

Application Potentials of AI Technologies in Pork Production: An Analysis Along the Value Chain

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Abstract

The pork industry is currently characterized by fierce competition, labor shortages, and tight margins. Considering these challenges, the application of artificial intelligence (AI) technologies could deliver significant benefits by increasing material yield and reducing the labor intensity of processes. Due to limited financial and personnel resources, the challenge is to identify the most promising combinations of process step and AI technology. Therefore, a benefit/effort assessment based on 17 expert interviews was carried out, mapping each processing step of the pork value chain with available AI technologies. Prioritization logic was developed to guide AI implementation in pork production. As a result, visual analysis methods in the area of pig fattening offer the greatest added value combined with relatively low implementation effort and low costs. In addition, comprehensive health monitoring supported by AI can significantly increase the material yield. During the research, it has become evident that data collection for correlation analyses is crucial for continuously optimizing parameters.

Keywords: Artificial Intelligence (AI), Labor Efficiency, Material Yield, Meat Production, Pork Production, Process Optimization

Introduction

Pork has long been the most popular meat in Germany. Germany is the second-largest pork producer in Europe after Spain. Although pork still accounts for roughly one-third of total German meat consumption, pork consumption has been declining significantly, especially over the past five years. Within that time frame, pork consumption has seen a disproportionately steep drop of approximately 18%. (Bundesanstalt für Landwirtschaft und Ernährung et al., 2025) At the same time, the consumer price index for pork rose by around 28% in just three years. (Statistisches Bundesamt, 2025a) Fears of recession, a growing socio-political movement towards pork reduction in favor of perceived improvements in environmental sustainability and animal welfare, and declining purchasing power have fundamentally changed consumer habits, exerting enormous pressure on the industry. Hence, companies in this sector are facing several important challenges driven by a combination of economic, political, and socio-cultural developments.

The causes of the rising production costs are manifold: increasing costs in pig farming due to surging energy and raw material prices (e.g., feeding costs rose by approximately 40% between 2018 and 2023) (Statistisches Bundesamt, 2025b) as well as the high labor intensity of the processes. The pork industry has traditionally been characterized by high labor intensity. Many tasks, particularly in slaughtering, processing, and packaging, still require significant manual labor. Despite a

high degree of repetitive work steps, these tasks are difficult to automate due to their need for precision, dexterity, and flexibility. This dependence on available workforce combined with rising wages is placing additional strain on pork-processing companies, especially slaughterhouses. In this context, statutory minimum wage regulations play a pivotal role. Introduced in Germany in 2015, the minimum wage has since been significantly increased, which has driven up labor costs, particularly in labor-intensive pork-processing operations. Originally designed as a protective measure for workers in low-wage sectors, the minimum wage has had substantial consequences for the pork industry. Traditionally reliant on unskilled or low-skilled workers, particularly in operational roles, the industry has seen a dramatic rise in personnel costs due to these legal requirements. These costs are often passed on to consumers through price increases. Furthermore, Germany's labor market is under pressure due to demographic changes. A growing shortage of skilled workers is affecting the pork industry, as the physically demanding nature of the work and generally poor working conditions deter potential employees.

To remain competitive, pork companies must act. For an industry traditionally reliant on manual labor, the logical step is to enhance overall process efficiency. (Lacerda et al., 2025) This means reducing labor intensity wherever possible while seeking ways to optimize material usage (e.g., improving material yield) (Joseph, 2025) In this context, automation and AI have come into focus (Teixeira et al., 2025)

AI has already proven to be highly effective in agriculture (for example (Ali et al., 2024), in fieldwork (Kaiser et al., 2024),

and quality assurance (Lario et al., 2025)) by increasing productivity (Luo et al., 2024) and handling labor-intensive, repetitive tasks. (Komar Priatna et al., 2025) While numerous AI implementation and optimization approaches already exist, e.g., in plant production (Ganapathysubramanian et al., 2024) and the dairy sector (Beducci et al., 2026), the industrial pork production sector appears to be largely underexplored regarding AI applications. Therefore, it is assumed that significant benefits could also be realized by implementing AI-based systems in the process steps of pork production. To close the identified research gap, this research aims to analyze which AI application potentials exist to optimize labor usage and material yield per process step in industrial pork production.

The identification of AI application potential in the pork industry requires a precise definition of the scope. The terms "AI" and "pork industry" each encompass a wide range of applications, processes, and systems. One of the first goals of this paper is to narrow the scope of the term "pork industry" to the physical flow of goods, i.e., the primary operational activities as key drivers of labor intensity and material yield. These processes were identified, understood, and subdivided into meaningful stages.

