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A cross-sectional study for predicting tail biting risk in pig farms using classification and regression tree analysis

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ABSTRACT

Tail biting in pigs has been an identified behavioural, welfare and economic problem for decades, and requires appropriate but sometimes difficult on-farm interventions. The aim of the paper is to introduce the Classification and Regression Tree (CRT) methodologies to develop a tool for prevention of acute tail biting lesions in pigs on-farm. A sample of 60 commercial farms rearing heavy pigs were involved; an on-farm visit and an interview with the farmer collected data on general management, herd health, disease prevention, climate control, feeding and production traits. Results suggest a value for the CRT analysis in managing the risk factors behind tail biting on a farm-specific level, showing 86.7% sensitivity for the Classification Tree and a correlation of 0.7 between observed and predicted prevalence of tail biting obtained with the Regression Tree. CRT analysis showed five main variables (stocking density, ammonia levels, number of pigs per stockman, type of floor and timeliness in feed supply) as critical predictors of acute tail biting lesions, which demonstrate different importance in different farms subgroups. The model might have reliable and practical applications for the support and implementation of tail biting prevention interventions, especially in case of subgroups of pigs with higher risk, helping farmers and veterinarians to assess the risk in their own farm and to manage their predisposing variables in order to reduce acute tail biting lesions.

1. Introduction

Tail biting in pigs has been an identified behavioural problem for decades. It has serious economic consequences for pig producers through increased production costs due to lower daily gains, increased susceptibility to secondary infections, a higher antibiotic use and decreased market value arising from less-uniform batches and carcass condemnations (Schrøder-Petersen and Simonsen, 2001). Moreover, acute lesions after tail biting have welfare implications for the animals involved. Unfortunately, understanding the true causation of tail biting is difficult because of its sporadic and unpredictable occurrence, which often thwarts formal experimental approaches (Edwards, 2006). Various factors, including diet, health, environmental stressors, stocking density and climatic environment have been suggested to influence risk for tail biting occurrence (Taylor et al., 2010). However, the complexities of their interrelationships in a model that predicts tail biting risk are far from clear. An understanding of interactions may be key to explaining much of the current lack of risk factor confirmation across studies, and assist in the design and analysis of other related epidemiological studies.

Although attributing a reliable degree of risk of acute tail biting lesions to a specific farm is problematic due to the multifactorial origin of the problem, determining the relative contribution of predisposing factors enables farmers and veterinarians to decide appropriate on-farm interventions. Indeed, the inability to prevent occurrence of the behaviour reliably under commercial farm conditions has resulted in the majority of pig farms throughout the world considering it necessary to dock the tails of all piglets as a preventative measure. This, in itself, constitutes both an animal welfare and an ethical issue, as highlighted in the EU Directive 2008/120 on minimum standards for the protection of pigs, which restricts routine tail docking and emphasises the need to find alternative preventative strategies. Moreover, information about consequences of tail docking avoidance in a prolonged rearing cycle, as in case of the heavy pig production, are limited.

In an attempt to better characterize tail biting in heavy pigs, an initial descriptive epidemiological study was conducted (Scollo et al., 2016). Some risk factors emerged between bitten and unbitten populations, although no one factor clearly separated the two groups and it was not possible to predict tail biting outbreaks. Traditional linear, correlative methods can be difficult to apply to combinations of

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continuous and categorical variables, especially if the roles of the variables are context dependent. Moreover, if a process is multifactorial, its causes may not be revealed by correlations (Durst and Roth, 2012). For these reasons, in the present study a classification and regression tree analysis (CRT) was used to detect potential interactions on a multilevel basis. CRT (Camp and Slattery, 2002) has been previously used in human medicine as a means of examining the complex interactions or patterns of risk factors and treatment options in a variety of diseases, such as colon (Hess et al., 1999), gastric (Silvera et al., 2014) and lung (Papathomas et al., 2011) cancers. In the zoological sector, CRT was used to predict biological evolution in freshwater fishes (Ruesink, 2005) and in rodents (Durst and Roth, 2012), and to weigh risk factors associated with a colony collapse disorder in honey bees (VanEngelsdorp et al., 2010). CRT analysis is highly flexible since it can cope with a mixture of variable types in the same analysis (continuous, ordinal, or nominal), and does not require stringent theoretical or distributional assumptions of more traditional methods such as cluster analysis or discriminant analysis (Camp and Slattery, 2002).

