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Towards an industry-wide, multilevel evaluation framework for pig meat inspection: potential applications and implementation challenges

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A B S T R A C T

Meat inspection (**MI**) data can be useful as a monitoring tool of animal health and welfare on farm, thereby enhancing the sustainability and productivity of livestock. There is also concern about certain limitations of these data, primarily related to the quality and harmonisation of inspections across various slaughterhouses. In our study, we investigated the development of a cross-slaughterhouse ranking system for farmers using MI data. The integration of new digital tools in Germany, such as the web-based database Qualifood®, offers new opportunities for collecting and utilising MI data across different slaughterhouses, enabling at the same time digital feedback of these information to livestock farmers. To accomplish our research goal, MI data over a period of 5 years (2020–2024) was exported from Qualifood®. Our analysis was conducted using MI data from both cattle and pig farms. However, this manuscript focuses on presenting the statistical analysis model using pig data and the category "respiratory health" as a representative case study. We presented an annual overview of reference values -the so-called basic risk- for respiratory health findings using generalised linear mixed models. The basic risk of respiratory health findings for pigs showed a gradual decline from 14.4% in 2020 to approximately 12.0% in 2024. The calculated basic risks establish a reference for normal finding rates and provide a baseline assessment of respiratory health in southern Germany based on MI data. Furthermore, we estimated the variability of key random effects derived. Across all years, SDs for farm and delivery levels remain relatively stable between the selected and full datasets, indicating consistent variability at these levels. However, the slaughterhouse-level SDs are substantially higher in the full dataset compared to the selected slaughterhouses suggesting notable heterogeneity in reporting or detection practices across facilities. This underlines the importance of slaughterhouse selection when conducting cross-facility analyses and benchmarking. Towards a cross-slaughterhouse evaluation, we compare the farmer-specific risks and the basic risk using the concept of relative risk, also known as risk ratio. Our model demonstrates how recent advancements in digitalisation enable the evaluation of MI data across multiple slaughterhouses, underscoring the importance of region-wide, digital, and standardised MI data collection as a foundation for consistent and reliable cross-slaughterhouse assessments. By addressing inconsistencies in recording quality, our model can support a data-driven decision-making for farmers, industry stakeholders, and veterinary authorities, ultimately reinforcing the entire agricultural value chain and animal health and welfare management.

Implications

We investigated the potentials of meat inspection data for evaluating animal health and welfare on farms. By modelling respiratory health trends in pigs and identifying differences in inspection practices, we highlight the need for standardised data collection. Using digital tools and an existing database, we assessed the feasibility of cross-slaughterhouse benchmarking. Our statistical model supports real-time feedback to farmers and data-driven decision-making, with relevance beyond Germany. These findings show that meat inspection data can provide valuable insights into on-farm health and welfare, helping improve monitoring, transparency, and management across the agricultural value chain.

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Introduction

In Europe, animal health and welfare and the existing husbandry conditions of farm animals have been a matter of public concern for several decades (Luca et al., 2021; Thorslund et al., 2017). Scientists and welfare specialists are constantly validating methods and protocols that can be used to assess the welfare status of farm animals, with primary research goal of making animal welfare objectively measurable (Fraser, 2003; Botreau et al., 2007; Fraser, 2009; Czycholl and Büttner, 2015). This is also a goal of the European Food Safety Authority (EFSA, 2012). In several European countries, the implementation of more welfare standards in animal housing is a major objective at a political level as well (Heerwagen et al., 2015). Furthermore, the ongoing digital transformation has revolutionised animal farming and livestock management, and digitalisation can significantly influence the monitoring of animal welfare and welfare (Buller et al., 2020). Digitalisation has also automated and interlinked many routine slaughterhouse processes. Thus, during the process of slaughter, a significant amount of data is meanwhile digitally recorded, including diagnostic information and findings from the official ante- and postmortem meat inspection (**MI**).

For a large proportion of consumers, meat is an essential part of their diet and the hygienic requirements for meat products are correspondingly high in the European Union (**EU**). Under Regulation (EU) 2017/625 farm animals must be officially inspected before and after slaughter if their meat is intended for human consumption (Keller, 2023). Official veterinarians and their specialised assistants are responsible for performing the ante- and postmortem MI. Thus, MI is historically recognised as a tool to identify meat unfit for human consumption, ensuring food safety and quality (Stärk et al., 2014). Nowadays, digital MI is widely implemented and stands as one of the longest–running systems. Scientific research has acknowledged the usefulness of this data source as a suitable tool for surveillance and monitoring of animal health and welfare on farm level (Comin et al., 2023; Losada-Espinosa et al., 2021; Grosse-Kleimann et al., 2021; Nienhaus et al., 2020; Teixeira et al., 2016; Harley et al., 2012). While scientists demonstrate that valid conclusions regarding animal health and welfare can be drawn from evaluating MI findings, they also raise a concern about certain limiting factors of these data, associated primarily with inspection quality and harmonisation (Grosse-Kleimann et al., 2021; Correia-Gomes et al., 2016; Stärk et al., 2014).