Application-oriented AI systems can be categorized into four main types: Natural Language Processing (NLP), Natural Image Processing (NIP), Expert Systems, and Robotics. NLP systems enable machines to understand, and process spoken or written language, for example through virtual assistants or automated transcriptions (Du et al., 2021) NIP systems analyze visual information, detect patterns and objects in image data (Burton-Barr et al., 2024), and are already applied in fields such as medical diagnostics and agricultural yield forecasting (Tian et al., 2025) Expert systems combine structured knowledge bases with logical reasoning to support complex decision-making (Yan et al., 2025) at an expert level (Deng et al., 2023), as seen in sectors like energy or healthcare. (Mamyrbayev et al., 2025) Robotic systems, particularly Robotic Process Automation (RPA), automate rule-based processes and, when enhanced by AI (Cheng et al., 2022), can increasingly handle unstructured data, making them suitable for a wide range of applications from administrative tasks to intelligent, fully automated production environments (Mahala et al., 2024)

Based on this foundation and the described delineation, this paper aims at identifying specific AI application potentials in the relevant process section. (Machucho & Ortiz, 2025) The focus is not only on exploring the theoretical implementation possibilities and potential benefits of AI in these processes (Tokkozhina et al., 2025), but also on

examining the possible challenges (Jamwal et al., 2025) associated with such implementations. (Basulo Ribeiro et al., 2023) These include estimates of required investments in IT infrastructure and projections of the specialist personnel needed (Aleca & Mihai, 2025) This dual perspective will enable the derivation of a benefit/effort analysis of implementing individual systems and help prioritize implementation projects (Mashkoo et al., 2024) based on descending benefit/effort ratios. In specific terms, this analysis investigates how technological progress in process automation and AI applications can influence and optimize the physical production processes (Li et al., 2025) in the pork industry.

Given the complex and multi-layered nature of both the pork industry and AI technology, selecting an appropriate research method is critical.

Methods and Materials

Fig. 1 provides an overview of the overall applied research methodology. To address the identified research gap, the primary aim of this study is to derive practical and applicable recommendations for pork processing companies regarding the integration of AI-based systems to maintain long-term competitiveness. The structure of the empirical investigation is guided by four central research questions, which collectively form the backbone of this inquiry. These questions are discussed and answered in a differentiated manner throughout this study:

(1) Current applications and future potential of AI technologies in pork production: Which AI technologies are already being successfully applied within which processes of the pork industry, and which processes could potentially benefit from the implementation of additional AI systems in the future?

(2) Realizable potentials using AI systems: What potentials could be realized through the use of AI systems in pork industry processes to improve material yield and employee productivity? (Yuan & Agaian, 2023)

(3) Challenges and risks in the implementation of AI-based systems in pork production: What specific challenges and risks may arise in the operational implementation of AI-based systems within the pork industry? (Frater & Mushininga, 2025)

(4) AI systems with the greatest added value in the pork industry and required expertise for implementation (benefit/implementation effort assessment): Which AI-based systems offer the greatest added value to specific processes of the pork industry, and which professional competencies are required to ensure successful implementation? (Shahid & Mishra, 2024)

