UNIVERSIDADE PAULISTA – UNIP

LEANDRO CIGANO DE SOUZA THOMAS

OPTIMIZATION OF ENVIRONMENTAL MONITORING OF POULTRY PRODUCTION THROUGH PARACONSISTENT ANNOTATED EVIDENTIAL LOGIC Eτ

SÃO PAULO

2025

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GRADUATE PROGRAM IN PRODUCTION ENGINEERING

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Dissertation presented to the master's Program in Production Engineering of Universidade Paulista – UNIP, as a partial requirement for obtaining the Master's degree in Production Engineering.

Area of concentration: Operation Systems Management.

Line of research: Quantitative Methods in Production Engineering.

Research project: Quantitative, Computational, and Technological Methods in Production Engineering.

Advisor: Prof. Dr. Jair Minoro Abe

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SÃO PAULO

2025

CATALOGUE FILE

Thomas, Leandro Cigano de Souza.
Optimization of environmental monitoring of poultry production through paraconsistent annotated evidential logic Eτ / Leandro Cigano de Souza Thomas. – 2025.
124 f. : il. color.

Dissertação de Mestrado Apresentada ao Programa de Pós-Graduação em Engenharia de Produção da Universidade Paulista, São Paulo, 2025.
Área de concentração: Gestão de Sistemas de Operação.
Orientador: Prof. Dr. Jair Minoro Abe.

1. Paraconsistent logic. 2. Environmental monitoring. 3. Broiler production. 4. Animal welfare. 5. Data analysis. 6. Sustainable innovation. I. Abe, Jair Minoro (orientador). II. Título.

Ficha elaborada pelo Bibliotecário Rodney Eloy CRB8-6450

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DEDICATION

I dedicate this Master's thesis to my mother, Ivoni Cigano de Souza Thomas (*in memoriam*), and to my father, Jomar Thomas (*in memoriam*). They were wonderful people and fundamental pillars in my life. They served as my foundation throughout this trajectory, always believing in my dreams, encouraging me to overcome challenges, and reminding me, above all, to uphold my values and virtues.

I also dedicate this work to my wife, Jaqueline Almeida Thomas, for all her support, affection, and patience throughout this journey. I thank you for your care and for standing by my side, motivating me even during the most difficult moments of this process. Your partnership was essential for me to complete this work. I love you very much.

Finally, to my daughter, Rebeca Almeida Thomas, and my son, Levi Almeida Thomas, for teaching me lessons I never imagined I would learn. The love I feel for you motivated me to persevere, to seek a better future for our family, and to leave a legacy demonstrating that knowledge frees and transforms us into better people. Above all, may we respect our values and seek humility, always remembering that our dreams can come true.

The author.

ACKNOWLEDGEMENTS

First, I would like to express my deepest gratitude to my advisor, Prof. Dr. Jair Minoro Abe, for his invaluable guidance, patience, and wisdom throughout this academic journey.

I also extend my sincere thanks to Prof. Dr. Irenilza de Alencar Nääs and Prof. Dr. Thayla Morandi Ridolfi de Carvalho Curi for contributing to the inception of my research project, offering valuable insights, and providing essential data for the construction of this dissertation.

I offer my appreciation to the professors who, with patience, dedication, and vast knowledge, assisted me in the maturation, learning, and development of this thesis.

I am grateful to my family, classmates, and friends who stood by my side during this period, always encouraging me to move forward.

My gratitude goes to the CAPES Graduate Support Program for Private Education Institutions (PROSUP – 88887.940472/2024-00) for granting the Master's scholarship, which was crucial in allowing me to dedicate myself to the production of this study.

I also thank the Graduate Program in Production Engineering at Universidade Paulista (UNIP) for the opportunity to make this dream a reality.

Finally, this Master's degree has been of great significance to my personal, academic, and professional life. The many lessons learned have made me a better person and demonstrated that I can navigate paths that previously seemed unclear. It was, undoubtedly, a significant journey for my intellectual growth, teaching me that there are no limits to the realization of our dreams.