In Bavaria, Germany, the Fleischprüfring Bayern developed the web-based platform Qualifood® to centralise data from the slaughter process and provide digital feedback to stakeholders across the agricultural value chain. The platform, now implemented in over 30 slaughterhouses across Germany, enables digital recording of MI findings and performance data. The unique infrastructure formed the basis of the "Bavarian Animal Welfare Monitoring" (Bayerisches Tierwohl Monitoring) project, funded by the Bavarian State Ministry of Agriculture, Forestry and Tourism and supported by our scientific work. Among the primary objectives, the development of a cross-slaughterhouse benchmarking system was identified as a key goal. This system aims to identify the performance of farms and establish a baseline assessment of animal health in southern Germany, based on findings from MI data.

The present manuscript focuses on the description of the process towards developing a cross-slaughterhouse ranking system. To make such a comparison, it is imperative to establish reference values for the frequencies of the considered findings. These reference values should define what is considered a normal number of findings. As no existing reference distribution is available, one needs to be derived from the data at hand. For this estimation, we utilise generalised linear mixed models. By using these models, we can determine the probability of an observation's occurrence under specific conditions within a dataset. These reference values are subsequently referred to as the "basic risk" associated with a particular finding or a defined category of findings.

Our objective was to illustrate how ongoing digital transformation is creating new opportunities for the systematic collection and analysis of MI data across multiple slaughterhouses. In addition, we sought to provide insights into the potential benefits and challenges associated with implementing an integrated, industry-wide, multilevel statistical model for MI records. By presenting the statistical analysis model using the exemplary case of "respiratory health", we aimed to demonstrate the potential of MI data as a valuable instrument for monitoring animal health and welfare at the farm level. Additionally, we sought to identify issues with the recording quality and variability of MI data in south Germany and discuss our efforts to address these problems. Furthermore, the model shows how meat inspection data can support evidence-based decisions for farmers, veterinary authorities, and the livestock sector more broadly, offering a scalable approach that can be applied across different regions (national and international) and systems.

Material and methods

Data pool and cross-slaughterhouse mapping

For our analysis, a uniform data model was required, to interlink all the information into the specific producer identification (**ID**) number and to generate a basis for statistical evaluation. Two large datasets, covering millions of pigs and cattle slaughtered annually from all slaughterhouses in south Germany, were exported as.csv files from the database for the period 2020–2024. Specifically, MI findings data includes information on organ health (respiratory, cardiac, gastrointestinal and liver), partial condemnation, external injuries and alterations (abscesses, ear lesions, arthritis, dermal alterations and bursitis), whole carcass condemnation, as well as animals not approved for slaughter. The exported dataset also includes performance data such as slaughter weight, commercial and fat class, as well as general farm information, including monitoring indicators (e.g., antibiotic treatment index, quality programmes), farm type and size, and housing system. Animals are categorised by species (cattle or pig) and slaughter group (e.g., dairy cow, heifer, young bull, steer, fattening pig). Each entry displays variables such as age, slaughter date, slaughter number and pseudonymised ear tag number, farm ID, and slaughterhouse ID.

Although unified standards for MI are set by the EU, at each slaughterhouse, the MI findings may have different numbering or coding and description or terminology. This complicates the comparability of findings and makes feedback towards the agricultural value chain difficult. To enable cross-slaughterhouse analysis, Qualifood® introduced a standardised mapping system that translates individual slaughterhouse MI codes into uniform "veterinary findings ID codes." This harmonisation modernised data collection and improved code consistency, particularly across south Germany, providing a robust data basis for our study.

Selection of slaughterhouses for final analysis

To ensure reliable scientific conclusions, slaughterhouses were filtered and selected based on both statistical indicators and empirical insights. Following the categorisation of findings, data quality assessments were conducted across all facilities. Slaughterhouses demonstrating consistent and high-quality MI recordings were selected for analysis. Thus, anonymised MI findings data from 12 pig slaughterhouses from south Germany were explicitly selected for the statistical analysis, in the period from 2020 to 2024. To summarise, a total of 19 951 917 fattening pigs builds the data basis for our analysis. In detail and spread over the years, data from 4 617 503 (2020), 4 441 317 (2021), 3 902 585 (2022), 3 478 443 (2023), and 3 512 069 (2024) pigs were used. The final selection of slaughterhouses was determined not only by statistical but also by empirical considerations. Our insights gained through ongoing conducting topic-related training courses and discussions in recent years with the veterinary authorities responsible for recording MI findings -driven by the information technology (**IT**) system implemented by the Fleischprüfring- have also influenced the final selection of the selected slaughterhouses.

Integrated data structure and selection of a representative case study

The focus of the manuscript is on describing the statistical model using the diagnostic category 'respiratory health' as a representative case study based on pig data. A corresponding analysis of cattle data, using the same statistical model, is currently in preparation and is scheduled for publication in the future. To support this objective and present the results in a meaningful way, a subset of variables from the dataset was processed and included in the analysis. The primary outcome variable for MI data is binary: a value of 1 indicates a recorded respiratory disease, while 0 indicates no finding. For the selected diagnostic category, animals do not have multiple findings recorded simultaneously.

In theory, a single animal within a delivery could exhibit multiple findings within a given category, potentially resulting in more findings than animals. However, this is excluded in our current analysis, given that our current approach determines for each finding category whether an animal has at least one positive finding. This ensures that animals with multiple findings within the same category do not disproportionately influence the results. Moreover, this method avoids the overrepresentation of individual animals and emphasises the overall incidence of findings rather than frequency or severity, leading to more reliable and equitable assessments across groups. The final dataset also includes several structural variables: the date of animal delivery and slaughter, the date of the official meat inspection and anonymised farm and slaughterhouse identifiers. Additionally, a qualitative classification of slaughterhouse inspection quality was added, where the latter distinguishes between "high" and "other" quality levels, based on internal expert evaluations and statistical analysis.