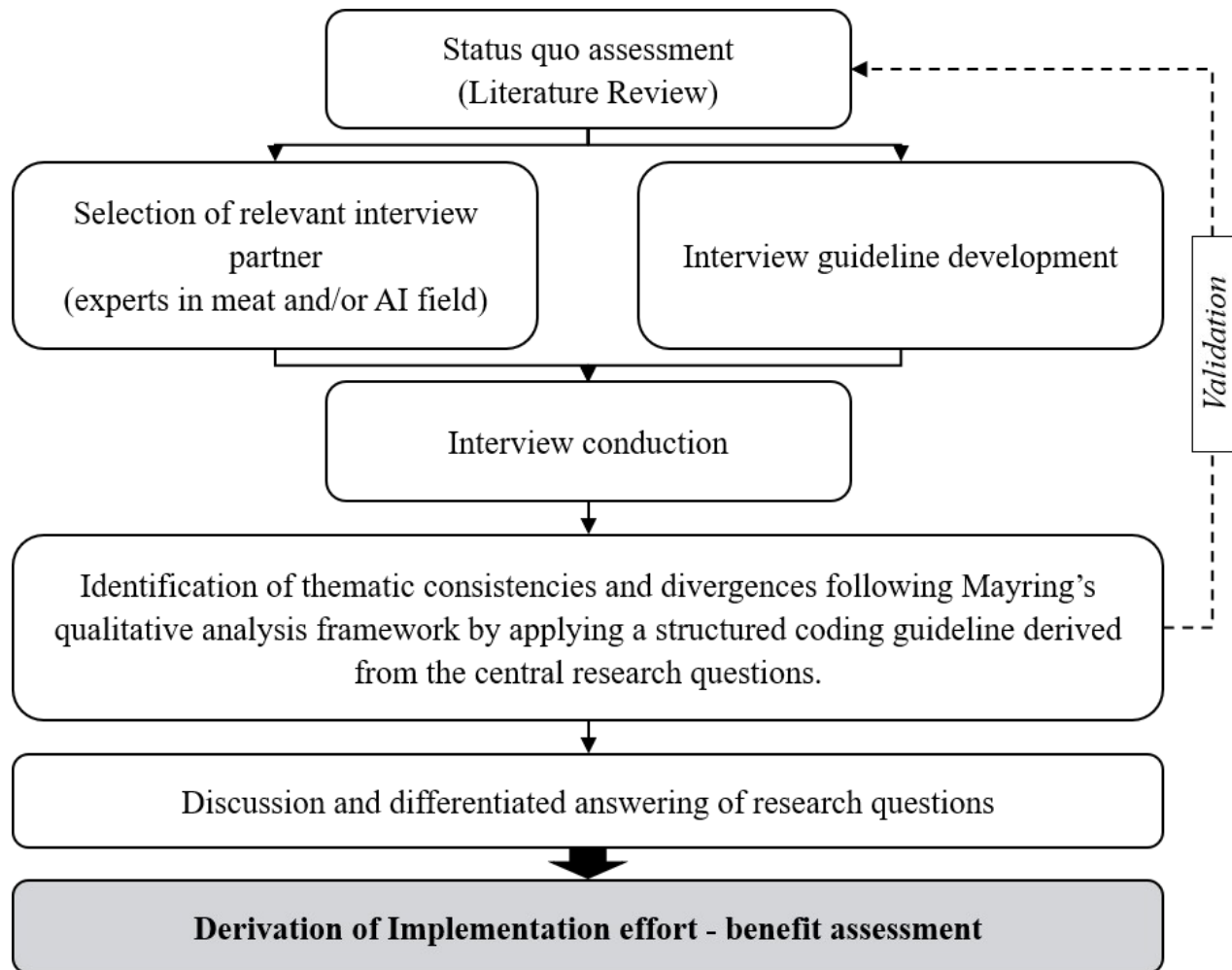


Fig. 1 Overview research methodology (own illustration)

Research Design

To adequately investigate the four research questions, it is imperative to apply a methodology that captures the complexity and contextual specificity of the two central domains: AI and the pork industry. These fields are characterized by their multifaceted operational landscapes, dynamic technological advancements, and intricate value chains. Consequently, the research design must allow for the exploration of latent structures, nuanced interrelations, and subjective expert perspectives that cannot be captured using rigid or purely statistical methods. Given the explorative nature of this study and the need for in-depth insights into practical applications of AI in the pork sector, a qualitative research approach was chosen, aiming to generate rich, context-bound insights. The expert interview format allows for flexibility in questioning, encouraging elaboration, and providing room for follow-up questions depending on the respondent's expertise and focus area. (Bogner et al., 2009)

Selection of Interview Partners

The validity and relevance of qualitative studies rely heavily on the purposeful selection of expert participants. In this research, 17 experts were selected based on their demonstrated experience and expertise in the domains of AI technology and/or the pork industry. Candidates were identified through a combination of professional networks, industry associations and targeted outreach to research institutions and technology providers active in the agri-food

sector. This purposive sampling approach ensured that participants possessed deep domain knowledge, practical implementation experience, and the ability to evaluate the feasibility and impact of AI applications from either a technological or operational perspective or, ideally, both. The sample size of 17 was considered sufficient as data collection proceeded until thematic saturation was reached, i.e., the point at which additional interviews no longer produced new codes or thematic content relevant to the four research questions. (Guest et al., 2006) The saturation was therefore assessed for the overall dataset as well as within each of the two participant groups. In the concluding interviews, both the group of practitioners and the group of AI and digitalization experts mostly reaffirmed the categories and insights that had already been identified and introduced no substantially new ones, suggesting that the number of respondents in each group was sufficient to capture the relevant perspectives.

As illustrated in Fig. 2, the 17 interview participants were assigned to two complementary groups based on their background: Selected participants in the first group include practitioners from agriculture and the meat industry who were interviewed to identify the process steps at which waste and manual labor currently accumulate. They contributed hands-on operational experience from pig farming, slaughtering, and meat processing as well as insights into the extent to which predictive quality control and animal welfare monitoring through real-time data and image analysis using deep learning techniques are already used. In addition, the second group consists of industry-focused AI and digitalization professionals

including members of AI task forces of pork industry consultancies and software providers. These participants mainly demonstrated expertise in the areas of AI strategies, data architectures, governance, and implementation.

Together, their perspective helped bridge the gap between technological possibilities and business-oriented deployment strategies, particularly in environments marked by legacy systems and operational inertia.



Fig. 2 Overview of 17 interview participants' background

The composition of the interview sample enabled a 360° perspective, balancing the technological supply side (AI developers, solution providers) with the industrial demand side (pork processors, quality managers), creating a comprehensive foundation for insight generation.