The author.

ABSTRACT

Broiler production is an essential segment of the agro-industrial chain, responsible for supplying the global market with accessible animal protein. Productive performance and animal welfare depend on the effective control of critical environmental variables such as temperature, humidity, ventilation, carbon dioxide concentration, and ammonia levels. Fluctuations in these parameters affect feed conversion, growth, and mortality, making environmental monitoring crucial for the efficiency and sustainability of poultry production. However, conventional data-analysis systems show limitations when confronted with conflicting, imprecise, or incomplete information, thereby compromising decision-making processes. In this context, this dissertation proposes the development and validation of an expert system based on Paraconsistent Annotated Evidential Logic Eτ (Logic Eτ), capable of classifying environmental conditions in poultry houses even under uncertainty and contradiction. The research adopts the Design Science Research (DSR) methodology, structured in three stages: (1) a systematic literature review on intelligent technologies applied to precision poultry farming; (2) the construction of a logical model applied to real data from three types of poultry houses (Blue House, Dark House, and Solid Wall); and (3) the development of a functional environmental classification application, implemented on a low-code development platform and supported by inferences derived from Logic Eτ. As scientific outputs of the research, three academic articles were produced in alignment with the DSR stages, and the Parabroiler Intelligent Environmental Classifier system was officially registered with the *Brazilian National Institute of Industrial Property (INPI)*, confirming its originality and practical applicability. The results show that the proposed system performs robust and consistent inferences, providing logical classifications and operational recommendations for adjusting environmental conditions. The developed artifact constitutes a decision-support tool capable of promoting stability, reducing losses, and increasing zootechnical efficiency. It is concluded that the application of Logic Eτ to poultry environmental monitoring represents an innovative, replicable, and scientifically grounded solution with the potential to drive technological and sustainable advances in the poultry industry.

Keywords: Paraconsistent Logic; Environmental Monitoring; Broiler Production; Animal Welfare; Data Analysis; Sustainable Innovation.

RESUMO

A produção de frangos de corte é um segmento essencial da cadeia agroindustrial, responsável por abastecer o mercado global com proteína animal de forma acessível. O desempenho produtivo e o bem-estar das aves dependem do controle eficaz de variáveis ambientais críticas, como temperatura, umidade, ventilação, concentração de dióxido de carbono e amônia. Flutuações nesses parâmetros afetam a conversão alimentar, o crescimento e a mortalidade, tornando o monitoramento ambiental determinante para a eficiência e sustentabilidade da atividade. Contudo, sistemas convencionais de análise de dados apresentam limitações diante de informações conflitantes, imprecisas e incompletas, comprometendo a tomada de decisão. Diante desse cenário, esta dissertação propõe o desenvolvimento e validação de um sistema especialista baseado na Lógica Paraconsistente Anotada Evidencial Eτ (Lógica Eτ), capaz de classificar condições ambientais em aviários mesmo sob incerteza e contradição. A pesquisa adota a metodologia Design Science Research (DSR), estruturada em três etapas: (1) revisão sistemática da literatura sobre tecnologias inteligentes aplicadas à avicultura de precisão; (2) construção de um modelo lógico aplicado a dados reais de três tipos de galpões (*Blue House*, *Dark House* e *Solid Wall*); e (3) desenvolvimento de um aplicativo classificador ambiental funcional, implementado em plataforma de desenvolvimento sem codificação (*low code*), com inferências baseadas na Lógica Eτ. Como resultados científicos da pesquisa, foram desenvolvidos três artigos acadêmicos alinhados às etapas da DSR, e o sistema Parabroiler Classificador Ambiental Inteligente foi oficialmente registrado no Instituto Nacional da Propriedade Industrial (INPI), comprovando sua originalidade e potencial de aplicação prática. Os resultados indicam que o sistema proposto realiza inferências robustas e consistentes, oferecendo classificações lógicas e recomendações operacionais para correção das condições ambientais. O artefato desenvolvido configura-se como ferramenta de apoio à decisão, capaz de promover estabilidade, reduzir perdas e aumentar a eficiência zootécnica. Conclui-se que a aplicação da Lógica Eτ no monitoramento ambiental avícola representa uma solução inovadora, replicável e cientificamente fundamentada, com potencial para impulsionar o avanço tecnológico e sustentável da indústria avícola.