Statistical analysis and model

This section details the steps taken towards establishing a comprehensive, multilevel statistical model for MI data across the industry. The goal was to create a model capable of evaluating and comparing farms in terms of animal health and welfare across multiple slaughterhouses. Central to this approach is the computation of a standardised scoring model, which enables benchmarking by calculating baseline risk levels for defined categories of findings. While the model primarily focuses on aggregated categories of findings, it is also adaptable for use with individual MI parameters when required. The construction of the scoring procedure, known as "the basic risk model", comprises the following steps: First, the estimation of the baseline risks for the defined MI finding categories for all livestock producers present in the data pool. Second, the calculation of farmer-specific risks for individual livestock producers. Third, the farmer-specific risks are compared with the estimated baseline risk. The following sections cover these steps.

Estimation of basic risks

We define the basic risk π as "the population–averaged probability of observing the group of findings in an animal". To estimate this basic risk from available data, a mixed-effects logistic regression model for binary data is used. This model consists of a fixed intercept together with random effects for farms, for deliveries nested within those farms, and for slaughterhouses. Thus, the individual animal serves as the observational unit, while the model accounts for the multilevel structure of the deliveries, farmers, and slaughterhouses. A formal specification of this model is presented in Supplementary Material S1.

Parameter estimation for this model was performed using the statistical programming language R, specifically through the template model builder approach implemented in the Generalised Linear Mixed Models using Template Model Builder (glmmTMB) package (Brooks et al., 2017). This has demonstrated both stability and speed. Upon estimating all unknown parameters, a marginal (population-averaged) estimate $\widehat{\pi}$ for the basic risk was derived using the Estimated Marginal Means (emmeans) package with bias correction for the non–linearity of the link function. This provides an approximation of the marginalisation over the random effect distribution. Alternatively, full Monte Carlo integration as proposed in Hedeker et al. (2018) can be implemented. However, given the magnitude of the estimated variance components in our models, the approximation was deemed appropriate.

Estimation of the farmer-specific risks

Within the regression model framework, deviations from the basic risk specific to each farmer are already estimated. This is accomplished using the corresponding random effects. However, this only accounts for farmers present in the historical data considered. To be able to make inferences about farmers for whom no historical data is available, data from current slaughterhouse deliveries must be utilised. The most accurate estimator for the risk of a particular upper group of findings is represented by the observed proportion of positively identified animals in a delivery of N animals, $\widehat{\pi}_j$. For a farmer j, this estimator can be computed as $\widehat{\pi}_j = n/N$. Here, n refers to the number of positively identified animals out of all delivered animals.

Up to now, we have only considered the point estimate of the farm-specific risk. This implies that results from farms with the same risk, but very different numbers of animals delivered, would not differ. Therefore, it is important to consider the uncertainty associated with the estimate. To address this, we used Wilson's Score Interval method to obtain upper and lower bounds for 95% confidence intervals for the farm-specific risk as recommended and given in Brown et al. (2001).

Scoring a meat inspection finding category: risk comparison

From the preceding steps in the model, both the calculated basic risks for individual finding groups and the farmer-specific risks are readily available. In order to develop a score for a MI finding category, we compare the farmer-specific risks and the basic risk using the concept of relative risk (**RR**), also known as risk ratio. This can be expressed as follows:

$$RR_j = \frac{\widehat{\pi}_j}{\widehat{\pi}}.$$

The relative risk can take on values from 0 to ∞. At a value of 1.0, the risks are considered equal. Values below 1.0 indicate a farmer-specific risk that is less than the basic risk, meaning that the farmer in question poses a lower risk. Values above 1.0 signify a farmer-specific risk greater than the basic risk, implying a higher risk as compared to the reference population. Therefore, a value of 2.0 can be interpreted as double the risk, and a value of 0.5 signifies half the risk.

The previous version of the relative risk has a drawback in that the higher, and therefore worse, score values are located above 1.0 and are open-ended. This sometimes leads to exceedingly high values that cannot be interpreted sensibly. Alternatively, the relative risk can be redefined as follows:

$$RR_j = \frac{\widehat{\pi}}{\widehat{\pi}_j}.$$

This is the inverse of the relative risk calculation according to the previous definition. Now, a higher risk for the farmer is expressed as 0 < RR < 1. In this context, a value of 1.0 can still be interpreted as a complete agreement with the basic risk, while a value of 0 signifies the greatest possible deviation in the negative sense. A value of 0.5 now suggests that the basic risk is only half as high as the risk associated with the farmer under consideration. By calculating the relative risk, we can derive a ranking value for each category of findings. This comparison facilitates a risk-oriented and cross-slaughterhouse ranking of farms per findings category. Uncertainty intervals for relative risks can be obtained by dividing the estimated base risk by the confidence limits for $\widehat{\pi}_j$. Note that RR_j is not defined if no animal has been positively identified, i.e. $\widehat{\pi}_j = 0$. In that case, it is advantageous to consider the inverse risk ratio $RR_j = \widehat{\pi}_j/\widehat{\pi}$.

