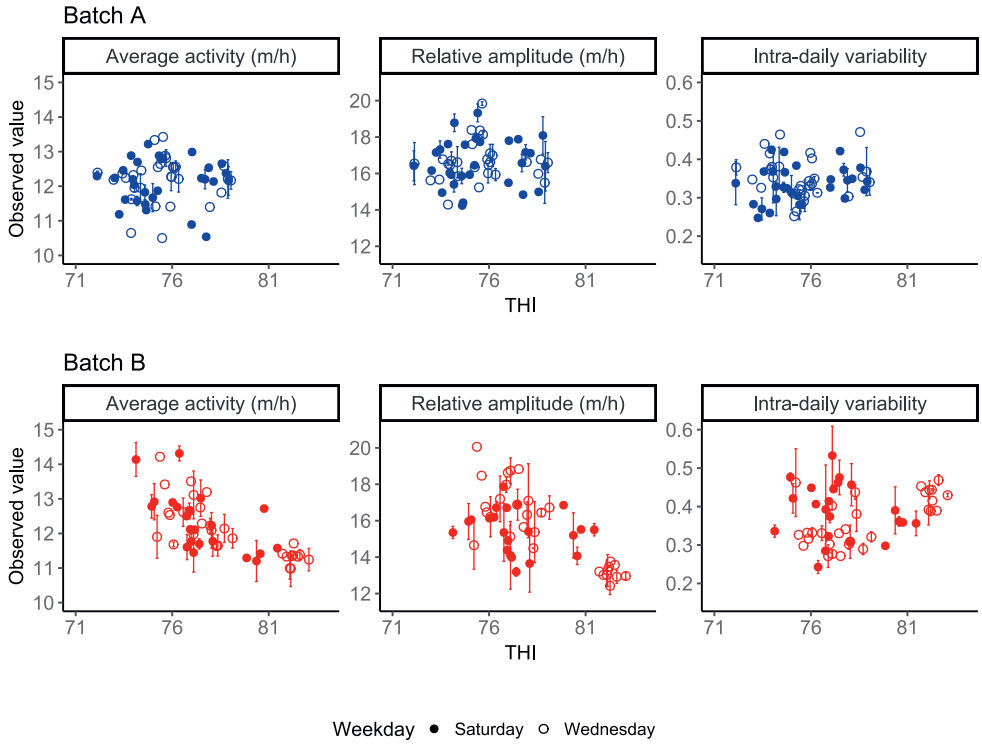


Figure 7. Associations between Mean average activity, relative amplitude, and intra-daily variability (± standard error) and THI for the two weekdays. This plot was based on a dataset including Wednesday (n=96) and Saturday (n=82). When multiple pens shared the same THI value, the data were averaged across pens, and error bars represent the standard error of the mean. When only a single pen contributed, the point is shown without error bars.

4. Discussion

This study aimed to investigate the consistency of pen-level activity patterns over time, obtained through a tracking-by-detection algorithm. We found a strong effect of week on all activity metrics, indicating clear changes over time. Average activity was relatively consistent across pens over time. However, for more complex activity metrics, such as relative amplitude and intra-daily variability, consistency across weeks was lower. THI also strongly affected activity patterns.

4.1. Consistency of activity patterns across weeks

Overall, we observed a strong effect of week on the three activity metrics. However, this effect was reflected differently in the two batches. In batch B, characterised by high THI, we observed a clear transition from a monophasic to a biphasic activity pattern, accompanied by

a decrease in average activity and relative amplitude and an increase in intra-daily variability. In batch A, characterised by relatively stable and low THI, no clear transition to a biphasic pattern was observed, and the activity metrics fluctuated across weeks, without a clear direction or transition toward a biphasic pattern.

The results observed in batch B are consistent with previous studies reporting that pigs become less active with age (Bolhuis et al., 2005; Luo et al., 2020) and that their activity pattern shifts from a single peak to two distinct peaks over time (Schouten, 1986; Bus et al., 2023; Yang et al., 2024a; Orsini et al., 2025), although this shift has not been consistently reported across studies (Ocepek, 2026). The decrease in average activity in batch B (approximately 1.5% per week averaged across weeks 2-12) was comparable to the 0.1 to 1.4% decline in locomotion reported previously (Bolhuis et al., 2006; Luo et al., 2020). This decrease is likely related to reduced space availability due to the increase in body weight (Petersen et al., 1995) and the reduction in active behaviours such as exploration and locomotor play (Bolhuis et al., 2005; Luo et al., 2020).

Environmental factors may also have contributed to the association between week and activity metrics in this study. In batch B, THI increased over the growing-finishing period and was particularly high during the last two weeks. Higher THI was associated with lower average activity, consistent with previous studies reporting reduced activity with high temperature and humidity (Huynh et al., 2005; Kim et al., 2008). This likely reflects a thermoregulatory response, as reducing activity helps limit heat production (Vermeer and Aarnink, 2023). Furthermore, as pigs grow and gain body weight, they produce more metabolic heat and need more energy for cooling, and therefore become more sensitive to high temperatures. Overall, both age and the increase in THI likely contributed to the activity pattern observed in batch B, with THI, further accentuating the decrease in average activity and relative amplitude.

The difference in environmental variables between the two batches may also explain the absence of a clear transition towards a biphasic activity pattern in batch A. Besides THI, daylight may have contributed to the observed results and the difference in the activity patterns observed in the two batches. In batch A, daylight duration was relatively short and progressively decreased, whereas batch B was exposed to longer daylight, with a peak during week 6 (yellow shading, Figure 3A). Previous studies have shown that activity patterns in pigs are partly driven by daylight, with activity peaks occurring during light periods and reduced activity during the dark period (Ingram et al., 1985; Lachance et al., 2010). The short

daylight in batch A may have contributed to an unstructured activity pattern, with a main activity peak occurring during the daylight period and a more diffuse distribution of activity during the dark period. The absence of a clear biphasic pattern in batch A may reflect lower synchronisation of activity outside the daylight period, resulting in a less pronounced peak in the dark period, when activity is averaged across pigs.

After adjusting for THI, average activity showed strong correlations between weeks in both batches, indicating a stable ranking of pens over time. This consistent pen effect on activity levels may be explained by social dynamics within the group, as competition can increase activity levels (Anil et al., 2006; Durand et al., 2023). Pens with highly dominant or aggressive individuals may exhibit higher average pen-level activity, as subordinate pigs are displaced or are staying active, waiting to access key locations, such as feeders, occupied by these dominant animals. In contrast to average activity, relative amplitude and intra-daily variability showed weaker and less consistent correlations, suggesting that pens were less consistent in the peak and fragmentation of their activity patterns.

4.2. Consistency of activity patterns between weekdays

In this study, associations between weekday (Wednesday and Saturday), week, and THI were not consistent across activity metrics. In batch A, where THI variation between weekdays was limited, weekday differences in activity metrics were minimal. In contrast, batch B showed stronger and more variable associations between weekday and activity metrics across weeks and THI, likely explained by the variation in THI between weeks and weekday within the same week (especially in weeks 10 and 12). Furthermore, activity was assessed on only two days per week, one day during the week (Wednesday) and one day during the weekend (Saturday). Therefore, differences in the management of the farm and farmer activities between weekdays and weekends may have contributed to the observed variation in activity metrics, independently of THI. These findings highlight the importance of collecting activity data on multiple days per week, not because the metrics vary greatly between days, but because noise or environmental variation may affect data quality and a single day may not reflect the entire week. Therefore, future applications on farms would require careful consideration, especially when selecting the days to record data.

4.3. Limitations of our study and potential for future applications

This study focused on three activity metrics calculated from the distance moved obtained through a tracking-by-detection algorithm. While distance moved provides a practical measure of activity and enables detailed analyses of circadian rhythms, it relies only on location and does not fully capture the actual behaviour. For example, pigs that are lying and resting and pigs that are standing but not moving appear similar in the data, even though they may be performing different behaviours such as feeding, drinking, or exploring the enrichments. Therefore, future studies would also gain further insights by including the detection of postures or specific behaviours, in addition to distance moved. Furthermore, in this study three metrics were selected, capturing different aspect of the activity pattern, with a focus on the overall activity (average activity), the contrast between active and rest periods (relative amplitude), and the fragmentation (intra-daily variability). Other metrics may also be informative for assessing health status or welfare of pigs, such as measures capturing cyclicity of activity or synchrony between pigs (van Dixhoorn et al., 2024), and could be further investigated.

In our study, activity metrics were corrected only for THI. However, other environmental variables likely also influenced activity patterns. THI was confounded with the factors daylight, CO_2, and ammonia, so its specific association with the activity metrics cannot be separated from these other environmental variables. In addition, this study included two batches with limited combinations of THI across weeks and weekdays, and covered only a restricted range of possible combinations. Therefore, the association between week, weekday and the activity metrics should be interpreted with caution, as they cannot be fully separated from the environmental variables, which reflects the complexity of commercial farm conditions. Importantly, this study shows that environmental variables should be included in future applications, such as defining activity patterns to identify deviations associated with welfare issues.

Furthermore, individual factors may also have contributed to the observed activity metrics. For example, individual welfare and health status (Salak-Johnson et al., 2004; Nordgreen et al., 2018), genetic background (Hollifield et al., 2024), sex (Holinger et al., 2015; Luo et al., 2020; van der Zande et al., 2022), coping strategies and other personality traits (Bolhuis et al., 2005; Finkemeier et al., 2018; Ferreira et al., 2025) may have played a role in shaping activity patterns. In our study, individual activity patterns were not investigated due to the

technical challenge associated with tracking to maintain the identity of individuals over long periods of time. Relying on individual activity patterns may be more appropriate for future applications to identify deviations in activity patterns associated with welfare issues, as group-level activity patterns may mask individual variation. For example, in Orsini et al. (2025), group-level activity did not predict tail biting, whereas individual activity was found to be associated with a higher frequency of tail biting. Furthermore, monitoring individual-level activity would enable tailored interventions for individual pigs. Therefore, future studies would benefit from focusing on individual-level activity patterns to identify individual baseline activity patterns for further identifying health and welfare issues.

5. Conclusion

To conclude, group-level activity decreases over time, but seems, nevertheless, relatively consistent across groups of pigs. Environmental variables, including THI, strongly affect activity level and patterns, sometimes causing large within-week fluctuations. Future applications of activity measurements on farms, as an early warning signal of health or welfare problems, require careful considerations, especially regarding the selection of the days used for monitoring activity.

Supplementary Materials

Figure S2. Scatterplot matrix of ammonia, CO_2, THI, and daylight, including Spearman correlations and density distributions.

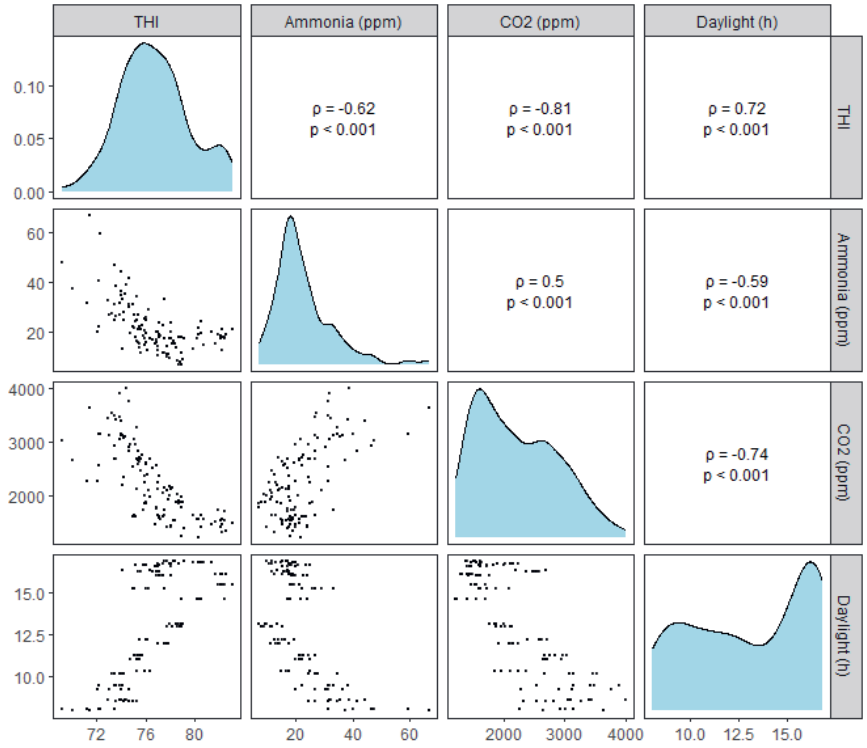


Figure S1. Group-level activity patterns of each pen for batch A (blue) and batch B (red).

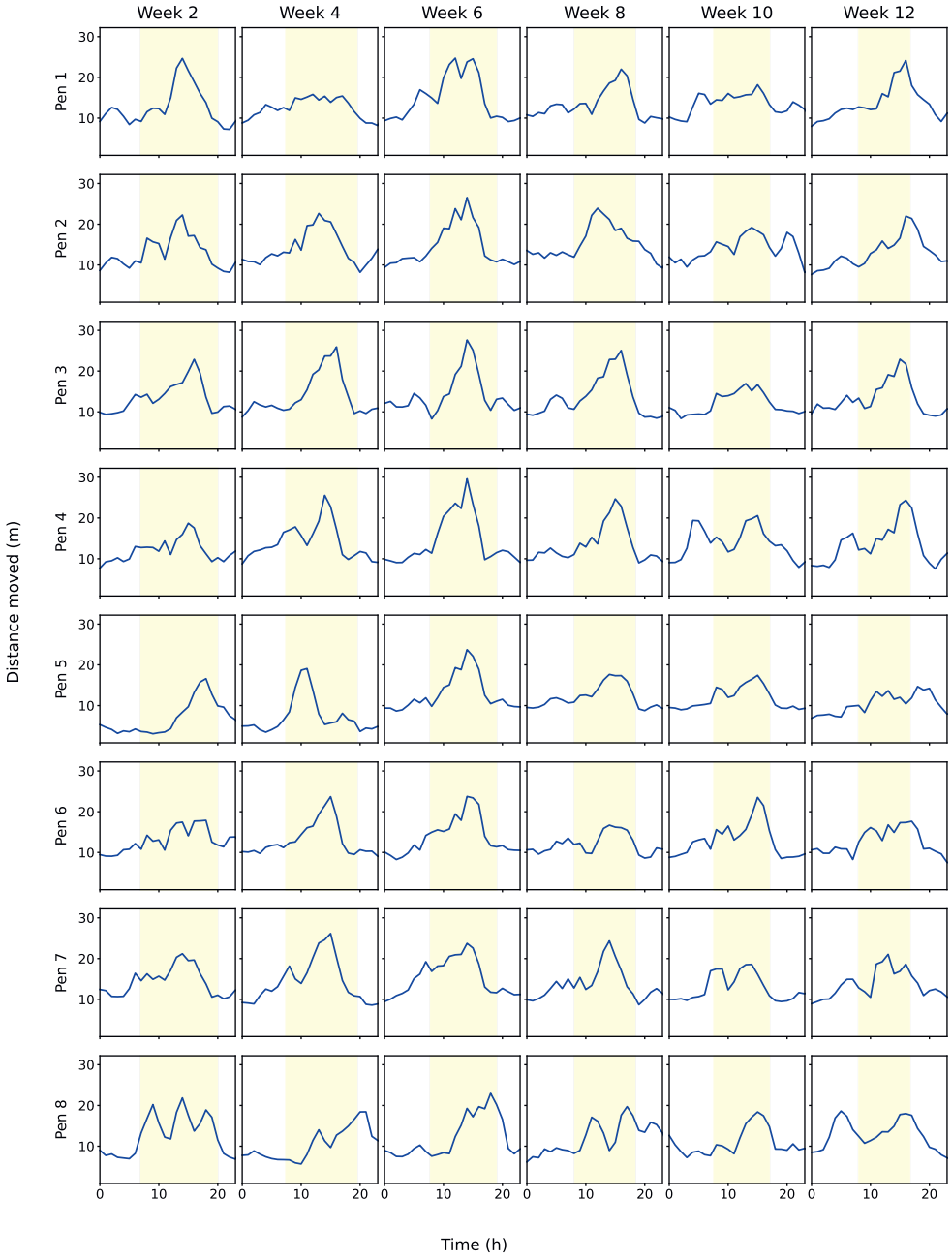
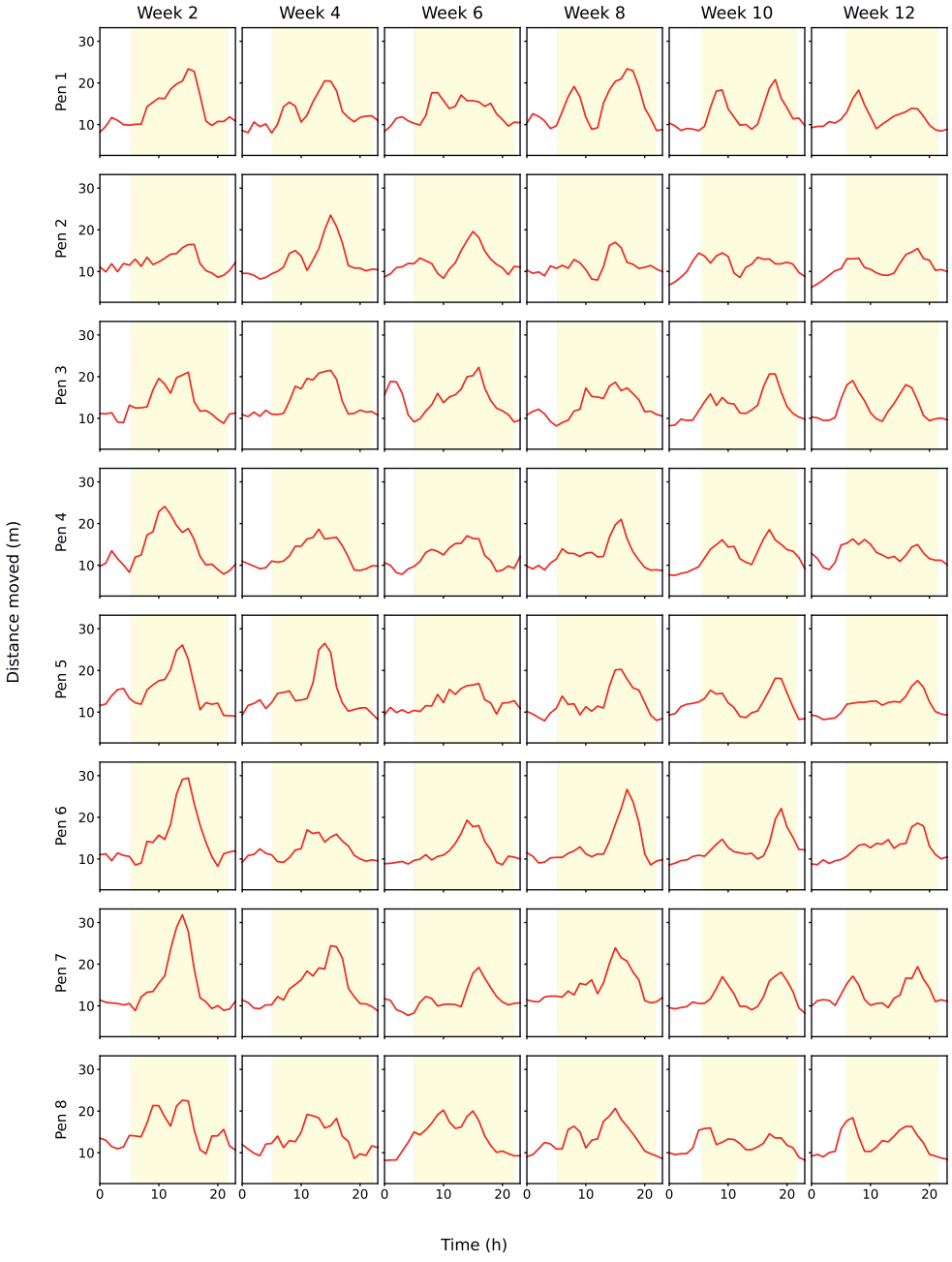


Figure S1. (continued)



Chapter 4

4

Chapter 4

Activity and synchrony patterns obtained by a tracking-by-detection algorithm as potential predictors of tail biting at pen and individual level in pigs

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Abstract

Tail biting is a major welfare concern in pigs. Timely interventions may help to reduce its spread in an outbreak. However, tail biting is usually detected only at an injury stage. Therefore, early indicators are needed to predict outbreaks. While previous studies have suggested that pen-level activity increases before a tail-biting outbreak, early identification of individual biters and victims could allow more targeted interventions, such as removing the biter or the victim. However, the link between individual activity and tail biting remains unclear, and identifying biters and victims based on activity patterns requires long-term individual monitoring, feasible only through automated methods. This study aimed to examine whether a change in activity and synchrony patterns obtained by a tracking-by-detection algorithm is predictive of tail damage at pen level, and to investigate whether activity measurements are related to performing and receiving tail biting at individual level. Nine pens with tail damage (i.e., damage pens) were selected across three batches of growing pigs (n=30 pens in total), in which at least one pig had a tail wound on two consecutive observation days (where D_0 refers to the first observation day). Each damage pen was matched with a control pen showing no pigs with tail wounds on the same days. Tail biting, including the identities of the biter and victim, was scored from videos of damage pens on D_{-5}, D_{-2}, and D_{+1}. A tracking algorithm was applied on several days around the detected tail damage (D_{-9}, D_{-5}, D_{-2}, and D_{+1}) to calculate the distance moved by each individual. The average daily distance moved in the pen did not affect the probability of a pen to become a damage pen ($P>0.05$). However, in damage pens, positive relationships between the frequency of tail biting and individual activity on some days preceding the damage were found. For example, higher individual distances moved on D_{-9} were associated with increased tail-biting frequencies on D_{-5} ($P<0.001$), and those on D_{-5} with increased tail-biting frequencies on D_{-2} ($P<0.05$). No relationships between activity synchrony on the days preceding tail damage and the probability of a pen becoming a damage pen or the frequency of biting were found. This study suggests that individual activity, measured with tracking data, may serve as a potential predictor for identifying biters. However, the heterogeneity of tail biting may limit the development of a simple and generalised method for predicting tail biting based on automatic activity monitoring.

1. Introduction

Tail biting is a major animal welfare and economic issue in modern pig production (Schroder-Petersen and Simonsen, 2001; Bracke et al., 2004). This damaging behaviour may occur in isolated cases or drastically escalate and spread within groups in an outbreak (Taylor et al., 2010). The incidence of tail biting has been associated with external factors, such as a high stocking density (Laskoski et al., 2019), an imbalanced diet (McAuley et al., 2022; Minussi et al., 2023), or a stimulus-poor environment (Van de Weerd et al., 2005). However, the exact underlying drivers of tail biting in individual pigs remain unclear, and outbreaks occur even when known risk factors are mitigated by, for example, providing rooting substrates or increasing the size of the pen (Alban et al., 2015). To minimise tail biting, farmers commonly resort to tail docking the pigs, which considerably reduces the chance of a pig being bitten (Hunter et al., 2001). Tail docking is, however, a controversial procedure, associated with physical pain and behavioural distress (Morrison and Hemsworth, 2020) that does not address the underlying reasons for a pig to start tail biting. Still, tail docking is widely practised in many European Union member states, despite an increased societal pressure for a complete ban and its prohibition as a routine measure in the European Union since 2008.

One alternative strategy to limit the negative impacts and spread of tail biting within a group could involve early-stage intervention. Early-stage interventions when tail biting is likely to escalate, such as removing individuals (biters or victims) or providing extra enrichment materials, have shown potential to limit the spread of the behaviour (Zonderland et al., 2008; Chou et al., 2019). However, monitoring of tail biting relies mainly on human observations and tail biting is generally only detected by the farmer at an injury stage, when the tail is wounded and bleeding (Fraser, 1987). At this stage, tail biting has already majorly impacted pig welfare, and intervention strategies may then be too late to prevent escalation into an outbreak. Therefore, there is a need to develop other solutions based on early indicators to predict a tail-biting outbreak.

In the days preceding a tail-biting outbreak, specific changes in the behaviour of pigs have been described at pen level (Larsen et al., 2016). For example, pigs have been reported to spend more time manipulating objects and exploring the ears and the tails of their pen mates in those days (Ursinus et al., 2014a), which aligns with the idea that tail biting is a redirection of the intrinsic need for foraging and exploratory behaviours towards pen mates (Taylor et

al., 2010). Furthermore, activity has been reported to be higher in a pen before a tail-biting outbreak. Ursinus et al. (2014a) reported a positive correlation between active behaviours (walking, standing and playing) during weeks 8-15 post-farrowing and the occurrence of tail biting during weeks 16-23. In accordance with these results, Statham et al. (2009) found that, in the four days before a tail-biting outbreak, pigs in outbreak pens spent more time standing and less time lying inactive and sitting compared to pigs in control pens. These studies thus demonstrate the potential of using changes in activity as a predictor of a tail-biting outbreak.

While previous research has focused on predicting outbreaks at pen level, early identification of individual biters and victims may provide valuable additional information for targeted intervention. Potential treatments at an individual level have been proposed to prevent the escalation of a tail-biting outbreak, such as removing biters and/or victims from the pen (Schroder-Petersen and Simonsen, 2001; Zonderland et al., 2008) or coating bitten tails in substances with an aversive taste (Arey, 1991). Individual pigs seem to differ in propensity to perform tail biting or being bitten (Beattie et al., 2005; Zonderland et al., 2011), which could, for instance, be related to genetics (Breuer et al., 2003) or fulfilment of their individual nutritional needs (Ursinus et al., 2014b). Furthermore, it remains unknown whether individual pigs exhibit distinct behavioural changes that would allow for the separate identification of biters or victims at an early stage. While activity levels during outbreaks have been investigated at pen level, only limited studies have examined activity changes preceding outbreaks at the individual level. Zonderland et al. (2011) found an increase in "restlessness" in the victim before an outbreak, indicated by an increase in the frequency of posture changes, compared to the control pig. However, their study was limited to a restricted observation window in the late afternoon on the four days preceding an outbreak.

While tail biting has been suggested to occur more frequently during the active period (Zonderland et al., 2011), changes in the activity at both the pen and the individual levels could potentially occur during the inactive period too. These changes may result in disruption of circadian rhythms or activity synchrony. Pigs generally exhibit an activity pattern with a small peak of activity in the morning and a larger peak in the afternoon (Haer and Merks, 2010) where they engage in feeding, social and exploratory activities, and rest outside this activity peak (Zwicker et al., 2015). A loss of synchrony between individuals and perturbation of the circadian rhythm have both been suggested as potential indicators of welfare issues (Wedin et al., 2018a; Wagner et al., 2021; Bus et al., 2023a), which could be

used at both individual and pen level. However, these indicators remain poorly studied, as their study requires continuous monitoring of activity over an extended period.

In recent years, computer vision algorithms have shown promising results in monitoring group and individual activity over extended periods (Larsen et al., 2021; van der Zande et al., 2021). In addition, two studies investigated the use of optical flow to detect changes in group movement preceding outbreaks. Optical flow captures changes in general movement patterns by analysing changes in brightness in a moving image (Beauchemin and Barron, 1995). Li et al. (2020) observed an increase in mean optical flow in outbreak pens across the three days before and during an outbreak. Conversely, Larsen et al. (2020) did not find any differences in mean optical flow in control pens and outbreak pens before an outbreak (Larsen et al., 2020). While optical flow offers computational simplicity, it only records the overall amount of movement within a pen and does not capture subtle movements (Larsen et al., 2020) or allow for monitoring movements at the individual level. Unlike optical flow, tracking-by-detection algorithms can identify individual pigs, enabling the investigation of changes in activity patterns at the individual level. Tracking-by-detection is a computer vision approach that first detects individuals in each video frame and then links these detections across frames to construct trajectories for each individual (van der Zande et al., 2021; Guo et al., 2023b). A previous study has demonstrated the potential of tracking-by-detection algorithms in detecting sickness responses based on individual activity patterns (van der Zande et al., 2022). However, to our knowledge, activity patterns from tracking-by-detection algorithms have not yet been explored in relation to tail biting, but could potentially be used to predict tail-biting outbreaks.

This study aimed to examine whether a change in average activity, circadian activity pattern and synchrony obtained by a tracking-by-detection algorithm is predictive of tail damage at the pen level. Additionally, we investigated whether these activity measurements are related to performing and receiving tail biting at the individual level. For that purpose, pens containing pigs with tail damage were selected and matched with control pens on the same days.

2. Material and methods

2.1. Animals and housing

The pens examined in this study were selected from three batches of tail-docked growing-finishing pigs (with approximately 5 cm of tail remaining) at a Topigs Norsvin (pig breeding company, 's-Hertogenbosch, the Netherlands) commercial farm in Germany. The pigs were reared between December 2020 and August 2022. Pigs arrived at 10 weeks of age, at a body weight of (mean ± sd) 25.4 ± 0.4 kg and remained for around 14 weeks. Pigs were housed in 10 pens per batch with 11 pigs per pen (n = 330 pigs in total) with a space allowance of 1.03 m^2/pig. The pens were allocated across five rooms. Each pen contained pigs of the same sex, with either barrows in half of the pens and gilts in the other half (batch 1) or with only barrows (batches 2 and 3). Each pen had a fully-slatted floor and was equipped with two drinking nipples with *ad libitum* access to water, and one electronic feeding station. Pigs were fed *ad libitum* with a commercial dry feed based on a proportion of crude protein adjusted to the weight range (Bus et al., 2023a). Enrichment materials were provided in compliance with European Union and German animal welfare legislation and consisted of a chain with plastic rings or a wooden block, and in the second and third batches, due to altered German legislation, an extra feeder from where pigs could obtain chopped straw mixed with straw pellets by manipulating a chain. Pigs received natural lighting through windows, and no artificial lighting was provided except during human presence in the room. Pigs were identified by a coloured symbol sprayed on their backs twice per week. Out of these 30 pens, 18 pens were selected for this study (see details below).

2.2. Data collection

All pens were equipped with a camera (Lorex, 4KSDAI168, Canada) mounted above the pen under a slight angle. Videos were recorded with a frame rate of 15 frames per second (fps) and a resolution of 1280 by 720 pixels. Videos were collected and remotely stored on an hourly basis in a cloud platform.

Inspecting pigs to identify damage pens

Twice a week, on Tuesdays and Fridays, all pigs were examined by a single observer who assessed their general health and skin damage using a detailed protocol (Bus et al., 2023b; Bus et al., 2024). Tail damage was assessed using a 0 to 5 scoring system, i.e., score 0 = no damage, score 1 = small bite marks are present, score 2 = small wound (<2cm) is present, tail

length is intact, score 3 = medium wound (>2cm) is present, tail length is intact, score 4 = medium wound (>2cm) is present, part of the tail is missing, and score 5 = severe wound, the tail is completely missing (picture examples provided in Bus et al., 2023b). For this study, pens with tail damage problems were selected when at least one pig had received a tail score of 2 on two consecutive days of observation (either Tuesday and Friday or Friday and Tuesday). Throughout this study, we will refer to these pens as "damage pens", and to the first and second days on which tail damage was scored as 2 or higher as D_0 and D_s ,respectively. The analysis in this study focuses on days D_{-9}, D_{-5}, D_{-2} and D_{+1}, using D_0 as the reference point. These four days were selected because the spray marks were visible, which allowed us to follow individual pigs. For simplification, we will refer to days D_{-9}, D_{-5}, D_{-2} and D_{+1} as the "days preceding the tail damage". Although D_{+1} follows the first tail damage score, it is also included in this group, as it precedes the second tail damage score.

Matching of damage and control pens

In total over the three batches, nine pens were identified as pens with tail damage (damage pens). Each damage pen was retrospectively matched with another pen (control pen), with pigs of the same age present within the same batch on the farm, to do the comparison on the same dates. It was required that the selected control pens had a low incidence during the matching period (with a maximum of one pig having a wound, corresponding to score 2, but not observed on two consecutive days of observation of tail damage) and were not situated in the same room as the damage pen to prevent behavioural contagion (Reimert et al., 2017; Larsen et al., 2020). The tail damage scored at the farm for the damage pens and matching control pens (referred to as a pair from here onwards) are presented in Figure 1. A description of the sex, breed, hours of daylight, external temperature and humidity averaged over the four days of the study is given in Table 1, as these factors have been suggested to be associated with tail biting (Breuer et al., 2003; Van de Weerd et al., 2005; Taylor et al., 2010).

Table 1. Description of the pairs of pigs selected for the study (each pair includes a damage pen and a matching control pen).

Pair	Batch	Sex	Breed[1]	D_0[2]	Daylight[3]	T_{ext} (°C)[4]	H_{ext} (%)[5]
Pair 1	1	Barrows	P x (LW x L)	67	9h21	-0.3 ± 5.5	87.2 ± 7.9
Pair 2	1	Gilts	P x (LW x L)	70	9h31	-2.8 ± 6.5	85.0 ± 7.5
Pair 3	2	Barrows	LW x L	63	9h35	9.7 ± 3.1	86.1 ± 9.8
Pair 4	2	Barrows	LW x L	53	10h12	10.9 ± 2.7	81.5 ± 8.6
Pair 5	3	Barrows	LW x L	85	15h29	18.7 ± 2.7	70.5 ± 16.1
Pair 6	3	Barrows	LW x L	26	16h20	17.8 ± 3.3	69.5 ± 17.0
Pair 7	3	Barrows	LW x L	96	14h52	21.5 ± 2.6	61.8 ± 19.8
Pair 8	3	Barrows	LW x L	12	15h57	16.9 ± 2.7	69.1 ± 17.6
Pair 9	3	Barrows	LW x L	12	15h55	16.9 ± 2.7	69.1 ± 17.6

[1]P: Piétrain, LW: Large White, L: Landrace, [2]D_0: The first day when tail damage was scored, expressed as the day after arrival (pigs arrived at the age of 10 weeks), [3]Daylight: Duration of natural sunlight during D_0, [4]T_{ext}: Average temperature outside over the period of the study, [5]H_{ext}: Relative Humidity outside over the period of the study, [4,5]mean ± sd between D_{-9} and D_{+1} , based on Open-Meteo.com (Zippenfenig, 2023) with the location of the farm.

2.3. Data analysis

Tracking algorithm

The days of video recordings (24h) were analysed by a tracking algorithm on D_{-9}, D_{-5}, D_{-2} and D_{+1}, with the same dates for the matched pairs of both the damage and the control pens.

The tracking algorithm, described in Huo et al. (2023), was trained on 22,384 annotated frames, extracted from 96 video segments spread across different days and pens. The algorithm was based on bounding box multi-object detection and developed with an Enhanced Cascaded Association Flow (ECAF). This method refines the tracking-by-detection strategy by incorporating an additional matching stage that utilises the actual count of pigs to avoid generating unnecessary tracks. ECAF considers motion dynamics and appearance features for each detection to establish a robust foundation for tracking and arranging historical appearance features in a list where each entry corresponds to a specific range of detection confidence scores. This setup enhances visual matching across various levels of occlusion, significantly improving tracking accuracy without solely depending on the most recent frame. This algorithm achieved a performance of 98-99% for Multiple-Object Tracking Accuracy (MOTA) and Identity F1 score (IDF1), along with a 0.56 score for

Identity Switch (IDSW) in short-term videos ranging from 5 to 30 minutes. After running the algorithm, the tracking data of the damage pens was corrected manually. The entire day of video was scanned to identify the switches between bounding boxes and reassign them to the correct individual, using the individual marks sprayed on the back of the pigs for identification. On average, 3.8±4.2 (mean ± sd) identity switches occurred per hour. The output of the tracking algorithm was down-sampled to 0.5 frames per second.

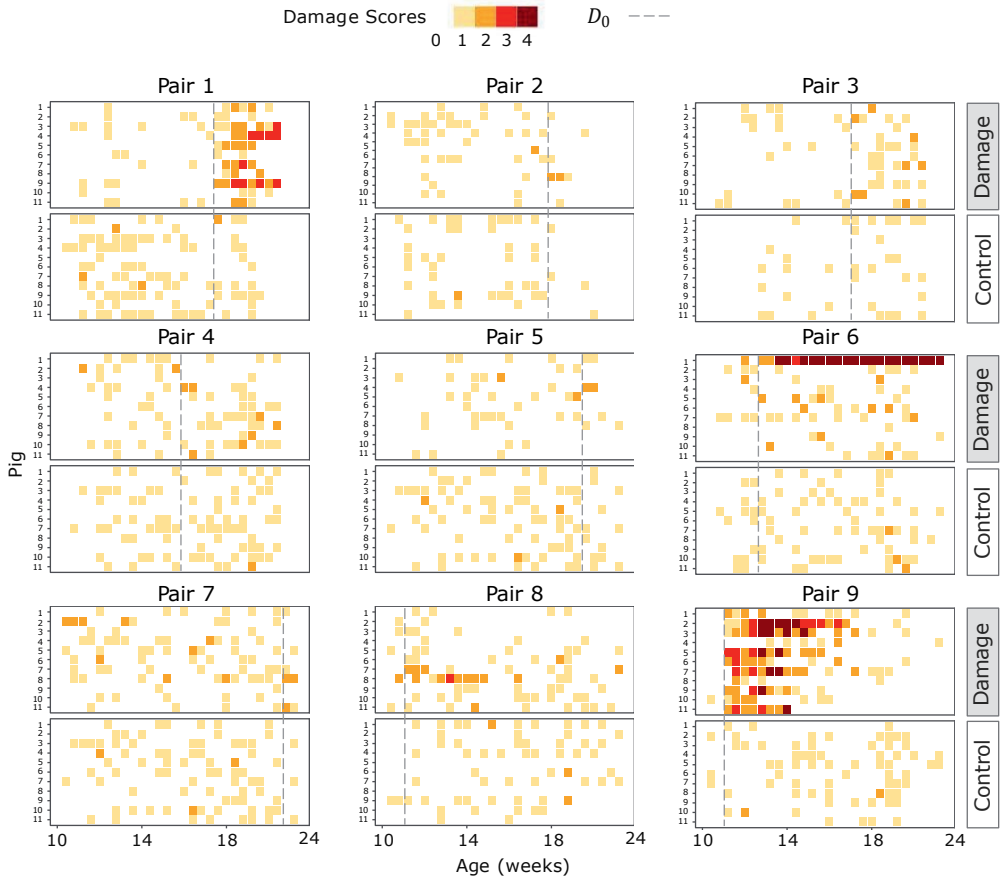


Figure 1. Tail damage scores of each pig in each pair (damage vs. control pens) throughout the fattening period. D_0 indicates the day when the first tail damage (according to the criteria of the selection of a damage pen) was scored.