Palavras-chave: Lógica Paraconsistente, Monitoramento Ambiental, Produção de Aves de Corte, Bem-Estar Animal, Análise de Dados, Otimização Agrícola.

UTILITY

This dissertation underscores the strategic importance of poultry farming for global food security, particularly given the continuous growth in food demand and the necessity of adopting sustainable production practices. Within this framework, the study proposes the application of an expert system based on Paraconsistent Annotated Evidential Logic Eτ for the environmental monitoring of poultry houses. The objective is to address challenges related to climate control and the interpretation of conflicting, inaccurate, and incomplete data. Developed according to Design Science Research (DSR) methodology principles, this research integrates intelligent technologies applied to production efficiency, animal welfare, and environmental impact mitigation, aligning with the Sustainable Development Goals (SDGs) established by the United Nations.

This analysis contributes significantly to scientific advancement by applying Logic Eτ, to propose a new theoretical and methodological model for environmental control in production environments. Regarding professional practice, it offers a functional decision support artifact capable of optimizing poultry house environments, reducing waste, and increasing profitability. For public policy, the results suggest a need for regulations that encourage the use of sustainable technologies and investment in environmental monitoring infrastructure. Despite literature advancements in intelligent systems for poultry farming, significant gaps persist regarding the use of non-classical logical approaches, such as Logic Eτ, for processing environmental information subject to uncertainty. This dissertation seeks to bridge this gap by proposing an inference model capable of operating under conditions of uncertainty, with potential for replicability in other precision agriculture contexts.

The motivation for this work stems from the urgent need for sustainable and efficient solutions in the poultry sector. A background in Production Engineering combined with an interest in emerging technologies drove the formulation of this innovative approach, which integrates paraconsistent logic with environmental monitoring. The study's contribution is twofold: theoretical, by advancing the application of Logic Eτ; and practical, by providing a scalable operational artifact. In conclusion, this research offers a significant impactful contribution to both academia and the productive sector.

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LIST OF ABBREVIATIONS AND ACRONYMS

ABNT – Brazilian Association of Technical Standards
AHP – Analytic Hierarchy Process
ANP – Analytic Network Process
PPF – Precision Poultry Farming
BH – Blue House (Type of Aviary)
CSV – Comma-Separated Values
CO_2 – Carbon Dioxide
DSR – Design Science Research
DH – Dark House (Aviary Type)
Eτ – Paraconsistent Annotated Evidential Logic Eτ
Logic Eτ – Paraconsistent Annotated Evidential Logic Eτ
AI – Artificial Intelligence
IoT – Internet of Things
INPI – National Institute of Industrial Property
SDG – Sustainable Development Goals
PDF – Portable Document Format
PLF – Precision Livestock Farming
USCP – Unit Square Cartesian Plane
SLR – Systematic Literature Review
SUS – System Usability Scale
SW – Solid Wall (Aviary Type)
Tbs – Dry Bulb Temperature
RH – Relative Humidity
HCI - Human-Computer Interaction

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1 INTRODUCTION

1.1 Initial Considerations

Poultry production is a vital component of the global food industry, providing a significant portion of animal protein essential for human consumption. However, the efficiency and sustainability of this sector face complex obstacles, a primary challenge being the dynamic interaction between environmental conditions and bird welfare (Tuyttens et al., 2022; Brassó et al., 2025).

In poultry farming, ensuring optimal environmental conditions in housing facilities is critical to maintaining the health, performance, and well-being of birds. Factors such as temperature, humidity, and air quality exert a substantial influence on important metrics, including growth rates, feed conversion efficiency, and mortality rates among broilers. Fluctuations or deviations in these parameters can significantly affect both the economic viability and ethical standards of poultry production (Oliveira et al., 2006; Sousa et al., 2016).