Results

This section presents the results of a representative case study in which the proposed approach was applied to actual pig data, using the category 'respiratory health' as an example. The estimation of the basic risk for this category is based on MI findings recorded for deliveries to the respective slaughterhouses between 2020 and 2024. Table 1 provides an overview of the number of farms, deliveries, and animals processed at the selected slaughterhouses during this period.

Annual overview of variance components and basic risk for respiratory health findings (2020–2024) for the selected slaughterhouses

On average, MI data from approximately 4.10 million fattening pigs from the selected slaughterhouses annually were used as a basis for the estimation of the basic risks. The analysis included 4 634 (2020), 4 352 (2021), 3 867 (2022), 3 401 (2023), and 3 176 (2024) farms housing fattening pigs. Table 2 summarises the basic risk estimates, expressed as a percentage with a corresponding 95% confidence interval, for respiratory health findings derived from MI data between 2020 and 2024 alongside the estimated SDs and variance partition coefficients (**VPCs**) of random effects of the three hierarchical levels from the multilevel statistical model: slaughterhouse, farm, and delivery. For each year, the table also reports the number of farms, deliveries, and animals included in the analysis, along with the percentage of units with at least one recorded respiratory finding. VPCs are calculated based on the latent variable approach which divides the estimated variance of a random-effect term by the sum of all variances plus the variance of the logistic distribution (π^2/3).

Across the 5-year period, the SD for slaughterhouse effects increased notably, rising from 0.82 in 2020 to 1.47 in 2024. Farm-level variation remained relatively stable, fluctuating narrowly around 0.60–0.65. The delivery-level SD showed minor fluctuations, reaching its peak in 2024 at 0.92. The VPC values reveal that initially, the delivery level accounted for the largest share of variance, whereas over the past 3 years, this has been driven by slaughterhouse effects. The basic risk of respiratory health findings showed a gradual decline from 14.4% in 2020 to approximately 12.0% in 2024. The associated uncertainty intervals widened in recent years, particularly in 2024 (5.2; 24.4).

Exemplary presentation of the score model for the category "respiratory health"

Table 3 offers additional details about the model and presents the estimated basic risk and corresponding scores for the diagnostic category "respiratory health" across three selected farms (A, B, and C) with a comparable number of pigs slaughtered over a period of 6 months (01 July 2024 – 31 December 2024). The basic risk for the population has been estimated at 12.0%. For each farm, the number of affected animals (n), the observed risk with 95% confidence intervals (**CI**), and the standardised score with its 95% CI are reported. It should be noted that the analysis is based on the conventional definition of the risk ratio (RR), not the inverse form. Farm A showed a markedly lower respiratory health risk (4.1%) compared to the basic risk, resulting in a score of 0.28, indicating better-than-average health outcomes. Farm B exhibited a significantly higher risk (41.8%), with a corresponding score of 2.89, suggesting poorer performance in this category. Farm C had a moderate risk (16.4%) and a score of 1.13, placing it slightly above the basic risk level. These results allow for benchmarking farm-level performance relative to the broader dataset and highlight differences in animal health outcomes across farms.

Estimated variability in key random effects on respiratory health findings across years

To gain a deeper understanding of the factors influencing respiratory health outcomes in pigs, we estimated the variability - expressed as SDs and VPCs - of key random effects derived from MI data collected between 2020 and 2024. The three sources of variability examined include slaughterhouse, farm and delivery level. These key random effects provide insights into the relative contribution of each factor to the overall variability observed in the data. The results are presented in Table 4 and are shown for both a subset of selected slaughterhouses and for the entire dataset including all slaughterhouses.

Farm-level variability

The estimated SDs of the farm-level random effect for the finding category "respiratory health", across the years 2020–2024 reflect the degree of variability in respiratory health outcomes attributable to differences between farms. Over all years, the SDs remain relatively stable, ranging between 0.60 and 0.65. Specifically, for selected slaughterhouses, the SD remained consistent at around 0.63–0.65 from 2020 to 2023, before declining to 0.60 in 2024. For all slaughterhouses, the values also remained steady, fluctuating between 0.64 and 0.65 over the same period, with a slight decrease to 0.61 in 2024.

Delivery-level variability within farms

The estimated SDs of the delivery-level random effect within farms for the category respiratory health, across the years 2020–2024 capture the variation in respiratory health findings across different animal deliveries from the same farm, as modelled in the hierarchical statistical framework. The delivery-level variability remains relatively stable over the 5-year period, with values ranging from 0.84 to 0.92 in the selected sample, and 0.90–0.99 across all slaughterhouses. Consistently higher SDs are observed in the full dataset including all slaughterhouses.

Table 1
Overview of the number of pig farms, deliveries, and animals processed at the selected 12 slaughterhouses between 2020 and 2024.