Interview Guideline Development

Two distinct interview guides were developed, one tailored to experts from the pork industry and one for AI professionals (Table 1.). The decision to create two separate guides stems from the highly specialized knowledge bases of each expert group and the necessity to approach them using domain-appropriate language and framing. The interview guide for pork industry representatives focused on process structures, pain points, current automation levels, quality assurance procedures, and potential areas of improvement. In contrast, the guide for AI experts focused more on technological capabilities, data requirements, existing AI use cases in industrial settings, and barriers to implementation. Both guides were structured around open-ended questions, allowing for flexibility in the interview process. The semi-structured format provided a framework to ensure coverage of all relevant topics while leaving room for participants to introduce additional perspectives and experiences. The dynamic nature of the interviews occasionally required adaptations in the question sequence or additional probing questions to deepen certain lines of inquiry. This approach aimed not only to gather factual knowledge, but also to capture expectations, uncertainties, and strategic considerations that are particularly important in fields marked by technological change and regulatory scrutiny.

Analytical Framework and Data Evaluation

Given the unstructured and context-rich nature of the interview data, a qualitative content analysis following the methodology developed by Mayring was applied. This method is particularly suitable for systematically identifying patterns, categories, and meanings across multiple qualitative data sources. It enables the reduction of complex data while preserving essential content structures relevant to the research objectives. Among Mayring's suggested analytical procedures, summarizing, explicating, and structuring, the study adopted a structuring content analysis with a focus on thematic categorization. This procedure facilitates a cross-sectional comparison of content across all interviews, allowing for the identification of thematic consistencies and divergences. (Mayring, 2022) The analysis proceeded in several steps:

- (1) Transcription of all interviews to produce a clean, analyzable text corpus.
- (2) Development of a coding guideline based on the predefined research questions and theoretical framework. This guideline included main categories and subcategories with clear definitions and coding rules (Table 2.).
- (3) Deductive category application: Interview transcripts were segmented into relevant units of meaning and assigned to the appropriate categories.
- (4) Generalization of findings: The categorized passages were synthesized into abstracted statements that captured shared insights, contextual factors, and points of divergence.
- (5) Interpretation and integration: The findings were interpreted in light of the overarching research questions and contextualized within the broader literature.

This process allowed for a coherent and replicable interpretation of qualitative data while maintaining the depth and contextual richness inherent to the interview content.

To systematically fragment the interview transcripts, a coding guideline (2) was established to isolate and generalize relevant statements for the targeted answering of the four defined research questions. This coding guideline is therefore structured around four main categories derived directly from the four research questions. Within each of these main categories, relevant statements from the interview transcripts were clustered in a way that supports answering the respective research questions (Table 2).

Results

Current applications and future potential of AI technologies in pork production

The development of AI-based systems within the pork industry is currently at varying stages: while some applications are already operating successfully in pilot projects, others remain in conceptual phases. There is a broad consensus among interviewees that AI has the potential to deliver significant long-term value to the industry. AI-driven systems are already being used in pig farming, especially for monitoring health and growth performance (Q1.1). These systems analyze visual characteristics and acoustic signals to detect abnormalities early and initiate appropriate interventions. For instance, acoustic analysis systems have been successfully tested in turkey farming, while visual monitoring solutions are more commonly used in pig production. A prime example is the "OptiSort" system, which uses optical measurements to sort pigs into different feeding zones based on size and weight, enabling optimized feeding, accurate determination of the ideal slaughter time, and automated routing of animals to the abattoir. However, individual animal identification is not yet part of this system. Other developments, such as the "Ringelretter" ("tail saver"), use optical analysis to assess tail condition as an early indicator of stress or health issues, automatically triggering preventative actions like the application of bitter substances to prevent tail biting. Another initiative, the "Glass Pig" project, is in the early testing phase and aims to leverage AI-based image recognition not only to estimate live weight, but also to assess potential carcass value prior to slaughter. This would provide farmers with greater transparency of pricing and settlement processes in slaughterhouses.

Overall, it became evident that AI has begun to make its way into the pork sector, although most systems are still in development (Q1.2). The existing systems primarily target early process stages, especially pig fattening, with a focus on optimizing feed allocation, monitoring animal health, and establishing transparency and data correlations (e.g., between feed intake and daily weight gain). In the interviews, little evidence was found that AI is currently in use in later processing stages. However, technological advancements suggest that existing AI solutions could, in theory, be applied to other areas of the pork supply chain. For example, optical health monitoring systems used in turkey production to optimize antibiotic use are reportedly being adapted for pig farming to enable more precise medication delivery. AI-assisted robotic systems, as already successfully used in the medical field, could also be applied to slaughtering and carcass cutting. Various sensors could measure fat and skin thickness and analyze each animal's anatomy to determine the ideal point of incision or the optimal cutting pattern for pork processing.

Furthermore, optical AI systems could be employed to classify and assess individual pork components by recognizing different cuts (e.g., fillet, loin, belly), evaluating their quality and weight, and directing them toward appropriate processing,

storage, or sale. Similar classification models are already in use for evaluating the quality of crops and fruits, such as grains or strawberries, based on structural attributes. Such systems could also reliably detect anomalies, like abscesses, bruising, or muscle degeneration and automatically remove or reassign the affected pork pieces to products where structural flaws are less critical (e.g., salami production). The continued development of AI and its underlying technologies, models, and algorithms opens promising prospects for widespread adoption across the pork industry. Existing technologies such as “OptiSort” could be further developed to enable individual animal identification and tracking, allowing for comprehensive data collection on weight gain, health developments, and potentially even hormone levels for advanced data-driven decision-making. This would enable detailed correlation analyses based on historical data, making animal welfare and growth performance measurable and controllable. Such individualization would support precise, data-driven decision-making to optimize key factors like feed composition and quantity, barn climate, structural design, and medical care.