Despite the recognized importance of environmental monitoring in poultry farming, conventional methodologies are often insufficient to address the complexities associated with data acquisition and analysis. The prevalence of uncertainties, contradictions, and inconsistencies in environmental data represents a significant hurdle for traditional monitoring systems, necessitating a more robust approach (Gupchup et al., 2019; Erhan et al., 2020).

In response to these concerns, this research explores the potential of an expert system based on the Paraconsistent Annotated Evidential Logic Eτ (Logic Eτ) for monitoring environmental conditions to optimize broiler production. By integrating Logic Eτ, this framework manages inconsistent or contradictory information that may arise in environmental monitoring systems, aiming to transform how poultry farmers perceive, interpret, and respond to dynamic environmental conditions (Martinez et al., 2024). The research was conducted according to the principles of Design Science Research (DSR) methodology, which guides the development of technological artifacts applied to the solution of complex problems.

This leads to the central research question: *How can an expert system based on Logic Eτ contribute to the optimization of broiler production, considering the environmental variability of poultry houses and its effects on performance and animal welfare?*

This question encapsulates the intersection of productivity, environmental monitoring, and animal welfare in poultry farming. By exploring the synergies between Logic Eτ and environmental monitoring, this study seeks to offer practical insights and solutions to improve the efficiency, sustainability, and ethical standards of poultry production (Martinez et al., 2024).

The significance of this research extends beyond academia, impacting poultry farmers, industry stakeholders, and consumers. By promoting a deeper understanding of the relationships between environmental variables, bird performance, and welfare outcomes, this study has the potential to promote more resilient, humane, and environmentally conscious poultry production (Sevegnani et al., 2017; Santos et al., 2020).

The subsequent sections of this dissertation present a comprehensive review of the existing literature, the investigation objectives, the proposed methodology, and a discussion of the expected results and their implications. Through rigorous analysis and innovative thinking, this work seeks to contribute to a more sustainable and ethical future in poultry farming.

This research has also yielded three scientific articles: a bibliometric review accepted for presentation at KES 2025; a paper detailing the logical model and Eτ-based inference structure; and a full paper accepted for publication at AISS 2025, demonstrating both academic relevance and international impact.

1.2 Justification

Bird health and welfare are pivotal factors for the efficiency of poultry production, as environmental variables such as temperature, humidity, and air velocity directly influence growth, feed conversion, and mortality. Fluctuations or inadequate conditions in these parameters can cause heat stress, respiratory problems, and other diseases, thereby compromising zootechnical performance and production profitability. Adequate environmental monitoring and control minimize the birds' energy expenditure on thermoregulation, favoring growth, feed efficiency, and the overall sustainability of the production system (Medeiros et al., 2006; Oliveira et al., 2006; Navarini, 2014).

Conventional environmental monitoring systems often fail to capture fluctuations and inconsistencies, leading to delayed responses and suboptimal management decisions.

Consequently, the inability to detect and respond quickly to changing environmental conditions can result in prolonged exposure of birds to suboptimal environments, compromising their welfare and performance. This limitation highlights the need for advanced monitoring systems capable of providing accurate data for efficient decision-making (Silva et al., 2020; George; George, 2023; Krause et al., 2023).

The application of Logic Eτ offers an innovative solution to the challenges of environmental monitoring in poultry houses. This approach enables the effective handling of inconsistent or contradictory data, which is common in real-world sensing environments. Such inconsistencies can occur, for example, when two temperature sensors record divergent values at the same location, when momentary reading failures occur due to condensation or dust on sensors, or when humidity and ventilation measurements indicate conditions opposite to those observed empirically. Logic Eτ makes it possible to interpret these ambiguous scenarios in a controlled manner, offering a more robust and reliable analysis of environmental conditions. This ability to integrate and interpret complex information contributes to overcoming the limitations of conventional monitoring systems, allowing for more accurate and efficient management of the poultry environment (Abe; Silva Filho; Costa Neto, 2022; Martinez et al., 2024).