Considering that no examples of studies using this methodology in the field of pig production are provided in published studies, this paper sought to provide a clear introduction to the CRT methodology and explain how and why CRT analysis could be applied in swine research. The aim of this study was to use CRT analysis to identify the interrelationships between, and the discriminatory value of, a broad range of objectively measured explanatory risk factors for acute tail biting lesions in a sample of commercial farms rearing heavy pigs, and to estimate the importance of each variable to predict the farms with potential tail-biting issues. A CRT analysis was chosen because it can calculate absolute risk of tail biting in subgroups within the sample, each with its own set of risk factors and cut points, which may assist in better-targeted intervention strategies.

2. Materials and methods

2.1. Farms sample

A cross sectional study was carried out involving a convenience sample of 67 commercial pig farms located in Northeast Italy (Scollo et al., 2016), available to be involved in the study. In this area, heavy pigs are reared for specialised Protected Designation of Origin (PDO) ham production, and slaughtered at around 170 kg of weight and nine month of age. This area supplies 84.8% of the national production (ISTAT, 2011). In particular, farms involved in the study came from three of the four Italian regions with the highest density of pigs (Lombardia, Veneto and Emilia Romagna) and the greatest average farm sizes (Lombardia: 1840 pigs per farm; Veneto: 527; Emilia Romagna: 1054; other Italian regions except Piemonte: 73) (ISTAT, 2011). Each farm was first contacted by telephone and informed of the project in order to obtain consent for a visit. Visits were carried out during the hot season from March to October 2014 by two trained veterinarians. Due to the lack of information relating to some risk factors (no answers, input errors, etc.) only 60 farms were suitable for subsequent use in the analysis. A sample size of 60 statistical units is enough to calculate an odds ratio equal to 2, having an expected prevalence of the outcome equal to 25% (prevalence of disease of tail biting in the farm population, Scollo et al., 2016) with a confidence level at 90% and a relative precision of 60%.

2.2. Data collection

Data collection was performed through a farmer interview and an on-farm visit in order to collect the most complete data-set. At the start of the visit, farmers completed a face-to-face questionnaire, including farm and management characteristics relating to a total of 36 different issues assessed (Scollo et al., 2016). Further collection of data on-farm was carried out by an observer after the farmer interview had been completed, and allowed verification of the answers which could be corrected if necessary. Furthermore, environmental and microclimate data were instrumentally collected using a DRAGER X-am 7000 (Dräger Safety AG & Co. KGaA, Lübeck, Germany) for ammonia and CO_2 levels in the barns. During this phase, the number of pigs with tail lesions was recorded in all the pens. Although it was impossible to identify every mild lesion generated during the previous stages of the cycle, severe lesions generated in the earlier stage of life and a proportion of mild lesions induced early in life which develop into severe lesions in later stages, would still be detectable later on (Smulders et al., 2008).

The number of tail lesions was recorded using a binomial method, scoring as zero the animals without any lesions, and as one the animals with tail injuries ranging from superficial scratches with blood to missing parts of the tail due to severe biting. Live observations were made from outside the pen, to minimize the disturbance, but the observer entered the pen for further checking when the severity of the lesion was in doubt. Further information is presented in Supplementary Methods.

2.3. Statistical analysis

A Classification and Regression Tree (Breiman et al., 1984) approach was adopted on the data set (STATISTICA, version 13 © Dell Inc.) including in the models both continuous and categorical predictors. Two different models were used in the study, the first used the presence or absence of tail biting at the farm (binary outcome, Classification Tree Analysis – CTA), while the second analysis considered the prevalence of affected animals (continuous variable, Regression Tree Analysis – RTA). In both analyses, 24 measures of risk were used as independent or predictor variables (Table 1) and they were selected from the original data set (36 attributes recorded by questionnaire) based on the presence of variability in the answers. Therefore, attributes that were constants in the sample of the farms were discarded. To quantify the effect of selected predictors in the CTA, risk ratio (RR) and 95% confidence intervals for probability to observe tail biting were calculated. For this calculation, the counts of units inside each resulting node were used through cross-tabulation contingency tables and a chi-square/Fisher's exact test (Camp and Slattery, 2002).

To validate the CTA model, an additional validation dataset was collected in 25 farms between June and July 2017, and the sensitivity, specificity and misclassification rate were calculated. Furthermore, for RTA the association measures between predicted and observed values were used to evaluate the acceptability of the method. Pearson correlation coefficient and a regression model were calculated. Further information is presented in Supplementary methods.

For graphs produced by both methods, the splits closer to the root of the tree are typically more important (yield greater improvement in the fit of the model) than those that are closer to the bottom of the tree. This approach does not consider the important predictive power of predictors excluded from the tree. Furthermore, for both analyses, all the 24 predictor variables were classified according to the importance ranking on a 0–100 scale (Breiman et al., 1984). The "importance" in this case identified some predictors that for many splits provided the second best alternative to the actual predictors reported in the tree.