There is also a high potential for AI applications in later processing stages (Q1.3). For example, robotic units supported by AI, similar to those used in the medical field, could be adapted to perform not only basic but also complex cuts in slaughtering and carcass processing at industrial speed and precision, significantly reducing the need for manual labor. In piglet rearing, AI-based video systems could support efficient birth monitoring by automatically tracking birth onset, counting piglets, and monitoring birth intervals. Based on predefined parameters, such a system could trigger alerts (e.g., via a traffic-light signal system) to allow for timely human intervention. Looking ahead, the most promising potential lies in enabling individual animal identification and tracking, thereby allowing for more precise management of fattening and animal welfare. Additionally, the automation of slaughtering and processing through AI-powered robotics appears feasible.

Beyond their use in primary production processes, AI could also significantly enhance demand forecasting and supply chain management in the future. This would allow pork to be produced, slaughtered, and delivered in line with actual market demand helping to reduce overproduction, overfeeding, waste, and costs throughout the value chain. Data-driven models enable farms, slaughterhouses, and retailers to coordinate more efficiently, aligning with market needs and reducing logistical expenses while increasing overall process efficiency. (Muñoz-Grillo et al., 2024)

Realizable potentials using AI systems

Initial pilot projects and conceptual AI solutions already show considerable promise in the pork production process. According to experts, the most significant quantitative and qualitative advantages lie in the precise monitoring of animal weight and health. These systems enable demand-driven feeding, which improves fattening performance while reducing feed usage. This leads to higher market grades (e.g., optimal slaughter weight and lean pork ratio) and lower input costs. Experts estimate that such systems can increase the share of top-grade pigs by at least 10%, equivalent to roughly €8 per pig or €40,000 annually for a mid-sized operation of 5,000 pigs, excluding additional savings from reduced feed usage (Q2.1).

AI-based systems like “Ringelretter”, help detect early signs of stress and improve animal welfare, ensuring

compliance with regulatory standards. Such improvements may also qualify farmers for welfare subsidies, thereby significantly increasing profitability. Furthermore, AI technologies that enable early detection of disease or aggressive behavior could prevent outbreaks and reduce both medication costs and revenue losses due to lower carcass quality. AI systems also hold strong potential to reduce labor intensity in fattening operations, which are still highly dependent on manual monitoring. By automating health and maturity assessments, AI can not only take over repetitive tasks but also generate valuable data for continuous optimization of parameters such as feed composition or barn climate. Although difficult to quantify, this could significantly enhance workforce efficiency, as only exceptional cases flagged by the AI would require human intervention (Q2.2).

Looking ahead, further development of existing AI systems, such as individual animal recognition and fully personalized feeding and health monitoring, offers even greater potential. Such systems would allow for fine-tuned, data-based optimization of the fattening process, enhancing herd health and productivity (Q2.3). In addition, data insights could support innovation in feed and pharmaceutical development. AI-powered imaging systems could also improve quality monitoring and reduce classification errors, saving costs from returns or misgrading. These technologies may ultimately automate carcass grading, enhance transparency, and optimize billing processes. In piglet production, AI can also realize potential by supporting birth monitoring, reducing piglet mortality, and enabling more efficient staff allocation. Future robotic systems driven by AI may take over large parts of the cutting and processing work, though this will require further technical development (Q2.4). To summarize, the use of AI in the pork industry offers measurable benefits in both material yield and labor efficiency. Current systems have already demonstrated real-world value, and future enhancements could multiply these gains. In addition, the data generated by AI systems will drive transparency and enable continuous evidence-based process improvement across the entire value chain.

Challenges and risks in the implementation of AI-based systems in pork production

While experts broadly agree (Hána & Lameijer, 2026) on the significant potential of AI systems (Bosch et al., 2022) in the pork industry, their widespread implementation remains limited. This is primarily due to several key challenges and risks. One of the most critical obstacles is the availability and quality of input data required to train and operate AI models effectively. In many cases, the necessary sensor infrastructure, particularly in rural areas, is mostly insufficient. Incomplete or poor-quality datasets can compromise the reliability of AI outputs, leading to inaccurate decisions. Experts emphasize that different AI models are required depending on the nature and quality of the data available, which significantly impacts the complexity and cost of development. Applications based on image or video processing, e.g., in pig fattening or quality control are generally less complex and costly than robotics-based systems for slaughtering, which also demand high levels of process safety due to the use of autonomous cutting tools. Moreover, existing process structures and species-specific characteristics must be considered to ensure long-term effectiveness.