The development of an artifact based on Logic Eτ, facilitates environmental monitoring and decision support. This system can generate timely alerts and specific recommendations, assisting poultry farmers in making informed decisions promptly. By optimizing environmental conditions, the system promotes more efficient and sustainable poultry production. The use of advanced technology for monitoring and analysis enables a rapid response to environmental changes, minimizing negative impacts on birds, and improving production efficiency (Liu et al., 2024).

1.3 Objectives

1.3.1 General Objective

The overall objective of this dissertation is to develop a Paraconsistent Expert System for the monitoring of environmental conditions in poultry houses, using Logic Eτ. This system aims to optimize broiler production by constructing an artifact that captures data, applies to the model, and efficiently classifies environmental conditions.

1.3.2 Specific Objectives

To achieve the general objective, the research was divided into the following specific objectives:

- SO1: To identify the challenges faced by broiler producers in the use of smart technologies in precision poultry farming.
- SO2: To develop an expert system using Paraconsistent Annotated Evidential Logic Eτ, that addresses the challenges identified in the first objective, qualitatively classifying the analyzed parameters: temperature, relative humidity, air velocity, carbon dioxide, and ammonia.
- SO3: To develop an application based on the Logic Eτ expert system to assist poultry farmers in decision-making.

1.4 Structure of the Work

This Master's dissertation adopts a mixed-methods (quantitative–qualitative) design within an article-based format and is composed of three scientific articles. The first article examines emerging technologies applied to precision poultry farming. The second article proposes and validates a logical model for environmental control based on Paraconsistent Annotated Evidential Logic Eτ. The third article presents the functional environmental classification application developed as a technological artifact of this research in detail.

The dissertation is organized into six interdependent chapters.

Chapter I presents the initial considerations, including an introduction to the research topic, its justification, objectives, and the delimitation of the scope of the study’s scope.

Chapter II contextualizes the research problem by addressing the challenges of environmental control in poultry houses and the limitations of conventional approaches.

Chapter III comprises the theoretical framework, synthesizing the scientific foundations on precision poultry farming, the Internet of Things (IoT), Logic Eτ, and critical environmental variables.

Chapter IV describes the methodology adopted, based on the Design Science Research (DSR) approach, structured in three stages that guide the development and validation of the proposed artifact.

Chapter V presents the results and discussion, highlighting the scientific and practical contributions of the research.

Finally, Chapter VI outlines the final considerations and indicates avenues for future work, consolidating the contributions of this study to both the scientific advancement and practical application of precision poultry farming.

CHAPTER II

2 CONTEXTUALIZATION OF THE PROBLEM

In the context of modern poultry farming, particularly in broiler production, environmental management has emerged as a primary factor in ensuring production efficiency and animal welfare. Furthermore, the growing global demand for chicken meat and the advancement of sector technologies require new approaches to environmental control within poultry houses. Factors such as temperature, relative humidity, air velocity, carbon dioxide, and ammonia have a profound impact on the health and growth of birds (Nääs et al., 2010; Oliveira et al., 2006). Consequently, this chapter aims to contextualize the challenges faced by poultry farmers in environmental control, focusing on the utilization of emerging technologies such as the Internet of Things (IoT), Artificial Intelligence (AI), Big Data, and Cloud Computing. Following this, the limitations of current technologies and existing gaps in data processing and analysis will be discussed, with specific emphasis on the shortcomings of classical logic for environmental control (Rasheed et al., 2022; Lashari et al., 2023; Silva et al., 2024).

2.1 Technological Growth and Global Demand

In recent years, the poultry sector has experienced significant growth, driven by the increasing global demand for chicken meat. This surge in demand necessitates greater productivity and efficiency in poultry breeding and management processes, placing pressure on producers to meet these requirements sustainably. To address this challenge, emerging technologies such as IoT, AI, Big Data, Cloud Computing, and Automation have played a pivotal role in the digital transformation of poultry farming (Rasheed et al., 2022; Lashari et al., 2023; Silva et al., 2024).