Behaviour annotations to calculate the frequency and duration of biting and being bitten

To calculate the frequency and duration of biting and being bitten in the damage pens, videos were observed using The Observer software XT16 (Noldus Information Technology, Wageningen, The Netherlands). The behaviours were observed for 12h per day, with continuous observations every second hour on days D_{-5}, D_{-2} and D_{+1} relative to the damage, where D_0, was the day of the first observation of damage according to the criterion. D_{-9} was not included in the observations to reduce the labour workload. Tail biting was described as "Nibbling, sucking, chewing or (forcefully) biting the tail of a pen mate". Tail biting was scored by three observers, reaching an inter-observer reliability score of Cohen's kappa > 0.75 after training. Tail biting behaviour was scored as a state, and instances with an interruption of more than 1 second within the behaviour were considered as two separate events for that behaviour. For each event, individual identity was recorded for both the biter and the victim.

2.4. Calculations

All calculations were done in Python (version 3.13.2., Python Software Foundation, Wilmington, Delaware, USA).

Average tail damage score

Figure 1 shows that some damage pens had high tail damages scores, whereas other pens just met the criteria (e.g., damage pen of Pair 1 versus Pair 2). In addition, some pens showed a minimal difference in tail damage between control and damage pens (e.g., Pair 2). We introduced the average tail damage score as a quantitative measure to account for variation in tail damage scores between pens and not only limit the prediction to the binary control and damage pens categories. The average tail damage score per pen was calculated using Equation (1) as the mean score across the two consecutive observation days used to select the damage pens (D_0 and D_s) and across all individuals of the pen. In this equation, Damage (D_0) and Damage (D_s) represent the tail damage scores on days D_0 and D_s, respectively, for each individual k in a pen of n individuals.

$$average\ tail\ damage\ score = \frac{\sum_{k=0}^{n} Damages\ (D_0) + Damages\ (D_s)}{2n} \quad \text{(Equation 1)}$$

Distance moved

The distance moved of each bounding box was calculated by comparing the centroid of the same bounding box in two consecutive frames sampled at 0.5 frames per second. Equation (2) from the Pythagorean theorem was used, where xt and yt are the coordinates of the centroid of the bounding boxes at frame t, and xt +1 and yt+1 are the corresponding coordinates at frame $t + 1$.

$$distance\ moved = \sqrt{(x_{t+1} - x_t)^2 + (y_{t+1} - y_t)^2} \quad \text{(Equation 2)}$$

The pen-level distance moved was calculated as the average distance moved per individual, by summing the distance moved per frame for each pig and dividing it by the number of pigs in the group. The average distance moved was then smoothed by calculating a rolling mean (i.e., averaging over a moving window) with a 3h window. This window was chosen to reduce the noise while maintaining the activity pattern (Supplementary Figure S1). For both control and damage pens, the pen-level activity was calculated based on the non-corrected tracking data. We concluded that the identity switches did not affect the calculation of the pen-level activity, as the pen-level distance moved calculated with the non-corrected tracking data was highly correlated (Pearson correlation, r=0.92) with the distance moved calculated with the corrected tracking data (Supplementary Figure S2).

As the tracking data was corrected only for the damage pens and not for the control pens, the individual analysis only focused on inter-individual differences within the damage pens. The distance moved was calculated based on the corrected tracking.

Comparison of the circadian activity patterns

Circadian activity patterns were compared in two contexts: between damage and control pens on the same day and between individual pigs within the same day (referred as synchrony).

To compare circadian activity patterns, a cross-spectral analysis was performed, as described by Schmidt et al. (2012). The average coherence score was calculated as the correlation between the peak frequencies of the two time series, ranging from 0 (no similarity) to 1 (perfect similarity). This approach focuses on the timing of the peak and the period, rather than on the amplitude of the signal. To reduce the fluctuations due to the high sampling rate of the tracking data and capture more stable movement patterns, a sinusoidal model was fitted

to the time series before calculating the coherence score. Coherence scores were standardised using a Fisher-z transformation before statistical analyses were performed.

At pen level, synchrony scores were calculated based on the non-corrected tracking data, as the tracking data were corrected only for the damage pens. This seems to be a reasonable approach as the Pearson correlation between synchrony scores from corrected and non-corrected tracking was relatively high (r=0.83, Supplementary Figure S3). The synchrony score per pen was calculated by computing the coherence score between each pair of bounding boxes (referred as bounding boxes and not pigs here, as we used the non-corrected tracking) within the pen and averaging it across the pairs. For example, if we consider a pen with the bounding boxes 1, 2, and 3, the coherence for each pair was calculated (1-2, 2-3, and 1-3), and the average was calculated as the pen-level synchrony score.
At the individual level, the synchrony score was calculated in the damage pens based on the distance moved from the corrected tracking data. The synchrony score per pig was calculated by computing the coherence score between each pair of pigs within the pen and averaging it per pig. For example, if we consider a pig A, the coherence score for each pair that includes pig A was calculated (such as pig A and pig B, pig A and pig C, etc.) and averaged to obtain the individual synchrony score for pig A.

2.5. Statistical analysis

All statistical analyses were performed in RStudio (version 2024.04.2, R Foundation for Statistical Computing, Vienna, Austria).

Regression models were built using the *lmer* and *glm* functions from the *lme4* package (Bates et al., 2024) to determine if activity and synchrony were predictive of a pen becoming a damage pen or of the average tail damage score. Separate models were built for each day (D_{-9}, D_{-5}, D_{-2} and D_{+1}) to predict the outcome variables (pen type and average damage score). Given the high correlation between the distance moved and the age of the pigs (Spearman's correlation: r = -0.67, P<0.001), distance moved and synchrony (y) were first corrected for age using a linear regression model (Equation 3).

$$y = \beta_0 + \beta_1 * age + \varepsilon_{corr} \text{ (Equation 3)}$$

The residuals ε_{corr} (i.e., the distance moved and the synchrony corrected for age) were then included as the predictor in the regression models (Equation 4, Equation 5). Pen type was

included as a binary response (1 = damage pen, 0 = control pen) using a logistic regression (Equation 4), while average tail damage score was included as a quantitative variable in a linear regression model (Equation 5). The average tail damage score was log-transformed to normalise the residuals. Pair was first introduced in the model as a random effect, but was then removed in the final model to avoid singularities due to the small sample size.

$$logit\big(P(pen\ type = 1)\big) = \beta_0 + \beta_1 * \varepsilon_{corr} \quad \text{(Equation 4)}$$

$$log(average\ tail\ damage\ score) = \beta_0 + \beta_1 * \varepsilon_{corr} + \varepsilon \quad \text{(Equation 5)}$$

Similarly, at the individual level, the distance moved and synchrony averaged for each pig were corrected for age (Equation 3). Linear mixed models were used to test if distance moved and synchrony could predict the frequency and duration of either biting or being bitten (Equation 6). Pen was added in the model as a random effect (u_{pen_i}). Frequency and duration of biting and being bitten, noted as y_{ij}, were first log-transformed to normalise the residuals, with *i* referring to the individual pig and *j* to the day of observation. The linear mixed models were run separately for each combination of day and predictor (distance moved, synchrony), corrected for age ($\varepsilon_{corr_{ik}}$), using values from either the same day or the preceding days (*k*, with $k \leq j$) to predict the outcome variables (frequency and duration of biting or being bitten). For example, to analyse the frequency of biting on D_{-2}, three models were run separately: one model with the distance moved on D_{-9} as the predictor, another model with the distance moved on D_{-5}, and a last one with distance moved on D_{-2}.

$$log\big(y_{ij}\big) = \beta_0 + \beta_1 * \varepsilon_{corr_{ik}} + u_{pen_i} + \varepsilon_{ij} \quad \text{(Equation 6)}$$

These models were run separately to reduce the risk of overfitting given the limited sample size and to capture potential day-specific effect. Given the exploratory nature of the analysis, we did not correct the *P values* for multiple comparisons, but interpreted the results with caution.

In this study, *P* values were considered statistically significant when below 0.05, and *P* values between 0.05 and 0.1 were considered to indicate trends.

3. Results

3.1. Pen level

Average activity

The average distance moved on days preceding tail damage (D_{-9}, D_{-5}, D_{-2} and D_{+1}) did not affect the probability of a pen to become a damage pen (Figure 2). In addition, no relationship was found between the average distance moved on preceding days and the average tail damage score in each pen (Figure 2). We can note that for pairs 2 and 8, numerically, the damage pen moved on average more than the control pen on all four days. However, for other pairs, such as 1 and 3, the average distance moved on preceding days was nearly identical for both the damage and control pens. Even for pair 9, where tail damage was the most severe and impacted the majority of pigs in the damage pen (Figure 1), no notable differences regarding distance moved were observed between the damage and control pens.

Circadian activity pattern and synchrony of activity

Figure 3 presents the circadian activity pattern over the four days (D_{-9}, D_{-5}, D_{-2} and D_{+1}) of the nine pairs of pens, sorted by age. Visually, we can note that activity patterns seemed to change with the age of the pigs, with a decrease in the amplitude of the peak of activity with age (Figure 3). In addition, when pigs were younger (<20 weeks), their activity seemed to follow a pattern with a single peak in the late afternoon (Pairs 8, 9, 6, 4, 3, 1 and 2, Figure 3), whereas when they grew older, this pattern seemed to shift to two distinct peaks with one in the late morning and another in the late afternoon (Pairs 5 and 7, Figure 3). These overall trends suggest a similar activity pattern in the damage and the control pen within each pair and each day, with high average coherence scores between damage and control pens.

The average synchrony score across the four days was 0.80 ± 0.15 (mean ± sd), ranging from 0.32 to 0.97 for the damage pens and 0.74 ± 0.19, ranging from 0.28 to 0.94 for the control pens. The average synchrony score on preceding days (D_{-9}, D_{-5}, D_{-2} and D_{+1}) did not affect the probability of a pen to become a damage pen (Figure 4). In addition, no relationship was found between the average synchrony score and the average tail damage score in each pen (Figure 4). We can note that the control pen in Pair 5 had a noticeably lower synchrony score on D_{-5}, D_{-2} and D_{+1} compared to the other damage and control pens.

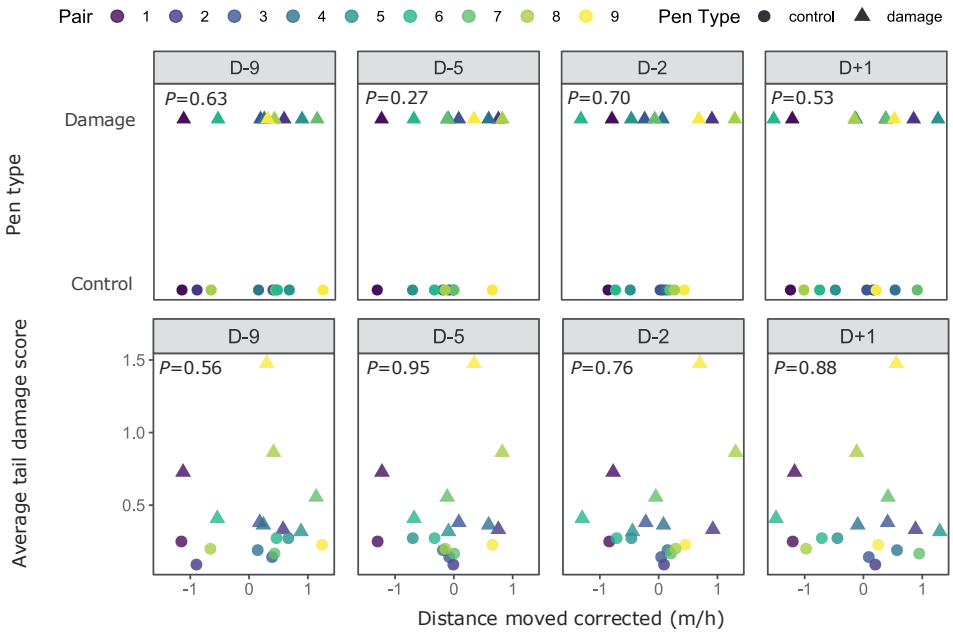


Figure 2. Prediction of the pen type and the average tail damage score with the distance moved on D_{-9}, D_{-5}, D_{-2} and D_{+1}. The *P* values indicated on the plot are the result of a logistic regression for the pen type (damage pen vs. control pen) and a linear regression model for the average tail damage score over all the pigs in the pen and the two consecutive days. The average distance moved was calculated with a rolling mean (window size = 3h) and was corrected for age.

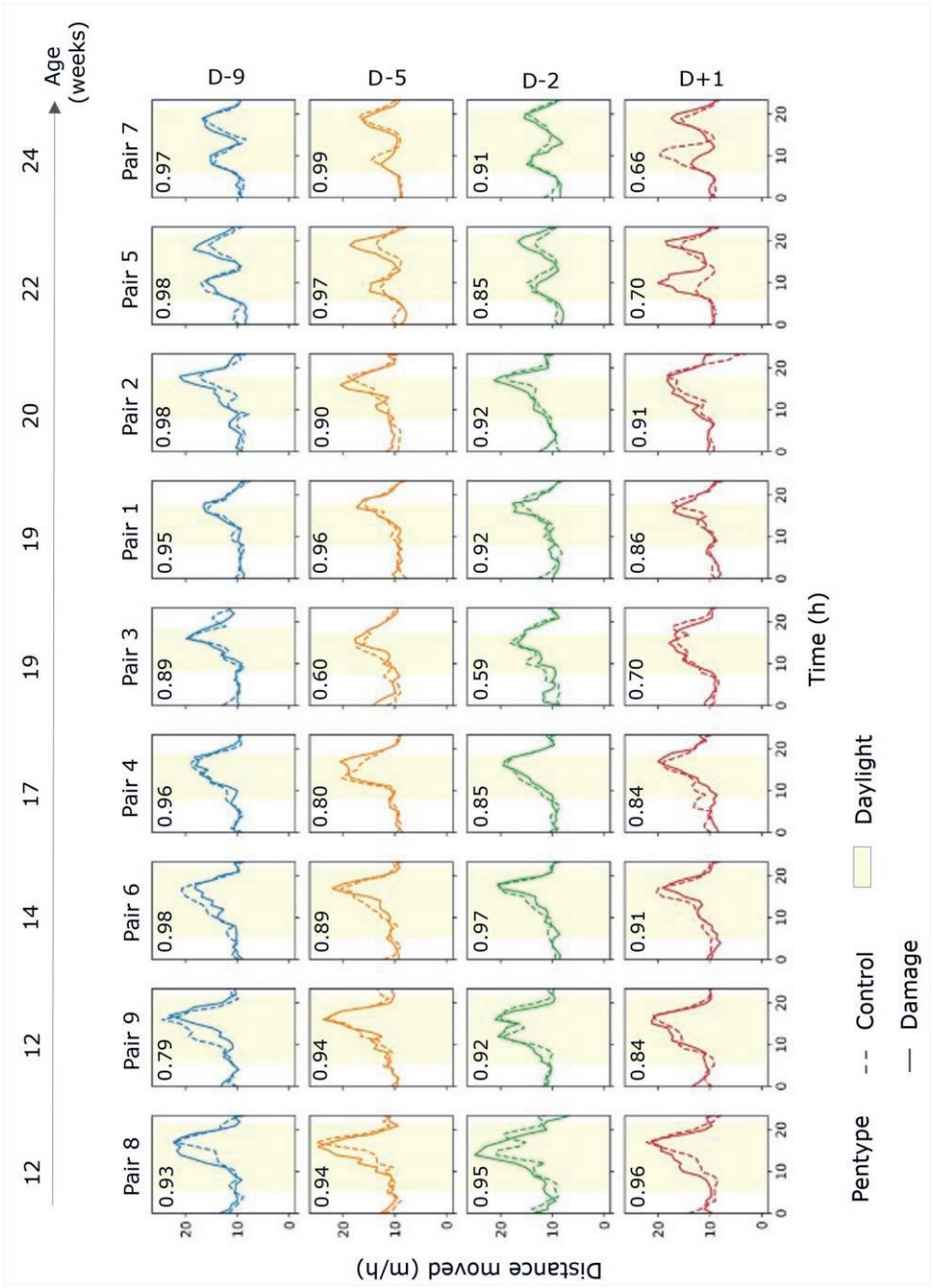


Figure 3. Circadian activity pattern on D_{-9}, D_{-5}, D_{-2} and D_{+1} of the nine pairs (damage and control pens), sorted by age. Coherence scores between the circadian activity pattern of damage and control pens of pigs within each pair are indicated in the top-left corner of each subplot.

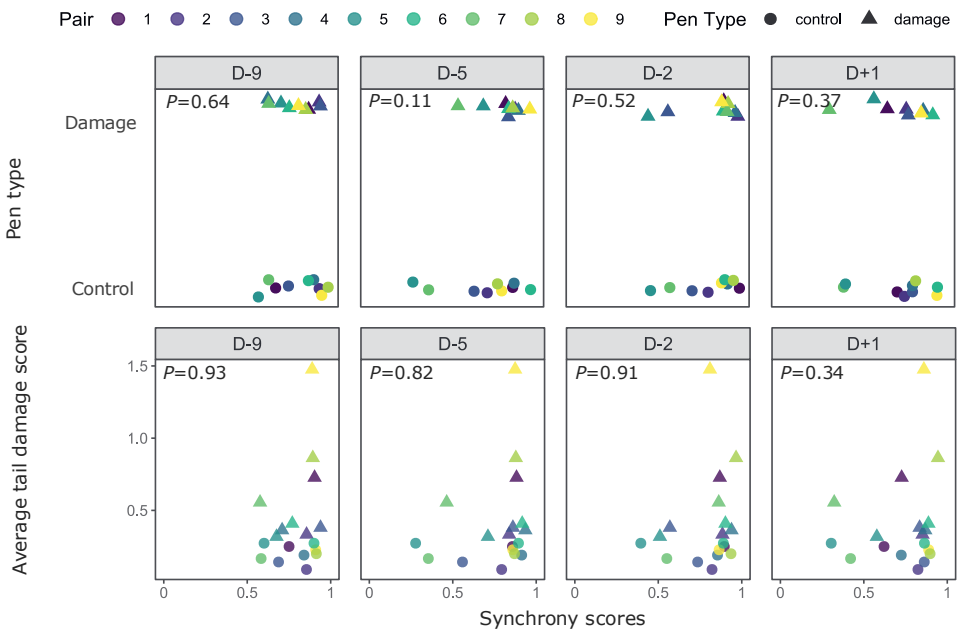


Figure 4. Prediction of the pen type and the average tail damage score with the synchrony of the circadian activity pattern score on D_{-9}, D_{-5}, D_{-2} and D_{+1}. The *P* values indicated on the plot are the results of a logistic regression for the Pen type and a linear regression model for the Average tail damage score. The synchrony score has been corrected for the age of the pigs.

3.2. Individual level

Average activity

On D_{-2} and D_{+1}, a positive association was found between the distance moved and the tail biting frequency (Figure 5, both $P<0.05$), meaning that more active pigs engaged in tail biting more often on these days. This relationship was, however, not observed on D_{-5}. In addition, several positive associations between the distance moved on certain days and the frequency of tail biting on following days were also observed (Figure 5). Pigs with a higher distance moved on D_{-9} performed tail biting more frequently on D_{-5} ($P<0.001$) and D_{-2} ($P<0.05$), and pigs that moved more on D_{-5} performed tail biting more frequently on D_{+1} ($P<0.05$). Similarly, a positive association was found between the distance moved and the duration of tail biting on D_{-2} ($P<0.001$, see Figure 5). Pigs with a higher distance moved on D_{-9} performed tail biting longer on D_{-5} ($P<0.05$), and pigs that moved more on D_{-5} performed

tail biting longer on D_{-2} (P<0.05). We can note that the significant associations might be driven by a few individual pigs showing a strong relationship between activity and tail biting, while this was less clear for other pigs. In contrast, no significant association was found between the distance moved and the frequency and duration of being bitten, either on the same day or on following days (Figure 5). We can, however, note that pigs bitten for longer durations on D_{-5} and D_{-2} tended to have a higher distance moved on those days, and the same trend was found for frequency of receiving tail biting on D_{-2}.

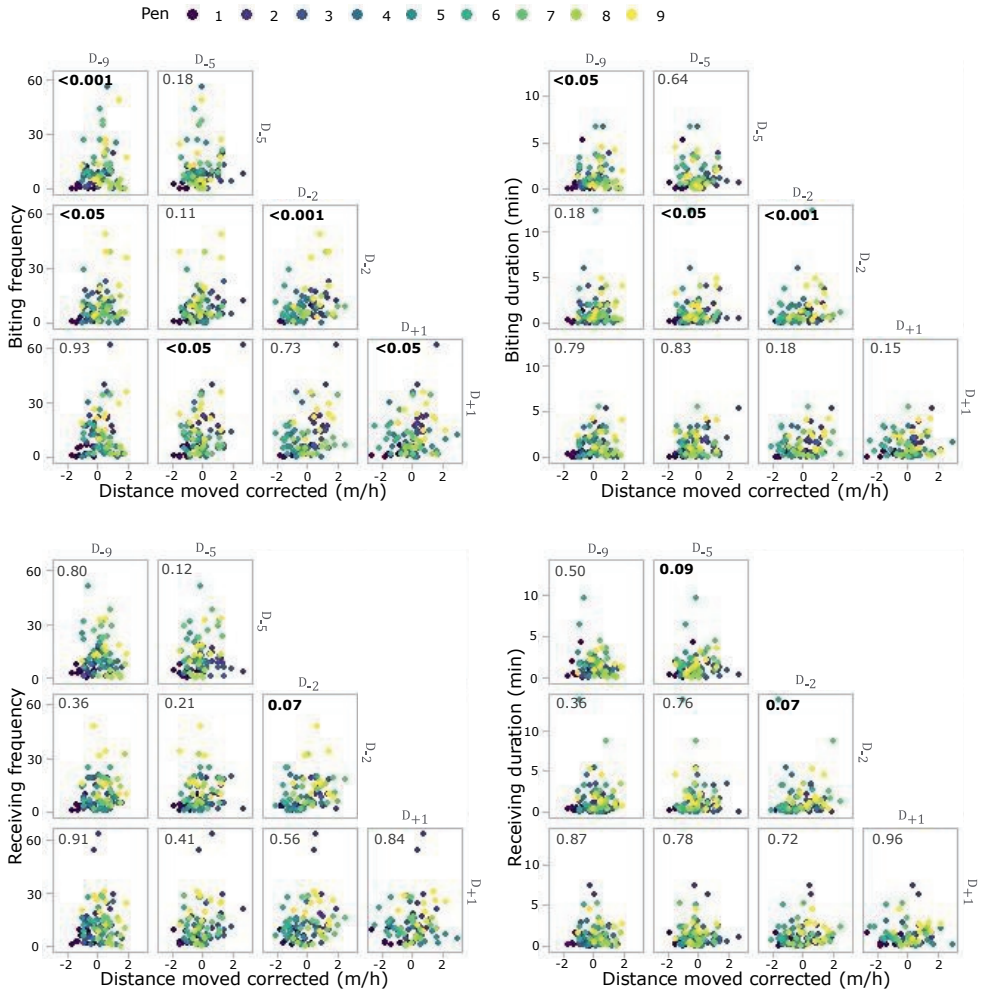


Figure 5. Prediction of the total frequency and duration of tail biting and receiving (based on 12h observation) of each pig with the distance moved on D_{-9}, D_{-5}, D_{-2} and D_{+1}. The P values indicated on the plot are the results of linear mixed models for the distance moved, corrected for age.

Circadian activity pattern and synchrony of activity

Figure 6 illustrates the circadian activity pattern of two damage pens (Pair 6 and 9) out of the nine studied, chosen for their severe tail damage. In the damage pen of Pair 6, pig 1 had severe tail damage that persisted throughout the fattening period (Figure 1). In the damage pen of Pair 9, severe tail damage was scored on multiple pigs (Figure 1).

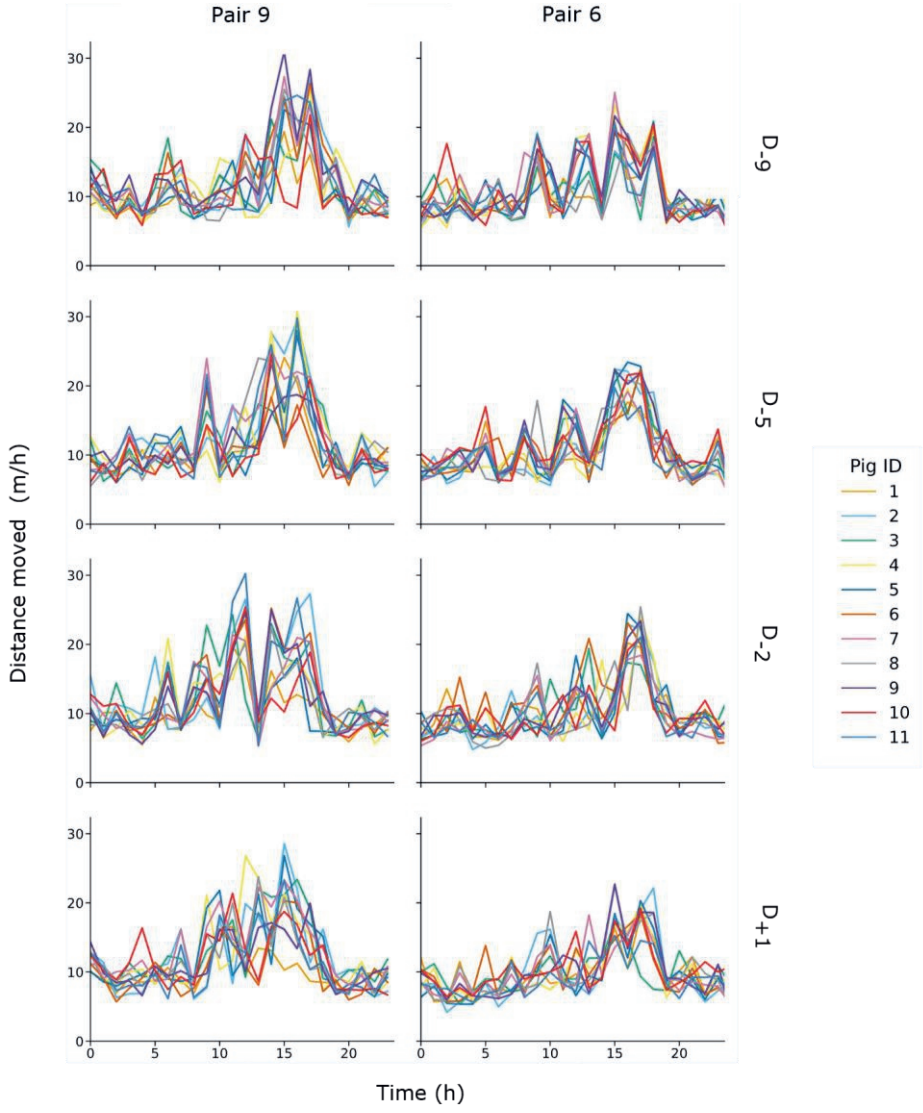


Figure 6. Example of circadian activity pattern on D_{-9}, D_{-5}, D_{-2} and D_{+1} of the damage pens of Pair 6 and 9 for the 11 different pigs within those pens.

Visually, we can note that although all the pigs of the same pen seem to have their main peak of activity simultaneously, the amplitude of these peaks varies. In addition, several individuals had noticeable peaks of activity before the main peak. For example, for Pair 9, D_{-5}, between 5 and 10 am, specific pigs (6, 7, 9, and 11) exhibited a peak in activity, which was balanced by pigs with lower activity levels (1, 2, 3 and 4). As a result, no distinct peak was observable at that time at the pen level (Figure 3). In addition, some pigs exhibited a peak of activity when the rest of the group was relatively inactive. For example, on D_{+1}, pig 10 and pig 5 (Pair 9 and 6, respectively) had a peak of activity around 5 am, whereas the other pigs were inactive. Finally, in Pair 6, we can note that pig 1, the one with persistent tail damage, had a lower activity level compared with the other pigs in most of the peaks.

Across the four days, the mean and standard deviation of the synchrony score per pig was 0.74 ± 0.23. No positive association was found between the synchrony score of individual pigs and the frequency or duration of performing and receiving tail biting on the days preceding the tail damage (Figure 7, *P*-values > 0.05). This indicates that biters and receivers were neither more nor less synchronised in the days preceding tail damage.

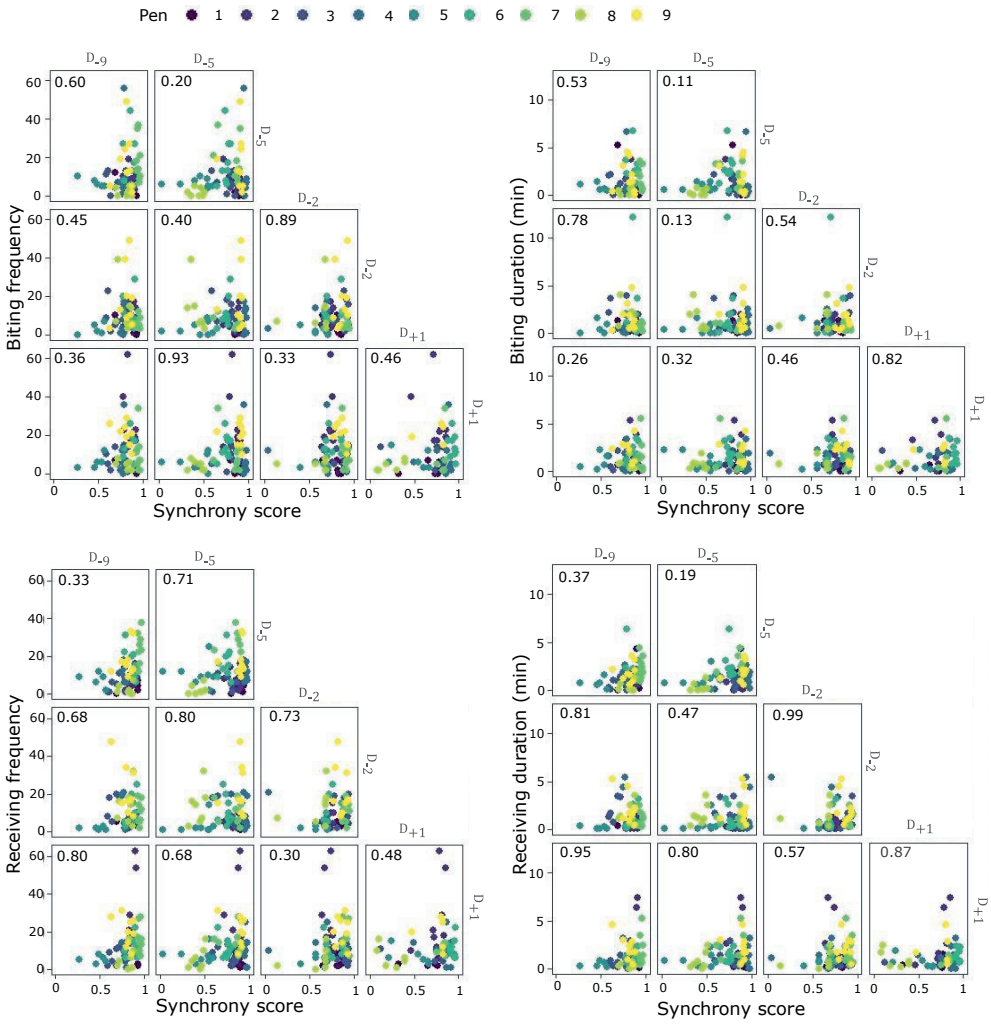


Figure 7. Prediction of the frequency and duration of tail biting and receiving of each pig with the synchrony score on D_{-9}, D_{-5}, D_{-2} and D_{+1}. The *P* values indicated on the plot are the results of a linear mixed model for the synchrony score, corrected for age.

4. Discussion

4.1. Predicting tail damage with the pen-level distance moved

This study aimed to examine whether a change in activity, circadian activity pattern and synchrony obtained by a tracking-by-detection algorithm can be used to predict tail damage

at the pen level and to investigate whether activity measurements are related to performing and receiving tail biting at the individual level. In this study, distance moved and synchrony at the pen level did not predict if a pen would become a damage pen. However, a positive relationship was found at the individual level between the frequency and duration of performing (not receiving) biting and the distance moved on some of the preceding days.

In this study, the distance moved at pen level did not predict if a pen would become a damage pen. Our results differ from previous studies, in which pigs in pens with tail damage were more active than those in control pens in the 96 hours (Statham et al., 2009) or five days (Larsen et al., 2019a) before tail damage was observed. Several reasons may explain the difference between our results and those reported in other previous studies.

First, the smaller contrast between damage pens and control pens in tail damage our study (for example, in Pair 2 and 5, Figure 1) may explain why we did not observe any clear differences between the two groups. The definition of an outbreak pen from Statham et al. (2009) was more severe than ours, including visible blood and at least two pigs with partial tail loss. Similarly, Larsen et al. (2019a) classified a pen as a damage pen if at least one pig had a bleeding tail wound. In contrast, we classified pens as damage pens if at least one pig had a wound, regardless of the presence of fresh blood or (partial) loss of the tail. We chose this definition, as predicting less severe tail damage, for example, a pig with a wound, remains important and may reduce pig welfare, increase the risk of infection, and potentially result in carcass condemnation. Furthermore, pigs in our study were tail-docked, whereas in Statham et al. (2009) and Larsen et al. (2019a), the tails were intact. This difference may have resulted in a lower incidence of tail biting in our study, leading to less severe consequences and no change in activity in the damage pens on preceding days. Nevertheless, the lack of difference between control and damage pens, even in the severe cases (for example, in the damage pens of Pair 6 and 9, Figure 1) suggests that even with more serious damage no effects of the distance moved on the probability of a pen to become a damage pen would have been found. However, as this observation is based on only two pens with more serious damage, it should be interpreted cautiously.

Second, our study included only nine damage pens that presented significant heterogeneity in factors such as the age at which the damage was scored, the temperature, the humidity and the lighting conditions (Table 1). We can note that previous studies where activity was found to be a potential predictor of tail damage were also based on relatively small sample sizes, with the number of damage pens used including 6 (Statham et al., 2009) and 24 (Larsen et

al., 2019a). In our study, there was considerable variability in the severity of damage and the number of pigs affected as well. For example, Pair 1 and 9 experienced an outbreak with multiple pigs showing severe damage, whereas Pair 6 had only one pig with severe damage, and Pairs 2 and 5 just met the criteria (Figure 1). This also potentially suggests heterogeneity in the exact underlying cause and the type of tail biting. Our study may have captured the three types of tail-biting behaviours described by Taylor et al. (2010), namely, "two-stage", "sudden-forceful" and "obsessive", each of them potentially leading to different consequences on the activity on the days preceding the damages. Thus, even with a larger sample size, the high heterogeneity between pens may mask the potential relationship between these two variables at the pen level.

Third, our method of scoring activity by calculating the distance moved with tracking data differs largely from other studies where the activity was scored with direct observations, including details of postures (lying, standing, sitting, walking). It is important to note that, although Statham et al. (2009) observed an increase in standing and sitting postures and a decrease in lying inactive in pens with severe outbreaks compared to matched control pens, these shifts in posture did not lead to any changes in overall locomotion. We calculated activity levels based on the distance moved using tracking data, a relatively simple method to implement at the group level that offers the advantages of objectivity, long-term monitoring, and scalability. However, with this approach it was not possible to distinguish between different types of posture, such as lying versus inactive standing or sitting. The combination of tracking algorithms with posture detection algorithms, such as the one developed by Riekert et al. (2020), could further help to identify more subtle indicators of restlessness at pen level.

Fourth, our methods allowed us to study the activity continuously during the entire day with a high sampling rate, whereas, for example, in Larsen et al. (2019a) activity level was observed by scan sampling every 10 min during 6h, spread between 06:00 and 00:00h. Although our high sampling rate (0.5 frames per second) provides a more detailed activity pattern, it has potentially introduced noise, making the differences in activity between tail damage and control pens less pronounced than with a smaller sampling rate. In addition, changes in activity in damage pens may be more pronounced during specific times of the day and averaging the activity over the full day could dilute this difference. However, we can note that according to the analysis of the circadian activity patterns, which showed very

similar patterns between control and damage pens, focusing on different time windows may not lead to significantly different results. Furthermore, we limited our study to four days (D_{-9}, D_{-5}, D_{-2} and D_{+1}), as the spray marks were visible on those days, allowing us to perform annotations and to correct identity switches. Other days that had to be skipped in our study, such as D_{-1} may have been a key day to predict the damage with activity level. Future analyses focusing on specific time windows, different days and using different sampling rates could provide valuable insights and potentially lead to different results.

Lastly, Larsen et al. (2020) also did not observe a difference in activity, measured with optical flow, between outbreak and damage pens, but observed that both outbreak and matched control pens increased their activity level at pen level because of potential contagion. In our study, though, contagion of the control pen by the damage pen is unlikely to explain our results, as control pens were located in a different room than the damage pens. However, they could potentially both be exposed to the same environmental factors, such as weather events or farmer visits, leading to no different results between damage and control pens.

To summarise, the absence of a relationship between the activity on preceding days and the likelihood of a pen to become a damage pen likely reflects the heterogeneity of tail biting that was captured in our study, including the underlying causes, severity and type of tail biting. Our results suggest that increased activity does not occur in all cases before tail biting, highlighting the complexity of this behaviour.