AI systems can only function in a reliable way after a proper training phase with sufficiently high-quality data (Nota et al., 2024). Achieving this will require substantial investment in hardware and software, which is technically feasible but financially demanding (Q3.1) (Muratovic et al., 2025). In addition to these technical hurdles, a critical non-technical barrier is the human factor. Implementing AI systems often entails major changes to established workflows and job roles. In a traditionally conservative industry like pork production, this can lead to resistance. Employees may fear that their expertise will become obsolete or that they will eventually be replaced by technology. Decision-makers may be hesitant due to concerns over high implementation costs and financial risks. However, the greatest obstacle lies in challenging long-standing mindsets and operational habits. The sector is often shaped by traditional practices perceived as sufficiently reliable, making it difficult for new technologies to gain acceptance. This skepticism is further reinforced by the demographic structure of the industry as many farm owners and managers belong to an older generation that tends to be less tech-savvy and more resistant to change (Q3.2).

AI systems with the greatest added value in the pork industry and required expertise for implementation (Implementation Effort-Benefit Assessment)

For the concluding determination of the AI systems with the greatest added value to the pork industry and required expertise for implementation, a dedicated "benefit/implementation effort assessment" has been derived (Table 3) (Q4). The matrix differentiates between four AI system types: Natural Language Processing (NLP), Natural Image Processing (NIP), Expert Systems, and Robotic Solutions. This matrix assigns each of them to relevant process steps across the four production stages: piglet production, fattening, slaughtering, and pork processing. The term "n.a." ("not applicable") reflects use cases that were not discussed by the experts and are therefore classified as not relevant for this study. As the implementation effort correlates with the challenges and risks involved in implementing a system, the effort assessment also represents the respective challenge and risk assessment.

To enable a comparison of the potentials and the efforts/risks, the qualitative information has been quantified by a grounded logic to derive index values for both the potential and the effort (1 = min; 3 = max). First, the number of interview participants mentioning a certain AI system in regard to a process step is represented in the "mention rate (M)". Second, if mentioned, the potential (P) and the effort/risk (E/R) for each system in every process step were evaluated as "low," "medium," or "high". The numbers of "low," "medium," and "high" ratings were counted for each system in every process step, weighted by the Likert scale (values 1, 2, and 3), and divided by the number of interview participants mentioning this aspect. The qualitative benefit assessment encompasses not only the short-term, directly realizable advantages, but also considers future potential. Future potential by technological advancements comes mainly from the optimization of correlation analysis or automated parameter optimization based on continuous data collection, such as in health monitoring or feed efficiency optimization in pig fattening. The relevance (R) of a system in a certain process step is given (y = yes) if at least three experts mentioned the topic ($M > 17\%$) and the potential (P) is evaluated with a Likert value > 1 ,

otherwise the relevance is considered as absent ($n = \text{no}$) and will therefore not be considered in the following as well (Table 3.).

Discussion/Implications

Prioritization of AI systems in pork production

Drawing upon the expert assessments and the benefit/implementation effort matrix (Table 3.), several key insights have emerged regarding the prioritization, feasibility, and long-term strategic potential of AI-based applications across various process stages (Q4.1).

High-Benefit/Moderate-Effort Use Cases (Top Priority): The matrix highlights that the most promising implementation scenarios lie in the combination of Natural Image Processing (NIP) and Expert Systems like recurrent neural networks for effective pattern recognition during the early production steps, specifically in feeding, medical care, animal inspection, and the selection of appropriate pork components for certain products. (Siahaan & Asrol, 2023) Farrowing/postnatal monitoring also has a high potential rating with medium effort but warrants further examination since it is derived with a relatively low mention rate of 18%. While the implementation effort is assessed as moderate, the expected benefit in terms of increased material yield and reduced labor intensity is substantial. These use cases, therefore, represent top-priority targets for operational AI integration and are viewed as most promising with high return on investment.

Mid-Priority Use Cases in Downstream Processes: In slaughtering and processing, AI systems, particularly the combination of NIP and expert-based rule systems, offer considerable added value. Prominent examples include carcass grading and quality assessment, selection of pork components based on product-specific criteria, animal inspection prior to slaughtering, and optimization of fresh pork packaging. Despite a higher degree of implementation complexity, these applications are expected to reduce waste, improve consistency, and enhance product quality. Their strategic value lies primarily in standardization and traceability, which are increasingly relevant in both domestic and export markets.

High-Potential but High-Complexity Use Cases (Long-Term Focus): The full automation of cutting and carcass disassembly using complex robotic systems is considered one of the most transformative AI applications within the pork industry. Such systems could drastically reduce labor costs and improve hygiene and safety standards. However, the technical complexity (including motion control, real-time adaptability to carcass geometry, process safety), in combination with the current economic infeasibility, positions this use case firmly in the long-term strategic horizon. Moreover, existing robotic systems (e.g., those used in surgical environments) do not yet offer the speed and throughput capacity required for industrial-scale pork processing. Hence, while highly attractive in theory, these systems require significant advancements in both hardware performance and cost-efficiency before wide-scale deployment becomes viable (Q4.3).