Consequently, these technological innovations facilitate the optimization of processes, improve product quality, and reduce the consumption of resources such as water and energy. Among these technologies, IoT has emerged as one of the most widely adopted in poultry houses, as it enables the monitoring of environmental and operational variables, such as temperature, humidity, air velocity, and air quality, using high-precision sensors. The integration of IoT and AI has empowered producers to precisely adjust environmental conditions, increasing production efficiency and avian health, while simultaneously meeting global demand in a more sustainable manner (Malika et al., 2022).

2.2 Key Emerging Technologies in Poultry Farming

Among the innovations applied to precision poultry farming, emerging technologies in environmental control in poultry houses stand out. The following are some technological solutions used in the sector.

2.2.1 Internet of Things (IoT)

The Internet of Things (IoT) is widely recognized as a critical tool for monitoring environmental variables in poultry houses, including temperature, relative humidity, air velocity, carbon dioxide, and ammonia. High-precision sensors provide the foundation for effective environmental control, generating data essential for preventing heat stress in birds, a factor that directly impacts performance and health. Furthermore, IoT systems facilitate the prediction of failures in ventilation and climate control equipment, enabling proactive adjustments before critical issues arise. Practical applications of IoT in poultry houses include systems that automatically modulate ventilation based on real-time humidity or temperature readings, thereby ensuring a stable environment for the birds (Kim; Lee, 2022).

2.2.2 Big Data and Cloud Computing

The utilization of Big Data in environmental monitoring enables the large-scale analysis of sensor-generated data. Concurrently, Cloud Computing facilitates the real-time processing, storage, and accessibility of this data, ensuring that vital information regarding poultry house conditions can be accessed remotely at any time. These technologies are essential for analyzing vast volumes of production data, empowering poultry farmers to identify patterns and trends, such as temperature and humidity fluctuations, that directly impact production performance and bird health (Astill et al., 2020; Selle et al., 2023).

2.2.3 Automation and Robotics

Automated systems for feeding, ventilation, and temperature control are established contributors to improved operational efficiency. Robotics, specifically, can be utilized to perform repetitive tasks, such as regulating environmental conditions in production facilities, with greater precision and reduced reliance on manual intervention. Additionally, automation enables poultry farmers to monitor poultry house conditions more effectively, ensuring the maintenance of an optimal environment for bird development (Ozenturk et al., 2023).

2.3 Challenges in Environmental Control of Poultry Houses

Despite the advantages offered by emerging technologies, environmental control in poultry houses faces several challenges. The following sections discuss the primary difficulties encountered in the collection and analysis of environmental data:

2.3.1 Variability and Complexity of Variables

The interaction of factors such as temperature, humidity, gas concentrations, and feed intake can significantly impact the thermal comfort and health of the birds, necessitating continuous monitoring and constant adjustments. Furthermore, spatial variability within poultry houses presents a significant challenge, as it creates microclimatic zones where environmental conditions may differ substantially, thereby affecting bird welfare. These microclimatic zones can be identified and monitored with greater precision using technologies such as IoT, which enables real-time data collection from distributed points within the poultry house, ensuring that all environmental aspects are effectively controlled (Liu et al., 2024).

2.3.2 Data Volume and Management:

The vast amount of data collected by IoT sensors presents challenges regarding efficient management and analysis. In poultry houses, real-time data collection generates massive volumes of information that, if not processed adequately, can overwhelm traditional data processing systems. This data overload impedes rapid and effective decision-making, particularly in critical situations requiring immediate response. The implementation of solutions based on Big Data and Cloud Computing offers a method to address this growing volume, enabling the processing and analysis of large datasets with greater efficiency and effectiveness (Franzo et al., 2023).