3. Results

Five variables (stocking density, ammonia level, number of pigs per stockman, type of floor and timeliness in feed supply) were relevant in both classification and regression trees. Moreover, gender management and farm size entered the regression tree analysis.

3.1. Classification tree analysis

Five of the potential 24 variables remained in the classification generating 8 splitting nodes (Fig. 1), considering that one variable

Table 1
Description of predictor variables for acute tail lesions in heavy pigs retained for the CRT analysis; the aim was to identify the interrelationships between, and the discriminatory value of, these variables in a sample of 60 Italian commercial farms visited in 2014.

Variable name	Variable type	Description
Rearing phase	Dichotomous	Weaning or fattening animals
Pigs per stockman	Continuous	Number of pigs per stockman
Size of the farm	Continuous	Number of pigs simultaneously present in the unit (farm capacity)
Respiratory disorders	Dichotomous	Presence or absence of episodes of respiratory disorders requiring medical treatment during the cycle
Enteric disorders	Dichotomous	Presence or absence of episodes of enteric disorders requiring medical treatment during the cycle
Stocking density	Dichotomous	Lower or equal the threshold specified by the legislation in force (EU Council Directive, 2008/120/EC)
Type of floor	Dichotomous	Slatted or full concrete[a]
Mixed gender	Dichotomous	Presence of males and females in the same pen or single gender
Ammonia levels	Continuous	Ppm in the environment
CO_2 levels	Continuous	% in the environment
Olfactory estimation of air quality	Dichotomous	Perception of mucosal irritation and adverse air quality by the operator
Heating management	Dichotomous	Presence or absence of heating systems for the maintenance of thermo-neutral temperature
Cooling management	Dichotomous	Presence or absence of cooling systems for the maintenance of thermo-neutral temperature
Ventilation	Dichotomous	Natural, mechanical
Space at trough	Dichotomous	Sufficient or not sufficient space to allow simultaneous feeding of all animals
Meal distribution	Dichotomous	Manual, automated
Feed supply	Dichotomous	Restricted or ad libitum
Meal timeliness	Dichotomous	Never *versus* often feeding animals with delay
Type of feed	Dichotomous	Pellet or liquid meal[b]
Mixing management	Dichotomous	Animals mixed or not after allotment in the barn
Drinkers	Dichotomous	Presence of drinkers in the lying area
Grouping by size	Dichotomous	Penmates are grouped or not by size and lighter pigs are systematically removed from the pen
Enrichments	Dichotomous	Presence, absence
Tail length after docking	Dichotomous	Tipped or short docked[c]

[a] in case of a partially slatted floor, it was classified as slatted or full concrete based on the largest floor area.
[b] no farm provided dry meal.
[c] no farm did not dock tails.

appeared three times (number of pigs per stockman). The sample initially split on animal density in the pens. Farms that reared pigs with a density not lower than that required by the legal standards for animal welfare constituted the higher risk group (cases = 67%; RR = 3.8; 95% CI = 1.8–8.0; P = 0.002). Among these farms, those which showed ammonia levels greater than 2.7 ppm had the tendency to show higher prevalence of tail biting occurrence compared with those that showed lower ammonia levels (cases = 86%; RR = not estimable; P = 0.083).