Non-Relevant or Not Yet Applicable Use Cases: Certain process steps, such as castration or the estimation of optimal insemination times, were either marked as not relevant or not addressed (n.a.) in the expert interviews and are therefore also not relevant. This is primarily due to their low variability, or minimal need for systematization. Similarly, Natural Language Processing (NLP) technologies were only

sporadically mentioned (mostly in the context of documentation or medical data recording) and were not seen as impactful in most operational process steps.

Managerial Implications and strategic outlook

The study findings confirm that near-term implementations of AI in the pork industry should prioritize image-based classification systems combined with rule-based expert systems in upstream processes (e.g., feeding and health management) and quality assurance tasks (e.g., carcass grading, packaging optimization). These technologies are relatively mature, and several projects are already in pilot phases (e.g., OptiSort, DigiSchwein) showing demonstrable benefits in both yield optimization and process efficiency. The critical success factor across all application areas remains the availability and quality of structured data (Adeoye et al., 2023). As such, companies should focus initial efforts on building a scalable data architecture (Bimonte et al., 2025) and ensuring the availability of necessary sensors and infrastructure. (Balakrishnan et al., 2020) In addition to the technical considerations, the human factor emerged as a pivotal element in the implementation process (Kirwan, 2025). Employee acceptance (Islam & Zhou, 2024), organizational readiness for change (Boyacı & Söyük, 2025), and the willingness to adopt data-driven practices (Fengkuo et al., 2025) in an agricultural environment are essential for the successful integration of AI systems. Companies are therefore advised to collaborate with specialized implementation partners, such as AI solution providers and implementation consultants (Arbaiza et al., 2024), to overcome technical and organizational barriers (Da Tavares et al., 2025) while capitalizing on shared data networks for continuous optimization (Q4.2). (Alhammadi, 2025)

Conclusion and Recommendations for Further Research

Based on qualitative interviews with 17 industry experts, showing strong consensus on key issues, it was demonstrated that AI systems hold significant potential to enhance efficiency and value creation in the pork industry, particularly through improving material yield and reducing labor intensity. The findings confirm that the application potential of AI technologies is not merely theoretical but is already beginning to show measurable impact in selected operational processes. The expert assessments and the benefit/implementation effort matrix indicate that top priority should be given to Natural Image Processing (NIP) combined with expert systems (e.g., recurrent neural networks) in early production stages, particularly feeding, health and animal monitoring, inspection, and component-specific selection as these applications promise high benefits with moderate implementation effort. In downstream stages such as slaughtering and processing, NIP and rule-based systems also provide significant added value (e.g., carcass grading, quality assessment, and packaging optimization), but with higher complexity. Fully automated cutting and carcass disassembly through advanced robotics are considered highly transformative in the long term, but currently remain technically complex and economically unfeasible, as throughput capacity, real-time adaptability, and especially cost-efficiency are not yet sufficient for industrial-scale deployment. Certain use cases (e.g., castration or optimal insemination timing) were rated as not relevant or not applicable, and Natural Language Processing (NLP) played

only a minor role, mainly in documentation contexts, with limited operational impact.

Further research should focus on the quantitative validation of the identified high-priority AI use cases through case-specific business modeling. While the present study provides a structured prioritization based on expert assessments and a benefit–effort matrix, the actual implementation of AI systems ultimately depends on their economic viability at the firm level. Future studies should therefore develop standardized evaluation frameworks that translate operational improvements (such as yield increases, labor cost reductions, quality stabilization, and waste minimization) into monetary terms and integrate them into investment appraisal models (e.g., NPV, IRR, payback period). Attention should be given to sensitivity analyses, as the profitability of AI applications is likely to vary significantly depending on, e.g., plant size, wage levels, throughput volumes and raw material price volatility. Empirical pilot studies and simulation-based approaches could provide empirical data for validating these business cases and for identifying threshold conditions under which AI adoption becomes economically feasible.

Appendix 1: Semi-Structured Interview

Table 1. Structure, themes and guiding questions of the interviews with meat/AI experts