2.3.3 Data Reliability and Quality Issues

One of the primary challenges in precision poultry farming is the reliability of data collected by sensors. Over time, sensors can experience drift or lose accuracy due to hardware failures, environmental fouling (dirt accumulation), or component wear, all of which compromise measurement integrity. This degradation results in conflicting, inaccurate, or incomplete data, hindering environmental analysis and, consequently, impeding appropriate decision-making. Furthermore, traditional monitoring systems relying on analog sensors or manual methods often fail to detect anomalies with the precision offered by emerging technologies. The deployment of advanced digital sensors, integrated with automated calibration protocols, can mitigate these failures, ensuring more accurate and reliable measurements.

2.3.4 Conflicting, Inaccurate, and Incomplete Data

In many instances, sensor-collected data is incomplete, lacking crucial information required for effective environmental control. Moreover, the presence of conflicting and contradictory data, often resulting from sensor malfunction or extreme environmental conditions, generates uncertainties that degrade the quality of analysis. These inconsistencies obstruct the implementation of effective solutions for improving environmental conditions. The application of Paraconsistent Annotated Evidential Logic $E\tau$ and data fusion methods, which can process uncertainties and contradictions, presents an effective solution to resolve these issues and ensure robust data analysis.

2.3.5 Impact of External Variables

External factors, such as extreme weather conditions, power supply interruptions, and connectivity instability, also complicate environmental control. These unpredictable events render monitoring systems vulnerable and less effective by interfering with sensor functionality and data transmission. The implementation of power backup systems and the utilization of real-time monitoring technologies designed for robustness against external failures can minimize the impact of these variables, ensuring stable environmental control.

2.4 Limitations of Classical Logic in Data Processing

Classical logic, which is widely utilized in the processing of environmental data, adheres to strict principles based on binary truth—specifically, the Principle of Bivalence, where a proposition is considered exclusively true or false. This framework operates without accounting for uncertainties, ambiguities, or contradictions inherent in real-world data. While effective in deterministic scenarios, classical logic exhibits serious limitations when processing the conflicting, inaccurate, and incomplete data characteristic of the dynamic environment within poultry houses.

In the context of environmental control, classical logic struggles to effectively analyze these inconsistencies. For instance, when temperature or humidity measurements display slight variations or temporary sensor flaws, a classical system may force a binary decision based on a rigid threshold. This inability to process nuance can lead to erroneous decisions, such as inappropriate adjustments to ventilation or feeding systems. In a sensitive environment like a poultry house, such rigid responses can result in critical failures in temperature control or bird management.

2.4.1 Stress in Birds

Heat stress and discomfort resulting from environmental control failures are exacerbated by the inefficiency of classical logic in analyzing imprecise data. Consequently, the system's inability to adapt to ambiguous data can sustain suboptimal production conditions, causing severe physiological and behavioral stress in the birds. This negatively impacts growth rates and immune health. The direct consequence is significant economic loss, manifested through reduced productivity and increased mortality rates (Lashari et al., 2023).

2.4.2 Financial and Environmental Impacts

Classical logic can lead to inefficiencies in environmental control, such as excessive energy and water consumption, due to its inability to process data representing natural environmental variations. This rigidity can result in elevated operating costs, including increased energy expenditures and suboptimal water resource utilization, as well as broader environmental impacts, as control systems fail to adjust efficiently to dynamic conditions.

2.4.3 The Limitation of Classical Logic

A fundamental limitation of classical logic is its requirement for clear, non-contradictory data to function correctly. When applied to dynamic and complex environments like poultry houses, where environmental variables are in constant flux and measurements often contain margins of error, classical logic fails to provide robust analysis. Furthermore, it is unable to adequately address uncertainties arising from missing or contradictory data, often resulting in environmental control decisions based on erroneous assumptions.

2.4.4 The Solution: Paraconsistent Annotated Evidential Logic Eτ

Logic Eτ offers an approach that resolves these issues by enabling the flexible and effective processing of conflicting, inaccurate, and incomplete data. Unlike classical logic, Logic Eτ permits the coexistence of contradictory evidence and the evaluation of the degrees of evidence associated with each data point, providing a more accurate analysis in uncertain situations.