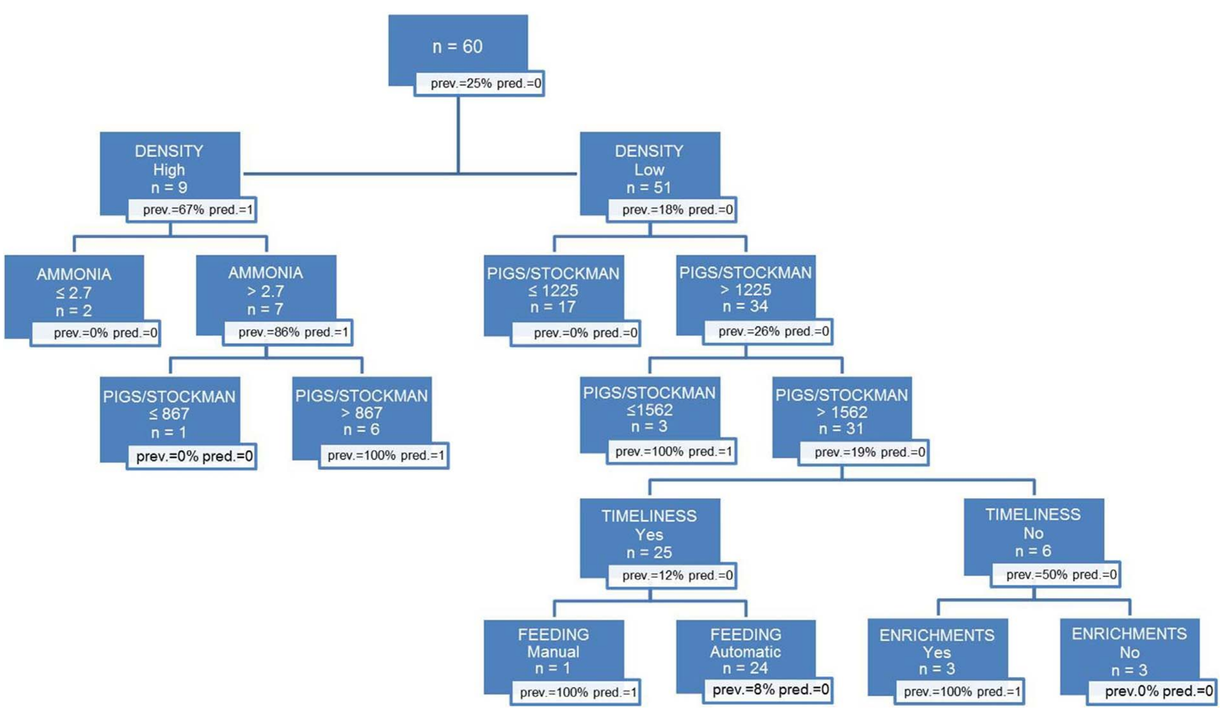

Fig. 1. Classification tree used to predict the risk of tail biting occurrence in heavy pigs. Data were collected in 2014 in 60 Italian commercial farms. Five of the potential 24 variables remained in the classification generating eight splitting nodes (stocking density, ammonia levels, number of pigs per stockman, timeliness in feed supply, and environmental enrichments) considering that one variable appeared three times (number of pigs per stockman).
N = number of farms per subgroup;
Prev. = percentage of farms in the node with presence of tail biting;
Pred. = predicted value (0 = no tail biting; 1 = presence of tail biting); when the percentage of farms with tail biting in the node is > 50%, pred. = 1.

Additionally, the risk appeared to be increased by the number of pigs per stockman, with those with more than 867 pigs per person more likely to be tail biting cases (cases = 100%; RR = not estimable; P = 0.008).

The number of pigs per stockman was a variable that increased the risk of tail biting occurrence also in farms that reared animals with a density lower than required by the law (cases = 18%; data split at > 1225 animals/stockman; RR = not estimable; P = 0.019). The number of pigs per stockman yielded three splits within the tree, potentially suggesting a level-response relationship between the variable and risk (Silvera et al., 2014). According to these analyses, farms with > 1225 pigs per stockman went on to further subdivisions and those which had < 1562 pigs per stockman showed the greater risk of tail biting occurrence (cases = 100%; RR = 5.2; 95% CI = 2.5–10.6; P = 0.002). For farms with > 1562 pigs per stockman, timeliness in feed supply entered the model, with those delivering meals with frequent delay more likely to be tail biting cases than controls (cases = 50%; RR = 4.2; 95% CI = 1.1–15.7; P = 0.034). Caution must be adopted with those predictors involved in higher order interaction; that is, those which are higher-level predictors (added lower in the tree), since these are the nodes that are more problematic with respect to small sample sizes and overfitting. Results of terminal nodes are shown in Supplementary results.

In terms of variable importance to predict the pens with potential tail biting issues, the five predictor variables with the strongest overall discriminating power were mixed genders (power: 100.00), timeliness in feed delivery (power: 65.4), ammonia levels (power: 62.8), number of pigs per stockman (power: 56.6) and farm size (power: 50.4) (Fig. 3).

3.2. Regression tree analysis

Eight of the candidate variables were selected in building the regression tree, generating nine splitting nodes (Fig. 2) and considering that ammonia level appeared two times. This tree included also some variables not selected in the classification tree analysis and did not involve others that were previously selected. Based on this tree, farms that showed ammonia levels higher than 28 ppm showed a tail biting frequency of 3.8%. Among farms with lower ammonia levels, a second split involved type of floor, showing a higher prevalence of tail biting in the case of a full concrete solid floor (0.5% vs 0.1% with slatted floor). Based on this tree, animals reared on a full concrete solid floor and allotted in single-gender pens showed an increased frequency of tail lesions (1.8% vs 0.2% in case of mixed genders). In animals allotted in mixed-genders pens, prevalence appeared to be affected by the farm size (0.6% when > 3800 pigs vs 0.02% when < 3800 pigs). For animals reared on a slatted floor, prevalence of tail lesions was higher in farms that reared animals with a density not lower than required by the law (0.4% vs 0.04%). Pigs reared at lower than legal density requirements showed an increased prevalence of tail lesions when ammonia level was greater than 12.1 ppm (0.2% vs 0.02%). Results of terminal nodes are shown in Supplementary results.