4.2. Predicting tail biting behaviour with the individual distance moved

In this study, a positive association between the individual distance moved on some preceding days, including D_{-9}, and tail biting frequency and duration were found, suggesting that biters are more active on the days before tail damage occurs. This result aligns with previous studies that found that tail biters engaged in more “active exploration” behaviour (Bagaria et al., 2022), meaning they explored enrichment materials (Zonderland et al., 2011) and body parts of their pen mates (Zonderland et al., 2011; Munsterhjelm et al., 2013) more. The individual distance moved on D_{-9} was positively associated with the frequency of biting on D_{-5} and D_{-2}, whereas the distance moved on D_{-5} could only predict the frequency of biting on D_{+1}. This result indicates that biters already have a high activity several days before their tail-biting behaviour results in tail damage to the victim (D_{-9}). However, on days closer to the tail damage (D_{-5}), biters may differ in how active they are. In addition, the significant associations between activity and tail biting might have been driven by a few individual pigs

showing a strong relationship, while this association was less pronounced for other pigs. Therefore, caution should be taken to avoid overlooking individual biters that did not become noticeably more active before the tail biting outbreak.

No associations were found between the distance moved and the frequency and duration of being bitten in the days before tail damage. This result is in contradiction with previous studies, which showed that pigs receiving more tail biting were more active and restless on the days leading up to tail damage (Zonderland et al., 2011). This might reflect the differences in stages of escalation and in the nature of performance (standing, lying) between pens and outbreaks captured in our study. Previous studies have described different types of tail biting (i.e., two-stage, sudden-forceful, obsessive, and epidemic (Taylor et al., 2010; Valros, 2018) and the reactions of the receivers through the different types and stages of tail-biting outbreaks (Fraser, 1987). For sudden-forceful and obsessive tail biting, the victim is likely to react by avoiding the biter, which may lead to an increase in activity of the victim. In contrast, the victim may show a different activity response in the two-stage tail-biting type. In the pre-injury stage, the biter lightly chews the tail of another pen mate, a behaviour typically performed while both pigs are lying down and with little response from the victim. In the damaging stage, the victim initially reacts by head-knocking or by avoiding the biter, but gradually becomes apathetic, resisting less and spending more time lying down (Sambraus, 1985). In our study, we may have potentially captured all victim reactions, including tolerance, escape, and apathy. Our findings highlight the heterogeneity among victims' reactions and the difficulty of drawing general conclusions about activity patterns in response to tail biting. This heterogeneity limits the development of a simple and generalised method for predicting tail biting based on automatic activity monitoring. Furthermore, in our study, we used a rolling mean with a 3h window size to smooth the distance moved. Choosing this relatively large window size reduced the potential noise caused by the high frequency of the data, and helped to filter out some less relevant movements (Figure S1). However, this approach may also have attenuated some short and abrupt peaks of activity, potentially linked to an immediate reaction of the victim. Therefore, our analysis is more likely to reflect the overall activity trend, rather than the short-term reactions of the victims.

4.3. Predicting tail biting behaviour with (a)synchrony of the circadian activity pattern at the pen and individual level

In this study, we did not find any association between the pen-level synchrony and tail damage. In addition, no relationships were found between the synchrony of individual pigs before damage and their frequency and duration of biting or being bitten. This result aligns with Wagner et al. (2021), who found no difference in synchrony, calculated as the number of pigs showing the same posture, between outbreak and control pens. Overall, we can note that despite the presence of tail biting, the synchrony of activity between pigs was relatively high, meaning that pigs within the same pen tend to have a peak of activity at the same time. The circadian activity pattern is known to be highly driven by all external stimuli such as daylight (Ingram et al., 1985; Simonsen, 1990; Nagare et al., 2021), availability of resources (Haer and Merks, 2010; Zwicker et al., 2015) and internal stimuli such as age (Docking et al., 2008; Chen et al., 2016). Pigs from the same age and exposed to the same environment are thus likely to exhibit similar circadian activity patterns, and that is also what we found. In addition, it has been suggested that pigs have a strong motivation to perform behaviours, such as resting, feeding, exploring and foraging synchronously (Zwicker et al., 2015). These natural tendencies may maintain activity synchrony, even in the presence of tail biting. Alternatively, the presence of a single feeding station per pen may also have caused some level of asynchrony among pigs within the same pen, whether control or damage, as only one pig could feed at the same time, and this takes on average around 1h per pig per day (Bus et al., 2024). Furthermore, as discussed in the previous section, tail biting might have led to a different response from the biter and the victim with different consequences for the synchrony score. Tail biting might result in disruption of the circadian activity pattern, with biters being more active at certain times of the day, potentially leading to a lower synchrony score. However, during inactive periods, biters may move around and target different pigs, who may change location to lie down somewhere else or become more active in response. In addition, biters might increase their exploration of the enrichments, which might become more attractive to other pigs (Zwicker et al., 2015). As a result, this may induce a peak of activity at the same time, resulting in a high synchrony between pigs, whereas in other cases, both biters and victims may lie down when tail biting occurs, resulting in little or no change in the pen's overall synchrony. Therefore, the impact of tail biting on synchrony depends on the specific behavioural responses of both the biter and the victim.

4.4. Other potential predictors

In this exploratory study, we focused on predicting tail biting based on relatively broad measures of activity (i.e, the distance moved per pig per day and timing and period of dominant peaks of the activity patterns). These measures provide a useful starting point, but they may not capture more subtle activity changes associated with tail biting. For example, comparing the distance moved between days or examining activity on specific periods (for example, during the night) may provide supplementary insights that may be valuable to explore in further studies.

In addition, the tracking data can also provide location information that may be used to develop other potential predictors. For example, proximity to enrichment would be valuable to consider in future studies, as increased exploration of enrichments has been suggested to be a potential predictor of tail biting (Zonderland et al., 2011; Ursinus et al., 2014a). One approach could be to quantify proximity to enrichments over time by calculating the average distance between the centroids of each pig's and enrichment's bounding boxes over time, as described in Orsini et al. (2025). However, our dataset was not suitable for analysing proximity to enrichments, as the enrichment was located close to the drinker and feeder, potentially leading to confusion between exploration of the enrichment and drinking and feeding behaviours.

In this study, we focused on predictors based on a tracking algorithm, but monitoring tail biting itself and identifying the pigs involved would be a more straightforward approach. However, only a few studies so far have focused on developing such algorithms, and continuous monitoring of individual biting events remains technically challenging. The main challenges include the false detection of tail-biting events and the difficulties in recognizing milder forms of tail biting where the victim pig does not show a clear reaction or when both pigs are lying (Liu et al., 2020; Hakansson and Jensen, 2023). For instance, the video-based tail biting recognition algorithm of Liu et al. (2020) is accurate but only detects cases of tail biting in which the victim escapes, likely missing events of the two-stage tail biting type. In addition, behaviour algorithms also need to be connected to tracking algorithms to accurately identify the biter and the victim. Given these limitations, we decided to focus on tracking-based predictors as an alternative approach in this study.

Furthermore, other predictors of tail damage, such as tail posture (Lahrmann et al., 2018; Wedin et al., 2018b), feeding (Wallenbeck and Keeling, 2013; Viitasaari et al., 2015) and drinking patterns (Larsen et al., 2019b) have been explored in previous studies. While feeding and drinking are relatively easy to measure automatically with sensors, these measures are not specific (Larsen et al., 2019b) and have limited value for predicting tail damage (Bus et al., 2024). Tail position seems to be a good predictor of victims of tail biting, however, measuring tail posture remains technically challenging and may require costly cameras (D'Eath et al., 2018). Future studies would benefit from combining information from different sensors and computer vision algorithms to better predict tail-biting outbreaks.

4.5. Perspectives for preventing tail-biting damage

Our results suggest that individual activity could be used as a predictor to identify potential future biters though not victims. This information might open the door to early warning systems and targeted intervention to prevent or stop an outbreak, for example by removing biters based on their activity level. However, caution should be taken as responses to tail biting seem to vary largely between days and individuals, including biters, potentially limiting the reliability of early detection.

It is important to note that implementing such early warning systems in practice would require monitoring individual activity continuously and over months. Despite recent progress to accurately track pigs, monitoring individual pigs housed in groups remains significantly challenging (Guo et al., 2023a; Huo et al., 2023). Some of these challenges include the loss of the identity of individuals and identity switches. In this study, the tracking data was manually corrected, which is labour-intensive and not feasible for large-scale practical implementations. Future studies would benefit from combining multiple devices for individual tracking, for example by combining tracking-by-detection algorithms with radio frequency identification systems from feeders (Mora et al., 2024) or with the detection of individually-coloured ear tags (Schmidt et al., 2022).

Furthermore, in this study we showed that the activity level and patterns are strongly influenced by age. Previous studies have shown that pig activity is influenced by other individual factors, such as sex and health status (van der Zande et al., 2022; Yin et al., 2025), and external factors, such as housing conditions, temperature, daylight, environmental enrichments, and feeding systems, affect pig activity (Costa et al., 2009; Nasirahmadi et al., 2015; Yang et al., 2018). Therefore, using activity measures to detect individual biters would

require integrating these factors to define an individual baseline given specific conditions and accurately identify deviation for these pigs.

In this study, we examined the relationship between potential predictors and quantitative measures (frequency, duration) of tail biting or being bitten, rather than comparing these predictors across different pig classes, such as biter, victim, biter/victim, or neutral as proposed in previous studies. Our approach offers greater statistical power and avoids the need to set thresholds for classifying pigs, which have been defined in multiple ways across studies (Brunberg et al., 2011; Zonderland et al., 2011; Ursinus et al., 2014a). However, it is important to note that for practical applications, such as developing early warning systems to prevent tail-biting outbreaks by removing biters when noticing a high activity level, defining clear thresholds to initiate the alert would still be necessary. Thresholds would be needed to define when a pig is a biter and also on the activity itself. Rather than setting fixed thresholds, future studies could explore the development of a dynamic model that allows for the adjustment of thresholds. This model could incorporate an "expert-in-the-loop" approach, enabling farmers to assess and adjust thresholds based on their experience and farm-specific conditions (van Veen et al., 2025).

In conclusion, in the current study, no relationships between pen-level activity patterns and the probability of a pen to become a damage pen were found. However, positive associations were found between individual-level activity on some of the days preceding the tail damage and the frequency and duration of tail biting. These results suggest the potential of using individual activity monitoring to early identify potential biters and prevent tail damage. However, our findings also highlight the heterogeneity in the reactions of individual pigs (victims and biters) during tail biting. Therefore, caution should be taken, as not all biters and victims may display the same response, which would complicate the implementation of early warning systems.

Supplementary Materials

Choice of the window size for the rolling mean

In this study, we calculated the activity based on a tracking-by-detection algorithm providing data at 0.5 frames per second. While this high sampling rate provides a very detailed activity pattern, it may also potentially introduce noise. The goal of this study was to analyse the overall activity, therefore, we needed to smooth the data before the analysis to preserve the general activity pattern while reducing potential noise. We compared the activity patterns built with a rolling window with different window sizes (1h, 2h, 3h, 6h; Figure S1). With a 1h window, the signal remains noisy, with several peaks, more likely due to small fluctuations (e.g. pigs changing postures) than due to real movements. A 2h window reduces some of this noise but still produces a fragmented signal. Applying a 3h window results in a clearer and smoother activity pattern, and reduces short-term fluctuations while preserving the main daily pattern. In contrast, a 6h window smooths the data, causing the loss of the general pattern. For example, in pair 7, the biphasic activity trend in the damage pen becomes less distinct. Overall, the comparison suggests that a window size of 3h provides the best compromise between noise reduction and preservation of the main peaks of the pattern. Therefore, we selected a 3h window size for the analyses.

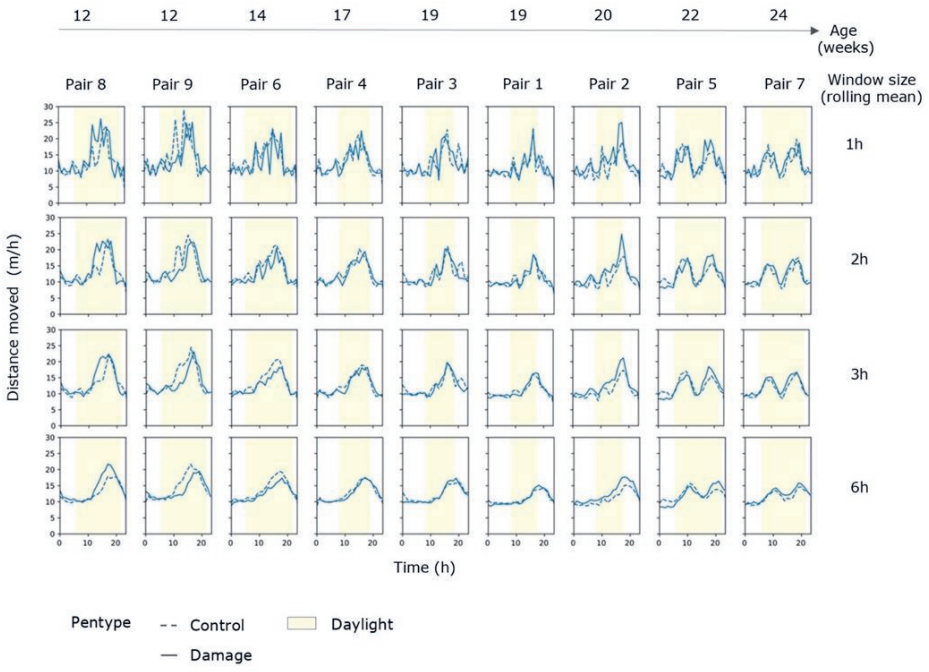


Figure S1. Circadian activity pattern on D_{-9} of the nine pairs of pigs (damage and control pens), sorted by age built with rolling mean of different window sizes (1h, 2h, 3h, 6h).

Comparison between corrected and non-corrected tracking outputs

The identity switches were corrected in the tracking results of the damage pens. Since the tracking data of the control pens was not corrected manually, it was necessary to first investigate the effect of the identity switches on the pen-level measures before using them in our analysis. For that purpose, we used the tracking data of the damage pens, where both the tracking data corrected and non-corrected tracking data were available. We compared the distance moved calculated at the pen level between corrected and uncorrected data (Figure S1), and similarly for the synchrony (Figure S2). The results showed a high correlation (r=0.92) for distance moved, indicating that non-corrected data could still be used for pen-level analysis. For synchrony, the correlation was lower (r=0.83), but pens with extreme low or high synchrony in the corrected tracking data also showed similar values in the non-corrected data. Therefore, we decided that it was reasonable to keep it in our analysis while interpreting the results with caution.

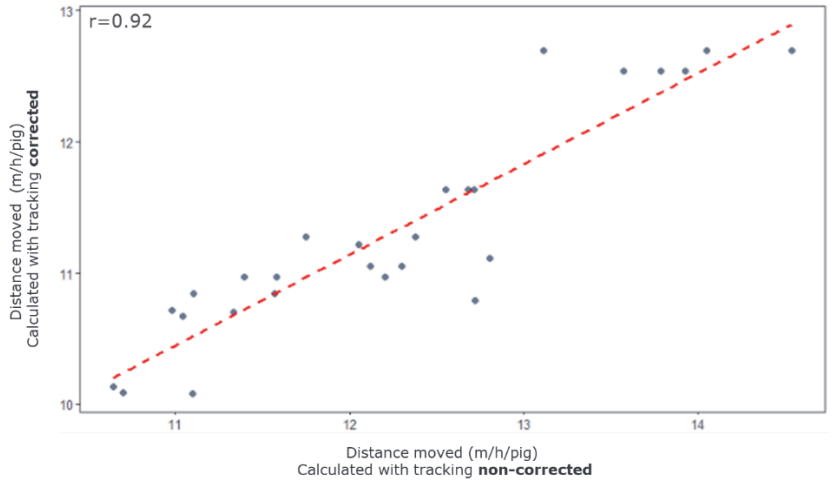


Figure S2. Correlations between the distance moved calculated with the tracking corrected and the distance moved calculated with the tracking non-corrected for the damage pen. The r indicated was calculated with a Pearson correlation. The average distance moved was calculated by summing the distance moved per frame for each pig, dividing it by the number of pigs in the group, and smoothing it with a rolling mean (3h window). The tracking data was corrected manually by identifying the switches between bounding boxes and reassigning them to the correct individual.

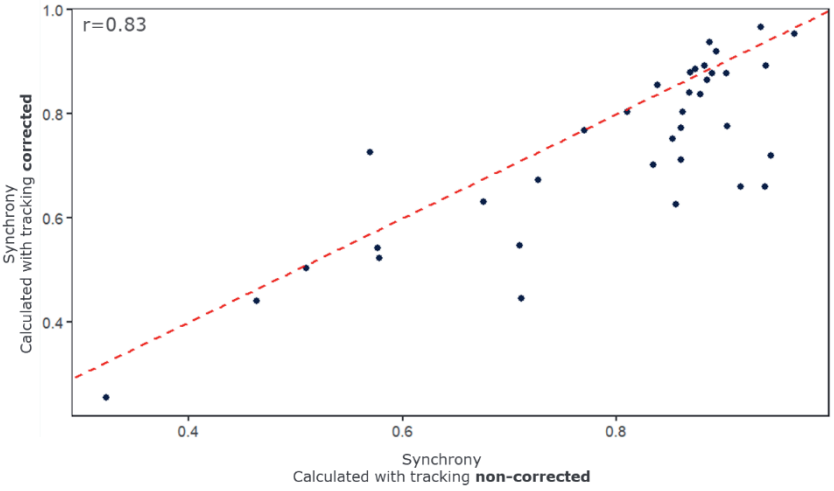
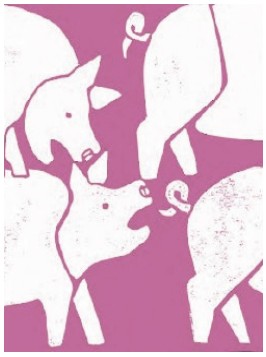


Figure S3. Correlations between the synchrony calculated with the tracking corrected and the synchrony calculated with the tracking non-corrected for the damage pen. The r indicated was calculated with a Pearson correlation. The average synchrony was calculated for each day and pen by averaging the coherence score of all the circadian activity patterns of pairs of pigs within that pen. The tracking data was corrected manually by identifying the switches between bounding boxes and reassigning them to the correct individual.



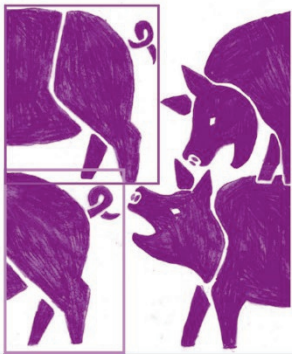




5







Chapter 5

Chapter 5

Who interacts with whom? Estimating individual and dyadic variation in proximity, tail biting, and ear biting in pigs using generalised linear mixed models

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Abstract

Understanding individual differences and preferences in social interactions is important for improving pig welfare. This study investigated whether individual pigs differ in their proximity to other pigs and in performing and receiving ear and tail biting, and whether, after accounting for individual differences, certain dyads (i.e., pairs of pigs) spend more time in proximity or engage in biting more frequently than others. A total of 99 pigs housed in nine pens were observed over three days. Ear and tail biting were manually annotated for 12 h per day, and proximity between pigs was derived from a tracking-by-detection algorithm as the average distance between dyads. Social interactions were analysed as dyadic observations using generalised linear mixed models, including individuals and dyads as random effects to partition variance. Individual effects accounted for 24.0-37.1% of the variance in performing and receiving ear and tail biting, and 2.9% for proximity, while dyadic effects explained 5.8-12.2% of the variance in these interactions ($z > 2$). This study demonstrates that social interactions are shaped by both individual and dyadic factors, and introduces a dyadic modelling approach that can be applied in future research to better understand variation in social interactions.

1. Introduction

Animals living in groups, especially in natural populations, do not engage equally in social interactions. Some individuals consistently interact more frequently than others within the group (Brent et al., 2013; Blaszczyk, 2018). This individual variation in social interaction, referred to as sociability, has been suggested as a personality trait (Gartland et al., 2022). In addition to individual variation in sociability, gregarious animals may interact non-randomly and tend to associate and direct their behaviour towards specific individuals (Silk et al., 2006; Kalbitz et al., 2016; Moscovice et al., 2017). Such consistency in partner choice over time may help individuals to better predict and anticipate the consequences of their future interactions (Massen et al., 2010).

Domestic pigs *(Sus scrofa domesticus)* are highly social animals that engage in a variety of interactions. Their social structure is maintained through a combination of low-intensity aggression, threat and avoidance (Beilharz and Cox, 1967; Jensen, 1982), as well as affiliative behaviours, such as social play, social nosing or lying in proximity to pen mates (Camerlink et al., 2022). On commercial farms, however, the limited space allowance compared to natural conditions reduces the ability for pigs to express their individual social tendencies, and to develop social preferences and maintain individual relationships (Durrell et al., 2004; Li et al., 2018). Still, even under commercial conditions, pigs may vary in their tendency to interact with conspecifics (Forkman et al., 1995; Ambruosi et al., 2024), and may exhibit social preferences, given evidence from previous studies for relatively weak but discernible partner preferences in social nosing, close proximity during rest and exploration (Durrell et al., 2004; Goumon et al., 2020; Camerlink et al., 2022). Farmed pigs may also engage in damaging behaviours like ear and tail biting, which can cause stress and wounds in victims. These behaviours are generally interpreted as foraging or exploratory behaviours redirected to pen mates in the absence of suitable rooting substrates or adequate feed, or as responses to frustration, rather than behaviours driven by social motivation. Variation among individuals in performing or receiving damage is supported by previous studies, indicating that individual characteristics, such as genetics (Breuer et al., 2003; Gorssen et al., 2024; Hegedűs et al., 2025), individual nutritional needs (Ursinus et al., 2014), and health status (Czycholl et al., 2023), play a role in the development of damaging behaviours. Whether pigs develop preferences in the context of damaging behaviours is largely unknown. Only a few studies have investigated preferences in tail biting, with inconsistent results (Zonderland et al., 2011; Li et al., 2018), and preferences in ear biting have not yet been studied. Therefore, further

research is needed to better understand whether biters consistently target specific victims in tail and ear biting.

A number of behavioural studies have investigated individual variation in social interactions, but the approaches used have important limitations. Previous studies have typically classified biters and victims into distinct categories. For example, Ursinus et al. (2014) distinguished tail biters from non-biters and victims from non-victims using binary traits, whereas Brunberg et al. (2011) defined categories based on the frequency of performing or receiving tail biting, classifying biters into three groups (non-performers, low performers, high performers) and victims into three corresponding groups (non-receivers, low receivers, or high receivers). Although such classifications provide a simple approach for investigating the individual characteristics of biters and victims, the categorisation criteria used are not consistent across studies, and the cut-off points between classes are often arbitrary. As a results of the cut-off points pigs with similar frequencies may be placed in different categories, and pigs with different frequencies may be grouped together. Moreover, quantitative information regarding the frequency or duration of performing and receiving bites is lost, as pigs within the same category are considered equivalent.

Social preferences in pigs have mostly been investigated using permutation tests, in which the observed frequency of interactions between pairs of animals is compared with a random distribution (Durrell et al., 2004; Goumon et al., 2020; Clouard et al., 2024; Seddaiu et al., 2025). This distribution is generated by repeatedly shuffling the observed data to estimate the range of interaction frequencies expected under random association (Farine, 2017). Permutation tests are particularly useful for analysing social structure, as each individual may be involved in multiple interactions, and therefore the observations are not independent, which is an assumption of parametric tests (Croft et al., 2011). However, the use of permutation tests to analyse social structure within a group also presents several limitations. Firstly, researchers need to choose among multiple approaches for generating a random distribution, such as shuffling interactions or permuting the identities of individuals, with permutations optionally constrained to specific groups or time periods (Farine, 2017). Different methodological choices may generate different random distributions, potentially influencing the conclusions drawn (Hobson et al., 2021). Secondly, permutation tests typically generate results per group, making them well-suited for investigating social preferences within a single large group over an extended period, as is commonly done in studies on natural populations. However, this approach limits the generalizability across

multiple groups. In pigs, permutation tests have been applied to study social preferences in affiliative behaviours, but these studies have generally focused on only a small number of groups, including a single group of 10 pigs (Seddaiu et al., 2025), one group of 24 pigs (Goumon et al., 2020) or two groups of 12 pigs (Clouard et al., 2024) or 16 and 17 pigs (Durrell et al., 2004). While these studies provide valuable insights into social preferences, pigs are usually housed in multiple pens on commercial farms, making traditional permutation-based approaches less suitable for broader inference across groups. Furthermore, in these studies, social interactions were monitored through manual observation, which is labour-intensive and therefore limits the number of pens that can be included. However, recent advances in automated monitoring methods are making it increasingly feasible to quantify social interactions, including damaging behaviours (Liu et al., 2020; Hakansson and Jensen, 2023; Odo et al., 2024; Guo et al., 2025) or spatial proximity (Orsini et al., 2025a), across a large number of groups. Therefore, there is a need to move from traditional approaches towards new quantitative approaches that can capture social interactions across multiple groups.

As an alternative to permutation tests, generalised linear mixed models (GLMMs) account for non-independence in the data and are therefore particularly useful for investigating social interactions (Kenny et al., 2020). GLMMs are statistical models that incorporate both fixed and random effects. In behavioural studies, random effects are often included in GLMMs models to account for repeated observations, for example, at the level of the individual or pen, but limited attention is given to the variance explained by these effects or their individual estimates. In contrast, in genetic studies, random effects are used to estimate the proportion of variance attributable to factors such as individual, pen or genetic effects. While traditional genetic models typically include the individual as a random effect, social interactions inherently involve at least two individuals. To address behaviours where two or more individuals contribute to a phenotype, social (genetic) models can be used. For example, Wang et al. (2023) proposed a GLMM to investigate the genetic basis of aggressive behaviour in turkeys by including random effects for both the initiator and the receiver. In addition, Han et al. (2022) proposed to model aggression in pigs by including the dyad (pair of initiator and receiver) as an additional random effect, alongside the initiator and the receiver effects. These recent studies provide a novel framework for simultaneously investigating individual variation in social interactions and the variation attributable to specific pairs of individuals, which can be interpreted as a social preference.

The aims of this study were, first, to investigate whether individual pigs consistently differ in their distance to other pigs, and in performing and receiving ear and tail biting, and second, after accounting for individual differences, to investigate whether certain pairs of pigs spend more time in proximity, or engage in biting more frequently than other pairs. For that purpose, GLMMs were applied to separate the different sources of variation observed in the distance between pigs, tail biting and ear biting, including individual variation between pigs and variation between pairs of pigs.

2. Materials and Methods

All methods complied with the European Directive 2010/63/EU and Dutch law on the protection of animals used for scientific purposes. As no invasive or harmful procedures were applied, approval of the experimental protocol by an institutional or licensing committee was not necessary, conform to Dutch (Article 1 Wet op de Dierproeven, 2021, https://wetten.overheid.nl/BWBR0003081/2021-07-01) and German (Article 7 Tierschutzgesetz, 2022, https://www.gesetze-im-internet.de/tierschg/BJNR012770972.html) legislation. The methods applied in the study were performed in accordance with the ARRIVE guidelines and regulations (du Sert et al., 2020).

2.1. Animals and housing

This study was carried out at a Topigs Norsvin commercial farm in Germany on a total of 9 pens (2.55 × 3.70 m, n = 11 pigs per pen, single sex) selected among 30 pens from three different batches, for the presence of a severe tail wound (see section 2.2.1). The pigs used in this study were the same as those of the damage pens described Orsini et al. (2025b). The tail-docked pigs arrived around 10 weeks of age and were housed in fully-slatted pens, equipped with two drinking nipples and one electronic feeding station. Pigs had *ad libitum* access to water and to a commercial dry feed with a proportion of crude protein adjusted to their weight range (Bus et al., 2023b). Enrichment materials were provided in compliance with European Union and German animal welfare legislation and consisted of a chain with plastic rings or a wooden block, and in the second and third batches, due to altered German legislation, an extra feeder from where pigs could obtain chopped straw mixed with straw pellets by manipulating a chain. The pens were naturally lit through windows, with artificial lighting used only during human presence in the room.

2.2. Data collection

Part of the data used in this study was originally collected to investigate the use of activity patterns obtained by a tracking-by-detection algorithm as predictors of tail biting, as presented in Orsini et al. (2025b).

Selection of the pens

This study focused on three different days before and after a tail wound was observed in a specific pen (i.e. D_{-5}, D_{-2} and D_{+1}, where D_0 is the day of the observation of the tail wound). The focus on these days was made possible by the bi-weekly assessment of tail damage of each pig using a detailed protocol (Bus et al., 2023a; Bus et al., 2024b) and by individual identification of the pigs via sprayed symbols on their backs. More details about these pens are presented in Table 1. Because the selection of the pens was based on the presence of a tail wound, the ages of the pigs on those three days varied largely between pens, ranging from 12 to 22 weeks of age. There was also a considerable variability between pens in both the severity of the tail wound and the number of pigs affected (see Orsini et al., 2025b). In some pens, several pigs had severe injuries, whereas in others, only a single pig was moderately affected.

Video recording

To study individual variation and preferences in the context of ear biting, tail biting, and distance, we first needed to record these behaviours. Videos were recorded in all the pens with one camera (Lorex, 4KSDAI168, Canada) mounted above the pen at a slight angle. Videos were recorded with a frame rate of 15 frames per second (fps) and a resolution of 1280 by 720 pixels. Ear and tail biting were observed manually based on videos, and the distance between pigs was calculated based on a tracking algorithm. Tail biting, ear biting and distance were determined on days D_{-5}, D_{-2} and D_{+1}.

Table 1. Description of the pens with tail damage selected for the study (adapted from Orsini et al., 2025b)

Pen	Batch	Sex	Breed[1]	D_0[2]	Daylight[3]	T_{ext} (°C)[4]	H_{ext} (%)[5]	# Pigs wounded[6]	Max severity[7]
1	1	Barrows	P x (LW x L)	67	9h21	-0.3 ± 5.5	87.2 ± 7.9	8	3
2	1	Gilts	P x (LW x L)	70	9h31	-2.8 ± 6.5	85.0 ± 7.5	1	2
3	2	Barrows	LW x L	63	9h35	9.7 ± 3.1	86.1 ± 9.8	2	2
4	2	Barrows	LW x L	53	10h12	10.9 ± 2.7	81.5 ± 8.6	2	2
5	3	Barrows	LW x L	85	15h29	18.7 ± 2.7	70.5 ± 16.1	1	2
6	3	Barrows	LW x L	26	16h20	17.8 ± 3.3	69.5 ± 17.0	3	4
7	3	Barrows	LW x L	96	14h52	21.5 ± 2.6	61.8 ± 19.8	2	2
8	3	Barrows	LW x L	12	15h57	16.9 ± 2.7	69.1 ± 17.6	2	2
9	3	Barrows	LW x L	12	15h55	16.9 ± 2.7	69.1 ± 17.6	10	4

[1]P: Piétrain, LW: Large White, L: Landrace
[2]D_0: The first day when tail damage was scored, expressed as the day after arrival (pigs arrived at the age of 10 weeks)
[3]Daylight: Duration of natural sunlight during D_0
[4]T_{ext}: Average temperature outside over the period of the study
[5]H_{ext}: Relative Humidity outside over the period of the study
[4,5]mean ± sd between D_{-9} and D_{+1} , based on Open-Meteo.com (Zippenfenig, 2023) with the location of the farm.
[6]# Pigs wounded: Number of pigs in the pen with at least one tail wound within the 2 weeks following D_0.
[7]Max severity: Maximum wound severity observed among pigs in the pen within the 2 weeks following D_0, scored as: 2: Small wound (< 2 cm), tail intact; 3: Medium wound (> 2 cm), tail intact; 4: Medium wound (> 2 cm) and part of the tail missing (see Bus et al. (2023a) for more details about the protocol)

Behaviour observations

Ear and tail biting were observed from video using The Observer software XT16 (Noldus Information Technology, Wageningen, The Netherlands). These behaviours were observed for 12h per day, with focal and continuous observations every second hour. Tail biting and ear biting were described as 'Nibbling, sucking, chewing or (forcefully) biting the tail/ear of a pen mate' (Orsini et al., 2025b). Tail and ear biting were observed by three observers, reaching an inter-observer reliability score of Cohen's kappa > 0.75 after training. They were scored as a state, and instances with an interruption of more than 1 second within the behaviour were considered as two separate events for that behaviour. For each event, individual identity was recorded for both the biter and the victim.

Tracking algorithm

Distances between pigs were calculated based on the output of a tracking algorithm run over 24h videos on the three days of observation. This tracking algorithm, presented in Huo et al. (2023), was based on bounding-box multi-object detection and developed with an Enhanced Cascaded Association Flow (ECAF). It achieved a performance of 98-99% for Multiple-Object Tracking Accuracy (MOTA) and Identity F1 score (IDF1), along with a 0.56 score for Identity Switch (IDSW) in short-term videos ranging from 5 to 30 minutes. After running the algorithm, the tracking data was corrected manually by detecting the switches between identity bounding boxes and reassigning them to the correct individual. The symbols sprayed on the back of the pigs were used for this correction step. The output of the tracking algorithm was down-sampled to 0.5 frames per second.

2.3. Traits

Ear and tail biting

Ear and tail biting between pairs of biter-victim (e.g. between pig id_1 and pig id_2) were quantified as a count, i.e. the total number of biting events occurring between the biter and the victim on a specific day. For ear and tail biting, each pair of pigs was represented by two records per day, depending on the direction of the interaction and the identity of the biter and the victim (see a subset of this dataset in Supplementary Materials Table 2). Records for a pair were zero when no biting event occurred between the biter and the victim. Each pen contributed 110 records per day.

Distance between pigs

All calculations of distance were done in Python (version 3.13.2). Proximity was measured per day based on the tracking results of each day described in the previous section. The Euclidean distance between the centroids of each pair of bounding boxes was calculated for every frame. Then, the distance between pairs of pigs (D) was calculated as the harmonic mean of these distances over the frames of each day (Equation 1),

$$D = \frac{n}{\sum_{k=1}^{n} \frac{1}{distance_{id_1 id_2}(k)}} \quad (1)$$

where $distance_{id_1 id_2}(k)$ is the Euclidean distance between the centroid of the bounding box of pig id_1 and pig id_2 in frame k, and n is the total number of frames. A harmonic mean is the reciprocal of the mean of the reciprocal variable, and is a way of averaging where small values (i.e., pigs that are closer in this study) receive greater weight. For example, the harmonic mean of distances of 1, 2 and 3 m equals 1.64 m, whereas the harmonic mean of distances of 2, 2 and 2 m equals 2 m. Hence, D is a continuous measure of distance where pigs who are close receive a higher weight. This formula, by including all the distances between pigs across all frames, captures both the proximity and the avoidance between pairs of pigs. In this study, we included all frames (using a 0.5 fps), meaning that the distance was computed for both active and inactive behaviours. The distance between pigs was calculated for each pair of pigs and for each day, meaning that each pair of pigs was represented by a single record per day in the dataset (see a subset of this dataset in Supplementary Materials Table 1). Hence, each pen contributed 55 records per day.

2.4. Statistical analysis

All statistical analyses were performed using ASReml-R (version 4.1.0.176) (Butler et al., 2023) in RStudio (version 2024.04.2).

The statistical models were built to address two research questions. First, (RQ1) whether individual pigs differ in their spatial proximity to other pigs, and in performing and receiving ear and tail biting. Second, (RQ2) whether pigs show preferences, meaning that certain pairs of pigs spend more time in proximity, or engage in biting more frequently than others, after accounting for individual variation.