SH	Metric	2020	2021	2022	2023	2024
1	No. of F	383	382	288	265	267
1	No. of D	4 255	4 153	3 340	2 594	3 080
1	No. of A	165 822	166 974	146 699	117 808	142 543
2	No. of F	1 033	1 083	1 088	1 016	1 003
2	No. of D	10 362	9 698	8 284	8 677	9 492
2	No. of A	893 745	813 482	643 796	673 481	769 359
3	No. of F	1 281	1 228	1 050	930	999
3	No. of D	11 094	10 905	10 015	8 728	8 197
3	No. of A	838 005	799 674	774 404	673 452	652 363
4	No. of F	270	418	327	252	287
4	No. of D	2 606	3 050	2 710	2 286	2 447
4	No. of A	103 885	128 831	99 386	82 437	93 315
5	No. of F	1 097	1 045	1 048	932	913
5	No. of D	11 696	11 526	11 299	10 481	10 937
5	No. of A	803 040	831 812	806 270	720 227	756 361
6	No. of F	492	469	388	248	
6	No. of D	3 566	3 151	2 882	1 253	
6	No. of A	207 590	179 810	161 111	71 823	
7	No. of F	335	395	398	358	322
7	No. of D	4 236	3 915	3 970	3 712	3 718
7	No. of A	310 032	289 265	284 659	288 138	307 446
8	No. of F	764	737	466	515	334
8	No. of D	7 002	6 655	4 804	4 240	1 719
8	No. of A	267 494	291 485	226 791	213 350	99 723
9	No. of F	958	836	572	489	421
9	No. of D	6 558	5 460	4 435	3 776	3 766
9	No. of A	381 708	338 397	298 690	260 426	267 907
10	No. of F	536	529	330		
10	No. of D	4 177	3 609	1 460		
10	No. of A	195 208	167 695	60 008		
11	No. of F	627	547	423	491	493
11	No. of D	7 236	6 829	6 040	5 627	6 098
11	No. of A	346 459	339 931	314 801	297 732	339 802
12	No. of F	343	323	245	197	230
12	No. of D	3 602	3 365	2 929	2 430	2 521
12	No. of A	104 515	93 961	85 970	79 569	83 250

Abbreviations: SH = Slaughterhouse (anonymised identification numbers:1–12); No. of F = number of farms; No. of D = number of deliveries; No. of A = number of animals.

Table 2
Annual summary of key metrics related to respiratory health findings for pigs based on meat inspection data collected from 2020 to 2024. The results are shown for the selected subset of slaughterhouses. For each year the table reports the number of farms, deliveries and animals included in the analysis along with the percentage of units with at least one recorded respiratory finding. The estimated basic risk is expressed as a percentage with a corresponding 95% confidence interval (CI) and reflects the average probability of observing a respiratory health finding across all deliveries. Additionally, the table includes the estimated SDs and variance partition coefficients (VPC) of the random effects at the farm delivery and slaughterhouse levels derived from the multilevel statistical model.

Year	No. of Farms	No. of Farms with finding (%)	No. of Deliveries	No. of Deliveries with finding (%)	No. of Animals	No. of Animals with finding (%)	Basic Risk (%)	95% CI	Farm SD	Farm VPC	Delivery SD	Delivery VPC	SH SD	SH VPC
2020	4 634	3 981 (85.9%)	76 390	58 733 (76.9%)	4 617 503	629 973 (13.6%)	14.4	9.8–20.6	0.63	0.08	0.86	0.15	0.82	0.13
2021	4 352	3 749 (86.1%)	72 316	55 537 (76.8%)	4 441 317	546 104 (12.3%)	12.8	9.2–17.5	0.64	0.08	0.91	0.16	0.69	0.10
2022	3 867	3 264 (84.4%)	62 168	46 114 (74.2%)	3 902 585	392 830 (10.1%)	10.8	6.7–16.7	0.65	0.08	0.84	0.13	0.95	0.17
2023	3 401	2 868 (84.3%)	53 804	39 980 (74.3%)	3 478 443	378 834 (10.9%)	11.9	6.6–20.4	0.65	0.07	0.87	0.13	1.14	0.22
2024	3 176	2 694 (84.8%)	51 975	39 257 (75.5%)	3 512 069	410 356 (11.7%)	12.0	5.2–24.4	0.60	0.05	0.92	0.13	1.47	0.32

Abbreviations: CI: confidence interval; SH = Slaughterhouse; VPC: variance partition coefficient.

Slaughterhouse-level variability

The estimated SDs of the slaughterhouse-level random effect for respiratory health findings recorded during meat inspection from 2020 to 2024 quantify the degree of variability attributable to differences between slaughterhouses. For the selected group of slaughterhouses, the SD values gradually increased over time, from 0.82 in 2020 to 1.47 in 2024. In contrast, the full dataset including all slaughterhouses shows consistently higher variability, with SD values ranging from 3.79 in 2020 to 2.94 in 2024, though showing a slight decreasing trend over the 5-year period.

Comparison of random effects variability

Based on the estimated VPCs, the random effects associated with farms contribute the smallest proportion to the total variance. This contribution decreases further when all slaughterhouses are included, reflecting the increase in overall variance. In the subset of selected slaughterhouses, the delivery and slaughterhouse levels each account for a comparable share of the total variance. However, over the past 2 years, variance at the slaughterhouse level has increased markedly. When analysing all slaughterhouses collectively, the slaughterhouse

Table 3
Estimated farm risk comparison and corresponding scores for the diagnostic category "respiratory health" across three pig farms (A, B and C). For each farm, the number of delivered animals (N), the number of affected animals (n), the observed risk with a 95% confidence interval (CI) and the standardised cross slaughterhouse score with its 95% CI are reported. The three farms delivered pigs to the selected slaughterhouses in 2024, with the basic risk for the population that year set at 12.0%. The estimated basic risk is expressed as a percentage and reflects the average probability of observing a respiratory health finding across all deliveries. Farm A presents the lowest score (0.28) and Farm B the highest (2.89).