In terms of variable importance to predict the pens with tail biting issues, the five predictor variables with the strongest overall discriminating power were ammonia levels (power: 100.0), mixed gender (power: 43.6), number of pigs per stockman (power: 40.7), timeliness in feed delivery (power: 34.4) and farm size (power: 33.6) (Fig. 3).

3.3. Validation of the models

Model fit of the CTA using the data from the original 60 farms gave a sensitivity of 86.7%, specificity of 100%, and therefore misclassification rate of 3.3%. The CTA, applied on the validation dataset, correctly classified 70% (sensitivity) of the farms with tail biting (7 out of 10, error of 30%) and 93.3% as intact tails (14 out of 15 correctly classified as farms reporting no tail biting – specificity), producing an overall error of 16.0% (total misclassification rate). Regarding RTA, the correlation between observed and predicted prevalence of tail biting (obtained by RTA) was 0.7 and the R^2 of the regression model was 0.5.

4. Discussion

A first on-farm intervention tool based on tail biting risk analysis was proposed by Taylor et al. (2012). The present study aimed to provide the basis for a more sophisticated tool which can take account of the interactions which occur between different risk factors. The CRT analysis tested here might strengthen the collaboration between scientists and farmers, throughout the veterinarian, for managing the risk factors behind tail biting on a farm-specific level, as suggested by EFSA (2014). Bracke et al. (2013) highlighted the current differing views on tail biting and docking between producers and scientists, and a Dutch study showed that producers did not always agree with the scientists regarding which factors are the most important reason for tail biting (Benard et al., 2014). For example, conventional Dutch farmers considered it reasonable to combat tail biting by teeth cutting or grinding, but minimized the value of environmental enrichments requested by the legislation (Bracke et al., 2013). The same authors indicated that farmers might ignore scientific information because it is not concrete enough, or too focused on specific factors. To enhance communication between science and end-users is therefore an important goal when trying to reduce the risk of tail biting (Valros et al., 2016). For these reasons, efforts in the present study were focused to provide a scientific model (CRT analysis) that considers the complexities of factor interrelationships but predicts tail biting risk with a high practicality on-farm. CRT analysis in epidemiological studies permits the identification of risk factors that are useful in disease diagnosis (Saegerman et al., 2004) as well as those that may play an important role in disease occurrence (Thang et al., 2008). In pigs, a CRT analysis was also reported in a Scientific Opinion of EFSA on a multifactorial approach on the use of animal and non-animal-based measures to assess the welfare of pigs (EFSA, 2014) in which it was used to investigate risk factors for tail biting in Welfare Quality® datasets from five European countries.

In the present study, both classification and regression tree analyses were used. The first aimed to predict if a farm will or will not experience a tail biting outbreak, while the latter aimed to predict the prevalence of tail lesions (i.e. the intensity of the problem) in a specific farm. The double purpose was previously considered in heavy pig production using traditional linear models by Scollo et al. (2016); however, CRT analysis presents the great advantage to produce results that are particularly easy to implement, understand and interpret in clinical cases. For this reason, CRT analysis has become increasingly popular in the medical field in general (Marshall, 2001) because a clinician can easily asses to which subgroup a specific patient (or farm, in this case) belongs, and can also determine which farm subgroups require special attention (Henrard et al., 2015). Additionally, it might be used as a decision-making tool allowing a farm to manage a specific risk factor in order to change its subgroup. Compared to traditional statistical methods (i.e. linear and multiple models, logistic regression), CRT analysis makes no assumptions about the distribution of dependent and independent variables, and can handle nonlinear outcome variables by means of partitioning; it can easily handle multicollinearity in explanatory variables by selecting the best splitter at each node in a flexible way; it has the ability to identify outlier values, which are automatically isolated in one separate node; and it can handle missing data and interactions (Henrard et al., 2015).