To address these questions, three separate GLMMs were fitted, one for each trait, using Equation 2 for the distance between pigs and Equation 3 for ear and tail biting. Each model was structured to partition the variation in the behaviours into individual variation between pigs and variation between pairs of pigs, while also accounting for the repeated observations over the days and the pens. For that purpose,

pig identity, interaction between pairs of pigs and pen were included as random effects. Day was included as a fixed effect, and the interaction between pig identity and day was included as a random effect to allow individual tendency to vary over time. The interaction between day and pen was removed from the model as it contributed negligibly. This resulted in the following models:

For distance, a linear mixed model was fitted (Equation 2), where $D_{Day,Pig,Pen}$ is the measure of distance between pairs of pigs; μ is the intercept; Day_i is the fixed effect of day; $(Pig_j + Pig_k)$ is the random effect of the individual pig (the two pigs making up the dyad and combined as a single pig effect); $Dyad_{jk}$ is the random effect for each pair of pigs; $\left((Pig_j + Pig_k) : Day\right)_{jki}$ is the random interaction effect between pig and day; Pen_l is the random effect of pen and ε_{ijl} the residual error. The code used to build this model in ASReml-R is presented in Supplementary Materials, Box 1.

$$D_{Day,Pig,Pen} = \mu + Day_i + (Pig_j + Pig_k) + Dyad_{jk} + \left((Pig_j + Pig_k) : Day\right)_{jki} + Pen_l + \varepsilon_{ijl} \quad (2)$$

The model had the following variance-covariance structure:

$$\begin{bmatrix} Pig_j + Pig_k \\ Dyad_{jk} \\ \left((Pig_j + Pig_k) : Day\right)_{jki} \\ Pen_l \\ \varepsilon_{ijl} \end{bmatrix} = \begin{bmatrix} \sigma^2_{Pig_j+Pig_k} & 0 & 0 & 0 & 0 \\ 0 & \sigma^2_{Dyad_{jk}} & 0 & 0 & 0 \\ 0 & 0 & \sigma^2_{\left((Pig_j+Pig_k):Day\right)_{jki}} & 0 & 0 \\ 0 & 0 & 0 & \sigma^2_{Pen_l} & 0 \\ 0 & 0 & 0 & 0 & \sigma^2_{\varepsilon_{ijl}} \end{bmatrix}$$

The percentage of the observed variance of each random effect was calculated using Equation (3.1), where each variance component was expressed as a percentage of the total observed variance. The total observed variance was calculated using 3.2. The code for these calculations in ASReml-R is presented in Supplementary Materials, Box 3.

$$\%Var_{effect} = \frac{\sigma^2 effect}{\sigma^2 total} \times 100 \quad (3.1)$$

$$\sigma^2_{total} = \sigma^2_{Pig_j+Pig_k} + \sigma^2_{Dyad_{jk}} + \sigma^2_{\left((Pig_j+Pig_k):Day\right)_{jki}} + \sigma^2_{Pen_l} + \sigma^2_{\varepsilon_{ijl}} \quad (3.2)$$

For ear and tail biting, separate GLMMs were fitted (Equation 4) with a log link function, where μ is the intercept; Day_i is the fixed effect of day; $Biter_j$ and $Victim_k$ are the random effects of the biter and the victim; $(Biter{:}\,Victim)_{jk}$ is the random effect of the directed pair of biter and victim; $(Biter{:}\,Day)_{ji}$ and $(Victim{:}\,Day)_{ki}$ the interactions with day; and Pen_l, the random effect of pen. In addition, a covariance $\sigma_{Biter_j,Victim_j}$ between the random biter

and victim effects was also fitted to estimate the correlation between the frequency of performing (tail or ear) biting and the frequency of receiving (tail or ear) biting. A Poisson distribution with a log link function was used for ear and tail biting to account for the count nature of the data. Because tail and ear biting did not occur between all pairs of pigs within pens, the dataset contained a high proportion of zero counts. Therefore, a negative binomial distribution was also tested, as it may be more appropriate for zero-inflated count data, but these models did not converge. The Poisson models showed similar directions and estimates as the non-converging negative binomial models; therefore, we decided to present the results from the Poisson model. The code used to build this model in ASReml-R is presented in Supplementary Materials, Box 3.

$$Frequency\ Biting_{\ Day,Biter,Victim,Pen} = \mu + Day_i + Biter_j + Victim_k + (Biter{:}\,Victim)_{jk} + (Biter{:}\,Day)_{ji} + (Victim{:}\,Day)_{ki} + Pen_l \quad (4)$$

The model had the following variance-covariance structure:

$$\begin{bmatrix} Biter_j \\ Victim_k \\ (Biter{:}\,Victim)_{jk} \\ (Biter{:}\,Day)_{ji} \\ (Victim{:}\,Day)_{ki} \\ Pen_l \end{bmatrix} = \begin{bmatrix} \sigma^2_{Biter_j} & \sigma_{Biter_j,Victim_j} & 0 & 0 & 0 & 0 \\ \sigma_{Biter_j,Victim_j} & \sigma^2_{Victim_k} & 0 & 0 & 0 & 0 \\ 0 & 0 & \sigma^2_{(Biter:Victim)_{jk}} & 0 & 0 & 0 \\ 0 & 0 & 0 & \sigma^2_{(Biter:Day)_{ji}} & 0 & 0 \\ 0 & 0 & 0 & 0 & \sigma^2_{(Victim:Day)_{ji}} & 0 \\ 0 & 0 & 0 & 0 & 0 & \sigma^2_{Pen_l} \end{bmatrix}$$

The percentage of variance attributed to each random effect was calculated on the latent scale of the Poisson distribution, following the procedure described by Nakagawa et al. (2017). The percentage of variance was calculated using Equation 3.1, with each variance component expressed as a percentage of the total variance in Equation 6.1. The total variance included both the sum of the variances attributed to each random effect $\sigma^2{}_{total\_random}$, and the variance of the Poisson distribution with a log link, $\ln\left(1+\frac{1}{\lambda}\right)$. The parameter λ was calculated using Equation 6.3, with β_{0_io} being the fixed intercept and $\sigma^2{}_{total\_random\_io}$, the sum of the variances of the random effects, both estimated from the intercept-only-model (i.e., the model including the intercept as the only fixed effect and all the random effects). $\sigma^2{}_{total\_random\_io}$ was calculated using Equation 6.2, following the same procedure used to calculate $\sigma^2{}_{total\_random}$. The code for these calculations in ASReml-R is presented in Supplementary Materials, Box 7.

$$\sigma^2{}_{total} = \sigma^2{}_{total\_random} + \ln\left(1 + \frac{1}{\lambda}\right) \quad (6.1)$$

$$\sigma^2{}_{total\_random} = \sigma^2{}_{Biter_j} + \sigma^2{}_{Victim_k} + \sigma^2{}_{(Biter:Victim)_{jk}} + \sigma^2{}_{(Biter:Day)_{ji}} + \sigma^2{}_{(Victim:Day)_{ji}} + \sigma^2{}_{Pen_l} \quad (6.2)$$

$$\lambda = \exp(\beta_{0\_io} + 0.5 \times \sigma^2{}_{total\_random\_io}) \quad (6.3)$$

The random effects $Pig_j + Pig_k$ (Equation 2), $Biter_j$ and $Victim_k$ (Equation 4) were used to address RQ1, i.e. whether there is variation between individual pigs in being in proximity to other pigs and in performing and receiving ear and tail biting. The random effects $Dyad_{jk}$ (Equation 2) and $(Biter{:}Victim)_{jk}$ (Equation 4) were used to address RQ2, i.e. whether pigs have preferences for specific individuals in ear biting, tail biting, and distance. For the random effects, we considered effects as significant with a z-ratio > 2.

3. Results

Table 2 presents the mean frequency with their standard errors of tail biting, ear biting and the distance between pigs over the three days of observations, and the percentage of pigs involved in tail and ear biting. Overall, ear biting occurred more frequently than tail biting. The highest frequency for both tail and ear biting was found on D_{+1} (with 10.7 events for tail biting and 13.8 events for ear biting). The frequency of ear biting increased over the three days, from 12.3 events on D_{-5} to 13.8 events on D_{+1}, whereas tail biting decreased on D_{-2} compared to D_{-5}. Most of the pigs performed or received ear and tail biting, with percentages ranging from 85.2% to 91.7% of the pigs, depending on the day and the category. However, biting did not occur between all possible pairs of biter and victim. Only 28.9 to 33.4% of all possible pairs were involved in tail biting, and 37.4 to 38.9% in ear biting. The mean distance between pairs of pigs was relatively stable across the three days, varying from 2.98m on D_{-2} to 3.05m on D_{+1}.

Table 2. Mean frequency (±SE) of tail biting, ear biting and distance between pigs over the three days studied, and percentage of pigs involved in ear and tail biting.

Day	D_{-5}	D_{-2}	D_{+1}
Tail biting			
Frequency (events/biter)	10.0 ± 1.26	8.69 ± 0.91	10.7 ± 1.05
Frequency (events/victim)	10.0 ± 0.94	8.69 ± 0.83	10.7 ± 1.00
Frequency (events/dyad)	0.83 ± 0.06	0.72 ± 0.05	0.89 ± 0.06
Tail biters (% of pigs)	81.5	86.1	86.1
Tail biting victims (% of pigs)	84.3	89.8	88.9
% Dyads involved in tail biting	31.5	28.9	33.4
Ear biting			
Frequency (events/biter)	12.3 ± 1.09	12.7 ± 1.06	13.8 ± 1.26
Frequency (events/victim)	12.3 ± 0.89	12.7 ± 0.99	13.8 ± 1.16
Frequency (events/dyad)	1.02 ± 0.06	1.06 ± 0.06	1.15 ± 0.07
Ear biters (% of pigs)	89.8	90.7	85.2
Ear biting victims (% of pigs)	88.0	91.7	89.8
% Dyads involved in ear biting	38.9	38.6	37.4
Proximity			
Distance between pairs (m)	2.99 ± 0.03	2.98 ± 0.03	3.05 ± 0.03

Dyad represents the pair of biter and victim. It is directional, meaning that two values exist per pair of pigs.

The variance of the random effects and their standard errors for tail biting, ear biting and proximity are presented in Table 3, and the estimate of the fixed effect day in the Supplementary Materials Table S3. No significant effect of day was found on any of the response variables (tail biting: Wald $\chi^2 = 3.68$, P = 0.16; ear biting: $\chi^2 = 0.25$, P = 0.88; proximity: $\chi^2 = 4.52$, P = 0.10, Supplementary Materials Table S3). For both tail and ear biting, individual pigs (biters and victims) explained a notable proportion of the variance on the latent scale in the model. Biters explained a larger proportion of the variance than victims, accounting for 34.6% in tail biting and 37.1% in ear biting, compared with 24.0% and 25.0% for victims, respectively. Individual biters and victims also varied in their frequency of biting and being bitten across days, as shown by the significant biter × day and victim × day interactions, although the proportion of variance explained by these interactions (between 5.2 and 8.2%) was much lower than that explained by pig. The positive and significant covariance between the biter and victim effects (with corresponding correlations for ear biting: $r = 0.98$ and for tail biting: $r = 0.84$, see Supplementary Materials Box S6 for calculations) indicates that pigs with a higher propensity to bite also tended to be bitten more

and vice versa. Dyad also contributed significantly to the variance on the latent scale in tail biting (10.7%) and ear biting (12.2%). This indicates that tail and ear biting were non-randomly distributed among pairs of biters and victims, with some pairs being more frequently involved in tail and ear biting than others in the group. Pen did not contribute significantly to the variance observed in tail and ear biting.

Individual pigs contributed significantly to the variation in proximity (2.9%), and this effect did not vary with the day of the observation. This suggests that pigs consistently spent more time closer (or further) to other pigs, although this effect explained only a small proportion of the overall variation. Dyad also contributed significantly to the distance observed between pigs (5.8%), indicating that the distance was not randomly distributed between pairs, i.e. some pairs of pigs were on average closer (or further away) than other pairs. Pen did not contribute significantly to the variation observed in proximity. However, a large proportion of the variation in proximity remained unexplained by our model (residual variance: 71%), meaning that the effects included in the model did not fully explain proximity.

Table 3. Variance components (random effects) for tail biting, ear biting and proximity

	Tail biting			Ear biting			Proximity		
Random effects	Est ± SE	% Var	z-ratio	Est ± SE	% Var	z-ratio	Est ± SE	% Var	z-ratio
Pig (Biter)	1.18± 0.23	34.6	**5.21**	1.17 ± 0.21	37.1	**5.56**	0.99 ± 0.35	2.9	**2.82**
Pig (Victim)	0.82± 0.16	24.0	**5.07**	0.79 ± 0.14	25.0	**5.43**			
Cov (Biter x Victim)	0.83± 0.16	-	**5.08**	0.95 ± 0.16	-	**5.99**			
Pig (Biter) x Day	0.28 ± 0.04	8.2	**6.24**	0.25 ± 0.04	8.0	**6.42**	0.34 ± 0.30	1.0	1.11
Pig (Victim) x Day	0.19 ± 0.03	5.5	**5.61**	0.16 ± 0.03	5.2	**5.71**			
Dyad (Biter x Victim)	0.37 ± 0.04	10.7	**9.63**	0.38 ± 0.03	12.2	**11.1**	1.96 ± 0.77	5.8	**2.53**
Pen	0.06 ± 0.21	1.9	0.31	~0	~0	~0	6.55 ± 3.58	19.4	1.83

Var: Variance, Est: Estimate, SE: Standard Error. z-ratio >2 are indicated in bold.

To illustrate the variation between pigs and between pairs of pigs, a case study is presented in Fig. 1. This figure presents the structure of the networks of one pen (Pen 1) on the three days of observations (D_{-5}, D_{-2} and D_{+1}) for the three social interactions (tail biting, ear biting and proximity). First, we can note visually that some pigs performed (e.g., *K* and *D*) or received (e.g., *A* and *G*) tail biting more frequently than others in the group, especially on D_{-5}. In addition, certain pairs of biters and victims were more involved in tail biting than other pairs; however, this was not fully consistent across the three days of observations. For example, *D* directed tail biting at a high frequency toward *A* on the three days. In contrast, *K* directed a high frequency of tail biting toward *G* on D_{-5}, but then on D_{-2} most of tail biting was directed toward *A*. Similar patterns appear for ear biting and proximity, with variation between pigs and pairs of pigs.

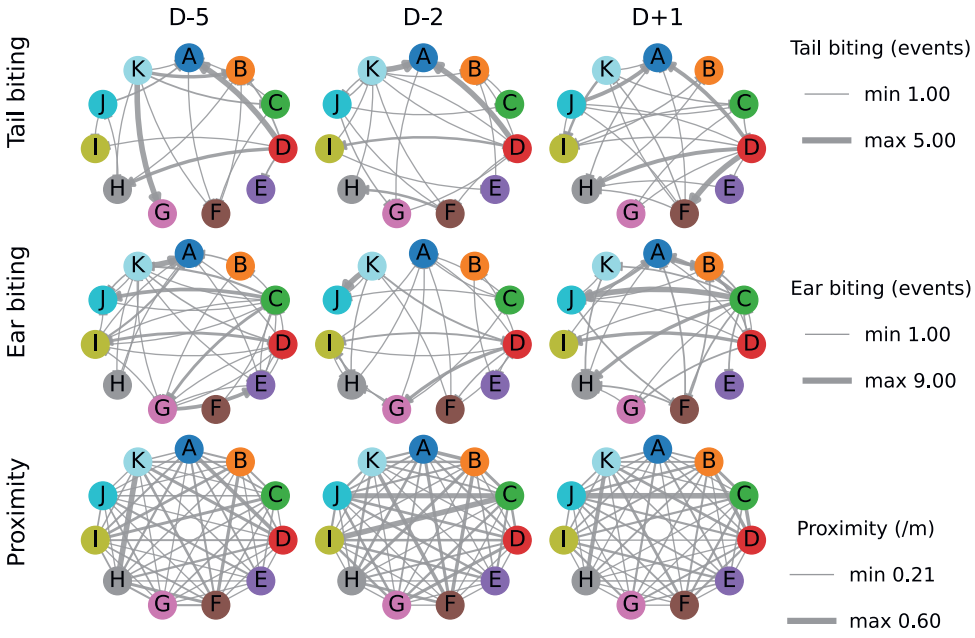


Figure 1. An example of the structure of the networks for one pen (Pen 1) on the three days of observations (D_{-5}, D_{-2} and D_{+1}) for three types of interactions (tail biting, ear biting and distance between pigs). The nodes represent the 11 pigs within the pen, and the edges (i.e., connections between the nodes) are proportional to the frequency of tail and ear biting and to the inverse of the average distance between pigs (1/D). Note that the inverse was used in this plot, so that visually pigs which are closer appear with a thicker edge.

Interestingly, the role of pigs can also be compared across the three social interactions. For example, on D-$_5$, *K* directed most tail biting toward *G*, whereas *K* directed ear biting mainly toward *A*. Regarding tail biting and proximity, *K* directed tail biting at a high frequency toward *G* on D-$_5$, and these two pigs were also further apart this day (as indicated by the thin line). In contrast, *C* directed ear biting at a high frequency toward *J* on D$_{+1}$, and these two pigs remained relatively in close proximity compared with other pairs of pigs. Furthermore, *I* was in close proximity to *C* on D-$_2$, but no tail or ear biting occurred between these pigs.

4. Discussion

This study aimed, first, to examine whether individual pigs consistently differ in their distance to other pigs, and in performing and receiving ear and tail biting, and second, after accounting for individual differences, to investigate whether certain pairs of pigs spend more time in proximity, or engage in biting more frequently than other pairs within the group. For that purpose, we applied GLMMs to partition the different sources of variation in the distance between pigs, and in the frequency of tail biting and ear biting, including individual variation between pigs and variation between pairs of pigs. Individual pigs explained a high proportion of the variance on the latent scale of tail and ear biting, and a statistically significant but much lower proportion of the variance on the observed scale of proximity. This result shows that pigs differ in their tendency to bite, receive bites or be in proximity (or further apart) to other pigs. For both tail and ear biting, this tendency varied across the three days of observation, as indicated by the significant effect of biter x day, and victim x day. Our results also indicate a non-random distribution among pairs of pigs for tail, ear biting and distance between pigs, with some pairs of pigs being more frequently involved in tail and ear biting, or spending more time in proximity (or further apart) than other pairs in the group.

4.1. Individual variation

Individual variation in tail and ear biting

Our results show that most pigs both performed and received tail and ear biting, with percentages ranging from 85.2% to 91.7% of the pigs involved in each role. To our knowledge, this is the first study to explore the proportion of pigs involved in ear biting. Our results on tail biting confirm the findings of Zonderland et al. (2011), who reported that already before a tail-biting outbreak, 82% of pigs performed tail biting and 96% received tail biting. During an outbreak, these proportions increased to 99% of pigs performing and 100%

receiving tail biting. In contrast, Brunberg et al. (2011) found that only 13.3% of pigs performed tail biting, and 24.7% received tail biting. These discrepancies are likely due to variations in observation methods. Brunberg et al. (2011) observed pigs for only 1 h per pen, whereas our study included longer and more frequent observations (36 h per pen over 3 days), and Zonderland et al. (2011) observed pigs for about 12 h per pen over 7 days. Given the sporadic nature of tail-biting events, the limited observation period used by Brunberg et al. (2011) likely reduced the probability of capturing all tail-biting events and, consequently, identifying all biters and victims. Furthermore, Brunberg et al. (2011) included both pens with and without tail-biting problems, while both our study and Zonderland et al. (2011) focused on pens with known tail-biting outbreaks.

We found that individual pigs explained a substantial part of the variation observed in the frequency of both performing and receiving tail biting. In line with our results, Zonderland et al. (2011) reported that one or a few pigs per pen performed and received significantly more tail biting than the pen average. Brunberg et al. (2011) reported marked variation among pigs involved in tail biting as biter and/or victim: 2.6% of pigs performed tail biting at a low frequency, and 10.7% at a high frequency, whereas 18% of pigs received tail biting at a low frequency, and 6.7% receiving at a high frequency. However, our approach to identifying variation in biting behaviour differed considerably from the methods used in both previous studies. In the current study, we assessed individual differences by using GLMMs to separate the different sources of variation contributing to tail biting, including individual variation between pigs, while also accounting for variation between pairs of pigs. Brunberg et al. (2011) defined classes based on the frequency of performing or receiving tail biting, including three categories for biters (non-performers, low performers, high performers) and three for victims (non-receivers, low receivers, high receivers), with thresholds between classes determined by visual observations. Zonderland et al. (2011) also used a GLMM to investigate individual variation in tail biting. However, they analysed the frequency of performing and receiving tail biting using separate models, meaning that they did not account for both the victim and biter individual in the same model, and the pair of biter and victim. In comparison to these two studies, our approach with GLMMs to test variation between individuals while accounting for pairs of biter and victim presents several advantages. First, by using the continuous information on the frequency of performing and receiving biting rather than classes, our models retain all variation and therefore improve statistical power. Furthermore, this approach avoids the need to define arbitrary cut-off points, which can result in pigs with similar frequencies being assigned to different classes, while grouping pigs with

quite different frequencies together in the same class. Third, by including the biter, the victim, and the pair of biter and victim as random effects in the same model, our analysis accounts for the non-independence between biting events, as tail and ear biting behaviours inherently involve interactions between two individuals. This approach captures both individual-level tendencies (e.g., pigs that frequently bite multiple pen mates) and dyadic patterns (e.g., specific pairs of pigs that interact more often than others), which would be missed when analysing biter and victim roles separately.

For both tail and ear biting, although less pronounced than the effect of pig, we also found a proportion of the variance explained by interactions between biter and day, and between victim and day. This indicates that pigs varied in their behaviour across days, with possibly some pigs being more consistent than others, in line with Ursinus et al. (2014). The degree of consistency of performing and receiving biting over days might also relate to the different types of tail biting as described by Taylor et al. (2010): "two-stage", "sudden-forceful", and "obsessive", which are associated with different motivations and could vary between the pens under study. For example, the "sudden-forceful" type is related to gaining access to a resource and may therefore be more occasional with less consistent biters than the "two-stage" type, related to foraging and exploration. Furthermore, tail biting can also spread rapidly across biters and victims within a pen (Zonderland et al., 2011; Valros, 2018) and therefore, pigs may shift into biter or victim over time.

Individual variation in proximity

To our knowledge, this is the first study investigating individual variation in proximity in pigs. Individual pigs varied in their distance to other pigs, indicating that some pigs spent more time close or further away from other pigs, despite the fact that they had limited opportunities to either avoid or approach pen mates due to the restricted space. The latter might possibly explain why a lower proportion of variation in proximity was explained by pig as compared with tail biting and ear biting. Previous studies suggested that pigs may differ in their sociability, i.e., their motivation to interact with conspecifics (Forkman et al., 1995; Ambruosi et al., 2024; Ferreira et al., 2025). However, it is unclear whether the difference in proximity we observed reflects this sociability. For sociability to be considered a personality trait, the behaviour should be stable across time and contexts (Réale et al., 2007). In our study, individual proximity was stable over three days as no interaction was found between day and pig effect, but the stability of proximity should be investigated over

a longer period to confirm its temporal consistency. Future studies should also investigate whether variation among individuals in proximity to other pigs is related to other individual traits than sociability, such as other personality traits, coping style, sex or genetics.
In addition, it remains unclear how pigs interact when they are in proximity to each other. Proximity may reflect both affiliative, aggressive and damaging behaviours. In this study, we focused on the days around tail wounds were observed, and we observed tail and ear biting occurring around ten times per pig per day (within the 12h of observation) for both performing and receiving. Therefore, close proximity may also be captured during ear and tail biting. However, ear and tail biting account for a very small proportion of the daily time budget (Bolhuis et al., 2006; Luo et al., 2020), as pigs spent a lot of time resting, whereas proximity was measured continuously throughout the day. Therefore, the measure of proximity in our study likely reflected other social interactions than ear and tail biting. In future work, it would be interesting to focus on proximity at rest or include specific affiliative behaviours, such as nosing.

4.2. Social preferences

Social preferences in ear and tail biting

We found that pigs have preferences in tail and ear biting, as demonstrated by the significant dyad effect. This result may indicate either that some pigs prefer to bite specific pen mates or that some pigs are more tolerant of being bitten by certain pigs. To our knowledge, only a few studies have investigated individual preferences in tail biting partners (Zonderland et al., 2011; Li et al., 2018) with inconsistent results, and none have examined this in ear biting. Apart from our study, evidence for non-random dyads was provided in Li et al. (2018), reporting that tail biters more frequently targeted pigs originating from the same litter than pigs from other litters. Preferences in tail and ear biting may also reflect differences in the underlying motivation for damaging behaviours. For example, some pigs may perform "sudden-forceful" tail biting to gain access to resources, such as food, water or lying space (Moinard et al., 2003; Taylor et al., 2010; D'Eath et al., 2014). These pigs may consistently target those pen mates that spend a longer time in the feeding station than other pigs, which is known to be moderately consistent with time (Bus et al., 2024a). In contrast, obsessive tail biters may actively search for any accessible tail to bite (Beattie et al., 2005; Van de Weerd et al., 2005) without preference for a particular victim.

Preferences in tail and ear biting may also reflect differences in pigs' tolerance to being bitten by specific pen mates. For example, some biters may bite the tail or the ears of their pen mates more forcefully than other biters and therefore be less tolerated by some victims. Taylor et al. (2010) suggested that the biters of the "sudden forceful" type of tail biting bite with more force than the biters of the "two-stage" type of tail biting. However, to reflect the results of our study, this interpretation assumes variation either among victims in pain tolerance or in the force of biting directed at different victims. Otherwise, biters with strong bite force would be avoided by all pen mates, and no dyadic variation would be observed. Pigs with already injured or sensitive tails or ears may tolerate additional biting less than other pigs (Simonsen et al., 1991), especially strong bite force, which could contribute to variation between dyads. Future research could explore these preferences by distinguishing different types of tail and ear biting, considering both the underlying motivation and the force of biting. Although challenging to differentiate, this could include categorising biting as tail (or ear) in the mouth, mild, moderate, or severe, as proposed by Brunberg et al. (2011).

Social preferences in proximity

We found that distance was not randomly distributed between pairs of pigs, as dyads contributed significantly to 5.8% of the variance in proximity. This indicates that pigs may have preferences for being in proximity or avoiding specific pigs. It aligns with previous studies suggesting that pigs can form preferential relationships under commercial conditions through allogrooming, social nosing, and proximity while lying (Durrell et al., 2004; Goumon et al., 2020; Clouard et al., 2024). However, in these studies, the preferences were found to have limited stability over time and across life phases (Durrell et al., 2004; Jowett and Amory, 2021). In our study, we were limited in our observations to three days, which did not allow us to investigate whether these preferences were consistent across a longer period of time. In addition, apart from reflecting preferences to stay close to specific pigs, our results may also indicate that certain pigs tend to avoid specific pigs. This is particularly relevant in our study, as we focused on days around tail damage, and some pigs likely avoided specific biters. Future studies could apply the same approach with GLMMs, as the one used here, to examine social preferences across the entire production period under normal conditions, in the absence of tail biting problems. It is important to note that the non-random distribution of the distance among pairs of pigs may also have reflected a shared preference for a location. Therefore, future studies would also benefit from studying proximity in groups of pigs housed in larger pens with more opportunities to move around.

4.3. Future application and conclusion

In this study, we proposed a new approach to assess individual differences and social preferences by using GLMMs and including individual pigs and pairs of pigs as random effects. Initially, we also aimed to investigate relationships between proximity, tail biting and ear biting, using multivariate models by combining the univariate models presented in this study. However, our study included 99 pigs and observations collected over three days, which limited the statistical power and did not allow us to perform these analyses. Therefore, comparisons between social interactions were only explored and illustrated in the case study presented in Fig. 1, where no clear visual indication was found that pairs of pigs in closer proximity were more likely to engage in tail or ear biting, nor that pairs involved in tail biting were also involved in ear biting. With the recent advances in technologies, especially in individual tracking (He et al., 2021; van der Zande et al., 2021; Guo et al., 2023; Huo et al., 2023) and behaviour recognition, such as tail biting (Liu et al., 2020; Hakansson and Jensen, 2023; Guo et al., 2025), the collection of large-scale datasets across many individuals and extended time periods may become possible in the near future. As a result, behavioural analyses may increasingly move toward such quantitative modelling approaches, enabling more powerful analyses of individual differences and social preferences in individual interactions. Furthermore, in this study, we showed that both individual pigs and pairs of pigs play a role in tail biting, ear biting, and proximity. However, we did not investigate what may explain these patterns. Future studies could therefore explore whether variation among individuals and pairs is associated with specific individual characteristics.

In conclusion, in the current study, both individuals and pairs of pigs explained a significant proportion of the variance of the observed tail biting and ear biting frequencies and the distance between pigs. Our findings also showed that individual variation across days contributed significantly to the observed variability. However, because this study was limited to a relatively short observation period, it remains unclear whether these individual and dyadic differences are stable over longer periods. The use of GLMMs, as presented in the current study, opens the door for future studies to investigate the consistency of individual variation and preferences over long periods of time, and across different interactions, as well as their link with individual characteristics. These analyses could provide insights into improving welfare by individualising and adapting management strategies and by including these traits in breeding programs.

Supplementary Materials

Dataset and models used in the paper

Proximity

A subset of the dataset used to analyse proximity is presented in Table S1, and the model applied to analyse this dataset (Equation 2) is described in Box S1. A particularity of this model is that the measure of distance is non-directional, meaning that there is only one row per dyad per day, and in this row, `pig_1` plays the same role as `pig_2`. Therefore, only a single effect for pig is estimated by combining `pig_1` and `pig_2`. This is implemented in the model using the `and()` function (see `pig_1 + and(pig_2))`, which ensures that both pigs in a dyad contribute equally to the same effect. The same approach is applied to the interaction between pig and day by specifying `pig_1:day + and(pig_2:day)`.

In addition, an argument `equate.levels = c("pig_1", "pig_2")` is added to the model to guarantee that the pigs within `pig_1` and `pig_2` are ordered and treated identically. This argument is necessary to ensure that pig (e.g., pig A1) is represented by the same effect regardless of whether it appears as `pig_1` or `pig_2`.

In Box S2, the results of the model are presented. According to the model specification, `pig_1` and `pig_2` are estimated as a single effect (reported as `pig_1`), and similarly for `pig_1:day` and `pig_2:day` (reported as `pig_1:day`).

Box S3 presents the code to extract the variance and calculate the total variance.

Table S1. Example of a subset of the dataset used to analyse proximity (referred to as *data_proximity*)

The distance is given in meters.

pen	day	pig_1	pig_2	dyad	distance
1	D-5	A1	B1	A1_B1	2.83
1	D-5	A1	C1	A1_C1	3.14
1	D-5	A1	D1	A1_D1	3.67
.	.	.	.		.
.	.	.	.		.
9	D+1	K9	J9	K9_J9	2.31

Box S1. Code to build the model in ASReml-R to analyse proximity

```
model_proximity <- asreml(
  fixed         = distance ~ day,
  random        = ~ pig_1 + and(pig_2) +
                    pig_1:day + and(pig_2:day) + dyad + batchpen,
  residual = ~ idv(units),
  equate.levels = c("pig_1", "pig_2"),
  data          = proximity_data,
  na.action     = na.method (x = "include", y = "include")
)
```

Box S2. Estimates of variance components for proximity

```
summary(model_proximity)$varcomp

             component  std.error  z.ratio   bound   %ch
pig_1        99.05063   35.09975   2.821975     P      0
pig_1:day    33.63934   30.07204   1.118625     P      0
pen          655.36919  358.45491  1.828317     P      0
dyad         196.03202  77.49555   2.529591     P      0
units!R      2391.87469 118.47888  20.188195    P      0
```

Box S3. Code to calculate the total variance for proximity

```
# Calculation sum variance random effects
vc <- summary((model_proximity)$varcomp
var_pig <- vc["pig_1","component"]
var_pig_day <- vc["pig_1:day", "component"]
var_pen <- vc["pen", "component"]
var_dyad <- vc["dyad", "component"]
var_random <- var_pig + var_pig_day + var_pen + var_dyad
```


Tail and ear biting

A subset of the dataset used to analyse tail and ear biting is presented in Table S2, and the model applied to analyse this dataset (Equation 4) is described in Box 4. In this model, we included a covariance between the `biter` and `victim` effects for the same pig. This was specified by including this term in the model: `str(~pig_id_biter + pig_id_victim, ~us(2):id(pig_id_biter))`, which fits a 2×2 covariance matrix for biter and victim within each pig identity. The estimated covariance matrix is reported in the results (Box S5) with `pig_id_biter+pig_id_victim!us(2)_1:1` the variance for the biter effect, `pig_id_biter+pig_id_victim!us(2)_2:1` the covariance between biter and victim, and `pig_id_biter+pig_id_victim!us(2)_2:2` the variance for the victim effect. Box

S6 presents the code used to extract the variance and covariance components from the model output and to calculate the correlation between the biter and victim roles. Box S7 presents the code to calculate the total variance on the latent scale from a Poisson distribution, following the procedure described by Nakagawa et al. (2017).

Table S2. Example of a subset of the dataset used for the model (referred to as *data_biting*)

pen	day	pig_id_biter	pig_id_victim	frequency
1	D-5	A1	B1	0
1	D-5	B1	A1	2
1	D-5	A1	C1	0
1	D-5	C1	A1	0
1	D-5	A1	D1	6
1	D-5	D1	A1	1
.	.	.	.	.
.	.	.	.	.
9	D+1	K9	J9	3
9	D+1	J9	K9	0

Box S4: Code to build the model in ASReml-R to analyse ear and tail biting

```
model_biting <- asreml(
  fixed   = frequency ~ day,
  random  = ~ str(~pig_id_biter + pig_id_victim, ~us(2):id(pig_id_biter))
            + pig_id_biter:day +
              pig_id_victim:day +
              pig_id_biter:pig_id_victim +
              pen,
  residual = ~ id(units),#Note: asr_poisson has a default value of  dispersion of 1
  family  = asr_poisson(),
  data    = data_biting)
```

Box S5: Estimates of variance components for tail biting

```
summary(model_biting)$varcomp

                                    component  std.error   z.ratio bound %ch
batchpen                          0.06417387 0.20803681 0.3084736     P   0
pig_id_biter+pig_id_victim!us(2)_1:1  1.18315052 0.22719246 5.2077014     P   0
pig_id_biter+pig_id_victim!us(2)_2:1  0.82987868 0.16373987 5.0682749     P   0
pig_id_biter+pig_id_victim!us(2)_2:2  0.81999917 0.16147114 5.0783018     P   0
pig_id_biter:day                  0.27838750 0.04458314 6.2442330     P   0
pig_id_victim:day                 0.18872263 0.03365592 5.6074131     P   0
pig_id_biter:pig_id_victim        0.36672346 0.03808385 9.6293694     P   0
units!R                           1.00000000         NA        NA     F   0
```

Box S6: Code to extract variance and covariance and calculate correlation

```
vc <- summary(model_biting)$varcomp
var_biter <- vc["pig_id_biter+pig_id_victim!us(2)_1:1", "component"]
cov_biter_victim <- vc["pig_id_biter+pig_id_victim!us(2)_2:1", "component"]
var_victim <- vc["pig_id_biter+pig_id_victim!us(2)_2:2", "component"]
cor_biter_victim <- cov_biter_victim / sqrt(var_biter* var_victim)
```

Box S7: Code to calculate the total variance on the latent scale from Poisson distribution

```
# Calculation sum variance random effects

vc <- summary(model_biting)$varcomp
var_biter <- vc["pig_id_biter+pig_id_victim!us(2)_1:1", "component"]
var_victim <- vc["pig_id_biter+pig_id_victim!us(2)_2:2", "component"]
var_biter_day <- vc["pig_id_biter:day", "component"]
var_victim_day <- vc["pig_id_victim:day", "component"]
var_dyad <- vc["pig_id_biter:pig_id_victim", "component"]
var_pen <- vc["pen", "component"]

var_random <- var_biter + var_victim + var_biter_day + var_victim_day + var_dyad +
           var_pen

# Intercept-only model

model_intercept_only_biting <- asreml(
  fixed   = frequency ~ 1,
  random  = ~ str(~pig_id_biter + pig_id_victim, ~us(2):id(pig_id_biter)) +
              pig_id_biter:day +
              pig_id_victim:day +
              pig_id_biter:pig_id_victim +
              pen,
  residual = ~ id(units),
  family  = asr_poisson(),
  data    = data_biting)

# Calculation sum variance random effects intercept-only model

vc_io <- summary(model_intercept_only_biting)$varcomp
var_biter_io <- vc_io["pig_id_biter+pig_id_victim!us(2)_1:1", "component"]
var_victim_io <- vc_io["pig_id_biter+pig_id_victim!us(2)_2:2", "component"]
var_biter_day_io <- vc_io["pig_id_biter:day", "component"]
var_victim_day_io <- vc_io["pig_id_victim:day", "component"]
var_dyad_io <- vc_io["pig_id_biter:pig_id_victim", "component"]
var_pen_io <- vc_io["pen", "component"]

var_random_io <- var_biter_io + var_victim_io + var_biter_day_io +
              var_victim_day_io + var_dyad_io + var_pen_io

# Calculation beta0 and lambda and variance of the deviation

beta0 = coef(model_intercept_only_biting)$fixed["(Intercept)", "effect"]
lambda = exp(beta0 + (0.5*var_random_io))
var_deviation <- log(1 + 1/lambda)

# Total variance
total_variance = var_random + var_deviation
```

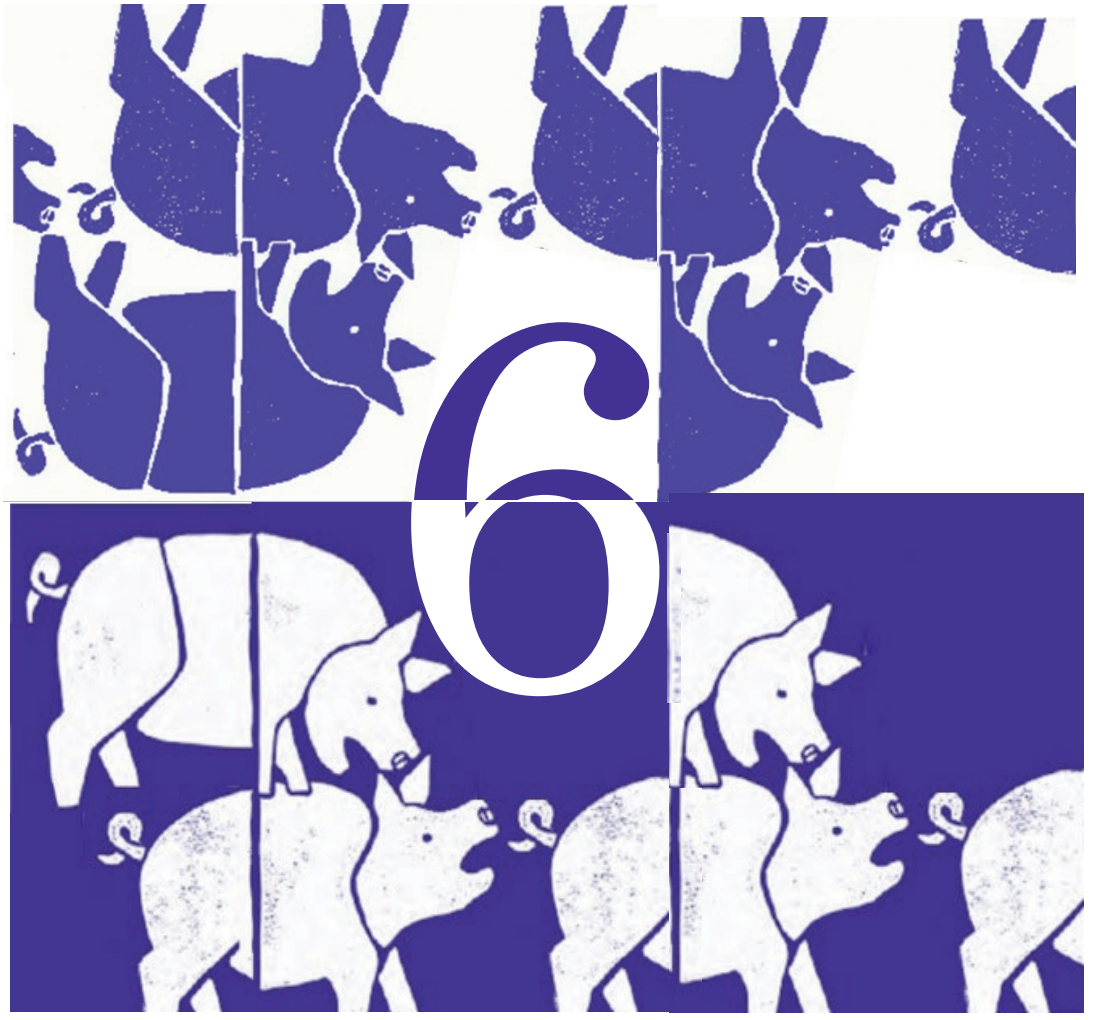
Summary of the fixed effect (Day)

Table S3 presents the estimate of the fixed effect of day on tail biting, ear biting and proximity. No significant effect of day was found on any of the response variables (tail biting: Wald $\chi^2 = 3.68$, $P = 0.16$; ear biting: $\chi^2 = 0.25$, $P = 0.88$; proximity: $\chi^2 = 4.52$, $P = 0.10$).