Expert Category (Meat/ AI)	# Question number	Question
Meat	1	Are AI-based systems already being used in the primary processes of your company? If so, which ones?
Meat	2	(If the answer to Question 1 is yes) What specific advantages and disadvantages have you observed as a result of implementing these AI technologies?
Meat	3	Are there (additional) areas within your operational production process where you see further potential for the use of AI, for example to reduce labor intensity or increase yield?
Meat	4	At which stages of production does the greatest yield loss occur, and to what extent do you see potential to optimize yield (e.g., optimal utilization of the entire pig) using AI-based systems?
Meat	5	In which areas of your production does the highest level of manual effort occur, and could you imagine these manual tasks being fully or partially replaced by AI-based systems in the future?
Meat	6	What challenges have arisen or could arise in the implementation of AI systems in your company, and how have you addressed or how would you address them? For example: • Integration into existing systems and lack of expertise • High implementation costs • Data security concerns
Meat	7	What long-term risks do you see in the use of AI technologies in the meat industry, and how do you address or how would you address them? For example: • Technological dependency and system failures • Lack of employee acceptance due to changing work structures • Legal uncertainties and regulatory adjustments
Meat	8	What measures have you taken or would you take to prepare your team to work with AI technologies, and what is particularly important to you when implementing an AI system?
Meat	9	In your opinion, what expertise and technological capabilities are essential for the successful introduction of AI in meat production?
Meat	10	Which AI-based systems do you believe could generate the greatest added value for your company, and what has prevented you from implementing them so far?
AI	11	What do you understand by the term artificial intelligence (AI) and AI-based system?
AI	12	In your view, which AI systems (e.g., Natural Language Processing (NLP), Natural Image Processing (NIP), expert systems, robotics) are currently the most relevant when it comes to replacing manual labor and maximizing material yield in operational production processes in general?
AI	13	Are you aware of AI technologies that could be applied in key primary processes of the meat industry? What adaptations would be required for their implementation?
AI	14	In which specific processes of the meat industry (e.g., piglet rearing, fattening, slaughtering, meat processing) do you see the greatest potential for the use of AI systems with regard to minimizing labor intensity and maximizing material utilization? <i>(At this point, the interviewee is explicitly encouraged to ask clarifying questions about the individual processes in order to provide a precise answer within the context of this study.)</i>
AI	15	What specific challenges and risks do you see in the implementation of AI systems in the meat industry, and how would you address them?
AI	16	What (economic) value do you expect from a successful implementation of AI in the meat industry, which AI systems do you consider particularly suitable in this context, and what know-how is required for successful implementation?

Table 2. Coding guideline.

Category	Label	Subcategory	Label
Q1	Current applications and future potential of AI technologies in pork production	Q1.1	Currently used AI technologies in the pork industry (and systems currently in the development phase)
		Q1.2	Theoretical application possibilities of currently available AI systems in other process areas of the pork industry
		Q1.3	Theoretical application possibilities of future AI systems in the pork industry
Q2	Realizable potentials using AI systems	Q2.1	Quantitative benefits of previous AI applications (and systems currently in the development phase)
		Q2.2	Qualitative benefits of previous AI applications (and systems currently in the development phase)
		Q2.3	Quantitative benefits of future AI applications
		Q2.4	Qualitative benefits of future AI applications
Q3	Challenges and risks in the implementation of AI-based systems in pork production	Q3.1	Challenges and risks in potential AI implementations in the pork industry
		Q3.2	Human factor in the implementation of AI systems
Q4	AI systems with the greatest added value in the pork industry and required expertise for implementation	Q4.1	AI roadmap and prioritization
		Q4.2	Required expertise for successful implementation
		Q4.3	Necessary investment needs

Table 3. Implementation effort - benefit assessment (M = Mention rate in %; P = Potential in Likert value; E/R = Effort/ Risk in Likert value; R = relevance yes or no; n.a. = not applicable).

Process	Relevant Process step	AI Systems																
		Natural language processing (NLP)				Natural image processing (NIP)				Expert system				Robotic				
		M	P	E/R	R	M	P	E/R	R	M	P	E/R	R	M	P	E/R	R	
Piglet rearing	Selection of suitable breeding sows and boars	n.a.				6	1.00	2.00	n	6	1.00	2.00	n	n.a.				
	Assessment of suitable fertilization time and fertilization	n.a.				6	1.00	2.00	n	6	1.00	2.00	n	n.a.				
	Farrowing and aftercare	n.a.				18	2.33	2.33	y	18	2.33	2.00	y	12	2.50	1.20	n	
	Castration	n.a.				n.a.				n.a.				n.a.				
Fattening	Feeding	n.a.				76	2.84	1.15	y	71	2.83	1.66	y	59	2.50	1.20	y	
	Medical care	24	2.25	3.00	y	59	2.80	1.40	y	59	2.90	1.50	y	n.a.				
Slaughtering	Slaughter animal inspection and stabling	n.a.				35	2.83	1.33	y	35	2.40	2.00	y	n.a.				
	Anesthesia	n.a.				n.a.				n.a.				n.a.				
	Killing	n.a.				35	3.00	3.00	y	35	3.00	3.00	y	35	3.00	2.50	y	
	Carcass grading	n.a.				35	2.80	2.00	y	35	2.80	2.00	y	n.a.				
	Carcass cutting incl. quality assessment	n.a.				35	3.00	3.00	y	35	3.00	3.00	y	35	3.00	3.00	y	

		AI Systems												
Process Meat processing														
	Selection of the "appropriate" meat components for certain products ~~Product~~ Process step	n.a.	47	2.75	1.38	y	47	2.63	1.75	y	n.a.			
	Fresh meat packaging	n.a.	35	2.66	2.33	y	18	2.66	2	y	18	2.33	1.33	y

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