The Classification Tree generated was able to classify correctly between 70 to 86.7% of all cases (considering the validation and the original data set respectively), showing a high efficiency. Among 24 variables used in the CRT analysis, four variables (stocking density, ammonia levels, number of pigs per stockman and timeliness in feed supply) stood out in both classification and regression trees. In the classification tree, stocking density was selected as the first partitioning variable. Consistent with past studies (Schrøder-Petersen and Simonsen,

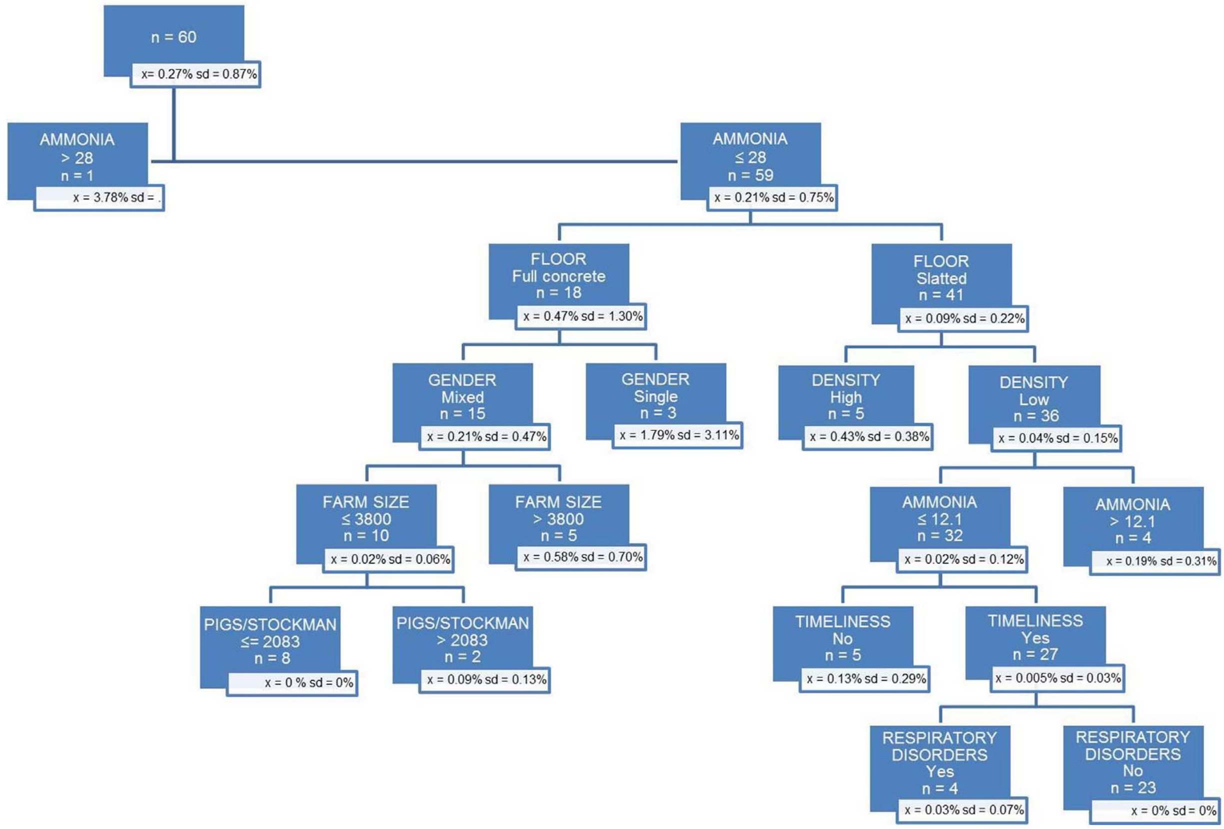

Fig. 2. Regression tree used to predict the prevalence of tail bitten pigs in heavy pigs farms. Data were collected in 2014 in 60 Italian commercial farms. Eight of the candidate variables were selected in building the regression tree (ammonia levels, type of floor, gender management, farm size, number of pigs per stockman, stocking density, timeliness in feed supply, and respiratory disorders) generating nine splitting nodes and considering that ammonia level appeared two times.
N = number of farms;
x = mean prevalence of affected animals;
sd = standard deviation of prevalence of affected animals.

2001; Moinard et al., 2003), this indicates that failure to observe at least the minimum legal requirements for stocking density is an important contributor to tail biting occurrence. As reported also by Scollo et al. (2016), it is not surprising that this variable acquires such importance in heavy pig production, considering that the current EU legislation prescribes space allowances for pigs only up to 110 kg live weight, thus leaving a critical gap in the definition of minimum space allowance for heavier animals. The evidence of such a strong effect of age and weight might represent the main cause of some different variables which emerged in the current analysis when compared with the EFSA report (2014) which used data from countries with a conventional slaughter (weight lower than 110 kg).