Table S3. Estimated fixed effect of day (D_{-2} and D_{+1} relative to D_{-5}) on tail biting, ear biting and proximity

Social interaction	Estimates		Wald χ^2	*P*-value
	D_{-2}	D_{+1}		
Tail biting	-0.08	0.13	3.68	0.16
Ear biting	0.04	0.05	0.25	0.89
Proximity	-0.51	6.30	4.52	0.10

Chapter 6



Chapter 6

Behaviour recognition of tail and ear biting in pigs using AI-based computer vision

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Abstract

Damaging behaviours in pigs, such as tail biting and ear biting, compromise animal welfare and farm productivity. Continuous monitoring of these behaviours is essential to intervene before escalation, gain insights into underlying causes and develop breeding programs to select pigs with lower genetic propensity for such behaviours. However, manual observations are impractical at a large-scale. To address this challenge, we propose a video-based behaviour recognition system that facilitates the automated monitoring of individual pigs. Two state-of-the-art video-based methods are investigated: SlowFast and Improved Multiscale Vision Transformers (MViTv2) for recognising tail and ear biting in pigs, by exploiting spatiotemporal domain features. Data are collected on a commercial pig farm. In total, 532 tail-biting events (63,815 frames) and 750 ear-biting events (78,132 frames) are annotated across seven pens of tail-docked pigs. Tail biting and ear biting are defined as nibbling, sucking, chewing, or biting the tail or the ear of a pen mate. The best-performing method is based on the MViTv2-S model, which enables efficient spatiotemporal modelling. The detection accuracies obtained for tail and ear biting are 72.22% and 72.37%, respectively. An important and novel aspect, to our knowledge, is that, for the first time, behaviour detection is developed without a posture requirement on the biter or the victim. The conducted experiments demonstrate the feasibility of computer-vision-based models for the recognition of damaging behaviours on commercial pig farms. This study is a crucial step towards the development of an automated early-warning system and breeding programs to reduce tail biting and ear biting.

1. Introduction

Tail and ear biting are serious behavioural issues in commercial pig farms, which greatly compromise both the welfare of the pigs and the income of the farmer (Bracke et al., 2004; Haigh and O'Driscoll 2019; Schrøder-Petersen and Simonsen 2001). These behaviours can cause severe damage to the victims, such as wounds or (partial) loss of the tail or ears, and infections. Tail and ear biting can occur in isolated cases involving only a limited number of pigs, or rapidly escalate into an outbreak within the group (Diana et al., 2019; Taylor et al., 2010). Tail biting has been widely studied and is known as a multifactorial problem with many risk factors, such as high stocking density (Laskoski et al., 2019), imbalanced diet (McAuley et al., 2022; Minussi et al., 2023), and stimulus-poor environments (Van de Weerd et al., 2005). Ear biting has been studied less frequently, but appears to have partly similar risk factors as tail biting (Diana et al., 2019). Both behaviours may be the result of pigs that redirect their natural need for foraging and exploration towards their pen mates when suitable rooting and chewing materials are absent (Brunberg et al., 2011; Camerlink and Turner 2013; Meer et al., 2017; Staaveren et al., 2024).

Effective methods for reducing the escalation of damaging behaviours are currently limited. For instance, tail docking is often performed to reduce the risk of tail biting. However, routine tail docking is prohibited in Europe, which increases the societal pressure to leave pigs' tails intact. Consequently, there is an urgent need to develop alternative measures to prevent tail-biting outbreaks. It has been shown that early-stage interventions at the pen level, such as providing (additional) enrichment materials, or at the individual level like removing the biter or the victim, can mitigate the escalation of these damaging behaviours into an outbreak (Chou et al., 2019; Haigh and O'Driscoll 2019). However, adding extra enrichment is not always practical. Instead, farmers typically only carry out routine observations of the pen and lack time to inspect the tail and ears of each pig due to the high workload and large-scale size of their farms. Therefore, the damage is generally detected only at an advanced stage with severe wounds. Moreover, inspection of the tail and ears allows the identification of only the victim, since tail and ear biting are sporadic behaviours that most likely hardly occur while the farmer is present, making it particularly difficult to identify the biter. This restricts effective intervention strategies to prevent an outbreak and limit escalation, particularly the timely removal of the individual biter.

In addition, there is evidence that tail and ear damage are heritable traits (Breuer et al., 2003; Canario and Flatres-Grall 2019; Gorssen et al., 2024; Hermesch and Guy 2019), which can be used in genetic selection programs to reduce damaging behaviours in future pig populations. This explains why previous studies have focused on tail and ear damage, rather than the behaviour that causes the damage itself. However, genetic analysis requires large-scale data from a significant number of individual pigs to accurately estimate the genetic parameters, whereas tail and ear damage are merely indirect measures for studying tail and ear biting and only provide information about the victim.

A large-scale deployment of automated monitoring systems capable of detecting tail and ear biting can provide valuable support to farmers and breeding companies to reduce these damaging behaviours. Video-based monitoring systems in combination with computer vision can potentially offer continuous monitoring at relatively low costs, with minimal disturbance to the pigs, requiring simple setup and maintenance only. Chen et al. (2020) reviewed that computer vision has shown promising results in recent years for the detection of simple behaviours in pigs, such as feeding, drinking, or walking. So far, automated recognition of social interactions between pigs has focused mainly on aggression (Chen et al., 2019; Haigh and O'Driscoll 2019; Lee et al., 2016; Oczak et al., 2014; Viazzi et al., 2014), mounting (Nasirahmadi et al., 2016), and play behaviour (Larsen et al., 2023), which are all characterised by the short distance between pigs and their rapid movements and rotations (Gan et al., 2021). Only a few studies have attempted to identify tail and ear biting with computer vision. Liu et al. (2020) developed a method to detect and locate tail biting, with an accuracy of 89.23%. Despite its high performance, this model did not detect tail-biting events that occurred without escaping and chasing movements. Moreover, the applied definition of tail biting, i.e. "biting a pen mate's tail, with a sudden reaction of the pen mate", excluded biting events in which the victim did not react, whereas both at early and later, severe stages of tail-biting victims did not always exhibit clear responses to being bitten. This shortcoming is partly related to the distinct types of tail biting that have been identified, i.e., "two-stage", "sudden-forceful", and "obsessive". Each is associated with different victim behaviours across their stages (Taylor et al., 2010). In sudden-forceful and obsessive tail biting, the victim typically reacts by avoiding the biter (Taylor et al., 2010), behaviours likely captured by Liu's algorithm (Liu et al., 2020). In contrast, in two-stage tail biting the biter starts by gently chewing the tail of a pen mate, usually while both animals are lying down and with little response from the victim. This form of biting may escalate into severe biting, especially when blood appears on the nibbled tails. The victim may react at first by head-

knocking or by avoiding the biter, but gradually becomes apathetic, resisting less and spending more time lying down (Sambraus 1985). Unfortunately, this type of tail biting is not included in the method of Liu et al. (2020). Furthermore, the development of their model is based on a relatively homogeneous dataset, with 247 events derived from two pens, each observed on a single day, which may have shown a particular type of biting and outbreak. In comparison, Hakansson and Jensen (2023) used a broader definition of tail biting, which also included tail biting events without a reaction from the victim to develop their model. This work was based on 208 tail-biting events scored from ten different pens prior to weaning. In their experiments, features were extracted from the entire frame, leading to the inclusion of extraneous information that introduced additional noise in the spatial domain. Their best-performing model achieved a major-mean accuracy of 71.3%. False negatives still occurred when pigs were lying and huddling or engaging in play/fight behaviours. Given the limitations in the presented works thus far, more research is required to recognise tail biting at an early stage. Automated detection of ear biting has been studied in one research group, including the individual pig identification and the localisation of regions of interest (paired pig heads) associated with ear-biting events (Odo et al., 2023, 2024). In addition, recognition models developed in previous studies have focused on either ear or tail biting, but no model has been designed to recognise both behaviours individually.

Despite these advances, automated recognition of ear and tail biting remains under-studied and methodologically constrained. Existing animal-focused approaches often rely on narrow operational definitions, limited recording contexts, or frame-level features that are sensitive to occlusions and pen-level clutter. In view of this growing but still limited body of research on animal behaviour recognition based on computer vision, it is potentially attractive to leverage more mature behaviour studies from human action recognition as interesting transferable backbones. Such models can be fine-tuned on pig data to learn robust appearance–motion representations, since tail and ear biting are spatiotemporal interaction events. Recognising such behaviours requires modelling appearance and motion across short clips—exactly the inductive bias encoded by mature human action recognition models (e.g., 3D CNNs (Carreira and Zisserman 2017; Feichtenhofer 2020), SlowFast-style dual pathway fusion (Feichtenhofer et al., 2019), and video transformers (Fan et al., 2021).

This work aims to develop an automated recognition model that can detect individual tail-biting and ear-biting events in pigs on commercial farms. We first investigate state-of-the-art methods in human action recognition. The models are trained on a large pig dataset, which

is manually annotated. Combined with the use of the 2D camera-based systems integrated with computer vision, this work facilitates the application of advanced deep learning technologies. All data from the original recordings are utilised for learning both appearance (spatial) and movement (temporal) features using deep networks. In this system, the bounding boxes of each pig are cropped from the video sequence and stored as a single-object video clip for behaviour recognition purposes. In this way, spatiotemporal features are retained as much as possible.

The contributions of this work include the following three aspects.

1. A computer-vision-based model is proposed for predicting tail-biting and ear-biting behaviours in pigs. A comprehensive investigation and comparison are performed for two state-of-the-art (human) action recognition networks: SlowFast and Improved Multiscale Vision Transformers (MViTv2) models.

2. The proposed method is specifically designed to detect individual ear-biting and tail-biting incidents in pigs, regardless of the activity level or posture of the biter and the victim.

3. The proposed model is developed using data collected from a commercial pig farm. The dataset contains a large number of annotated events with considerable variability (e.g., pens, age of the pigs, and lighting conditions). Additionally, the dataset includes precise localisation in the form of annotated bounding boxes, along with corresponding behaviour labels for the biter, categorising actions into tail biting, ear biting, and other.

2. Related Works

In computer vision, action recognition is one of the most challenging tasks, continuously drawing significant research interest. Numerous studies have investigated representations of spatiotemporal features for video analysis, including holistic feature-based methods (Lowe 2004; Hofmann 2001; Ke et al., 2007), RGB-D information-based methods, such as 3D-MHI (Lowe 2004), and Depth Motion Maps (DMMs) (Chen et al., 2015). Several studies utilised optical flow extracted from video sequences for movement analysis in applications, such as speed prediction and vehicle assessment (Balasundaram et al., 2019; Wang and Schmid 2013). Although optical flow effectively captures motion between consecutive frames, it has its limitations in the field of action recognition, since it solely focuses on

movement information without considering broader action patterns. The conventional methods often rely on handcrafted features for action recognition, typically involving stages of feature extraction and representation, computation of local descriptions, and final classification. Although these approaches have laid the foundation for video-based behaviour analysis, their performance is often constrained by their dependence on manually designed features and limited ability to generalise across varying contexts.

Convolutional neural networks (CNNs) such as AlexNet (Krizhevsky et al., 2012) and ResNet (He et al., 2016), have become standard backbone architectures due to their important breakthroughs in image analysis. The you-only-look-once (YOLO) series method is developing rapidly, branching out from the original object detection task to other tasks, such as pose estimation (Redmon et al., 2016). The pose estimation branch of YOLO utilises both bounding box and keypoint inputs at the frame level, enabling effective multi-feature learning. In particular, a study on the estimation of pig poses using the YOLOv8 pose estimation model has achieved a posture recognition accuracy of 99.33% (Guo et al., 2025). However, these methods are not suitable for action recognition in videos. The key difference between image and video processing is the possibility of capturing temporal information across video frames for comprehensive video understanding. Unlike static 2D images containing only spatial information, methods for video-based action recognition can integrate both spatial and temporal features to accurately capture dynamic actions and movement patterns.

Using deep networks for temporal representations in video analysis has gained increasing attention. Recent studies attempted to implement recurrent neural networks (RNNs) and their variants to extract spatiotemporal features (Liu et al., 2016; Yang et al., 2017). The primary advantage of RNN architectures is their ability to process sequential inputs, making them suitable for video processing tasks where each frame is treated as an element of a temporal sequence. Through this sequential modelling, the RNN model captures temporal dependencies and learns meaningful representations of dynamic features. However, a significant downside of RNN models is the long-term dependency caused by the vanishing gradient problem. To address this issue, long short-term memory (LSTM) was introduced by incorporating three gating mechanisms and the memory cell to regulate the flow of information and enable long-term dependency learning (Hochreiter and Schmidhuber 1997). However, training LSTMs is hampered by their susceptibility to overfitting, especially when working with limited datasets, like animal behaviour datasets.

Similarly, spatiotemporal features can be automatically extracted by 3D convolutional layers, addressing both spatial and temporal dimensions. The experimental results of another study (Ji et al., 2012) showed that the 3D CNN model outperforms other state-of-the-art handcrafted methods for action recognition. Although 3D CNN-based methods have been applied for action recognition tasks and have achieved good results, such as I3D (Carreira and Zisserman 2017), the improvement over the best handcrafted approach (iDT (Wang and Schmid 2013)) is not as significant as compared to the impact for image recognition. One major issue of 3D CNNs for video-based action recognition is the high computation cost compared to their 2D counterparts. For example, the number of multiple sum operations needed for an image in ResNet (He et al., 2016) is about 27 times lower than that of a temporally extended variant for video (Wang et al., 2018). The Expand 3D model (X3D) (Feichtenhofer 2020) is proposed to achieve high accuracy in the complexity trade-off for action recognition. X3D progressively expands a tiny base 2D image architecture into a spatiotemporal architecture by expanding along multiple axes, such as temporal duration and frame rate.

To further investigate 3D CNNs, researchers (Tran et al., 2015) have reconsidered the 3D CNN in the residual learning framework, which caused a breakthrough in image processing. They introduced a (2+1)D convolution block to factorise 3D convolution into two separate and successive operations for a 2D spatial convolution and a 1D temporal convolution. This factorisation effectively doubles the number of non-linear processing elements, compared to a network that uses full 3D convolutions with the same number of layers. The authors posed that the (2+1)D convolution block can represent more complex functions than a single 3D convolution. Meanwhile, factorisation leads to a more straightforward optimisation procedure. In this study, experiments demonstrated that ResNet with incorporated (2+1)D blocks, homogeneously added to all layers, achieved top performance on both the Kinetics and Sports-1M datasets.

Recently, research interests have developed towards employing a self-attention mechanism on images. In the field of natural language processing (NLP), transformers (Vaswani et al., 2017) have been proposed for machine translation based on mechanisms of self-attention. These mechanisms are utilised to extract the relationships between each word in a sentence and have been widely used in many NLP tasks. In general, a transformer uses blocks with two basic operations. The first block is an attention operation for representing *inter*element relations. The second is a multi-layer perceptron (MLP) to model relations between elements.

Directly applying such self-attention to images requires each pixel to relate to all other pixels in the vicinity. This imposes a considerable computational cost for realistic input sizes. For this reason, several approximations have been investigated.

Vision Transformer networks (ViTs) have demonstrated the strong potential of the application of transformers in computer vision, and achieved excellent results in image recognition (Dosovitskiy et al., 2020). These networks split an image into patches and offer the sequence of linear embeddings of these patches as input to a transformer, where image patches can be considered as tokens in an NLP application. However, there is a limitation to the application of ViTs. To obtain good performance in image recognition, the ViT models need to be pre-trained at a sufficient scale before assigning them to tasks with fewer data points. The fundamental reason for this limitation is that transformers lack some of the inductive biases inherent to CNNs, so they do not generalise well when trained with insufficient data.

To further develop ViTs, Multi-scale Vision Transformers (MViTs) are proposed for video/image recognition (Fan et al., 2021). MViTs connect the idea of multi-scale feature hierarchies with transformer-based models. Unlike conventional transformers that maintain a fixed channel capacity and resolution throughout the network, MViTs have several channel-resolution scaling stages. This network design learns a hierarchy from dense space features and simple temporal features to coarse space features and complex temporal features, since the stages hierarchically expand the channel capacity while reducing the spatial resolution. One benefit of this design is the presence of an implicit solid temporal bias, which is a lacking mechanism in ViTs.

3. Materials and methods

3.1. Data description

The data for this study was collected between December 2020 and August 2022 at the premises of a breeding company (Topigs Norsvin, Den Bosch, the Netherlands) at a commercial farm for growing-finishing pigs in Germany. The tail-docked pigs, spread across three batches, arrived at the age of 10 weeks (body weight: 25.4 ± 0.4 kg) and remained for around 12 weeks. One batch consisted of Piétrain × (Landrace × Large White) pigs, housed in single-sex pens containing both barrows and gilts, whereas the other two batches comprised Landrace × Large White pigs and included only barrows. The pigs were housed

in 10 fully slatted pens spread over 5 rooms. According to European regulation, the space allowance is 1.03 m^2/pig, with 11 pigs per pen. The pigs had *ad libitum* access to two drinking nipples and feed from an electronic feeding station. They were fed a commercial dry feed based on a proportion of crude protein adjusted to the weight range (Bus et al., 2023). Each pen contained as enrichment a wooden block, a chain with plastic rings, and an additional feeder from which the pigs could obtain chopped straw mixed with straw pellets by manipulating a chain. The pens were naturally illuminated through windows, and no artificial lighting was provided except during human presence in the room. A camera (model 4KSDAI168, Lorex Technology Inc., Markham, Canada) was mounted above each pen with a top-down view. Videos were recorded with a frame rate of 15 frames/sec. and a resolution of 1280×720 pixels. A mark was sprayed on the back of each pig to recognise them individually in the videos. Since tail-biting and ear-biting behaviours rarely occur, we selected and observed videos from the days preceding the identification of severely damaged pigs (Bus et al., 2023). This resulted in a total of 7 selected pens for annotation, spread across 3 batches and 12 different days. Each pen was annotated for 1-3 days, with the pigs' ages ranging from 14 to 22 weeks.

3.2. Data annotations

There are two primary branches of data annotation in this work: behaviour annotation and bounding-box annotation; both are continuous annotations (each frame).

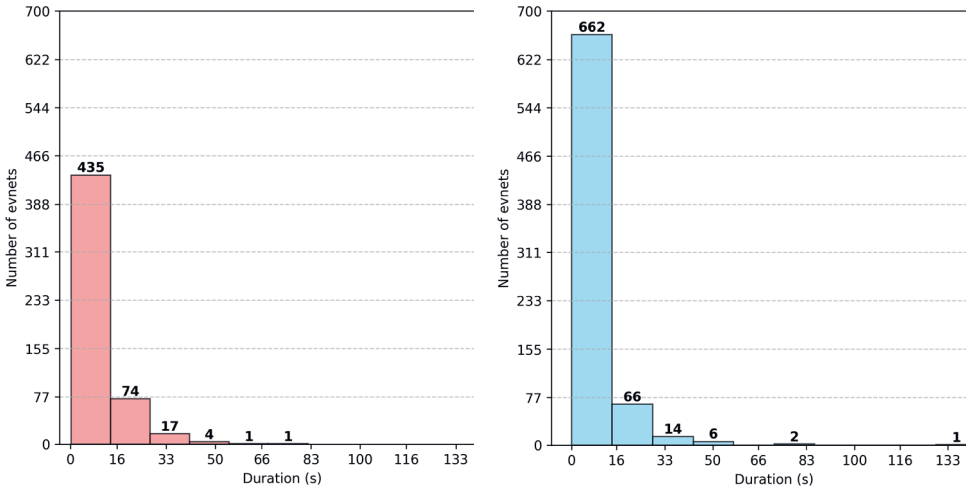
Prior to behaviour annotation, the observers carefully examined videos from entire days to identify segments of videos with tail-biting and ear-biting events. These events were then annotated using The Observer XT16 (Noldus Information Technology, Wageningen, The Netherlands), according to the definitions presented in Table 1. Three observers scored these behaviours after reaching an inter-observer reliability score of Cohen's kappa > 0.75. Behaviours were scored as a state, and instances with an interruption of more than 1 second within the behaviour were considered as two separate events for that behaviour. Examples of annotated frames are presented in Figure 1a for tail-biting events and in Figure 1b for ear-biting events.

Annotation of the bounding boxes was performed to locate individual pigs in each video frame. This process was performed using the computer vision annotation tool (CVAT) (Manovich and Sekachev 2019).

In total, 750 ear-biting events were annotated across 78,132 frames (5,209 seconds), and 532 tail-biting events across 63,815 frames (4,254 seconds). The duration of tail-biting events ranged from 1 second to 82 seconds (Figure 2a), and the duration of ear-biting events ranged from 1 second to 143 seconds (Figure 2b).

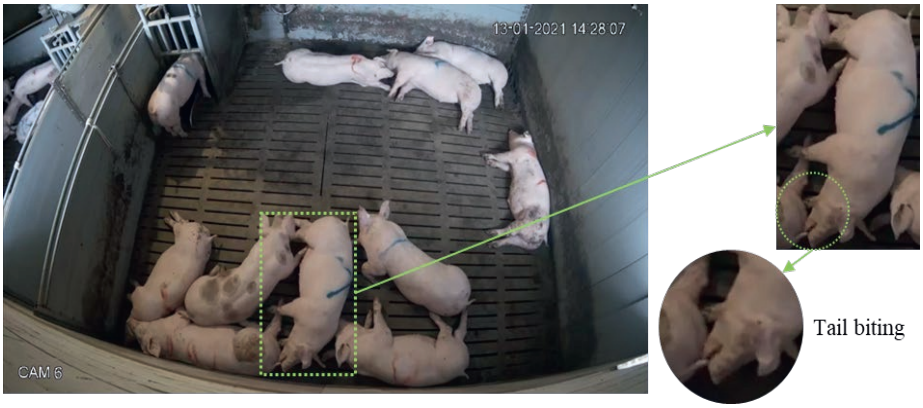
Table 1 . Ethogram with the description of the behaviours annotated in this study.

Behaviour	Description
Ear biting	Nibbling, sucking, chewing or (forcefully) biting the ear of a pen mate .
Tail biting	Nibbling, sucking, chewing or (forcefully) biting the tail of a pen mate.
Other	Any other behaviour.



(a) *Tail biting* (b) Ear biting

Figure 2. Histograms based on event counting, showing the frequency distribution of the duration of (a) tail-biting and (b) ear-biting events in the dataset.



(a) Tail-biting event example.



(b) Ear-biting event example.

Figure 1. Examples of frames containing (a) tail-biting and (b) ear-biting events, used for the development of the model. The biter is highlighted in each frame with a green dashed bounding box, which is used as an input to the network. The zoomed-in parts of the image highlight the specific biting event in more detail.

3.3. Behaviour recognition models

In this study, we leverage two state-of-the-art (SOTA) methods, SlowFast and MViTv2, in human action recognition, which effectively use spatiotemporal feature learning to enable robust performance.

SlowFast

The SlowFast model employs a dual pathway CNN architecture, where one pathway captures spatial semantic features, and the other focuses on obtaining action information that changes over time in the temporal dimension (Feichtenhofer et al. 2019). This design enables the model to effectively balance spatial detail with motion-sensitive information, making it well-suited for action recognition tasks.

The Slow pathway operates at a low frame rate (e.g. sampling 1/16th of the sequence of input frames) to capture detailed spatial semantics and contextual information. It leverages a deep network trained on images or sparse frames, updating slowly because of its lower sampling rate. In contrast, the Fast pathway samples frames at a higher rate (e.g. 1/4th of the frame sequence) to offer a higher temporal resolution with a lightweight architecture. This part focuses on rapidly changing motion and temporal variations. The network architecture of SlowFast is illustrated in Figure 3, comprising a low frame rate, low temporal resolution (Slow) pathway and a high frame rate, $\alpha \times$ the higher temporal resolution (Fast) pathway.

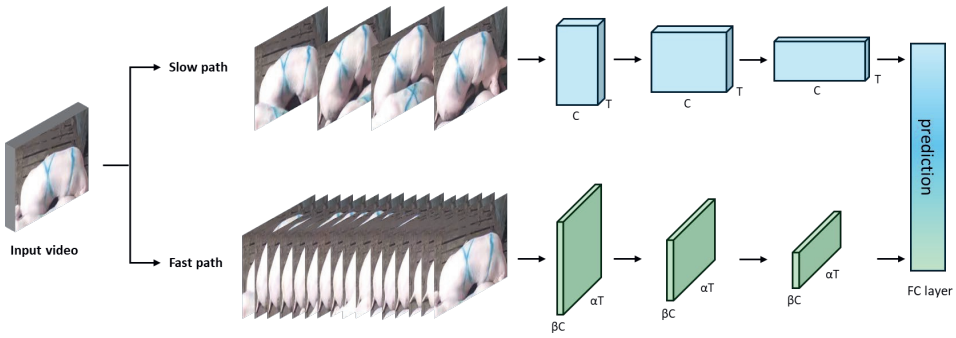


Figure 3. SlowFast network architecture, consisting of a Slow pathway and a Fast pathway, which are fused by lateral connections. The parameter C represents the channel number, parameter T denotes the number of frames sampled by the Slow pathway, while the Fast pathway samples αT frames, α times denser than the Slow pathway. The Fast pathway is lightweight by using a fraction of the channels (denoted by β, e.g. $\beta = 1/8$).

Lateral connections are employed to fuse features in optical-flow-based, two-stream networks (Feichtenhofer et al., 2016; Feichtenhofer et al., 2017). In the SlowFast model, this feature fusion stage enables the integration of multi-resolution information across the two pathways, allowing for the joint modelling of appearance and motion. However, each pathway operates independently, meaning that one is not explicitly aware of the

representations learned by the other. This architectural design optimally balances computational efficiency and accuracy, achieving state-of-the-art performance in action recognition and video understanding tasks. Finally, global average pooling is applied to the output of each pathway. The resulting feature vectors are concatenated and subsequently supplied to a fully connected classifier.

MViTv2

The Multiscale Vision Transformer v2 (MViTv2) model enhances the original MViT architecture by incorporating hierarchical vision transformers with multi-scale feature learning (Fan et al., 2021; Li et al., 2022). Unlike conventional convolutional approaches, which rely on local receptive fields, MViTv2 leverages self-attention mechanisms to model long-range dependencies across both spatial and temporal dimensions. Through hierarchical pooling, the model progressively reduces spatial resolution while increasing channel capacity, enabling an efficient coarse-to-fine feature extraction process that enhances representational power. The network architecture of the MViTv2 model is shown in Figure 4. In this network, the input video is initially partitioned into non-overlapping spatiotemporal patches (tokens) via 3D patch embeddings. The MViTv2 model follows a hierarchical structure in which token resolution is progressively reduced while channel dimensionality increases. At first, the input resolution is the largest and the number of channels is the smallest. As the network deepens, the channel capacity is expanded while the spatial resolution is reduced. This design generates a multi-scale feature pyramid, where the early layers operate at high spatial resolution to model simple low-level visual information, while the deeper layers model high-dimensional features that are spatially coarse but complex.

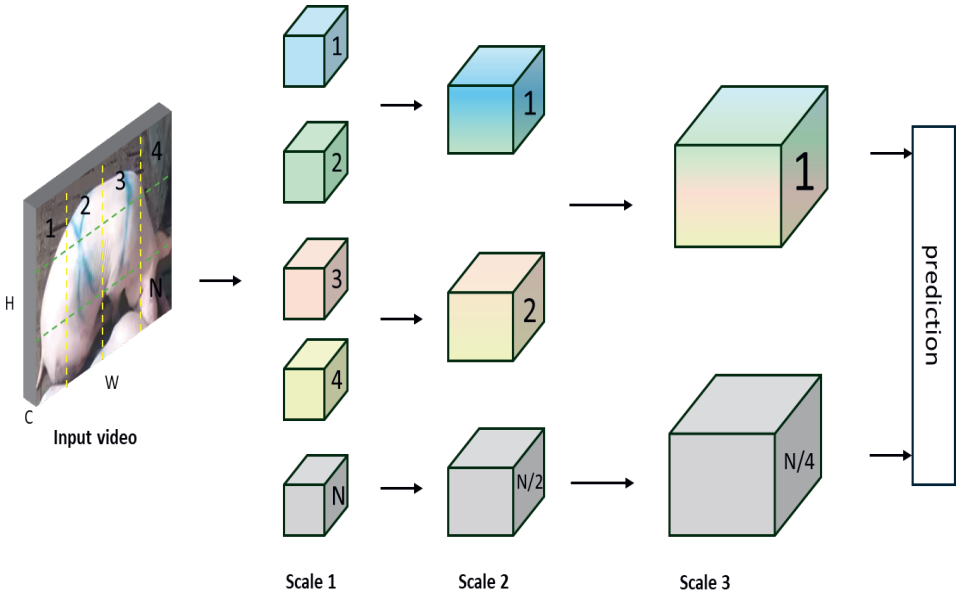


Figure 4. The MViTv2 architecture creates multi-scale feature hierarchies by combining dense spatial inputs with lightweight channel representations using transformers. The parameter C denotes the number of feature channels, while W and H represent the spatial width and height of the input image, respectively.

The additional benefit of this architecture is that it effectively reduces computational complexity while preserving rich multi-scale representations. Rather than applying global self-attention across all tokens, the MViTv2 model employs progressive token pooling to minimise the redundancy, thereby improving both efficiency and scalability. The attention-based pooling mechanism replaces conventional max-pooling with transformer-driven feature aggregation, enhancing cross-scale information fusion. Furthermore, the MViTv2 model introduces decomposed positional encoding, which separately encodes spatial and temporal embeddings to improve the capture of spatiotemporal relationships, a critical factor for action recognition tasks. Additionally, the adaptive optimisation of channel resolution dynamically adjusts channel dimensions during downscaling, striking a balance between computational efficiency and representational capacity. These architectural refinements enable MViTv2 to effectively model long-range dependencies combined with variable input resolutions, outperforming conventional CNN-based architectures and earlier transformer-based systems in complex spatiotemporal modelling tasks.

3.4. Evaluation metrics

To evaluate the performance of the behaviour recognition model for pigs, we employ evaluation metrics generally applied in human action recognition, i.e., Top-1 accuracy, individual classification accuracy, and inference time.

Top-1 accuracy reflects the overall accuracy, i.e. the ability of the model to confidently assign the correct prediction in cases where there are multiple possible actions. This makes it a key performance indicator for action recognition tasks. The Top-1 accuracy $A_{\text{Top-1}}$ provides a general sense of model performance, calculated as the ratio of correctly predicted instances to the total number of instances, which is specified by:

$$A_{\text{Top-1}} = \frac{N_{\text{correct}}}{N_{\text{total}}},$$

where N_{correct} denotes the total number of correct predictions, and N_{total} is the total number of predictions.

In addition to the overall classification accuracy, distinguishing the specific biting behaviours is important for practical applications in pig farming. Therefore, the individual classification accuracies for tail biting and ear biting are also calculated. The individual classification accuracy is specified by:

$$A_{\text{class}} = \frac{N_{\text{TP}}}{N_{\text{TP}} + N_{\text{FN}}},$$

where, for individual behaviour, N_{TP} denotes the number of true positives (TP), and N_{FN} is the number of false negatives (FN).

Furthermore, considering the real-world implementation of the system, it is essential to evaluate the inference time, measured in frames/sec. (fps), to assess the feasibility of real-time monitoring.

4. Results

4.1. Dataset summarisation

For this study, the behaviours of pigs are manually annotated in each frame with a bounding box and a behaviour class label. Next, for each video segment containing a behaviour listed in the ethogram, all frames in that segment are cropped to the bounding boxes of the animal exhibiting that behaviour. Finally, the dataset is divided into training, validation, and testing sets in a $8:1:1$ ratio. The detailed distribution of behaviour events across these subsets is presented in Table 2.

Since the original dataset exhibits an imbalanced distribution and limited data volume, data augmentation techniques are applied to enlarge and enhance the training dataset. The augmentation strategies include horizontal flipping, vertical flipping, and rotation over 90, 180, and 279 degrees, which help to improve the model's generalisation and mitigate the effects of data imbalance.

Table 2. Statistics of the experimental dataset for behaviour recognition.

Dataset parts	Event No. Total	Event No. Tail biting	Event No. Ear biting	Event No. Other
Training set	1733	425	600	708
Validation set	216	53	75	88
Testing set	219	54	75	90
Overall	2168	532	750	896

The numbers indicate the data distribution across the number of events per behaviour divided into three classes: tail biting, ear biting, and other.

4.2. Implementation details

The datasets are pre-processed identically for the SlowFast model and the MViTv2-S (small) model. Each event segment is sampled at a temporal stride of 8 frames, resulting in input sequences consisting of 8 frames. Then, all frames are resised to 224×224 pixels to construct the input video segment. This results in an input of 8×224×224×3, where the temporal dimension is 8, the number of channels is 3, and the height and width of the video are 224. All conducted experiments are executed without pre-training. The SlowFast model utilises a

baseline of ResNet-101 and is trained for 1,000 epochs, with a learning rate of 0.01 and a batch size of 16. The MViTv2-S model is similarly trained for 1,000 epochs, with a learning rate of 0.0001 and a batch size of 16. All experiments are executed on an RTX 2080Ti GPU (NVIDIA Corp, Santa Clara, CA, USA).

4.3. Behaviour recognition results

The results presented in Table 3 compare the performance of the two models SlowFast and MViTv2-S, for recognising tail biting and ear biting on the test dataset. Both models are evaluated with and without using data augmentation during training. The analysis highlights the impact of data augmentation on the recognition accuracy. The evaluation metrics include Top-1 accuracy, accuracy for tail biting, accuracy for ear biting, and inference time in fps.

The SlowFast model with data augmentation obtains the highest Top-1 accuracy of 81.36%. Both models improve by using data augmentation, where the MViTv2-S model achieves a 3.19% increase with the augmentation strategy.

For tail-biting recognition, the accuracy of the SlowFast model significantly improves with data augmentation, increasing from 57.41% to 74.07%. Similarly, the MViTv2-S model also shows considerable improvement, with the accuracy rising from 59.26% to 72.22%. While both models benefit from augmentation, the improvement is more pronounced in SlowFast.

For ear-biting recognition, the SlowFast model achieves 76.32% accuracy without augmentation, but its performance drops to 68.42% when augmentation is applied. In contrast, the MViTv2-S model shows a positive impact of data augmentation, with the accuracy improving from 67.11% (without augmentation) to 72.37% (with augmentation). This suggests that the MViTv2-S model benefits from augmentation in ear-biting recognition, whereas the SlowFast model exhibits reduced performance.

In terms of inference time, the small architecture of the MViTv2-S model facilitates computational efficiency, resulting in an inference time of 28.62 fps, which is 8 fps faster than the SlowFast model.

Table 3. Performance comparison of the two models for biting behaviour recognition, with or without data augmentation.

Model	Data augmentation	Top-1 Acc. (%)	Tail biting Acc. (%)	Ear biting Acc. (%)	Inference time (fps)
SlowFast	No	80.00	57.41	**76.32**	20.56
SlowFast	Yes	**81.36**	**74.07**	68.42	20.56
MViTv2-S	No	76.36	59.26	67.11	28.62
MViTv2-S	Yes	79.55	72.22	72.37	28.62

The table presents the Top-1 accuracies and behaviour-specific accuracies (Acc.). The highest scoring performance is in bold font.

Furthermore, the confusion matrix shown in Figure 5 illustrates the individual classification performance. For the targeted biting behaviours, the model achieves a balanced classification accuracy of around 72% for both ear biting and tail biting. However, some misclassifications occur between these two categories, with 20% of tail-biting events being incorrectly labelled as ear biting and 13% of ear-biting events being misclassified as tail biting. The confusion of tail biting with the category 'other behaviours' is more rare, as only 7% of tail-biting events are misclassified as 'other behaviour', and conversely, 6% of other behaviour is misclassified as tail biting. However, 14% of ear-biting behaviour is incorrectly predicted as other behaviour.

Figure 6 presents some examples of correct predictions for tail biting (Figures 6a and 6b) and for ear biting (Figures 6c and 6d). As shown in Figures 6a and 6c, both the victim and the biter are lying down. Figure 6b shows both the biter and the victim standing, while in Figure 6d, the biter is standing and the victim is lying down. These results show that the model successfully recognises the behaviours across different postures of the biter and victim.

Some examples of wrong predictions are visualised in Figure 7, where Figures 7a and 7b show confusion between ear biting and tail biting, while in Figures 7c and 7d confusion between tail biting and other behaviour is visualised.

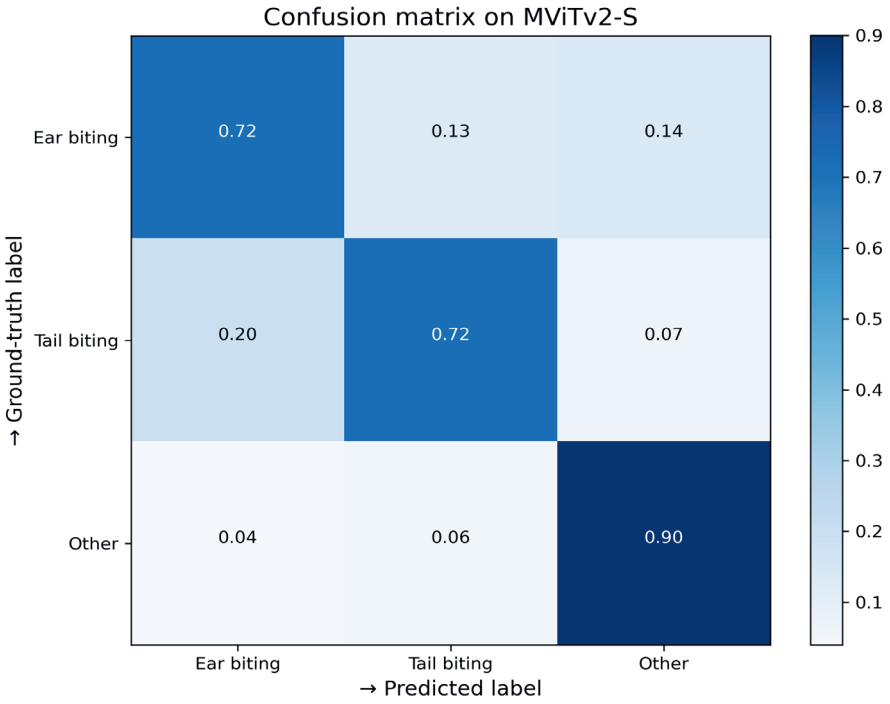


Figure 5. Results of the confusion matrix on the MViTv2-S model with data augmentation.