Category	N (Farm A)	n (Farm A)	Risk (Farm A)	95% CI (Risk A)	Score (Farm A)	95% CI (Score A)	N (Farm B)	n (Farm B)	Risk (Farm B)	95% CI (Risk B)	Score (Farm B)	95% CI (Score B)	N (Farm C)	n (Farm C)	Risk (Farm C)	95% CI (Risk C)	Score (Farm C)	95% CI (Score C)
Respiratory health	3 579	146	4.1	3.5–4.8	0.28	0.24–0.33	3 585	1 497	41.8	40.2–43.4	2.89	2.78–3.00	3 566	584	16.4	15.2–17.6	1.13	1.05––1.22

Abbreviations: N: number of delivered animals; n: number of affected animals, CI: confidence intervals.

Table 4
Summary of the estimated SDs and variance partition coefficients of key random effects from the multilevel model associated with respiratory health findings in pigs based on meat inspection data collected from 2020 to 2024. The three sources of variability examined include slaughterhouse, farm and delivery level. These estimates highlight how specific factors may influence the reporting or detection of respiratory health meat inspection findings. The results are shown for both a selected subset of slaughterhouses and the full dataset across all participating slaughterhouses.

Year	SH Group	Farm SD	Delivery SD	SH SD	Farm VPC	Delivery VPC	SH VPC
2020	selected	0.63	0.86	0.82	0.08	0.15	0.13
	All	0.65	0.93	3.79	0.02	0.05	0.76
2021	selected	0.64	0.91	0.69	0.08	0.16	0.10
	All	0.64	0.99	3.69	0.02	0.05	0.74
2022	selected	0.65	0.84	0.95	0.08	0.13	0.17
	all	0.64	0.90	3.47	0.02	0.05	0.73
2023	selected	0.65	0.87	1.14	0.07	0.13	0.23
	all	0.65	0.91	3.48	0.03	0.05	0.73
2024	selected	0.60	0.92	1.47	0.05	0.13	0.32
	All	0.61	0.93	2.94	0.03	0.07	0.66

Abbreviations: SH: slaughterhouse; VPC: variance partition coefficient.

level explains a significantly larger proportion of the total variance.

Discussion

The agricultural sector in Germany and Europe has been undergoing structural change in recent decades (Neuenfeldt et al., 2019). Digitalisation has revolutionised livestock farming, with the monitoring of animal health and welfare becoming increasingly connected to advancements in digital technology (Buller et al., 2020). With the technical infrastructure in place, science is investigating the extent to which MI data can serve as a reliable monitoring tool for animal health and welfare (Correia-Gomes et al., 2016; Vial, 2019). Our original study demonstrates how the integration of new digital tools and Industry 4.0 technologies in the Germanys meat industry, is creating new opportunities in how MI data can be collected and analysed across different slaughterhouses. By presenting the statistical analysis model using a representative case study, we further documented the status quo of animal health in the category "respiratory health" in south Germany based on MI findings and tracked its progression over recent years. The statistical analysis was able to provide important insights into the recording quality, variability and comparability of MI data from different slaughterhouses. The multilevel statistical model developed across various slaughterhouses demonstrated the added value that MI data can bring to the agricultural value chain in promoting animal health and welfare.

The recording quality of MI data is affected by many factors, and the results influence numerous actors in the agricultural value chain. Strengths and limitations of MI have been described in great detail, and particularly differences in terminology, frequency of recording and training of the recording person (meat inspector) make an assessment on a broad scale challenging (Alban et al., 2022; Stärk et al., 2014). In order to realise comparability and analysis of MI findings data, appropriate infrastructures are needed. Standardised recording along the slaughter line, digital data storage and comparableness are essential prerequisites for the use of slaughter data for further analysis (Alban et al., 2022; Stärk et al., 2014). Qualifood® provides farmers in south Germany with farm-specific evaluations of MI data available for each individual slaughterhouse. To add value in the efficient monitoring of animal health and welfare on farms, it seems beneficial to aggregate MI data and to generate comprehensive evaluations across slaughterhouses. The technical structure of Qualifood®, which integrates data from various slaughterhouses through standardised internal mapping, enabled us to conduct a deeper analysis aimed at evaluating MI data on a cross-slaughterhouse level, allowing us to explore statements regarding animal health and welfare based on these findings.

As previously noted, the final selection of slaughterhouses was guided by a combination of statistical and empirical considerations. The empirical foundation is built on continuous dialogue with meat inspectors and the veterinary authorities responsible for documenting MI findings across the twelve selected slaughterhouses. Through the IT system implemented by the Fleischprüfring, we can maintain regular communication with both groups. This ongoing exchange provides valuable insights into practical challenges and discrepancies in the recording of MI data across different slaughterhouses. In collaboration with state authorities, recent initiatives have focused on the continuous training of meat inspectors. These efforts aim to improve the quality of data collection and move towards full standardisation of recording practices in the coming years.

In addition to empirical factors, statistical considerations are related to the interpretation of the analysis of the slaughterhouse-level random effect for the respiratory health findings (Table 4). Notably, the full dataset including all slaughterhouses shows consistently higher variability. These results suggest the presence of substantial heterogeneity between slaughterhouses, especially when considering all facilities. This could reflect differences in inspection protocols, equipment, staff training, or operational conditions, all of which may influence how respiratory findings are detected and recorded. This finding highlights the importance of adjusting for slaughterhouse effects when benchmarking farm performance or interpreting meat inspection data for health monitoring. Without such adjustments, comparisons across farms could be skewed by facility-level biases.