As in the current analysis, Scollo et al. (2016) also found ammonia level as a factor able to discriminate between tail biting case or control farms. Smith et al. (1996) and Wathes et al. (2000) described ammonia as the primary noxious gas able to induce stress and consequent aversive behaviour in pigs, including tail biting. Even if ammonia level was selected as the second node in the classification tree, with a greater risk of experiencing tail biting outbreak in case of high stocking density and more than 2.7 ppm of ammonia in the air, the variable showed the greatest importance in influencing prevalence of tail lesions when levels exceed 28 ppm.

Pigs per stockman entered the classification tree model at three different nodes, suggesting a relationship between the occurrence of tail biting and taking care of animals. This finding confirms the hypothesis formulated by Moinard et al. (2003), who observed that the likelihood of tail biting increased with the pens per stockman ratio, and suggested further research on the topic. The involvement of the capacity of take care of the pigs as an important factor for welfare was also suggested for sows by Willgert et al. (2014), who observed an increased lameness rate only in medium producing farms rather than in high and low producing ones. In the present study, it is interesting to note that, in the case of stocking density lower than the legal standards, the farms at risk were only those with more than 1225 but less than 1562 pigs entrusted to the same stockman. The results might suggest a critical category of husbandry or housing system (and its level of technology and mechanization), in the middle between farms where stockmen with an average ability to give care to animals have responsibility for fewer pigs, allowing better animal management, and farms where a high level of mechanization and modern facilities allow excellent stockmanship also with a large number of animals per stockman.

Timeliness in feed delivery was the last variable involved in both classification and regression trees. Findings are in agreement with Scollo et al. (2016), and confirmed the increase of tail biting risk and prevalence in case of frequent variation in the timing of feed distribution. When pigs anticipate the arrival of meals that are provided with a delay, an increased motivation to feed might lead to oral manipulation of other penmates, or increased frustration, and potentially result in tail biting (Robert et al., 1991; Paul et al., 2007).

The variables regarding type of floor, presence of mixed genders in the same pen and farm size remained in the building of the regression tree, highlighting their influence on the prevalence of tail lesions. Floor type is thought to be a factor leading to tail biting when manure soiling predisposes to high concentrations of noxious gases and to the difficulty in maintaining a stable hierarchy on the slippery floor (Schrøder-Petersen and Simonsen, 2001). The hot Italian season during which this study was performed might have exacerbated these conditions. The relationship between gender and tail biting has been investigated by