(a) Ground truth: Tail biting, Predicted: Tail biting.



(b) Ground truth: Tail biting, Predicted: Tail biting.



(c) Ground truth: Ear biting, Predicted: Ear biting.

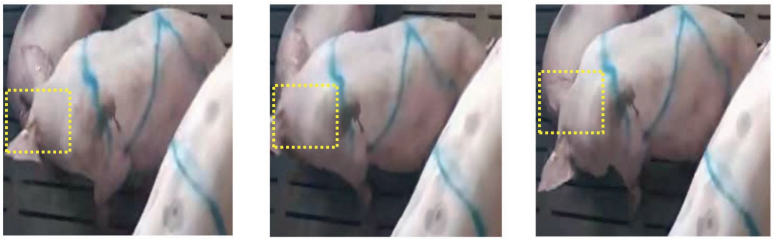


(d) Ground truth: Ear biting, Predicted: Ear biting.

Figure 6. Visualisation examples of correct predictions.



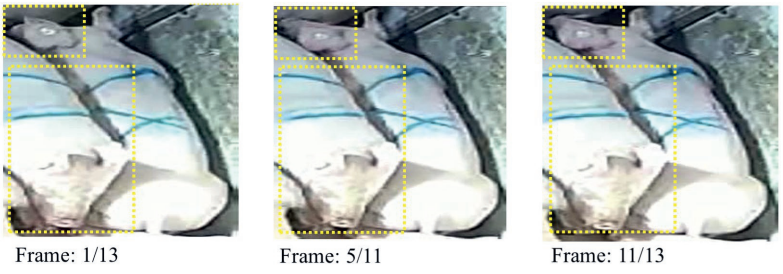
(a) Ground truth: Ear biting, Predicted: Tail biting.



(b) Ground truth: Tail biting, Predicted: Ear biting.



(c) Ground truth: Other, Predicted: Tail biting.



(d) Ground truth: Tail biting, Predicted: Other.

Figure 7. Visualisation examples of wrong predictions. The areas of confusion are highlighted within the yellow bounding box.

5. Discussion

5.1. Robustness through data variety and limited events

Data variety

In this study, we apply state-of-the-art computer vision methods to monitor tail biting and ear biting in group-housed pigs. Our methods are based on tail-biting and ear-biting events, regardless of the response of the victim, and the posture of the biter or the victim. Recognising tail and ear biting without active reaction of the pigs is highly valuable, since in most cases, and especially in the two-stage type of tail biting, the victim does not show visible reactions (Taylor et al., 2010). Furthermore, compared with previous work (Liu et al., 2020; Hakansson and Jensen, 2023), the proposed models are developed using a substantially larger dataset, with 750 ear-biting events and 532 tail-biting events, compared to the two previous studies on tail-biting detection, which were based on 247 events (Liu et al., 2020) and 208 events (Hakansson and Jensen, 2023). Additionally, the newly developed dataset includes events with pigs of different ages (from 14 to 22 weeks), housed in 7 different pens, and exposed to diverse lighting conditions, leading to improved robustness and generalisation. In contrast, Liu et al. (2020) focused only on two pens, with recordings limited to 8 hours of daylight on two specific days (day 8 and day 44), while Hakansson and Jensen (2023) used data from 10 pens but recorded only 2 hours per day on a single day (pre-weaning).

Recognition of damaging behaviours

The confusion matrix shown in Figure 5 highlights that the main errors occur between tail biting and ear biting, and not between either of the classes of damaging behaviours and the class of other behaviours. Misclassifying tail biting and ear biting is less critical than false negatives, where damaging behaviours are mistaken for other behaviours. Distinguishing damaging behaviours from other behaviours, even if some confusion between ear and tail biting occurs, is still valuable for improving pig welfare. Firstly, it has been shown that tail biters also perform more ear biting (Brunberg et al., 2011; Ursinus et al., 2014; Hakansson and Bolhuis 2021; Bagaria et al., 2022), which is relevant for the identification of the biter and genetic selection. Secondly, because tail and ear biting share common risk factors and can both be reduced through similar interventions, such as adding additional enrichment material, incorrect labelling of ear biting as tail biting or vice versa is less crucial for early warning purposes (Ursinus et al., 2014). This suggests that the system developed in this study

with the MviTv2-S model can already provide valuable insights for farmers to monitor and intervene to minimise damaging behaviours.

5.2. Input data and model limitations

The following limitations discuss challenges related to data limitations, model limitations, and limitations of visual information.

Data limitation

Unlike in human action recognition, where actions often have well-defined temporal structures and longer durations, tail biting and ear biting occur in much shorter time frames. This makes it more challenging for models to capture sufficient temporal features, increasing the likelihood of misclassifications or missed detections.

Furthermore, the low frequency of biting behaviours, such as tail biting and ear biting, poses a significant challenge. These behaviours are inherently rare and unpredictable but critical for monitoring pig welfare. Their infrequent occurrence results in imbalanced class distributions, which are addressed by implementing data augmentation during training. However, this limitation may still have a negative impact on model performance.

Additionally, the utilised data are all from a single farm. This results in a lack of farm diversity, thereby limiting the ability of the models to generalise across different farming scenarios. To enhance model robustness, future research should include data from multiple farms with diverse environmental conditions and pig appearance.

Model limitation

As shown in Table 3, the SlowFast model, both with and without data augmentation, exhibits instability in class-specific accuracies. The SlowFast model with data augmentation obtains the highest accuracy of 74.07% for tail-biting recognition, while the performance of ear-biting prediction remains relatively low at 68.42%. Notably, the accuracy for ear-biting decreases after applying data augmentation, indicating a lack of robustness in the model and suggesting that augmentation may not uniformly benefit all behaviour classes. In contrast, the MViTv2-S model demonstrates a more balanced performance, achieving accuracies of 72.22% and 72.37% for tail biting and ear biting, respectively. These results indicate that the MViTv2-S model is more consistent across the different behaviours, with a steady improvement after data augmentation. This suggests that the effect of data augmentation

varies depending on the specific behaviour being recognised. The final choice of the model may depend on the specific biting behaviour of interest and the trade-offs between accuracy and computational efficiency.

Limitations on visual information

The methods employed in this study focus solely on the biter for recognising tail biting and ear biting. As such, the visual information of the victim is limited, and this may have contributed to the misclassifications of these behaviours. For instance, in Figure 7a, the ear of the victim is lying on the floor. Generally, this is more typically the position of the tail, and, as such, the visual features are similar to those of the background in tail-biting events when the victim is lying down. In comparison, ear biting may occur commonly when the pig is lying ventrally with the ears slightly higher, making them more accessible to the biter. Another example of this limitation can be found in Figure 7b. Here, ear biting is recognised by the proposed algorithm instead of tail biting. Although more features of the victim are visible in this cropped frame (approximately half of the victim's body), the biter occludes part of the victim, including its tail, which may have led to the misclassification of tail biting into ear biting. The misclassifications in Figures 7c and 7d may be a result of the presence of another pig within the cropped frame, introducing additional noise, thereby negatively affecting the ability to correctly identify the behaviour.

Indeed, the confusion between tail biting and ear biting is likely due to the limited visibility of the victim and shared features between these two behaviours, such as the proximity of the biter to the victim and similar head movements around one part of the body of the victim. These challenges can be addressed by extending the cropped frame to also include the bounding box of the victim (Liu et al., 2020), or by focusing on the interaction area (Odo et al., 2023, Odo et al., 2024). However, these methods may potentially introduce additional noise and negatively impact the accuracy of the recognition of tail and ear biting. For instance, including a larger area in the frame may introduce irrelevant background information or body parts not involved in the interaction, leading to additional visual noise that can confuse the model. Indeed, as observed in our data, a number of misclassifications occur when another pig not involved in the tail-biting and ear-biting event is visible in the bounding box of the biter. This issue can be mitigated by using rotated bounding boxes (Liu et al., 2023; Odo et al., 2024) or using fully segmented pigs instead of bounding boxes (Tu et al., 2021) to only capture essential features of the biter and the victim. Furthermore, by incorporating key-point

detection of specific body parts from adjacent pigs, such as the ear and tail, it is possible to assess which body part is in close proximity to the head of the biting pig. This approach can enhance the differentiation between ear biting and tail biting, thereby improving the specific behaviour recognition accuracy as well as the overall accuracy (Guo et al., 2025).

5.3. Future improvements of behaviour classification

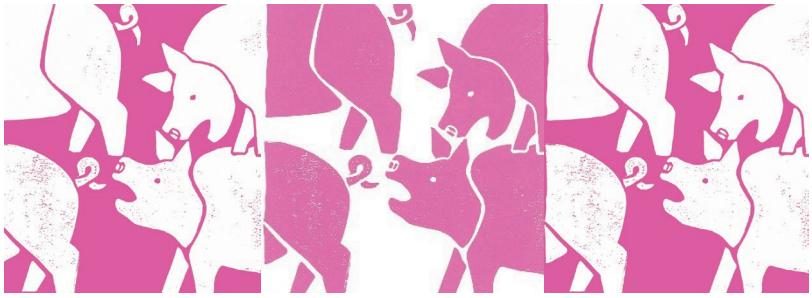
It should be noted that the class "Other" consists of a diverse range of distinguishable behaviours. In future work, the category "Other" could be labelled in more detail by specifying additional classes of behaviours. This can include behaviours that share common features with tail biting and ear biting, such as aggression or manipulating another part of the body of pen mates. This may help to reduce the confusion between real biting events and the class "Other", since this class now covers a very broad range in visual appearance.

Although we have focused on recognising ear biting and tail biting in this study, it is considered that other behaviours may lead to a more comprehensive evaluation of the welfare of pigs. The inclusion of behaviours that are assumed to reflect positive states, such as play or exploration of an enrichment in the pen, would provide further insights into positive welfare of pigs (Beattie et al., 2000; Douglas et al., 2012; Steinerová et al., 2024; Rault et al., 2025), which is gaining increasing attention (Rault et al., 2025). Developing a detailed classification system for pig social interactions is crucial for advancing social behaviour recognition algorithms and improving the overall monitoring of pig welfare.

6. Conclusion

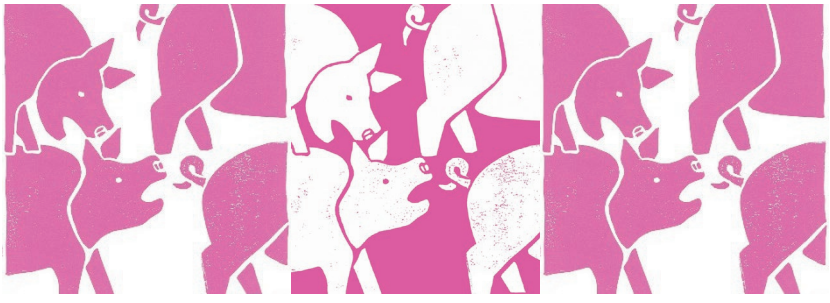
In this study, we have trained and compared two computer-vision-based methods for the automated recognition of tail-biting and ear-biting behaviours in pigs. This study presents a structured ethogram and a substantial, richly annotated dataset from a commercial farm for accurate categorisation of damaging behaviours. The investigation concentrates on the performance of two state-of-the-art models, i.e., SlowFast and MViTv2-S, and demonstrates that both models are capable of detecting these damaging behaviours, but with different performance characteristics. In particular, the MViTv2-S model shows promising results, achieving prediction accuracies of 72.22% for tail-biting and 72.30% for ear-biting behaviours. The proposed system represents a significant advancement in automated monitoring of pig behaviour, offering a first practical step for enabling early detection and intervention in commercial pig farming. The results demonstrate the feasibility and

effectiveness of using computer vision for behaviour recognition, with potential applications to improve animal welfare and reduce the negative impacts of tail biting and ear biting on farm productivity. By integrating such systems into realistic farming scenarios, farmers can make more informed decisions, ultimately improving both animal welfare and farm operations.



Chapter 7

7



Chapter 7

General Discussion

1. Introduction

In commercial farms, pigs are kept in groups where social interactions with pen mates play an important role in their welfare. Understanding these interactions is therefore essential for improving welfare assessment and guiding management practices. However, monitoring social behaviour at the scale of commercial production remains challenging using traditional observation methods. Computer vision technologies offer new opportunities for continuous and automated monitoring of pig behaviour at the individual level. Nevertheless, developing and validating these technologies is only the first step; the behavioural data they generate need to be translated into meaningful measures that improve our understanding of social interactions, individual variation in behaviour, and their links with welfare.

This thesis contributes to this goal by exploring the potential of using computer vision to monitor social interactions and activity patterns in pigs, with the overarching goal of improving pig welfare. This work was part of a larger project, conducted in collaboration with academic and industry partners, including ethologists, animal breeders, data scientists, and computer vision engineers.

Chapter 2 investigated how a tracking-by-detection algorithm can be used to investigate social networks in pigs based on spatial proximity and whether methodological choices regarding proximity definitions and sampling rates affect social networks of inactive pigs. Networks were constructed with five different definitions of proximity based on either the distance between the centroids or the overlap of the surfaces of the bounding boxes. Our results demonstrate that social network metrics are influenced by both proximity definition and sampling rate and that their impact varies for different network metrics. Clear differences between network metrics were revealed when using different proximity definitions. For example, the direct network metric degree centrality was less affected by proximity definitions and downsampling compared to the indirect network metrics eigenvector centrality and clustering coefficient. Moreover, network metrics differed in their sensitivity to downsampling, and this sensitivity was also affected by the chosen proximity definition.

Chapter 3 examined the long-term consistency of pen-level activity patterns of growing-finishing pigs, obtained by a tracking-by-detection algorithm. Activity patterns changed over time, with one batch showing a clear shift from a monophasic to a biphasic pattern, accompanied by lower average activity and relative amplitude and higher intra-daily variability, while the other batch, recorded in another season, showed no consistent trend.

Average activity was relatively consistent across pens over time, indicating that pens with higher activity in one week tended to remain higher in the other weeks. In contrast, relative amplitude and intra-daily variability showed lower consistency across weeks. Differences in activity metrics between weekdays were minimal when differences in Temperature-Humidity-Index (THI) were limited, whereas larger THI differences were associated with stronger and more variable weekday effects across weeks.

Chapter 4 examined whether a change in activity, activity pattern and synchrony obtained by a tracking-by-detection algorithm can be used to predict tail damage at the pen level and investigated whether activity measurements are related to performing and receiving tail biting at the individual level. In this study, distance moved and synchrony at the pen level did not predict whether a pen would become a damage pen. However, a positive relationship was found at the individual level between the frequency and duration of performing (not receiving) biting and the distance moved on some of the days before a tail biting outbreak occurred.

Chapter 5 investigated whether individual pigs differ in their proximity to pen mates (derived from a tracking algorithm) and in performing and receiving ear and tail biting, and whether, beyond individual variation, specific pairs of pigs spend on average more time in proximity or engage in biting more frequently than others. It introduces a novel modelling approach to assess individual differences and social preferences by partitioning variation in social interactions into individual and dyadic random effects. Our results show that both individuals and pairs of pigs explained a significant proportion of the variance of the observed tail biting and ear biting frequencies and proximity between pigs.

Chapter 6 developed a video-based behaviour recognition model to automatically recognise tail and ear biting of individual tail-docked pigs by applying two state-of-the-art methods. Our model was developed using 532 tail-biting and 750 ear-biting events, and allowed for variation in the response of the victim and the posture of the biter or the victim. These events were annotated on pigs of different ages (from 14 to 22 weeks), housed in 7 different pens, and exposed to diverse lighting conditions. The best model achieved detection accuracies for tail and ear biting of 72.22 % and 72.37 %, respectively, with confusion mainly between ear biting and tail biting.

The original goal of this thesis was to investigate the emergence and spread of tail biting and other social interactions through automated individual behaviour recognition. However, as

the project progressed, it became clear that achieving this objective was not straightforward. In particular, several technical challenges emerged during the development of the computer vision algorithms, as well as important methodological questions regarding how computer vision outputs, especially tracking data, can be used for behavioural research. Therefore, this General Discussion first discusses the technical challenges associated with using computer vision to monitor pig behaviour and presents recommendations and potential solutions for future research. It then reflects on how computer vision outputs can be translated into meaningful behavioural metrics. Finally, the broader implications of this research and its potential applications for behavioural research, farm management, and animal breeding are discussed, as well as the societal relevance of this work.

2. Automated approaches to study behaviour: technical challenges and recommendations

2.1. Tracking-by-detection algorithms to monitor behaviours at the individual level

In this thesis, most Chapters focused on individual behaviours, with the individual identification obtained through a tracking-by-detection algorithm using bounding boxes. In Chapter 2, a tracking-by-detection algorithm developed by van der Zande et al. (2021) was run on three consecutive days on 21 pens (six pigs of 15 weeks of age per pen). In Chapters 4 and 5, another tracking-by-detection algorithm developed by Huo et al. (2023) was run on four days in nine pens (11 pigs per pen, age ranging from 12 to 22 weeks of age). The algorithm developed by van der Zande et al. (2021) used You Only Look Once v3 (YOLOv3) to detect the pigs and Simple Online Real-time Tracking (SORT) to link detections from frame to frame and build their trajectories. The algorithm developed by Huo et al. (2023) used Enhanced Cascaded Association Flow (ECAF), a method that associates detections in multiple stages using both motion and appearance features. This approach is particularly appropriate for tracking pigs in crowded or occluded environments (Huo et al., 2023). Although not investigated in this thesis, other types of tracking algorithms could help to improve individual tracking, such as algorithms relying on key points that pinpoint different body parts (e.g., tail, ears, or nose) or segmentation, which provides the contour and exact pixels belonging to each pig. However, these algorithms also have limitations, as they may require even more computing resources and time to run.

Despite the use of advanced methods, tracking individual pigs over time without losing their identity remains highly challenging, particularly in small areas and among individuals with similar appearances. As a result, identity switches occur in the tracking results, meaning that the bounding box number (ID) initially assigned in the first frame to a pig is exchanged with the ID of another pig. In the study by van der Zande et al. (2021), individual pigs could be tracked without identity switches for an average of 22.3 minutes in a barren environment and 57.8 minutes in an enriched environment where pens were twice as large as those in the barren condition and included straw bedding. The difference in tracking duration between the two environments was likely due to the larger pen size in the enriched pens, which reduces the overlap between pigs and therefore decreases the occurrences of identity switches. In contrast, in Huo et al. (2023), individual pigs could be tracked for an average of 175min.

Although both algorithms achieved high performances, manual corrections of the identity switches were still needed before being able to analyse the data at the individual level. These manual corrections also required each pig to be marked with a distinct pattern on its back (with colour and symbol), to be recognised and distinguished from the others. In van der Zande et al. (2021), the algorithm generated a new ID when there was uncertainty in the tracking. These new IDs were used to trace back the identity switch and re-assign the correct identity based on the video output of the tracking and the marks on the pigs. In the tracking developed by Huo et al. (2023), the number of IDs was fixed to the exact number of pigs in the pen, to avoid generating new IDs and force the algorithm to find the most probable pig to assign the ID of each bounding box. While this step improved the performance of the tracking, it made the correction of the ID switches more challenging. We were required to go through the entire 24h video tracking output and follow each pig individually. This step, therefore, likely increased the probability of human error due to the demanding nature of the task. In the tracking data used in Chapters 4 and 6 (36 days in total, corresponding to nine damage pens recorded over four days per pen), ID switches occurred most frequently between 13:00 and 19:00 h (Figure 1), which corresponds to the period of high activity of the pigs, but were also observed outside this period, including during the night. In addition, this step was time-consuming and took, on average, seven hours per day per pig to correct the tracking of van der Zande et al. (2021), and four hours per day per pig to correct the tracking developed in Huo et al. (2023). This manual correction of the ID switches was the most limiting factor in increasing the number of days in the analysis.

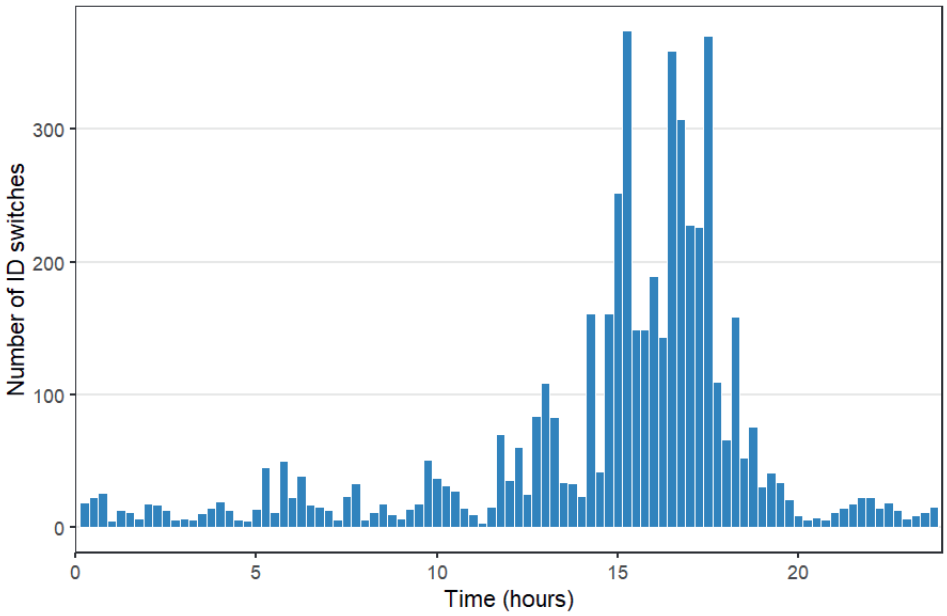


Figure 1. Distribution of ID switches across the day (0-24 hours). This plot is based on the tracking algorithm of Huo et al. (2023), run on 36 days. ID switches were identified manually and corrected for use in Chapters 4 and 5.

In practice, painting symbols on pigs' backs for long-term identification and correcting switches manually is not feasible. One potential solution for identifying individual pigs at the start and maintaining their identity over time is to combine tracking with automated identification, for example by using Radio-Frequency Identification (RFID) at the feeding station. RFID is commonly used at feeding stations on breeding farms and in gestating sows kept in large groups, to allow for individual feeding, but is less common for growing-finishing pigs.

First, RFID can be used to identify pigs during their first feeding visit by assigning a unique tracking ID to each RFID tag, corresponding to an individual pig. Because feeding events are not equally distributed over time, the starting hour of the tracking algorithm should be carefully considered. In case the tracking algorithm is not run continuously, pigs need to be re-identified with the RFID for every new tracking period. If pigs do not visit the feeding station for several hours after the start of running the tracking algorithm, then the tracking data collected during that period cannot be linked to specific pigs and would not be usable as individual tracking. For example, on day 4 (Figure 2), pigs 4, 5, 7, 8 and 9 were not identified at the feeding station before 5:00. This results in part of the individual tracking being lost

before that period. Therefore, the best starting hour should allow as many pigs as possible to be identified with the RFID, and as early as possible after the start. To determine the optimal starting time for running the tracking algorithm, we analysed one batch (10 pens, 11 pigs per pen) over 95 days from the same farm used in Chapters 3-6. For each potential starting hour, the cumulative percentage of pigs visiting the feeding station in the next hours was quantified and averaged across days and pens. Figure 2 shows that the choice of starting hour has a clear impact on how quickly pigs are identified. For example, when the tracking algorithm starts at midnight, approximately 90% of pigs are identified within three hours, whereas when it starts between 15:00 and 18:00, a slightly higher proportion of the pigs (95%) is already identified in a shorter time (two hours). Although starting in the afternoon (15:00–18:00) leads to the fastest identification of pigs with the RFID at the feeding station, it may be less convenient for analysis and for defining a full 24-hour day. In contrast, a morning starting time (e.g. around 07:00) is a more coherent choice and still ensures that a high proportion of pigs are identified shortly after the tracking algorithm starts (nearly 90% of pigs identified within the first two hours).

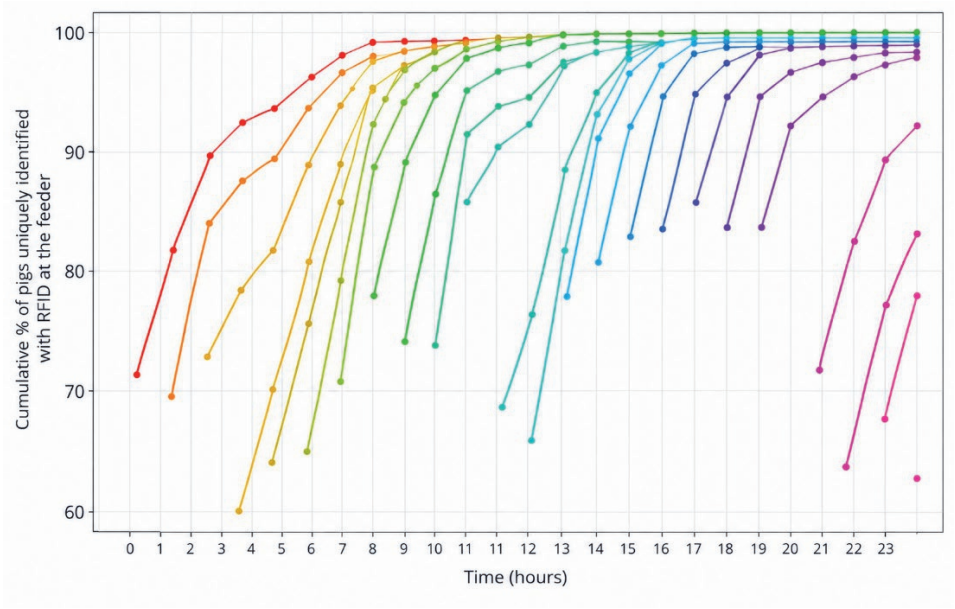


Figure 2. Cumulative percentage of uniquely identified pigs across different starting hours for running the tracking-by-detection algorithm used in Chapters 3, 4, and 5. This plot is built with RFID data from the feeding station from one batch (10 pens) over 95 days. Each point represents the mean across days and pens.

Second, identity can then be maintained over time by verifying the tracking ID at consecutive feeding events. With this approach, a pig identified via its RFID at the feeding station can be considered correctly tracked between two feeding events if it returns to the feeding station with the same tracking ID. The next step after verifying the identity with the RFID is to filter out tracking segments where an ID switch occurred and keep only the correct ones. It is important to note that using the RFID for correction requires a precise synchronisation between the feeding station and the camera.

To evaluate the feasibility of this approach, we combined tracking data for one of the batches of pigs used in Chapter 3 (47 days, 11 pigs) with RFID data from the feeding station. After filtering out the wrong tracking based on the RFID, pigs were correctly tracked for 8.1 ± 4.0 h (mean ± standard deviation) per day, corresponding to approximately 33% of the day. Figure 3 presents an example of the individual tracking available per pig after correction with the RFID for one pen and four days. Visually, we can note that pigs differ in how long and when they were tracked per day. For example, pig 1 was tracked for most of day 3 but only for a short period (during the afternoon) of day 4. In addition, on days 1, 2 and 4, pig 4 was tracked for a restricted period of time compared with other pigs. Apart from losing approximatively 33% of data on tracking, this approach has other limitations that should be taken into account for future studies. The variability observed in the tracking data, both between pigs within the same day and for the same pig across different days, may reflect individual differences in their feeding behaviour, as this method relies on the number of feeding events per pig per day and how these events are spread during the day. A previous study showed that pigs differed in their feeding strategies, including both the number of visits per day (nibbling versus meal eating), the timing of the feeding events (day versus day-night eating) and consistent versus inconsistent eating between days (Bus et al., 2024). These different feeding strategies will affect the duration and the timing of when pigs are tracked. A pig can potentially be tracked for a longer duration if it returns to the feeding station frequently, or if it returns to the feeding station soon after the active period, when ID switches have a higher probability of occurring. Therefore, correction of ID using RFID at the feeding station, may cause bias in losing track periods depending on the feeding pattern of individual pigs, which may be for example, related to their metabolic states or position in the hierarchy.

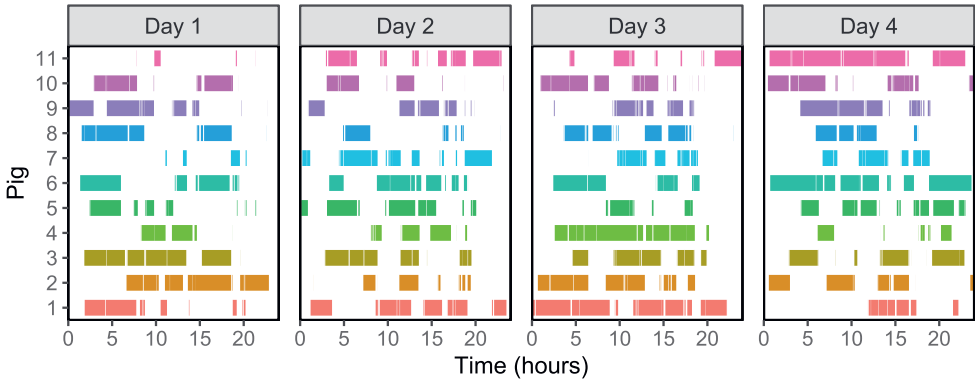


Figure 3. Example of the individual tracking available per pig after correction with the RFID at the feeding station, for one pen and four days. These plots use a subset of the tracking data used in Chapter 3. Each colour represents one pig, and only tracking segments where the bounding box ID remained consistent between feeding visits were retained. During periods without colours, ID switches occurred, and therefore this segment of tracking was removed.

As mentioned above, one limitation of relying on RFID at the feeding station is that it may introduce a bias in the temporal distribution of tracked data due to individual feeding patterns, as feeding events do not occur frequently enough to correct ID switches over the full period analysed. Therefore, alternative approaches for repairing ID switches that do not depend on feeding events should also be explored to improve individual pig tracking. Recently, it has been proposed to recognise pigs with a unique ear tag (each pig wearing an ear tag with a specific combination of colour and number) (Schmidt et al., 2022). Although this is a promising approach, it also requires developing an additional algorithm to localise the ear with the ear tag and classify the ear tag based on its visual features. Furthermore, two studies have investigated automated facial recognition of pigs in images with promising performance (Hansen et al., 2018; Marsot et al., 2020). Although this approach is not yet ready for applications in practice, it may become a viable solution in the near future, which could be further applied to identify pigs and repair ID switches.

Still, these approaches for repairing ID switches have limitations for research applications, as the individual tracking is not continuous, and therefore, the analysis of 24-hour circadian activity patterns is compromised. In addition, because the period of correctly tracked data does not overlap between pigs, analyses of social interactions, for example, proximity, and social network structures are also hampered.

2.2. Video-based recognition of damaging behaviours

Within the project, the tracking-by-detection algorithm was sufficiently developed to be applied in the behavioural studies in this thesis after manual assignment of pig ID and manual correction of ID switches, whereas the video-based behaviour recognition algorithm was not yet ready for application. Therefore, the behavioural analyses in Chapters 4 and 5 relied on manual annotations of damaging behaviours, which also served as training data for the algorithm developed in Chapter 6. In Chapters 4 and 5, we focused on pens with visible tail damage and annotated ear and tail biting on the days preceding the damage, therefore increasing the chance of capturing tail-biting events (and potentially ear biting). This approach was particularly efficient because tail and ear biting events are rare and sporadic, and are therefore difficult to identify in videos to develop an algorithm to recognise them automatically. With this approach, we were able to collect a substantial dataset, covering multiple pens, pig ages, time periods, and lighting conditions, that is larger and more diverse than those used in the few other studies that develop models to recognise damaging behaviours (see Chapter 6 for details on those previous studies).

In this project, the behaviour algorithm (Chapter 6) was developed in collaboration with computer scientists and ethologists, with regular discussions from the start about why these behaviours were relevant to recognise and how to define the behaviour classes given the nature of the behaviour and technical constraints. It is important to note that the development of behaviour recognition algorithms relies heavily on the quality of manual annotations. The annotations used to train and test these algorithms require the same level of rigour as behavioural studies based only on manual annotations, including the involvement of ethologists, the use of inter-observer reliability tests when multiple observers are involved, and in-depth discussions of behavioural definitions and ethograms. The definition of the behaviour is particularly important for behaviours such as “tail biting” or “ear biting” which may be defined differently across studies. For example, in Chapter 6, all types of “tail biting” were included, whereas Liu et al. (2020) focused only on tail-biting events with chasing movements of the biter, excluding subtle tail biting where the victim did not react, which actually occurs in a large part of the cases (Taylor et al., 2010). Similarly with “ear biting”, for ethologists specialised in pig behaviour, “ear biting” refers to a specific behaviour in which a pig gently chews or nibbles the ear of another pig, sometimes involving short, forceful bites (as the definition we used in Chapter 6). However, “ear biting” may also refer to an aggressive behaviour occurring within a sequence of fighting, including other

behaviours such as pushing or head knocking (McGlone, 1985). The distinction between these two types of biting the ears is important because they have different underlying motivations, causations, consequences and treatment. Language can sometimes be ambiguous, and this is not necessarily an issue in itself; however, it becomes problematic when definitions are not explicitly stated, as this can be misleading. For this reason, including a clear and transparent definition of the behaviour in papers associated with the development of a behaviour algorithm is essential, ideally accompanied by an image or video illustrating the behaviour.

The automated recognition of tail and ear biting developed in Chapter 6 constitutes a promising first step towards further applications to reduce tail biting and ear biting. Still, misclassifications occurred between the different classes, particularly between ear and tail biting (Chapter 6). For further improvement, key-point detection could be added to better distinguish whether the biter is targeting the ear or the tail of the victim and to reduce confusion between classes. Within this project, a multi-object key-point detection model was developed with six key points (tail, back, shoulder, nose, left ear, and right ear, Figure 4) and implemented to improve the performance of a pose estimation model (Guo et al., 2025). Following this work, a method is currently under development to correct the predictions of the behaviour recognition model based on key points by measuring the distance between the biter's nose and the ear and tail of the neighbouring pigs. Preliminary results suggest that this approach may help reduce confusion between the biting behaviour classes (unpublished).



Figure 4. Example of a frame showing the localisation of the six key points (tail, back, shoulder, nose, left ear and right ear)

For future applications, several further developments of behaviour recognition models would be highly relevant for behavioural research and application in breeding and on farms. First, in this work, we focused on detecting the biter; however, identifying both the biter and the victim in each specific interaction would be highly valuable. It could enable research into factors associated with receiving damaging behaviours, the identification of preferences within specific dyads, or selection against predisposition for receiving damaging behaviours in breeding programmes.

Furthermore, extending the approach to other types of social interactions, particularly positive ones, would be worthwhile for improving welfare. The original aim of this project was also to include other behaviours such as social play, nose-to-body, and nose-to-nose contacts. However, due to the technical challenges of developing these algorithms and the large number of annotated events required per behaviour, this work was limited to the recognition of tail and ear biting.

3. Translating computer vision outputs into meaningful metrics to analyse behaviours

While developing video-based algorithms is technically challenging, these methods generate highly valuable outputs. Video-based algorithms provide continuous data and can be applied across complete 24-h days and over extended periods, potentially covering the entire fattening period. Such extensive data were previously impossible to collect with manual observations. However, this high temporal resolution also results in extremely large and dense datasets, often containing substantial redundancy, even though meaningful day-to-day variation may still be present (as reported in Chapter 3). As a result, appropriate sampling strategies and temporal aggregation must be considered to reduce data volume while preserving relevant information. At the same time, interpreting video-based algorithms also requires careful consideration, which should not be overlooked. Raw outputs from video-based models, such as bounding boxes or trajectories, are not immediately interpretable. To perform behaviour analyses, these outputs must be translated into meaningful metrics that accurately reflect the behaviours of interest. This step is crucial to ensure that the data captured by the video-based algorithm can be reliably used for research, management, or breeding purposes.

3.1. Sampling strategies to capture behaviour

Monitoring pig behaviour during the entire growing-finishing period produces an enormous amount of data. For example, in the setup of the farm in Chapters 3-6, with 10 pens and one camera per pen, recording video at 15 frames per second over a 3-month fattening period results in approximately 1.17 billion frames. Processing this dataset with the tracking-by-detection algorithm used in this thesis (ECAF), able to process 10 frames per second, would take approximately 3.7 years. This duration only accounts for generating the raw tracking outputs, without performing any translation into meaningful behaviour metrics, such as calculating the distance moved by each individual, or the distances between pairs of pigs (with 11 pigs per pen, 55 pairs). Even though the time required to process such a large dataset can be reduced by running the algorithm on several videos at the same time, or by optimising the script, and is likely to decrease in the future, this clearly demonstrates the necessity of downsampling the tracking outputs. Several strategies can be implemented to reduce computation time, for example, by downsampling frames, or running the tracking algorithm on selected days, or selected hours of the day. These strategies are appropriate for behavioural analyses only if the data is sufficiently redundant, meaning that after downsampling, the data still reflects the behaviours of interest without overlooking any important patterns. The different strategies to reduce data processing with their advantages (noted as +++) and limitations (noted as - - -) are summarised in Table 1, and visualised with radar plots in Figure 5.

Table 1. Summary of sampling strategies for behaviour analyses, to reduce processing of data generated from automated monitoring systems.

Strategy	Continuous 24 h	Frame downsampling (fixed rate)	Frame downsampling (adaptive rate)	Reduced number of days	Reduced number of hours
Computational efficiency	- - -	+++	++	++	++
Capture circadian patterns	+++	++	++	++	-
Capture short events	+++	+	++	++	+
Robustness to environmental variation	+++	++	++	-	++
Comments / recommendations	Not feasible in practice	1 frame every 2–6 min *(Chapter 2)*	Requires extra step to define activity level	≥2 days/week Include environment and farm management in analyses *(Chapter 3)*	Focus on active periods when appropriate

The cells are coloured according to the strength (+++) and the limitations (- - -) of the strategy to analyse behaviours. +++ and - - - are in comparison with the continuous 24 h data.