Across all years, the SDs of the farm-level random effect remain relatively stable. The similarity of values between the selected slaughterhouses and the entire dataset suggests that farm-level variability in respiratory health is consistent regardless of the slaughterhouse sample used. The slight decrease in 2024 (to 0.60 for selected and 0.61 for all) may indicate a minor reduction in between-farm variability, which could reflect more uniform management practices or improvements in respiratory health across farms. Overall, these findings underline that farm-level differences contribute meaningfully and consistently to variation in respiratory conditions observed at slaughter.

The estimated SDs of the farm-level random effect are consistently higher when all participating slaughterhouses are included, as compared to the subset of selected facilities. Furthermore, selected slaughterhouses showed slightly more stable and lower within-farm delivery variability. This suggests that the subset of selected slaughterhouses may exhibit more uniform recording practices or represent more homogenous farm populations, contributing to lower intra-farm variability. In contrast, the broader dataset may include facilities with more diverse farm profiles, operational differences, or inconsistencies in data capture, leading to greater observed variability. However, over the 5-year period, the SD values for both groups remain relatively stable, with only minor year-to-year fluctuations. The stability of the delivery-level SD across years indicates that, while some variation exists within farms over time, these fluctuations are relatively consistent. These results may reflect differences in herd composition, management cycles, or seasonal effects, but also underline the importance of continuous, rather than one-time, evaluation of farm performance.

Quantifying this variability provides essential insights into where the greatest inconsistencies arise -be it at the level of farms, deliveries, or slaughterhouses- and supports the development of robust benchmarking and monitoring systems. Estimating these SDs within a multilevel model framework allows for a more accurate interpretation of respiratory findings and enhances the utility of MI data for decision-making in animal health, welfare, and production management.

In the swine sector, numerous studies can be found highlighting the usefulness of slaughter findings as a monitoring tool of animal health (Luca et al., 2021; Correia-Gomes et al., 2016; Devitt et al., 2016; Teixeira et al., 2016; Harley et al., 2012). In the context of herd monitoring or veterinary herd management in farms, MI data can be used as risk-based indicators and indicate which areas can be focused on first (Ghidini et al., 2021). Especially, the collection of organ findings at the slaughterhouse serves as a cost-efficient monitoring tool and enables the simultaneous acquisition of data from multiple farms (Correia-Gomes et al., 2016). Moreover, the various production and husbandry systems have certain weaknesses and advantages and a different influence on the health of the pigs (Alban et al., 2015).

In our study, we calculated the selected slaughterhouses' reverence values, known as "basic risks", assisting us to define what is considered a normal number of MI findings in south Germany for our representative case study (Table 3). The basic risk of respiratory health findings decreased from 14.4% in 2020 to approximately 12.0% in 2024, suggesting an overall improvement in respiratory health status. Comparable results were observed in previous studies (Comin et al., 2023). Moreover, the associated uncertainty intervals have widened in recent years, possibly indicating greater variability in prevalence estimates. Concurrently, a decline in the number of animals delivered has been observed, which may also impact the uncertainty of the documented prevalence. These patterns underscore the importance of accounting for multilevel effects in benchmarking and interpreting trends in animal health based on meat inspection data. By documenting the basic risks over the past 5 years, we were able to provide an overview of the progression of diagnostic probability for south Germany. Given that animal welfare is an important pillar of sustainable meat production and standard monitoring procedures are beneficial (Velarde et al., 2015), the continuous calculation and documentation of basic risks - initially for respiratory health and potentially for other diagnostic categories- can support the early identification of emerging trends and facilitate a deeper understanding of their underlying causes. As animal welfare risks vary by production stage and farm management objectives (Mandel et al., 2022; Wigham et al., 2018), in the case of fattening and meat production, the life cycle of the animals is predefined in terms of time (Mandel et al., 2022), ensuring the highest standards of animal health and welfare is therefore even more crucial.

In addition to the daily routine inspections, farmers monitor their livestock also by relaying on digital data systems (Eastwood et al., 2021). An advantage of digitalisation is the availability of various animal health data, available at both individual animal and herd levels. Another benefit is that these data remain accessible throughout the animal's on-farm lifetime and even after it leaves the herd, whether through sale, slaughter, or death. This makes traceability possible (Buller et al., 2020). In order to create added value for the livestock producer from the existing data, it is also necessary to link individual pieces of information in a meaningful and practicable way (Maisano et al., 2020; Nienhaus et al., 2020) and to build on this method of analysis and to integrate further farm-related information in the analysis procedure (Maisano et al., 2020; Ghidini et al., 2021). This manuscript presents the statistical analysis model and its application using the category of "respiratory health" as a representative case study based on pig data. The same methodological approach can be applied to all other defined meat inspection categories. Each category would yield its own distinct score, providing a foundation for the development of a comprehensive cross-slaughterhouse benchmarking system based on multiple diagnostic indicators. Furthermore, the model can be easily extended with additional factors. For example, further fixed effects can be included to account for seasonal trends, breed differences, or regional variation, enabling a more nuanced risk assessment. Another option is to implement a within-farm trend analysis, in which, alongside fixed effects for linear or categorical predictors, random effects for these predictors are also specified along the delivery-within-farm level. This approach would allow for a comparison of the effects of selected predictors across different farms, thereby enabling an additional form of monitoring. A more detailed exploration of these potential extensions to the multilevel statistical model lies beyond the scope of this paper and would warrant a separate publication.