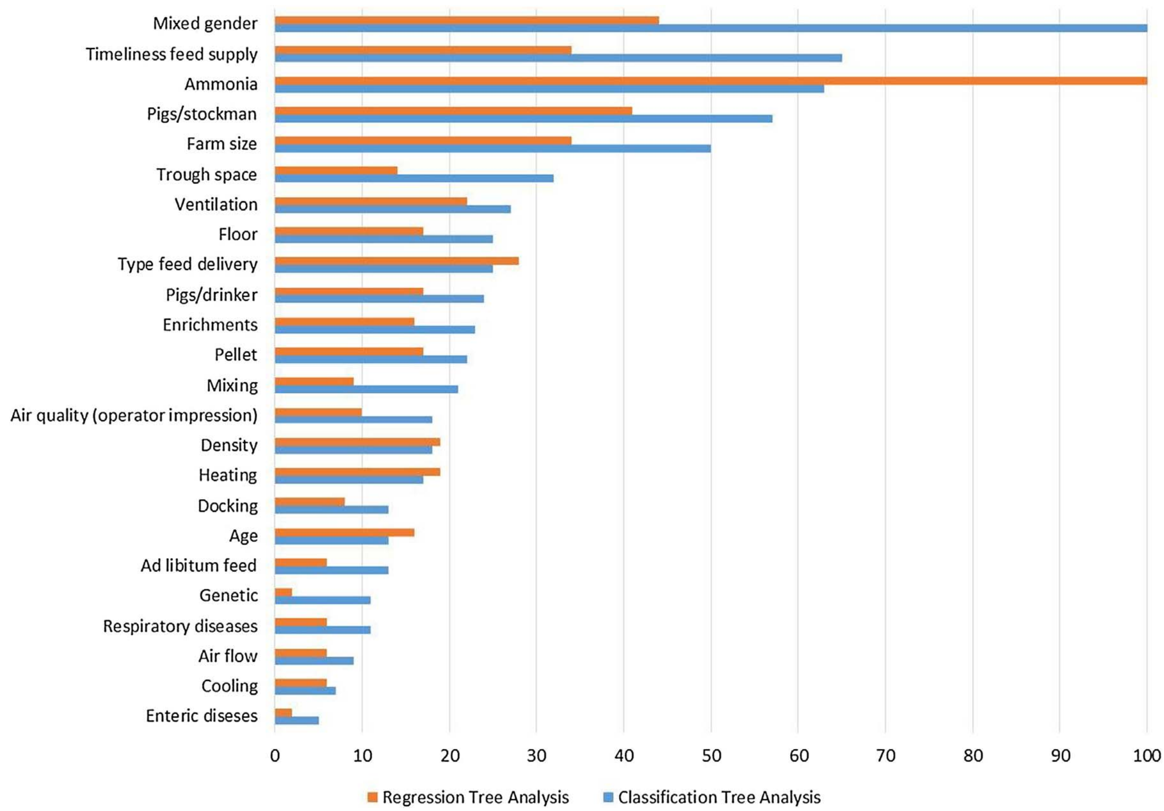

Fig. 3. Relative importance (scale from 0 to 100) of 24 predictor variables considered in the Classification Tree Analysis and in the Regression Tree Analysis. Data were collected in 2014 in 60 Italian commercial farms rearing heavy pigs.

several authors, but results are often conflicting (Schrøder-Petersen and Simonsen, 2001). In the heavy pig production, Scollo et al. (2013, 2016) did not find any influence of gender on tail lesions in pigs. However, the present study showed a greater prevalence of tail lesions in subgroups of animals reared in single-sex pens (1.8%) rather than mixed-sex pens (0.2%), in agreement with Zonderland et al. (2010) who already suggested a role of gender in tail lesion prevalence. Another variable that seems to influence tail lesion prevalence is the farm size, which predisposed to a higher percentage of bitten tails when over 3800 pigs were reared, in agreement with Chambers et al. (1995) who observed that tail biting was more likely to occur as herd size increased.

The influence on tail biting occurrence or prevalence of some other variables (presence of respiratory diseases, system of meal delivery and presence of environmental enrichment) was shown as minimal because they entered the trees only in the final nodes. This might confirm the multifactorial nature of the problem: each variable played a role only within its subgroup of animals. However, their biological importance in the current analysis should be not over-interpreted, due to the low number of herds belonging to some subgroups, or to the very low prevalence on tail biting in others. In particular, the relationships between tail biting and the presence of respiratory diseases or a manually operated system of meal delivery are in agreement with literature (Moinard et al., 2003; Walker and Bilkei, 2006), but results related to environmental enrichment are probably influenced by the field conditions of the study: farmers are likely to intervene once tail biting occurs, and enrichment provision may be a solution attempted after an outbreak begins.

In terms of the overall importance of different factors to predict the farms with potential tail-biting issues, it should be mentioned that the five most important variables, both for tail biting occurrence and for prevalence of tail lesions, were mixed-gender, timeliness in feed supply, ammonia level, number of pigs per stockman and farm size. Of these, only farm size was amongst the most important variables identified in the EFSA (2014) CRT analysis, though this did not include measurement of ammonia and also highlighted slaughter weight as giving rise to different risk populations.

The model advances our understanding of the underlying factors contributing to acute tail biting lesions and suggests that some risk factors have different importance in different subgroups. This might help farmers and veterinarians to assess risk in their own farm and to decide when it is reasonable to stop performing tail docking. The lack of a tool which can indicate safer individual farm conditions might contribute to the lack of confidence in stopping tail docking. The model therefore has implications also for the support and implementation of tail biting prevention interventions in case of subgroups of pigs with higher risk. For example, in farms with low stocking density and a high number of pigs per stockman, the tail biting risk can potentially be attenuated by farmer and veterinarian action to improve the timeliness of feed supply.

A limitation of the present study is that, because of the sample size, the interpretation of nodes representing a small subsample of the study population may become more questionable. The authors believe that this is acceptable for the purposes of hypothesis generation and illustration of the usefulness of the methodology for identifying risks for acute tail biting lesions. However, the lower nodes should not be over-interpreted in terms of biological importance but considered as potentially important variables for risk stratification.

5. Conclusions

The study suggests that CRT analysis can be a powerful tool for exploring the complexities of risk factors for acute tail biting lesions in swine farms, and offers a valuable alternative in cases involving data that are difficult to handle with the more traditional statistical methods. This analysis provides further evidence that tail biting is probably the result of several factors which, acting in concert, make farms more susceptible to an outbreak or to a high prevalence of lesions. The presented model provides an important tool with a more individualized approach for veterinarians and farmers to assess risk in heavy pig systems and intervene to reduce tail biting on-farm. The measures reported are practical and feasible to undertake in the managerial setting and, when applied, might have the potential to deliver a more streamlined approach to prevention.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.prevetmed.2017.08.001.

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