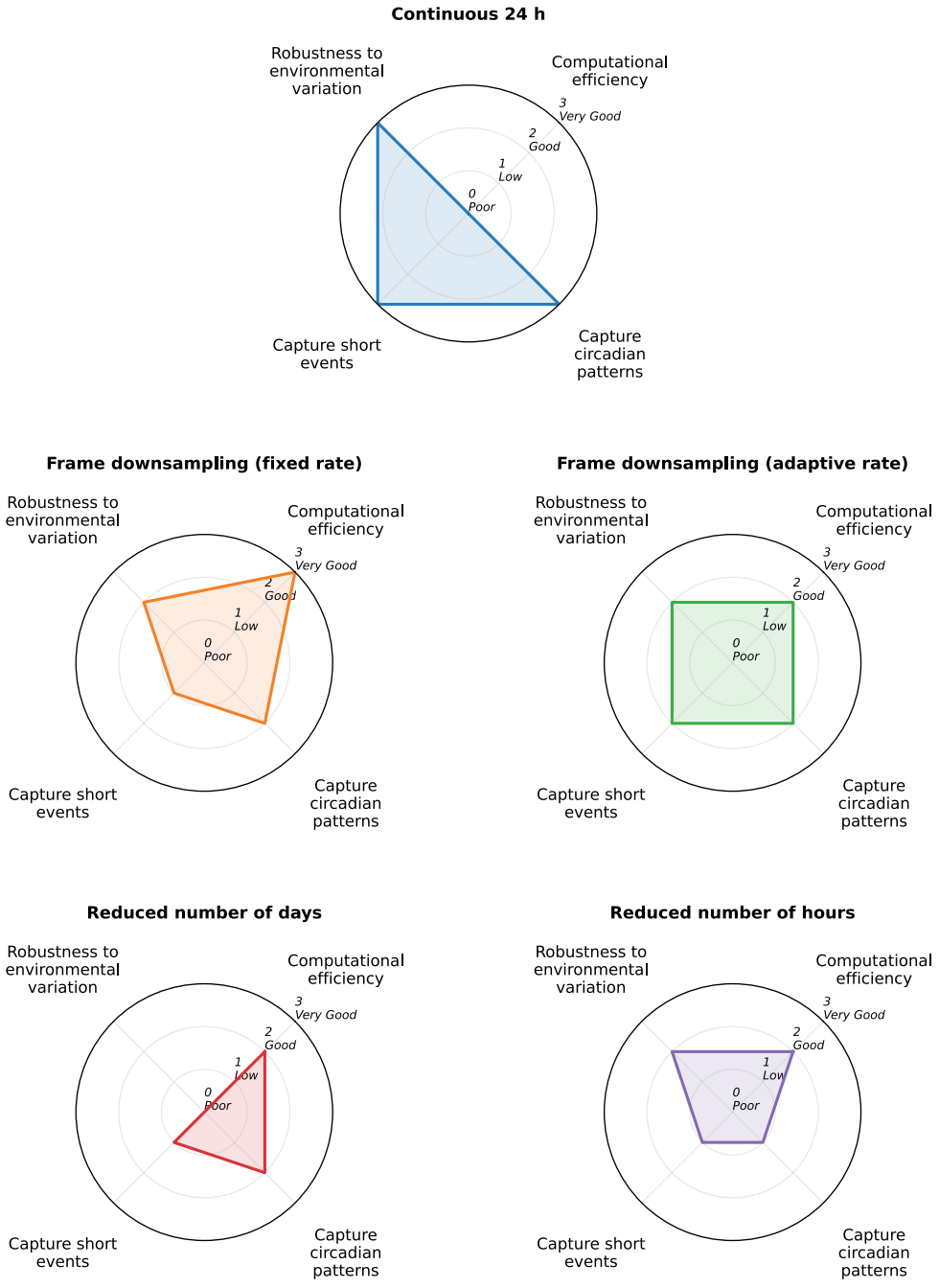


Figure 5. Comparison of sampling strategies to reduce data processing based on four criteria using radar plots.

In Chapter 2, we investigated a strategy to reduce computation time by exploring the effect of fixed downsampling frames, i.e. increasing the interval between frames, on social network metrics based on close spatial proximity during rest. This study showed that downsampling frames impacts the reliability of social network metrics, but that intervals between 2 and 6 minutes between frames provide representative estimates of network metrics when focusing on spatial proximity during rest. However, we also highlighted that the optimal sampling interval depends on the specific metric, housing conditions, and proximity definition. These findings demonstrate the importance of carefully selecting sampling intervals when using computer vision for social network analysis.

Rather than using a fixed sampling interval throughout the entire growing-finishing period, future studies and applications in practice could also consider using a flexible sampling interval, adjusted to the level of activity. For example, during the night, when pigs are generally less active (Ocepek, 2026), lower sampling frequencies may be sufficient to capture behaviours. In contrast, during periods of higher activity, it may be better to use a higher number of frames to ensure that behaviours are accurately captured. This way, short events, such as social interactions, would have a higher chance of being captured (++), compared to a fixed rate (+). However, this approach would also require an additional step, namely to first assess the activity level of the pigs and the consistency thereof, to be able to determine an appropriate sampling frequency, which may reduce computing efficiency (++), compared with a fixed frame downsampling (+++). These two approaches of downsampling, either with a fixed or a flexible rate, would both allow for analysing circadian patterns but with a lower resolution (++) than the continuous 24 h data, and preserve a reasonable robustness to environmental variation (++), as they will be less sensitive to day-to-day fluctuations of the environment.

Alternatively, behaviour could also be monitored only on a limited number of days, as in Chapter 3 where we focused the analysis on two days per week (Wednesday and Saturday) sampled every two weeks. This strategy improves computational efficiency (++) compared with this continuous 24 h data, while still making it possible to perform analysis of the circadian rhythm (++), and capturing short behaviour events (++), but only restricted to those specific days. However, this strategy is more sensitive to fluctuations of the environment (-) than the continuous 24 h data, as we found that when THI differed between days of the week, associations between weekday and activity metrics were found, with variable associations

across weeks. Furthermore, other environmental variables or differences in the management of the farm and farmer activities between weekdays and weekends may also have contributed to the observed variation in activity metrics, independently of THI. These findings highlight the importance of collecting activity data on multiple days per week and accounting for fluctuations in the environment, or in the age of the pigs, as we did in Chapter 4 by correcting the activity patterns for age before using them to predict tail biting. A trade-off between computational efficiency and robustness to environmental variation could be achieved by combining frame downsampling with sampling on multiple, but fewer, days. It is also important to note that when monitoring individual activity, the selection of recording days should also be guided by practical considerations. Although selecting days that are further apart within the week may better represent activity for that week, this may not be the most practical option, as it would require re-identifying individual pigs for each day, for example, by matching each RFID to the correct pig, whereas consecutive days would not require this step (see previous section).

Another option for downsampling could be to focus only on specific hours of the day. In this thesis, activity was monitored continuously over 24h for activity (Chapters 3 and 4). Although monitoring 24-hour activity allows for investigating circadian activity patterns, this is not always feasible and necessary. Focusing on the active period, where more active behaviours are likely to occur, including ear and tail biting, has often been proposed as a sampling strategy (e.g., Zonderland et al., 2011). In Chapters 4 and 5, for example, we did not observe ear and tail biting continuously but limited the observations to 12h per day, with continuous observations every second hour, to reduce the labour. Although the majority of ear and tail biting events occurred during daytime hours (07:00–19:00 h), a non-negligible number of tail and ear biting events were also observed during the night (Figure 6). Focusing on active periods may effectively reduce costs and time associated with data processing (++), but this approach still risks missing a proportion of relevant events (+), compared with this continuous 24 h data. The time period should therefore be carefully considered, particularly when applying behaviour recognition algorithms, such as the one developed in Chapter 6, to detect early signs of damaging behaviours.

To conclude, the choice of the recording period should be guided by both practical considerations, the specific research question, and the behaviour of interest. In some cases, focusing on the active period, on specific days, or increasing the interval between frames may

be sufficient to capture the behaviours of interest, while reducing the data processing. For rare and short behaviours, such as ear and tail biting, reducing the number of days or using adaptive frame downsampling is more appropriate, as these events are easy to miss but critical for assessing pig welfare.

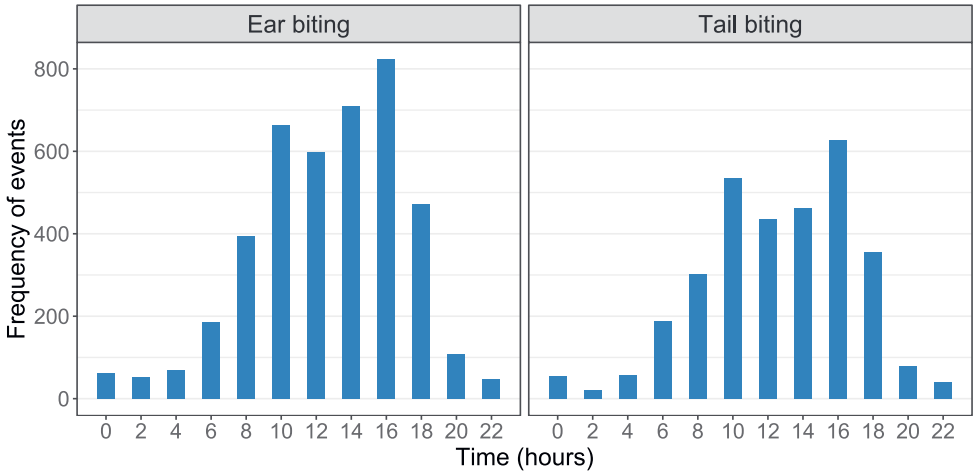


Figure 6. Distribution of ear-biting and tail-biting events. This figure is based on the total number of ear-biting and tail-biting events, summed across nine damage pens (99 pigs) and three selected days per pen used for analyses in Chapters 3 and 5.

3.2. Using spatial proximity, derived from a tracking-by-detection algorithm, as a proxy for social interactions

In Chapter 2, we proposed using spatial proximity derived from a tracking-by-detection algorithm built on bounding boxes to construct social networks. Relying on continuous tracking data creates new opportunities to quantify proximity over time. First, it allows to define proximity based on thresholds set with objective geometrical measures (e.g., distance between bounding-box centroids < 50 cm or bounding-box surface overlap > 20%), which are difficult to achieve objectively with human observations. Furthermore, instead of defining proximity based on a pre-defined threshold, to distinguish when pigs are considered far or close to each other, such data enables the use of all the distances between individuals, as the "WEIG" definition used in Chapter 2. Thus, as shown in Chapter 2, multiple definitions of proximity can be derived from tracking data, and the choice of definition may be critical for the conclusions drawn, especially due to the limited space available per pig in commercial

farms. Therefore, spatial proximity should be carefully defined and the definition selected according to what is intended to be captured. For example, we showed that using a threshold based on the bounding box centroid mostly captured pigs lying next to each other in a parallel ventral position, whereas using a threshold based on the overlap of the surface of the bounding box mostly captured pigs facing each other or lying tail-to-tail. Incorporating information on pig orientation, for example through segmentation or key points to identify the head and the tail, could help distinguish tail-to-tail from face-to-face interactions.

In Chapter 5, where we investigated variation in spatial proximity between individuals and between pairs of pigs, we chose to use a quantitative measure of distance, the inverse of the "WEIG" definition developed in Chapter 2, which computed the distance between pairs of pigs across the entire observation period in a harmonic mean. This definition was chosen as it does not require setting an arbitrary threshold to differentiate pigs in close proximity and further apart. Still, the use of spatial proximity raises important questions about what is actually being measured and what it reflects in terms of social interactions.

Although, to our knowledge, this work was the first attempt to investigate spatial proximity in pigs through a tracking-by-detection algorithm, previous studies based on human observations also used spatial proximity. Spatial proximity has often been associated with affiliative behaviours in pigs (Camerlink et al., 2022; Durrell et al., 2004; Goumon et al., 2020), with the assumption that pigs spending time next to each other are not actively avoiding each other, and that spatial proximity may reflect social preferences. While it may be assumed that pigs lying next to each other would also engage together in more active social behaviours, such as social nosing, previous studies have shown that lying in proximity is only weakly correlated with these behaviours (Camerlink et al., 2022; Clouard et al., 2024). In addition, due to the limited space available in commercial farms, pigs have little opportunity to choose or avoid specific pen mates. Therefore, proximity in commercial settings may mainly reflect housing constraints, or preference for a location, rather than affiliative behaviours and social preferences.

Moreover, proximity also occurs in the context of aggression or damaging behaviours (Agha et al., 2025; Charles et al., 2024; Li et al., 2018). For example, tail and ear biting may happen when pigs are lying next to each other in close proximity. To explore associations between damaging behaviours and proximity, we visualised the data used in Chapter 5 and examined the relationship between the distance between dyads and the frequency of ear biting and tail biting events (Figure 7). Overall, no clear linear trend was found between the average

distance between dyads and their frequency of ear biting or tail biting. Dyads with high frequencies of tail biting or ear biting were not consistently observed to be either closer or further apart compared with dyads with lower frequencies of those behaviours. The lack of a clear association between proximity and biting frequency may reflect the different types of tail and ear biting events captured in this study. For example, biters and victims may be observed for a long time in close proximity in the pre-damage of the two-stage type of tail biting, where the biter gently manipulates the tail of another pen mate when both pigs are lying down or at a later severe stage when the victim becomes apathetic and stops reacting (Taylor et al., 2010). In contrast, in the obsessive type of tail biting or when the victim already has damage, the victim is likely to react by avoiding the biter, and therefore pairs of biter and victim may be likely observed further apart. This may also reflect that pigs spend longer periods in close proximity to specific individuals for positive or neutral social behaviours, while directing damaging behaviours towards others, as illustrated in the exploratory case study presented in Chapter 5.

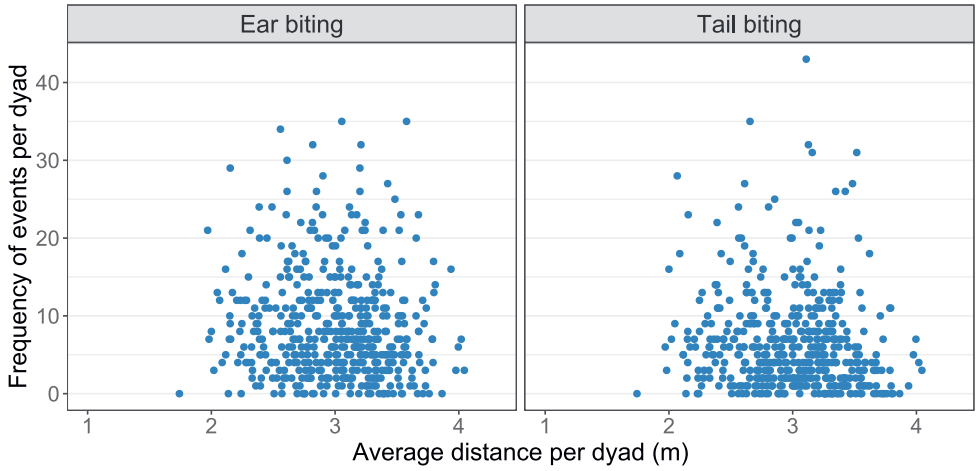


Figure 7. Relationship between the frequency of events, ear biting (left panel), tail biting (right panel) and the average distance per dyad. Data are based on manual annotations from nine pens with tail damage, with three observation days per pen included in the analyses (Chapters 3 and 5). Each point represents a dyad. Distance was averaged across the four days, and the frequency of tail and ear biting summed across the four days.

Overall, tracking data provides new opportunities to measure spatial proximity in an objective and quantitative way. However, in commercial farms, spatial proximity should be interpreted with caution, as pigs have limited space and social opportunities, and proximity may not reliably reflect social preference. Instead, it may also reflect preference for a location

or thermoregulation, which could be partly addressed by comparing patterns across different contexts (e.g. different environments or time periods), or by examining whether pigs actively select specific pen mates to lie next to, rather than simply observing that pairs of pigs are in proximity. Furthermore, more specific behaviours, such as play or social nosing, may provide better indicators of social relationships in housing systems with restricted space.

3.3. Using distance moved, derived from a tracking-by-detection algorithm, as a proxy for activity

In Chapters 3 and 4, activity was characterised by measuring the distance moved of individuals between consecutive video frames derived from tracking data, either at the group or at the individual level. Similarly to proximity, relying on continuous tracking data creates new opportunities to measure activity over time. Continuous 24-hour monitoring of activity allows not only the estimation of the average activity over the recording period, but also the investigation of the circadian activity pattern. For example, additional metrics such as fragmentation (e.g. intra-daily variability in Chapter 3) or peak-related measures (e.g. relative amplitude in Chapter 3) can be derived, and synchronisation of activity between pigs throughout the day can be investigated (Chapter 2). This is particularly relevant as perturbation of the circadian rhythm has been suggested as a potential indicator of welfare issues (Bus et al., 2023b).

However, while distance moved derived from tracking algorithms is relatively straightforward to implement, it relies only on location without considering what the pig is actually doing. As a result, pigs lying while sleeping are treated similarly to pigs that are standing without movement, even though they may be engaging in active behaviours, such as feeding, drinking or exploring enrichments. This could be addressed by integrating information on location, for example identifying whether the pig is at the feeding station, near the drinker, or near enrichments. In Chapter 2, we also needed to set a threshold to define activity versus inactivity, as we investigated proximity during inactive periods. Inactivity was defined as instances where the distance moved between two frames one minute apart was less than 20 cm. We intentionally opted for a simple definition, as the main focus of our paper was on defining proximity and not on inactivity. However, for further research, more attention should be paid to the definition of activity versus inactivity. Similarly to proximity, choosing one definition of activity rather than another may have consequences on the results obtained, and future work could explore alternative approaches, such as incorporating different speeds of movements rather than relying on a single threshold on the distance.

Furthermore, individual-level behavioural data are highly valuable for research, animal management, and breeding programs, but they are challenging to obtain. In contrast, monitoring behaviour at the pen-level is more straightforward, as it does not require individual identification and can still provide valuable insights into animal welfare, for example by detecting overall deviations associated with welfare or health issues. However, it does not allow for understanding individual variation or measuring phenotype to include in breeding programmes. In Chapters 3 and 4, we analysed pen-level activity metrics. For example, average activity at the pen-level was calculated by summing the distances moved by all bounding boxes and dividing by the number of pigs. For these analyses, we used non-corrected tracking data, meaning that some ID switches were present. An important step was to ensure that non-corrected tracking still provided reliable information at the group level, as we verified in Chapter 4.

Overall, while distance moved derived from tracking-by-detection provides a practical measure of activity and enables detailed analyses of circadian rhythms and synchronisation between pigs, it remains an indirect measure that does not capture the nature of the behaviour.

4. Implications of this research and future implementations

4.1. Directions for future research

Here, I discuss the broader role that automated behaviour monitoring may play in behavioural research, with a focus on interdisciplinary collaboration, methodological challenges, and opportunities for advancing the study of social behaviour and animal welfare.

The development of automated systems for monitoring behaviour requires collaboration between experts from different backgrounds, including ethologists, engineers, computer and data scientists, and commercial partners (Siegford et al., 2023). This type of collaboration is already ongoing, as seen in the increasing number of national (including this project) and international collaborative research projects. Several challenges arise from these collaborative projects, including differences in terminology, methods, and priorities across disciplines. Furthermore, careful attention should also be given to translating biological questions into problems that can be addressed using state-of-the-art automated techniques. Based on the experience in this project, I propose the following recommendations to support such collaborative projects: (1) early alignment of objectives and expectations, with clear goals, priorities, task distribution, and deadlines, and regular updates throughout the project;

(2) training through workshops, to improve mutual understanding across disciplines; (3) regular communication through scheduled meetings, shared working days, and online communication channels; (4) clear documentation of data, algorithms, decisions, and methods in shared repositories.

Although automated behaviour monitoring systems are expected to continue improving in the coming years, continuously monitoring behaviours of individual farm animals over long periods under commercial conditions will remain challenging. As a result, datasets may be incomplete, with missed or mis-detected behavioural events and animals being tracked only for relatively short, non-overlapping periods (as illustrated in Figure 3). Throughout this collaborative project, a recurring question from the computer vision experts was: "*How well does the algorithm need to perform to be applied in research?"* However, limited evidence was available in the literature to answer this question. Future research should therefore focus not only on improving algorithms, but also on (1) quantifying the impact of imperfect algorithms on biological conclusions, and (2) developing methods that explicitly account for these limitations. The first objective could be addressed through modelling and simulation approaches, by generating different levels and types of bias to evaluate how algorithm errors influence biological conclusions. The second could benefit from approaches developed in behavioural ecology, where researchers frequently deal with incomplete observations, particularly when studying large groups of animals in large spaces, where individuals may not always be visible simultaneously. Methods have been developed in this field to reduce bias in observation. For example, for studying social structures, the Half-Weight Index estimates the strength of associations between individuals while correcting for differences in the number of sampling periods in which each individual was observed (Cairns and Schwager, 1987; Whitehead, 2008). Similar approaches could be adapted to automated behavioural data to account for imperfect datasets and reduce sampling bias.

Importantly, although computer vision offers promising opportunities for monitoring behaviour, its application should be guided by biological meaning rather than technical feasibility. To improve welfare, the development of these monitoring systems should prioritise the identification and validation of indicators relevant for welfare before automating their detection. As animal welfare is not limited to reducing negative experiences but also includes promoting positive ones (Mellor et al., 2020), future research should develop automated recognition systems that also capture behaviours associated with positive experiences, including positive social interactions. A few studies have developed algorithms

to recognise positive social interactions in pigs, including social nosing (Gan et al., 2021), head-to-head contact (Wutke et al., 2021) and social play (Gan et al., 2021; Larsen et al., 2023); however, they have not yet been applied for research purposes. After validation, such automated systems could help to identify environmental factors and management strategies that promote positive social behaviours.

Understanding social interactions also requires identifying the individuals involved and characterising their roles within groups. Therefore, automated systems should be further developed not only to quantify social interactions but also to identify the individuals who initiate and receive them. This would enable investigation of whether individual social tendencies and preferences for specific pen mates are consistent over time, and how they relate to individual characteristics (e.g., personality, cognitive abilities, sex, genetics, or other production traits). To address these questions, future research will also benefit from the use of advanced quantitative statistical methods.

Traditionally, behaviour analyses of farm animals have relied on experiments with relatively small sample sizes and on predefined hypotheses, for example, testing whether animals exposed to different treatments differ in their behaviour. This hypothesis-driven approach typically focuses on statistical inference, using p-values to assess whether observed differences are statistically significant. However, analysing social structures requires moving beyond this type of analysis and focusing instead on developing robust methods to quantify individual behaviour within groups and capture the complexity and dynamics of interactions (Goursot et al., 2026). In this context, the datasets generated through automated systems enable data-driven approaches that may better reflect the structure of social behaviour. The development of this more robust method can be facilitated by integrating methods from other biological fields, such as animal breeding and behavioural ecology. In this thesis, we adopted two approaches, originally developed in other fields, for studying social structures. The social network analysis used in Chapter 2, a method commonly applied in behavioural ecology to study social structure in natural conditions (Bieber et al., 2019; Blaszczyk, 2018; Cheney et al., 2016; Kulahci et al., 2018), enables the derivation of quantitative metrics describing social structures, including individual centrality and group connectivity. Furthermore, the statistical method developed in Chapter 5, inspired by social genetic models from animal breeding (Bijma, 2014; McGlothlin and Brodie, 2009), allows identifying individual and dyadic variations in social interactions.

Future research could extend these approaches, which were limited to a few days in this thesis, across the entire growing-finishing period and a broader range of social interactions, including both positive and negative, to investigate the stability over time of individual social tendencies and preferences across behaviours. This could be achieved, for example, by combining the dyadic linear models with multivariate models to estimate correlations in individual tendencies across behaviours and over time, and in preferences for specific pen mates. Predictive models used in epidemiology to study the emergence or spread of a disease (Anacleto et al., 2015; Biemans et al., 2017) could be adapted to investigate how positive and negative social interactions emerge and spread through groups over time. Together, these approaches would help to characterise individual social tendencies and their stability over time within groups.

Understanding individual social tendencies is also important for animal welfare, as animals may vary in their social needs and in how they experience their social environment. For example, more sociable individuals are more likely to experience positive affective states when opportunities for social interactions are available, but may also be more negatively affected when such interactions are restricted (Goursot et al., 2026). Future research should further investigate how different combinations of individual characteristics within social groups, as well as the introduction or removal of individuals, affect social relationships and group dynamics. This could provide practical knowledge for developing management strategies that better account for individual variation in social tendencies and promote welfare.

4.2. Bridging science and farm practice to improve welfare

This thesis has contributed to identifying behaviours that are related to animal welfare and can be monitored automatically, such as tail and ear biting, activity patterns, or social preferences based on proximity. Current and future research based on automated monitoring will generate knowledge about the underlying mechanisms of social interactions and their drivers, which can be transferred to practice on commercial farms to improve pig welfare. This includes identifying best practices to prevent damaging behaviours from escalating (such as feeding strategies, housing systems, group composition, and breed selection), as well as advice on group management to limit stress and promote positive social interactions.

In addition to generating knowledge, automated behaviour monitoring systems could be translated into on-farm decision-support tools to guide management practices and improve

animal welfare. One promising implementation of automated monitoring on farm is the development of early warning systems to detect welfare issues, for example, outbreaks of damaging behaviours. Early warning systems require (near) real-time analysis of behavioural data to enable timely interventions.

Automated monitoring of tail and ear biting (Chapter 6) could contribute to early detection; however, farmers should not be notified for every single tail or ear biting event, as most pigs perform or receive tail and ear biting (Chapters 4 and 5), even if it does not result in immediate tail and ear wounds in all victims (Figure 8). In this thesis, activity was explored as one potential variable to predict tail biting (Chapter 4). Although increased individual activity was associated with tail biting on some days preceding damage, activity alone is unlikely to provide a sufficiently specific indicator, as it is also influenced by several factors, including environmental factors (Chapter 3) and individual characteristics (Hollifield et al., 2024; Luo et al., 2020; Ocepek, 2026). Therefore, effective early warning systems will likely require relying on deviations from individual baselines and integrating multiple feature variables, including environmental data, tail posture (D'Eath et al., 2021; Lahrmann et al., 2018; Wedin et al., 2018), feeding behaviour (Wallenbeck and Keeling, 2013), use of the enrichment (Eisermann et al., 2025; Eisermann et al., 2022), and vocalisation (Denis et al., 2025). These variables could be obtained from different sensor technologies, including computer vision-based behavioural monitoring, climate sensors, data from automated feeding stations, and acoustic monitoring.

Early warning systems may rely on supervised machine-learning approaches trained on annotated historical outbreak datasets to predict future outbreaks, rather than relying on predefined thresholds for individual variables. Machine-learning approaches are promising for building decision-support tools, as they can integrate multiple behavioural and environmental indicators to identify complex patterns associated with high risk of welfare issues (Durand et al., 2023) that may not be captured by predefined rules. However, their practical application requires large datasets and careful validation across multiple farms and conditions to ensure reliable predictions and meaningful biological interpretation under farm conditions.

Continuous automated behavioural monitoring can also generate useful information to guide routine farm management practices. For example, monitoring activity has practical applications for feeding strategies, as pigs with different activity levels may require different amounts and compositions of feed (Gaillard et al., 2020). On commercial farms, pigs are

generally fed a standard diet, which may not meet the needs of more active pigs and could, thus, compromise their welfare. At the same time, less active pigs may receive excess feed, resulting in higher costs and increased environmental emissions (Monteiro et al., 2017; Pomar et al., 2014). Monitoring individual activity could therefore help adjust feeding to each pig's requirements and improve welfare, production, and sustainability.

Finally, automated behaviour monitoring systems could contribute to promoting positive experiences on farms. Animal welfare has been conceptualised as the balance between positive and negative affective experiences, with this overall balance referred to as cumulative affect (Reimert et al., 2023; Webb et al., 2019). By continuously capturing behavioural patterns over time, automated monitoring systems could support the estimation of cumulative affect through the integration of behavioural indicators associated with both positive and negative experiences. In particular, by continuously characterising social relationships and individual behavioural profiles, future systems could support the formation and management of groups that promote social stability and positive interactions. For example, information on social preferences could help to maintain stable relationships during re-arrangement of groups, and group size and composition could potentially be adapted to better match individual needs. Such approaches would shift the objective of automated monitoring from detecting poor welfare towards designing environments that enable animals to express natural behaviours, develop positive social relationships, and improve animal welfare.

4.3. Opportunities to improve genetic selection

Although the initial domestication of pigs involved strong selection for behavioural traits such as tameness, breeding following domestication has focused mainly on improving individual production traits, with relatively little attention to (social) behavioural traits and welfare. This has been driven not only by breeding priorities (i.e. breeding goals, which define the traits targeted for improvement and have historically not prioritised welfare traits), but also by the practical challenge of measuring behaviour across a significant number of individual pigs. This is necessary to estimate genetic parameters required for constructing a selection index (i.e. a weighted combination of measured traits used to achieve the breeding goal).

In practice, human observations of pig behaviour are not feasible on a large scale, especially for behaviours such as tail and ear biting, which occur sporadically and unpredictably. More

recently, however, pig breeding organisations have become increasingly interested in selecting pigs that are less prone to perform or receive negative behaviours and that express more positive behaviours associated with better welfare. At the same time, advances in sensors and computer vision are slowly making it possible to measure behaviour at the individual level, providing new opportunities to include these traits in genetic selection programmes.

Behaviours can be included in breeding programmes if they are accurately phenotyped in a large number of animals, if individuals vary in their expression, and if part of these individual differences is genetically determined, meaning that the behaviours are heritable. In this thesis, we showed, at a small scale and in a limited number of pigs, that computer vision can be used to monitor individual behaviours, such as activity (Chapter 2) and proximity (Chapters 2 and 5), using a tracking-by-detection algorithm, and ear and tail biting behaviour (Chapter 6) using behaviour recognition models. In Chapter 5, we further showed that individual pigs differ in their propensity to be in proximity to others and to perform and receive tail and ear biting.

Activity, defined as time spent in different postures (lateral lying, sternal lying, sitting, standing) and distance moved and measured by computer vision algorithms, is heritable in pigs (Hollifield et al., 2024). Furthermore, although evidence in farm animals is limited and currently unavailable in pigs, a recent study in turkeys investigated two traits related to proximity: the number of pen mates within a 1-m radius and an individual's tendency to move towards areas with more or fewer pen mates (Wang et al., 2025). Significant individual and genetic variation were found for both traits, indicating that some animals have a greater tendency to remain close to others, whereas others prefer to keep their distance. Although these findings were obtained in turkeys, similar patterns may also exist in pigs.

Both activity and proximity could be considered in breeding programs. However, as discussed in the previous sections, these traits do not fully capture what pigs are actually doing when they are active or in proximity to their pen mates. Although activity may be relevant to include in breeding programmes, as it has been negatively correlated with production traits like growth and feed efficiency (Hollifield et al., 2024; Obermier et al., 2023), including these traits should be considered carefully. For example, breeding for less active pigs could also result in selecting animals that show fewer behaviours associated with positive welfare, such as play or nose-to-nose contact. Furthermore, breeding for pigs with higher tendencies to stay in close proximity to other pigs may result in selecting pigs with

tendencies to display both positive and negative social interactions. In the case of activity, rather than focusing on overall activity level, the capacity to recover activity after a challenge may be a more relevant target for breeding programmes, as it could be a measure of resilience (Gorssen et al., 2024). Overall, relying on specific behaviours, obtained through behaviour recognition models, such as the one developed in Chapter 6 to recognise tail and ear damage, may be more valuable for breeding programmes than using broader measures such as proximity or activity alone. There is evidence that tail and ear damage are heritable traits (Breuer et al., 2003; Canario and Flatres-Grall, 2019; Gorssen et al., 2024; Hegedűs et al., 2025; Hermesch and Guy, 2019), which can be used in genetic selection programs to reduce damaging behaviours in future pig populations. Most studies on the genetics of tail and ear biting have, however, focused on ear and tail damage, rather than the behaviour itself. This is disadvantageous as tail and ear damage are indirect measures for studying tail and ear biting and only provide information about the victim. The selection of the biters has been limited to social genetic models, in which the genetics of the biter are inferred by modelling the interaction between biters and victims based on the damage of the victim and the pen composition (Canario and Flatres-Grall, 2019). Furthermore, current selection strategies to reduce damage are typically based on damage scores measured at the end of the production pipeline. These scores reflect the cumulative consequence of damaging behaviour rather than the occurrence of damage throughout the production period or the damaging behaviour itself. However, individual monitoring of ear and tail biting at a large scale with computer vision may become available in the near future and could be further used to select pigs with a lower propensity to perform or receive damaging behaviours.

Since damage scores are often used as proxies for damaging behaviour, the associations between tail and ear damage scores and the frequency and duration of receiving tail and ear biting using data from Chapters 4 and 5 are visualised in Figure 8. Overall, there were no strong associations between these traits. Many pigs that frequently received tail or ear biting did not have severe damage scores. Similarly, pigs with the highest tail (or ear) damage scores were not necessarily those that experienced the most frequent or longest biting events. This is likely due to the force of biting, as some biters may bite strongly on a tail or ears, resulting in severe damage, even if short or for a limited number of times. In contrast, some pigs may bite lightly on the tail and the ears, resulting in no damage, even if they bite at high frequencies and for a long duration. Although exploratory and limited to phenotypic associations, these results suggest that tail and ear damage scores likely reflect a different trait from receiving tail or ear biting. Therefore, selection based on damage scores may not

be equivalent to a selection based on receiving damaging behaviours and would likely lead to selecting different pigs.

Determining which trait (i.e. damage or receiving damage) is more appropriate for selection depends on the breeding goal. Damage scores capture the visible outcome of (some) biting, whereas receiving biting reflects the exposure of the victim to a negative experience, even in the absence of visible damage. If the aim is to reduce physical damage, damage scores are appropriate. However, if the aim is to reduce negative experience, then the selection on receiving damaging behaviour may be more relevant. In practice, both contribute to improving welfare, but they target the problem on a different level.

Selecting against damaging behaviours may negatively affect production performance, as these behaviours have been reported to be negatively correlated with performance traits (Ursinus et al., 2014). A slight reduction in production could be considered an acceptable trade-off for improving welfare, but may require rethinking the production system to maintain farm profitability.

Furthermore, careful attention should be paid when selecting against tail and ear biting (or damage) to avoid compromising other desirable traits, such as positive behaviours. This can be addressed by including multiple phenotypic traits in breeding goals or by evaluating behaviour outcomes after selection. Automated systems for monitoring individual positive behaviours could also provide valuable support for this.

Furthermore, breeding should not only aim to adapt pigs to current environments, where systems may involve higher risks of damaging behaviours due to factors such as limited space and enrichment. It should also be accompanied by improvements in housing and management conditions.

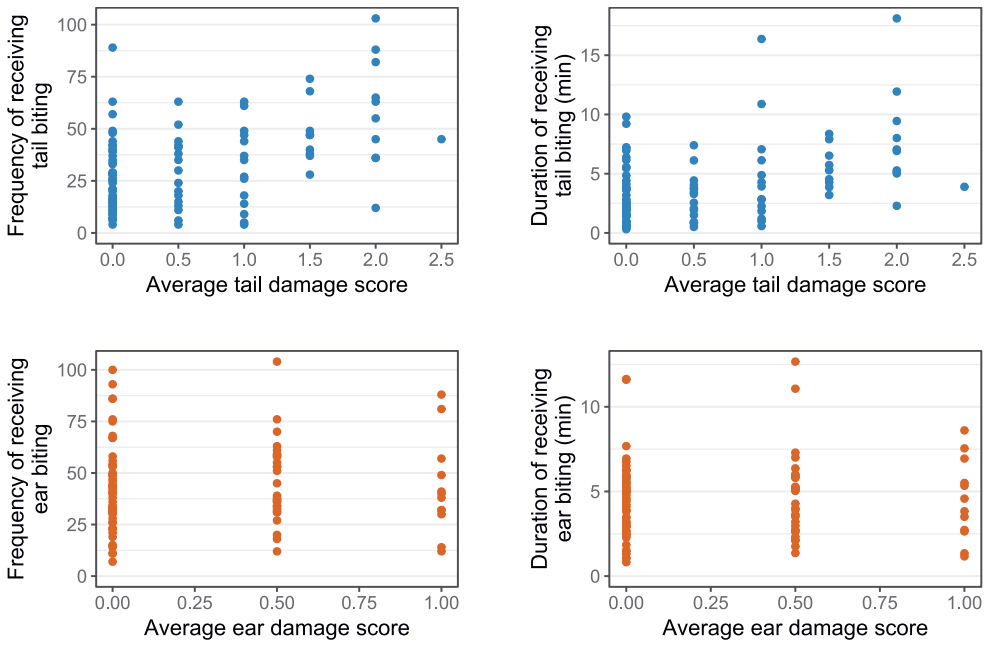


Figure 8. Relationship between the frequency (and duration) of receiving tail (or ear) biting events and the average tail (or ear) damage scores. The frequency and duration of biting events are calculated as summed over the three days of observations (D-5, D-2 and D+1) used in Chapters 3 and 5, and ear and tail damage averaged across the two days used in this study (D0 and D+2). Tail damage was assessed using a 0–5 scoring system (i.e., score 0 = no damage, score 1 = small bite marks are present, score 2 = small wound (< 2cm) is present, tail length is intact, score 3 = medium wound (> 2cm) is present, tail length is intact, score 4 = medium wound (> 2cm) is present, part of the tail is missing, and score 5 = severe wound, the tail is completely missing), and ear damage was scored with a similar 0-5 scale as tail damage, applied to ears (see Bus et al., 2023a).

4.4. Societal relevance, ethical considerations and adoption of PLF technologies

The agriculture sector faces growing pressure to produce more food despite a decrease in the number of farmers, climate change, and consumer expectations regarding sustainability and animal welfare. In this context, automated monitoring of behaviour offers new opportunities on farms to support this transition and face these challenges, but these systems also raise concerns. In this paragraph, I will broaden the discussion from computer vision to the use of a larger range of technologies on farms, which I refer to as precision livestock farming (PLF) technologies.