One important factor that remains unaccounted for in the current model is the potential influence of individual meat inspectors on MI findings. Given that meat inspectors operate within slaughterhouses but assess animals from various farms, their impact introduces a cross-level structure, potentially positioned between the farm and slaughterhouse levels. Variability in detection thresholds, diagnostic accuracy, and adherence to recording standards may systematically affect the data, potentially biasing farm-level or delivery-level estimates.

Due to the unavailability of inspector-specific identifiers in the current dataset, direct estimation of these effects was not feasible in this study. However, future iterations of the model could benefit from including meat inspector as a random effect nested within slaughterhouses and crossed with farm and delivery effects. This would allow for the partitioning of variance attributable to inspectors and could help distinguish between true differences in animal health and variability introduced by subjective interpretation. In practice, this would require systematic documentation of inspector IDs during each inspection event, ideally integrated into the existing IT infrastructure. This is, for example, feasible at the 12 selected slaughterhouses in our analysis, currently operating with the technical infrastructure provided by the Fleischprüfring. Incorporating this additional layer into the multilevel framework could improve model accuracy, enhance benchmarking validity, and support training needs by identifying inconsistencies in recording practices. Ultimately, the inclusion of inspector-level effects would contribute to a more robust and fair assessment of animal health and welfare based on MI data.

Overall our model serves as a valuable resource for enhancing farm management practices, thereby supporting sustainable livestock farming (Velarde et al., 2015) and improving animal welfare and comparable monitoring standards across regions. It enables data-driven decisions and real-time feedback to farmers, with potential national and international use. To maximise the practical relevance and applicability of our model, it is essential to tailor its outputs to the specific needs of different decision-makers within the pig production and meat inspection system. Each stakeholder requires distinct information to support their decision-making processes, and the model can be adapted to meet these demands accordingly. Pig producers require individualised evaluations of their farm's performance, ideally in the form of benchmarking against comparable peers. Individual Slaughterhouses benefit from having access to MI-based rankings of supplying farms, which could inform quality-based incentives such as premiums or penalties. Additionally, slaughterhouses have a vested interest in understanding how their own performance compares to that of other facilities. Veterinary Authorities could benefit from having access to output generated by the model, including slaughterhouse-level rankings. Consumers increasingly demand transparency in food production and high standards of animal welfare and are entitled to access general trends, but not individual animal data or personal-identifiable information related to slaughterhouses or farmers. Our model and the observed region-wide trends can be utilised to deliver updates to consumers, public and policymakers about the current state of farms, promoting trust and transparency (Alonso et al., 2020). Furthermore, ongoing methodological development will be essential to ensure the robustness of the model, incorporate emerging risk factors and data sources -such as records of antibiotic usage- and support the validation of results. By addressing these diverse needs through a multilevel model architecture, the system has the potential to serve as a robust tool for evidence-based decision-making across the entire value chain.

Conclusion

In our study, we presented how ongoing digital transformation is creating new opportunities for the systematic collection and analysis of MI data across multiple slaughterhouses. This approach was made possible by an existing database that enabled data collection on numerous slaughterhouses and millions of slaughtered animals in south Germany. We also provided insights into the potential benefits and challenges associated with implementing an integrated, industry-wide, multilevel statistical model for MI records. By calculating the basic risks for one exemplary case study, we further estimated the frequency distribution of MI findings in south Germany for respiratory health. Our findings offer new insights into monitoring animal health and welfare using MI data, enhancing our understanding of its value as a complementary tool to already existing farm-level diagnostic and monitoring tools. For our analysis, we selected a subset of slaughterhouses, based on statistical and empirical criteria and incorporated random effects in our statistical model. This approach enabled us to estimate basic risks while accounting for delivery, farm, and slaughterhouse variations. Despite some limitations, including the recording quality across slaughterhouses, this work lays a foundation for future research in standardised collection of MI data und cross-slaughterhouse evaluations. Further studies could investigate the applicability of our model on other MI diagnostic categories, providing a foundation for the development of a comprehensive cross-slaughterhouse benchmarking system based on multiple diagnostic indicators. Our findings underscore the importance of region-wide, digital, and standardised MI data collection. Such systems are essential to address inconsistencies in recording quality across slaughterhouses, thereby improving data reliability. The presented advancements in digitalisation and the establishment of a standardised datasets in regions in Germany equipped with this infrastructure have established a solid foundation for cross-slaughterhouse evaluations. This capability enhances decision-making not only for farmers but also for the livestock industry and veterinary authorities, thereby strengthening the entire agricultural value chain.

Supplementary material

Supplementary Material for this article (https://doi.org/10.1016/j.animal.2025.101577) can be found at the foot of the online page, in the Appendix section.

Ethics approval

Not applicable.

Data and model availability statement

Data are not available due to the General Data Protection Regulation (GDPR). Model available on request.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) did not use any AI and AI-assisted technologies.

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Declaration of interest

The authors declare that there is no conflict of interest.

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