Monitoring behaviour automatically provides opportunities to significantly improve animal welfare, as discussed in the previous sections of this chapter. In addition, improvements in welfare may also result in better economic performance for farmers; for example, reducing the prevalence of ear and tail biting would lower costs associated with carcass condemnation, veterinary treatments, and production losses (Kritas and Morrison, 2007; Sinisalo et al., 2012; Wallgren and Lindahl, 1996), while also contributing to a reduction of environmental footprint by improving efficiency. Furthermore, PLF technologies may enable individualised animal management, which can also reduce environmental impacts and economic costs by improving the use of resources (Pomar et al., 2010).

However, the implementation of computer vision techniques on farms depends on how well these technologies align with farmers' needs, expectations, and management practices. Several concerns among farmers have already been identified regarding the adoption of new technologies, such as the complexity of the PLF technology, the limited trust in the performance of the technology (McCaig et al., 2023), and the costs involved, without clear knowledge of the return on investment (Guarino et al., 2017). Furthermore, collecting continuous videos on farms also creates an ethical concern about privacy and confidentiality, as this could unintentionally lead to surveillance of workers and create uncertainty about who owns, accesses, and benefits from the data. Therefore, when developing and implementing technologies to support farmers in farm management, farmers should be involved in the process, including discussions about the technologies they want to use, the design of interfaces, and training, to ensure the technologies are useful and that they can understand and use the systems effectively. Government policy should also regulate the adoption of these technologies, especially in relation to data ownership, in order to prevent misuse.

Furthermore, consumer acceptance is also crucial for the adoption of these technologies. Although consumers expect PLF technologies to have positive effects on animal welfare and food safety, they also express concerns that they may further industrialise farming and contribute to a disconnection between the caretaker and the animals (Kopler et al., 2023). This perception may be reinforced by the fact that larger and more intensive farms are generally more able to invest and adopt automated systems (Gargiulo et al., 2018) and that the focus of the current PLF technologies adopted on farm is on production efficiency and farm profitability (Tuyttens et al., 2022). If these technologies enable the collection of welfare indicators on farms, including indicators of positive welfare, and communicate this information transparently to consumers, they may be perceived more positively. For example,

welfare indicators measured using PLF technologies have been proposed to inform consumers with labels indicating the level of animal welfare in animal-based food products (Ingenbleek and Krampe, 2022). In the Netherlands, a label to inform about animal welfare currently exists, namely the *Beter Leven* (In English: "Better Life") label, developed by the *Dierenbescherming* (In English: Society for the Protection of Animals). This certification awards products with a score from one to three stars based on several criteria related to housing and management conditions. For pig products, those criteria are currently the minimum floor space, loose housing of sows during farrowing, access to outdoor areas or pasture, weaning age and tail docking. However, this label does not take into account the behaviour or how animals experience this housing system. Therefore, new technologies could complement the existing labels to include behaviour indicators of welfare. For example, in the future, automated monitoring systems could provide a measure that summarises the balance between positive and negative experience throughout the entire production period (i.e., cumulative affect; Reimert et al., 2023; Webb et al., 2019). This measure could be integrated into existing welfare labels to provide consumers with information about the actual welfare of animals, rather than only on the conditions under which they are kept.

To respond to the societal demand for animal welfare and regulatory changes, pig farms may transition toward more sustainable systems in the near future, characterised by larger group sizes, more natural conditions, including exposure to daylight, and outdoor access. While these systems can improve overall welfare by allowing the expression of natural behaviour (Delsart et al., 2020), they also create more complex and variable environments. PLF technologies, especially those based on computer vision, are often poorly aligned with these environments, as they are typically developed and validated under controlled indoor conditions (Tuyttens et al., 2022). For example, computer vision algorithms require minimal variation of the light, a defined space that can be fully covered with cameras, and a homogeneous background to detect individual animals from their surroundings. Future development of PLF technologies should ensure these technologies support the transition toward more welfare-friendly systems, rather than adapting the housing systems to technological constraints.

Considering the opportunities and challenges discussed above, the adoption of PLF technologies by stakeholders may follow a pattern described by the Gartner Hype Cycle (Dedehayir and Steinert, 2016), where initial expectations about technologies exceed what can currently be achieved in practice. As PLF technologies have developed, they have

generated high expectations among different stakeholders, including farmers, researchers, industry, and consumers, regarding their potential to transform current practices and address challenges related to animal welfare, sustainability, and productivity. For researchers and breeders, these expectations also include the possibility of generating continuous, objective, and individual-level measures of animal behaviour. However, as these technologies move towards practical implementation, it is becoming apparent that a gap remains between expectations and real-world applications. Through further development, validation, and practical experience, stakeholders are gaining a more realistic understanding of the capabilities and limitations of PLF technologies.

In this context, the development and adoption of automated behaviour monitoring systems are moving beyond a phase of high expectations towards a more balanced view of what can currently be achieved in practice. This thesis contributes to this transition by providing further insight into the opportunities and challenges associated with automated behavioural monitoring systems under farm conditions. It demonstrates the potential of computer vision-based approaches for quantifying and analysing animal behaviour, while highlighting key considerations for their application under farm conditions. This opens the door to new opportunities to better understand animal behaviour and, ultimately, to improve animal welfare.



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Summary

In commercial systems, domestic pigs are kept in groups and develop social structures that are influenced by management practices and housing conditions. Pigs are highly social animals, and understanding their social interactions is important, as these interactions are a key component of welfare. Positive social interactions, such as playing or lying in close proximity, can promote welfare, whereas negative interactions, such as ear and tail biting, can severely compromise it. Activity also plays a key role in welfare assessment, as disruption in activity patterns can indicate welfare issues. In large commercial farms, identifying social structures, ear and tail biting, and activity patterns is nearly impossible by human observation. Computer vision algorithms may provide a promising solution by enabling continuous data collection and long-term monitoring of individual behaviour. However, current systems are not yet able to reliably detect all ear or tail biting events and to maintain identity over long periods of time for monitoring individual behaviours. Furthermore, it remains unclear how such methods can be applied in practice or what measures can be derived from computer vision algorithms to characterise behaviour. Therefore, this thesis explored the potential of using computer vision algorithms to monitor social interactions and activity patterns in pigs, with the overarching goal of improving pig welfare.

The data presented in Chapter 2 were collected from three batches of growing-finishing pigs housed at the research facilities of Wageningen University & Research (The Netherlands), with pigs allocated to either barren or enriched pens (n = 21 pens, 6 pigs per pen). The data presented in Chapters 3-6 were collected from three batches of tail-docked pigs housed on a commercial growing–finishing farm in Germany (n = 30 pens, 11 pigs per pen). On this commercial farm, the health status of each pig, including ear and tail damage scores, was assessed twice per week. All chapters included data collected either partially or entirely through computer vision techniques. Proximity between pigs (Chapters 2 and 5) and activity patterns (Chapters 3 and 4) were derived using tracking-by-detection algorithms based on bounding boxes. Ear and tail biting were manually annotated from videos (Chapters 4 and 5) and used to develop and validate a video-based behaviour recognition algorithm presented in Chapter 6.

Chapter 2 explored how a tracking-by-detection algorithm can be used to investigate social networks in pigs based on spatial proximity and how methodological choices regarding proximity definitions and sampling rates affect social networks. Five proximity definitions

were proposed, either based on the distance between the centroids or the overlap of the surfaces of the bounding boxes. Four of those definitions were binary, using a minimal threshold to distinguish pairs of pigs in close proximity from other pairs. The fifth definition was a novel quantitative definition of proximity, measured as the average distance between pairs of pigs over frames. For each proximity definition, the tracking data was downsampled at different sampling rates (with intervals between frames ranging from 2 seconds to one hour). Social networks were constructed for each combination of proximity definition and sampling rate, and four network metrics were calculated (i.e., degree centrality, eigenvector centrality, clustering coefficient, and radius). Our results demonstrate that social network metrics are influenced by both proximity definition and sampling rate and that their impact varies for different network metrics. For example, the direct network metric degree centrality was less affected by proximity definitions and downsampling compared to the indirect network metrics eigenvector centrality and clustering coefficient. Furthermore, the effect of the sampling rate on the network metrics depended on the proximity definition chosen. To preserve the structure of the social network and obtain reliable estimates of network metrics, downsampling should not exceed one frame every six minutes. This chapter proposed novel methods for investigating social networks in pigs based on spatial proximity derived from computer vision tracking data and highlighted important methodological considerations regarding the definition of proximity and sampling.

In the literature, changes in activity have been reported as a potential indicator of tail biting outbreaks. However, before such deviations can be reliably identified, it is essential to first characterise baseline activity patterns to distinguish normal fluctuations from changes associated with welfare issues. Therefore, Chapter 3 investigated the consistency of group-level activity patterns over time, while accounting for the temperature-humidity index (THI). The tracking-by-detection algorithm was run throughout the growing-finishing period in two batches, on two days (24h) per week, every two weeks. Three group-level activity metrics were derived from the tracking data: the average activity, relative amplitude, and intra-daily variability. We found that activity metrics changed significantly over time, although the direction of these changes varied between the two batches. In one batch, characterised by high THI, particularly during the final two weeks, activity shifted from a monophasic to a biphasic pattern over time, with decreasing average activity, relative amplitude and increasing intra-daily variability. The differences between the two days of the week in activity metrics were minimal. In contrast, the other batch, characterised by a relatively stable and low THI, showed fluctuating trends over weeks and more pronounced variation in activity

metrics between the two days of the week. Overall, these findings suggest that the consistency of group-level activity patterns over time is influenced by environmental factors, with THI contributing to fluctuations in activity. Therefore, these factors should be considered when selecting days and interpreting activity patterns for the development of reliable early warning systems for welfare problems.

After characterising group-level activity patterns and their variation over time, the next step was to explore whether activity patterns could indicate early tail-biting outbreaks. Although changes in activity before tail-biting outbreaks have been reported in the literature based on manual observations, they have not yet been investigated using computer vision approaches. Therefore, Chapter 4 investigated whether activity and synchrony patterns derived from a tracking-by-detection algorithm can predict tail damage at the group level and whether individual activity is associated with performing or receiving tail biting. Nine pens with pigs with tail damage (damage pens) were retrospectively selected based on damage scores recorded on farm. Each pen was matched with a control pen with pigs without tail wounds (control pens) on the same day. A tracking-by-detection algorithm was applied in both damage and control pens on four days around the tail damage to quantify average activity and synchrony at the group level and, within the damage pens, at the individual level. Tail biting events and identities of biters and victims were scored from video on three of these days. At the group level, average activity did not affect the probability of a pen becoming a damage pen. However, at the individual level, higher activity on days preceding tail damage was associated with increased tail-biting frequency on the following days. No associations were found between activity synchrony and the frequency of tail biting at both individual and group levels.

Chapter 5 investigated whether individual pigs differ in their proximity to pen mates and in performing and receiving ear and tail biting, and whether, beyond individual variation, specific pairs of pigs spend on average more time in proximity or engage in biting more frequently than others. It introduced a novel modelling approach for assessing individual differences and preferences by partitioning variation in social interactions into individual and dyadic random effects. The analysis was performed on the same dataset collected in damage pens for Chapter 4, with additional annotations for ear biting. Proximity was measured using a quantitative definition similar to the one developed in Chapter 2. Individual pigs explained a high proportion of the variance of tail and ear biting, and a statistically significant but much lower proportion of the variance of proximity. This indicates that pigs differ in their

propensity to bite, receive bites, and in their tendency to be in proximity to (or further apart from) other pigs. Moreover, a non-random distribution of interactions among pig pairs was found, while accounting for individual variation, with certain dyads being more frequently involved in tail and ear biting or spending on average more time in proximity (or further apart) than others within the group. This last result suggests that pigs have preferences for specific individuals in ear biting, tail biting, and proximity. Overall, this study demonstrates that social interactions are shaped by both individual and dyadic factors, and introduces a dyadic modelling approach that can be applied in future research to better understand variation in social interactions.

Chapter 4 demonstrated that individual activity in the days preceding the occurrence of tail wounds can be used to identify tail biters, which may allow earlier intervention to limit outbreaks. As a complementary approach, focusing on automatically recognising the biter, rather than indirect predictors, could also support earlier intervention before escalation. Therefore, Chapter 6 proposed a video-based behaviour recognition algorithm for the automated monitoring of individual tail and ear biting. Two state-of-the-art action recognition models were evaluated for recognising tail and ear biting. The annotations used to develop and validate these models varied substantially in the postures of victims and biters, pig age, and lighting conditions. The best-performing model achieved detection accuracies of approximately 72% for both damaging behaviours. Most misclassifications occurred between tail and ear biting, rather than between either of these behaviours and other non-damaging behaviours.

Chapter 7 synthesised the findings from the previous chapters and reflected on how this thesis contributes to bridging the gap between computer vision and behavioural research. First, the technical challenges associated with using computer vision approaches to monitor behaviour and potential solutions and recommendations for future work were discussed. For example, in tracking-by-detection algorithms, maintaining the identity of individual pigs over time remains a key challenge, and a solution for identity switches could be to integrate RFID data from feeding stations. I then examined how computer vision outputs can be translated into meaningful behavioural metrics. In particular, I reflected on sampling strategies for data collected at the frame level and proposed recommendations to guide the selection of appropriate sampling approaches in future studies. Furthermore, I summarised how spatial proximity and distance moved, derived from a tracking-by-detection algorithm, can be used as proxies for social interactions and activity, and discussed the limitations. Finally, the

broader implications of this research and its potential applications were discussed, particularly for future behaviour research, farm management and animal breeding. Finally, I discussed the societal relevance of this work by considering the role automated monitoring systems may play in supporting farmers, informing consumers, and facilitating the transition toward more sustainable and animal-centred production systems, while also addressing the ethical considerations required for their implementation.

To conclude, this thesis contributes to bridging the gap between computer vision and behavioural research. It demonstrates the potential of using computer vision data for behavioural research while highlighting important methodological considerations for its application. This thesis proposed novel methods that extend beyond traditional approaches to quantify and statistically analyse behaviour. This opens the door to new opportunities to better understand animal behaviour and, ultimately, to improve animal welfare.

Résumé

Dans les systèmes d'élevage commerciaux, les porcs domestiques sont généralement élevés en groupes et développent des structures sociales qui sont notamment influencées par les pratiques d'élevage et les conditions de logement. Le porc étant une espèce particulièrement sociale, il est essentiel de comprendre ses interactions avec ses congénères, car celles-ci constituent un élément important de son bien-être. En effet, les interactions sociales positives, telles que les comportements de jeu ou les affiliations avec des congénères, peuvent favoriser leur bien-être. À l'inverse, les interactions négatives, telles que les morsures d'oreilles ou de queue, peuvent fortement compromettre leur bien-être. Le niveau d'activité constitue également un indicateur important du bien-être animal. En effet, une modification des rythmes habituels d'activité peut être le signe d'une dégradation des conditions ou de l'état de bien-être des animaux. Dans les élevages commerciaux, l'identification de la structure sociale des groupes, des comportements de morsure des oreilles et de la queue ainsi que des rythmes d'activité est impossible à réaliser par la seule observation humaine. Les techniques de vision par ordinateur représentent ainsi une approche prometteuse, puisqu'elles permettent d'automatiser la collecte de données et d'assurer un suivi continu des comportements sur de longues périodes. Néanmoins, les systèmes actuellement disponibles présentent encore certaines limites. Ils ne permettent notamment pas de détecter de manière suffisamment fiable les comportements de morsure d'oreilles et de queue, ni de conserver l'identité individuelle des animaux sur des périodes suffisamment longues pour suivre leur comportement individuel. Par ailleurs, les connaissances sur la mise en œuvre pratique de ces méthodes et sur les indicateurs pouvant être dérivés des algorithmes de vision par ordinateur pour caractériser les comportements restent encore limitées.

Cette thèse s'est donc intéressée au potentiel des algorithmes de vision par ordinateur pour le suivi des interactions sociales et des rythmes d'activité chez les porcs. L'objectif général était d'évaluer comment ces technologies pourraient contribuer à une meilleure évaluation et, à terme, à une amélioration du bien-être des porcs.

Les données présentées dans le Chapitre 2 ont été recueillies auprès de trois lots de porcs en phase de croissance-finition, élevés dans les installations de recherche de Wageningen University & Research, aux Pays-Bas. La moitié des animaux était logée dans des enclos enrichis, et l'autre moitié dans des enclos conventionnels. Au total, 21 groupes de 6 porcs ont été étudiés.

Les données utilisées dans les Chapitres 3 à 6 provenaient de trois lots de porcs élevés dans un élevage commercial de croissance-finition situé en Allemagne. Dans cet élevage, les porcs étaient répartis dans 10 enclos de 11 animaux chacun. L'état de santé et de bien-être de chaque porc, notamment les lésions au niveau des oreilles et de la queue, était évalué deux fois par semaine.

L'ensemble des chapitres repose, en partie ou en totalité, sur des données obtenues grâce à des techniques de vision par ordinateur. La proximité entre les animaux (Chapitres 2 et 5), ainsi que leurs rythmes d'activité (Chapitres 3 et 4), ont été déterminés à partir d'algorithmes de suivi (« tracking »), à l'aide de boîtes englobantes (« bounding boxes »). Les comportements de morsure des oreilles et de la queue ont été annotés manuellement à partir des vidéos dans les Chapitres 4 et 5. Ces annotations ont ensuite servi à développer et à valider un algorithme de reconnaissance automatique des comportements à partir de vidéos, présenté dans le Chapitre 6.

Le Chapitre 2 s'est intéressé à l'utilisation d'un algorithme de tracking pour étudier les réseaux sociaux chez les porcs à partir de leur proximité spatiale. L'étude visait également à déterminer dans quelle mesure certains choix méthodologiques, notamment la définition de la proximité et la fréquence d'échantillonnage des données, pouvaient influencer les réseaux sociaux obtenus. Cinq définitions de proximité, reposant soit sur la distance entre les centroïdes, soit sur la surface de recouvrement des boîtes englobantes, ont été proposées. Quatre de ces cinq définitions étaient binaires et reposaient sur un seuil minimal permettant de déterminer si deux porcs étaient à proximité l'un de l'autre. La cinquième définition était quantitative et correspondait à la distance moyenne séparant deux porcs au cours de la période d'étude. Pour chacune de ces définitions, les données de tracking ont été sous-échantillonnées, avec des intervalles entre deux images successives variant de 2 secondes à 1 heure. Pour chaque combinaison de définition de la proximité et de fréquence d'échantillonnage, un réseau social a été construit. Quatre mesures de réseaux sociaux ont ensuite été calculées : la centralité de degré, la centralité de vecteur propre, le coefficient de clustering et le rayon. Les résultats ont montré que les mesures utilisées pour caractériser les réseaux sociaux étaient influencées à la fois par la définition de proximité et par la fréquence d'échantillonnage. Toutefois, l'importance de ces effets variait selon la mesure considérée. Par exemple, la centralité de degré, qui est une mesure directe du réseau, était relativement peu sensible aux différentes définitions de la proximité et au sous-échantillonnage. À l'inverse, les mesures indirectes, telles que la centralité de vecteur propre et le coefficient de

clustering, étaient davantage affectées par ces choix méthodologiques. L'influence de la fréquence d'échantillonnage dépendait également de la définition de proximité utilisée. Afin de préserver une structure du réseau social représentative et d'obtenir des estimations fiables des différentes mesures, les résultats indiquent que les données ne devraient pas être sous-échantillonnées au-delà d'une image toutes les six minutes. Ainsi, ce chapitre propose de nouvelles approches pour étudier les réseaux sociaux chez les porcs à partir de leur proximité spatiale, estimée grâce à des algorithmes de tracking. Il met également en évidence l'importance des choix méthodologiques lors de l'utilisation de ces données pour caractériser les structures sociales des animaux, notamment en ce qui concerne la définition de proximité et la fréquence d'échantillonnage.

Dans la littérature, un changement du niveau d'activité a été proposé comme indicateur potentiel d'épisodes de morsure de queue. Toutefois, avant de pouvoir détecter de manière fiable de telles déviations, il est essentiel de comprendre et de caractériser les rythmes d'activité de référence afin de distinguer les fluctuations normales des modifications susceptibles d'être associées à des problèmes de bien-être. Le Chapitre 3 a ainsi étudié la stabilité des rythmes d'activité à l'échelle du groupe au cours du temps, tout en prenant en compte l'indice température-humidité (THI). Un algorithme de tracking a été utilisé pour mesurer l'activité tout au long de la période d'engraissement dans deux lots, à raison de deux journées de suivi de 24 heures par semaine, toutes les deux semaines. Trois mesures d'activité ont été calculées à l'échelle du groupe à partir des données de tracking : l'activité moyenne, l'amplitude relative et la variabilité intra-journalière. Les résultats montrent que les mesures d'activité évoluent significativement au cours du temps, bien que la direction de ces évolutions diffère entre les deux lots. Dans l'un des lots, caractérisé par un THI élevé, notamment au cours des deux dernières semaines, le profil d'activité a progressivement évolué d'un rythme monophasique à un rythme biphasique. Cette évolution s'est accompagnée d'une diminution de l'activité moyenne et de l'amplitude relative, ainsi que d'une augmentation de la variabilité intra-journalière. Les différences entre les deux jours de suivi au cours d'une même semaine étaient faibles pour les différents indicateurs d'activité. À l'inverse, l'autre lot, caractérisé par un THI relativement stable et faible, présentait des tendances fluctuantes au cours des semaines ainsi qu'une variation plus marquée des indicateurs d'activité entre les deux jours de suivi. Dans l'ensemble, ces résultats suggèrent que la stabilité des rythmes d'activité à l'échelle du groupe au cours du temps est influencée par les facteurs environnementaux, le THI contribuant notamment aux fluctuations de l'activité. Ces facteurs devraient donc être pris en compte lors de la sélection des jours de

suivi et de l'interprétation des rythmes d'activité dans le cadre du développement de systèmes d'alerte pour la détection de problèmes de bien-être.

Après avoir caractérisé les rythmes d'activité à l'échelle du groupe et leur évolution au cours du temps, l'étape suivante consistait à déterminer si les rythmes d'activité pouvaient constituer des prédicteurs de l'apparition d'épisodes de morsure de queue. Le Chapitre 4 a ainsi étudié si les rythmes d'activité, obtenus à partir d'un algorithme de tracking, et leur synchronie, pouvaient prédire l'apparition de lésions de la queue à l'échelle du groupe, et si l'activité individuelle était associée au fait de mordre ou de subir des morsures de queue. Neuf groupes de porcs présentant des lésions de la queue (« enclos avec lésions ») ont été sélectionnés rétrospectivement sur la base d'observations en élevage. Chaque enclos a été apparié à un enclos contrôle contenant des porcs ne présentant pas de lésions de la queue (« enclos contrôle »). Un algorithme de tracking a été appliqué dans les enclos avec lésions et les enclos contrôles, au cours de quatre journées précédant l'apparition des lésions de la queue, afin de quantifier l'activité moyenne et la synchronie à l'échelle du groupe et, dans les enclos avec lésions, à l'échelle individuelle. Les épisodes de morsure de queue ainsi que l'identité des porcs mordeurs et mordus ont été annotés à partir des vidéos pour trois de ces journées. À l'échelle du groupe, l'activité moyenne n'a pas influencé la probabilité qu'une case soit classée comme enclos avec lésions. En revanche, à l'échelle individuelle, une activité plus élevée au cours des jours précédant l'apparition des lésions de la queue était associée à une fréquence plus élevée du comportement de mordre la queue au cours des jours suivants. Aucune association n'a été mise en évidence entre la synchronie de l'activité et la fréquence des morsures de queue, que ce soit à l'échelle individuelle ou à l'échelle du groupe.

Le Chapitre 5 a étudié si les porcs différaient dans leur proximité avec leurs congénères et dans leur propension à pratiquer ou à subir des morsures d'oreilles et de queue, et si, au-delà des différences individuelles, certaines paires de porcs passaient en moyenne davantage de temps à proximité l'une de l'autre ou étaient impliquées plus fréquemment dans des comportements de morsure que d'autres. Une nouvelle approche de modélisation a été proposée afin d'évaluer les différences et les préférences individuelles en décomposant la variabilité des interactions sociales en effets aléatoires individuels et dyadiques. L'analyse a été réalisée à partir du même jeu de données collecté dans les neuf enclos avec lésions du Chapitre 4, complété par des annotations supplémentaires du comportement de morsures d'oreille. La proximité a été mesurée à l'aide d'une définition quantitative similaire à celle développée dans le Chapitre 2. Les différences individuelles expliquaient une proportion

importante de la variance des morsures de queue et d'oreilles, ainsi qu'une proportion statistiquement significative, mais beaucoup plus faible, de la variance de la proximité. Ces résultats indiquent que les porcs diffèrent dans leur propension à mordre et à être mordus, ainsi que dans leur tendance à se trouver à proximité d'autres porcs ou, au contraire, à s'en tenir à distance. Par ailleurs, après prise en compte des différences individuelles, les interactions entre paires de porcs n'étaient pas réparties aléatoirement. Certaines dyades étaient ainsi plus fréquemment impliquées dans des morsures de queue ou d'oreilles. De la même façon, certaines paires passaient en moyenne davantage de temps à proximité l'un de l'autre ou, au contraire, plus éloignées l'un de l'autre que d'autres paries. Ce dernier résultat suggère que les porcs présentent des préférences pour certains congénères en ce qui concerne les morsures d'oreilles, les morsures de queue et la proximité. Dans l'ensemble, cette étude montre que les interactions sociales sont déterminées à la fois par des facteurs individuels et dyadiques, et propose une approche de modélisation dyadique qui pourra être appliquée dans de futurs travaux afin de mieux comprendre la variabilité des interactions sociales.

Le Chapitre 4 a montré que le niveau d'activité pouvait être utilisé pour identifier les porcs susceptibles d'être impliqués comme mordeurs dans les jours suivants et permettre une intervention précoce afin de limiter l'apparition et la propagation des comportements de morsure de queue. En complément de cette approche, la reconnaissance automatique du comportement de morsure de queue, plutôt que l'utilisation de prédicteurs indirects, pourrait également permettre une intervention précoce. Le Chapitre 6 a ainsi proposé un algorithme de reconnaissance des comportements à partir de vidéos pour assurer la détection automatisée des morsures de queue et d'oreilles à l'échelle individuelle. Deux modèles de reconnaissance de comportement ont été évalués pour reconnaître les morsures de queue et d'oreilles. Les annotations utilisées pour développer et valider ces modèles présentaient une forte variabilité en termes de postures des porcs mordeurs et mordus, d'âge des animaux et de conditions d'éclairage. Le modèle le plus performant a atteint une précision de détection d'environ 72 % pour chacun des deux comportements. La majorité des erreurs de classification correspondaient à une confusion entre les morsures de queue et les morsures d'oreilles, plutôt qu'à une confusion entre l'un de ces deux comportements et d'autres comportements non dommageables.

Le Chapitre 7 a synthétisé les résultats des chapitres précédents et a proposé une réflexion sur la manière dont cette thèse contribue à favoriser l'intégration de la vision par ordinateur dans la recherche en comportement animal. Dans un premier temps, les difficultés techniques

associées à l'utilisation d'algorithme de vision par ordinateur pour le suivi des comportements ont été abordées, ainsi que les solutions possibles et les recommandations pour de futures recherches. Par exemple, dans les algorithmes de tracking, le maintien de l'identité individuelle des porcs au cours du temps reste particulièrement difficile. L'intégration de données RFID provenant des stations d'alimentation pourrait permettre de corriger les erreurs d'identification. La manière dont les données issues de la vision par ordinateur peuvent être converties en indicateurs comportementaux pertinents a ensuite été examinée. Une attention particulière a été accordée aux stratégies d'échantillonnage des données collectées à l'échelle de l'image, et des recommandations ont été proposées pour le choix des méthodes d'échantillonnage appropriées. Par ailleurs, l'utilisation de la proximité pour caractériser les interactions sociales et de la distance parcourue pour caractériser l'activité, ainsi que leurs limites, a été discutée. Enfin, les potentielles applications de algorithmes de vision par ordinateur ont été abordées, notamment pour les futures recherches sur le comportement animal, la gestion des élevages et la sélection génétique. La pertinence sociétale de ces travaux a également été discutée, en considérant le rôle que les systèmes de suivi automatisé pourraient jouer pour accompagner les éleveurs, informer les consommateurs et faciliter la transition vers des systèmes de production plus durables et davantage centrés sur le bien-être des animaux, tout en prenant en compte les considérations éthiques nécessaires à leur mise en œuvre.

En conclusion, cette thèse contribue à favoriser l'intégration de la vision par ordinateur dans la recherche en comportement animal. Elle met en évidence le potentiel des algorithmes de la vision par ordinateur pour l'étude du comportement, tout en soulignant les considérations méthodologiques importantes à prendre en compte lors de leur utilisation. Cette thèse propose de nouvelles méthodes permettant d'aller au-delà des approches traditionnelles pour quantifier et analyser statistiquement les comportements. Elle ouvre ainsi de nouvelles perspectives pour mieux comprendre le comportement des animaux et, à terme, contribuer à l'amélioration de leur bien-être.

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For a long time, I imagined research as working independently. During this PhD, I learned that ideas cannot be built alone. Yes, we need space to think, to read, to try things out, to fail, to get stuck, to try again, and to do better. But what really helps an idea move forward is talking to other people, getting feedback, and hearing new ideas. Sometimes, it is a small conversation with a colleague who mentions a paper they have read, a presentation they attended, or a statistical method they have used. Sometimes, it is a question that makes you look at your research from a different angle, or someone telling you that the first few steps you have taken make sense.

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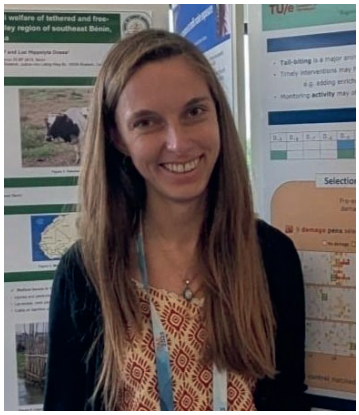
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From movement to meaning. From Paris to Wageningen. From Wageningen to…

« *Je suis en route*
J'ai toujours été en route
Le train fait un saut périlleux et retombe sur toutes ses roues
Le train retombe sur ses roues
Le train retombe toujours sur toutes ses roues. »

Blaise Cendrars, *La Prose du Transsibérien*

About the author



Clémence Orsini was born on the 9th of June 1997 in Paris, France. She completed a two-year intensive preparatory programme in biology, chemistry, physics, and geology, preparing for competitive entrance examinations to French engineering, agricultural, and veterinary schools. She was admitted to Institut Agro (formerly Agrocampus Ouest) in Rennes, France, where she obtained an engineering degree in agronomy (equivalent to an MSc) with a specialisation in animal sciences.

During her MSc, she completed a semester at Université Laval in Québec, Canada, and a practical internship at a goat farm in southern France. Alongside the regular programme, she chose to spend a year between the first and second years of her MSc gaining further experience in research through internships at several institutions, including Teagasc in Ireland, the National Stud in Switzerland, and Vetmeduni in Austria, working respectively with cattle, horses, and pigs. During her internship in Austria, she investigated the effects of environmental enrichment on piglets' welfare. Through this experience, she developed a strong interest in pigs, their behaviour, and their welfare. She subsequently completed her master's thesis at INRAE in Saint-Gilles, France, investigating the effects of light and environmental enrichment on sow behaviour.

After completing her MSc, Clémence started her PhD in the Adaptation Physiology group at Wageningen University & Research as part of the interdisciplinary IMAGEN project. Within this project, Clémence's PhD focused on analysing social dynamics and activity patterns in pigs using computer vision data, with particular emphasis on translating outputs derived from algorithms into meaningful measures relevant for welfare. She also contributed to the development and validation of video-based algorithms for automated behaviour monitoring.

Education and training certificate

With the educational activities listed, the PhD candidate has complied with the educational requirements set by the graduate school Wageningen Institute of Animal Sciences (WIAS) of Wageningen University & Research, which comprises a minimum of 30 ECTS (European Credit Transfer and accumulation System). One ECTS equals a study load of 28 hours.

The Basic Package	**2.9 ECTS**
WIAS - Introduction Day	2021
WGS - Scientific Integrity course	2023
WGS - Ethics in Animal Sciences course	2024
Introduction course on Personal Effectiveness	2022

Disciplinary Competences	**18.8 ECTS**
WIAS - Writing research or grant proposals	2022
WIAS - Image and Video Analysis	2021
WIAS - Computer Vision for Animal Scientists - Tracking and Pose Estimation	2022
WIAS/PE&RC - Statistics for Data Science	2022
WIAS - Fundaments of Animal Monitoring Systems Animal Tracking & Data Analysis	2023
WIAS - Fundamentals of Animal Emotion	2023
ABG-30806 (MSc course) Modern Statistics for the Life Sciences	2023
WIMEK - Big data exploration and object-oriented programming with Python	2023

Professional Competences	**4.8 ECTS**
Supervising BSc & MSc thesis students	2023
Start to Teach: Preparing Learning	2024
WIAS - The Final Touch	2021-2026
Board member PigWeb Junior Community	2025
In'to Languages - Scientific Writing	2023

Societal Relevance	**1.5 ECTS**
WIAS - Societal Impact of your Research	2024

Presentation Skills	**4 ECTS**
Oral - A tracking-by-detection method to study social networks based on proximity in pigs. WIAS Annual Conference, Ede, The Netherlands	2023
Oral - Social networks in pigs based on computer vision: impact of proximity definition. International Society for Applied Ethology, Tallinn, Estonia	2023
Poster - Optimal sampling interval to study proximity networks in pigs based on computer vision. European Conference on Precision Livestock Farming, Bologna, Italy	2024
Poster - Identifying tail-biters before damage occurs: A tracking-by-detection approach, International Society of Applied Ethology, Utrecht, the Netherlands	2025

Teaching competences	**5.1 ECTS**
Supervising 1 internship student	2022
Supervising 4 MSc thesis students	2022-2023
Supervising 1 BSc thesis student	2022
Supervising practical project IAS	2023

Total 35.6 ECTS

Publications

Guo, Q., Sun, Y., Orsini, C.A.E.M, Bolhuis, J.E., de Vlieg, J., Bijma, P., de With, P.H.N., 2023, Enhanced camera-based individual pig detection and tracking for smart pig farms. Computers and Electronics in Agriculture. 211, 108009.

Orsini, C.A.E.M., Hegedűs, B., van der Zande, L.E., Reimert, I., Bijma, P., Bolhuis, J.E., 2025, Impact of proximity definitions and sampling rates on social networks in pigs based on tracking using computer vision. Scientific Reports. 15, 1, 9759.

Orsini, C.A.E.M., Huo, S., Bus, J.B., Guo, Q., Sun Y., van der Zande, L.E., Langenhuizen P.P.J.H., de With, P.H.N., Bijma, P., Bolhuis, J.E., Reimert, I., 2025, Activity and synchrony patterns obtained by a tracking-by-detection algorithm as potential predictors of tail biting at pen and individual level in pigs. Animal. 101714.

Guo, Q.*, Orsini, C.A.E.M.*, Langenhuizen, P.P.J.H., Sun, Y., Huo, S., van Der Zande, L.E., Reimert, I., Bolhuis, J.E., Bijma, P., De With, P.H., 2026, Behaviour recognition of tail and ear biting in pigs using AI-based computer vision. Smart Agricultural Technology. 101713.

Orsini, C.A.E.M., Hegedűs, B., Bijma, P., Bolhuis, J.E., Reimert, I. Who interacts with whom? Estimating individual and dyadic variation in proximity, tail biting, and ear biting in pigs using generalised linear mixed models. (*Under review*)

Orsini, C.A.E.M., Huo, S., Bus, J.B., Boumans, I.J.M.M., Hegedűs, B., van der Zande, L., Langenhuizen P.P.J.H., de With, P.H.N., Bijma, P., Bolhuis, J.E., Reimert, I., Consistency of group-level activity patterns of growing-finishing pigs, obtained by a tracking-by-detection algorithm. (*Under review*)

Guo, Q., Langenhuizen, P.P.J.H, Orsini, C.A.E.M, Sun, Y., Huo, S., van Der Zande L.E., Bolhuis, J.E., de Vlieg, J., Bijma, P., de With, P. H. N. From Body to Head: Keypoint-Guided Localization and Geometric Correction for Ear-Biting and Tail-Biting Recognition in Pigs. (*Under review*)

*Authors contributed equally to the study

Conference proceedings

Orsini, C.A.E.M., Durand M., Gaillard, C. Feb 2022. Effect of environmental enrichment on the behaviour of pregnant sows. Poster presentation at 54th Swine Research Day 2021 (Journées Recherche Porcine), Online, 54, p.149-150.

Orsini, C.A.E.M., Hegedűs, B., van der Zande, L.E., Reimert, I., Bijma, P. & Bolhuis, J.E., Aug 2023, Social networks in pigs based on computer vision: impacts of proximity definition. Oral presentation at 56th Congress of the International Society for Applied Ethology (ISAE 2023). Tallinn, Estonia, p.18.

Orsini, C.A.E.M., Hegedűs, B., van der Zande, L.E., Bijma, P., Bolhuis, J.E. & Reimert, I., Oct 2024, Optimal sampling interval to study proximity networks in pigs based on computer vision. Poster presentation at 11th European Conference on Precision Livestock Farming (ECPLF 2024), Bologna, Italy, p.1737-1744.

Guo, Q., Pei, D., Sun, Y., Langenhuizen, P.P.J.H., Orsini, C.A.E.M., Martinsen, K.H., Nordbø, Ø., Bolhuis, L., Bijma, P. & de With, P.H.N., Feb 2025, Multi-Object Keypoint Detection and Pose Estimation for Pigs. Oral presentation at the 20th International Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications. Porto, Portugal, 3, p. 466-474.

Orsini, C.A.E.M., S. Huo, J. D. Bus, P.P.J.H. Langenhuizen, P. H. N. De With, P. Bijma, J. E. Bolhuis and I. Reimert, Aug 2025, Identifying tail-biters before damage occurs: a tracking-by-detection approach. Poster presentation at the 58th Congress of the International Society for Applied Ethology. Utrecht, The Netherlands, p.237.

Guo, Q., Orsini, C.A.E.M., Langenhuizen, P.P.J.H., Sun, Y., Huo, S., Van Der Zande, L.E., Reimert, I., Bolhuis, J.E., Bijma, P., De With, P.H., Aug 2025, Automated video-based recognition of tail and ear biting in pigs. Oral presentation at the 58th Congress of the International Society for Applied Ethology. Utrecht, The Netherlands, p.268.

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