2.4.5 Inconsistency Management

Logic Eτ can handle contradictory and inaccurate data, such as fluctuations in temperature or humidity readings, without compromising the overall quality of the analysis. It enables the system to make decisions based on partial evidence by weighing the favorable and unfavorable evidence for each proposition. This improves the precision of corrective actions, such as adjustments to ventilation systems or thermal control protocols (Abe, 2015).

2.4.6 Improving Data Reliability

Logic Eτ facilitates the fusion of diverse data sources, even if some are contradictory or incomplete, by attributing a degree of reliability to each input. This capability allows for more informed and reliable decision-making, which is particularly critical in environments like poultry houses where precise monitoring of environmental variables is essential for ensuring bird welfare (Abe, 2015).

2.4.7 Environmental Control Optimization

By handling inconsistent data with greater robustness, Logic Eτ facilitates the automatic adjustment of control systems, such as ventilation and temperature regulation, ensuring that optimal conditions are maintained. This results in a more stable environment for the birds, characterized by a lower risk of stress and greater efficiency in resource utilization (Abe, 2015).

2.5 Spatial Variability in Poultry Houses

Spatial variability within poultry houses presents a significant challenge to environmental control and bird welfare. In many cases, environmental conditions vary considerably from one point to another within the facility. This variability can lead to the formation of microclimatic zones, such as hot or humid spots, that are not easily detected by conventional sensors. The lack of uniformity in environmental conditions can induce stress in birds located in specific areas, negatively impacting their health, growth, and productivity (Curi et al., 2014).

2.5.1 Impact on Animal Welfare

Broiler chickens exposed to unfavorable microclimates can suffer from heat stress, which impairs their growth and health. This stress can result in a suboptimal feed conversion ratio, increased mortality rates, and lower weight gain, directly affecting productivity and production efficiency. Furthermore, heat stress can lead to increased water consumption and reduced appetite, impacting the overall performance of the birds (Faria et al., 2008).

2.5.2 Monitoring Challenge

Detecting these microclimatic zones is challenging, as variations in environmental conditions can be localized rather than uniform. Accurate detection requires advanced monitoring technologies capable of measuring environmental variables at distinct points within the facility. Temperature, humidity, air velocity, and gas concentration sensors must be strategically distributed throughout the house to ensure that all zones are adequately monitored. Additionally, these sensors must provide data to enable a rapid response to changing environmental conditions.

2.5.3 Application of Sensor Technology to Map Spatial Variability

Distributed sensor technologies can be applied to map spatial variability within poultry houses and identify critical microclimate zones. Through a network of IoT sensors installed at strategic points in the poultry house, it is possible to collect detailed data on environmental conditions. This sensor network enables the identification of areas with hot or humid spots, as well as variability in temperature and relative humidity throughout the space. Continuous data collection facilitates the generation of temperature and humidity maps that help producers visualize microclimate zones and rapidly identify any zones of concern.

2.5.4 Logic Eτ and Environmental Variables

Logic Eτ offers an effective solution for managing these spatial variations. By enabling the processing of contradictory or inaccurate data, Logic Eτ can be applied to environmental control systems; such as ventilation, heating, and cooling, to efficiently correct microclimatic variations. For example, if sensors indicate a hot zone in a specific part of the house, Logic Eτ can facilitate a paraconsistent analysis of the data to adjust ventilation specifically for the affected area, without disrupting zones that are already within ideal conditions. This ensures that the environment is maintained in a constant and optimal state for the birds, promoting improved animal welfare and operational efficiency (Abe, 2015).

2.6 Air Quality Impact

Air quality within poultry houses is a primary determinant of broiler performance. High concentrations of gases such as ammonia (NH_3) and carbon dioxide (CO_2) can be detrimental to bird health, compromising respiratory function and increasing susceptibility to disease. Furthermore, airborne dust particles can negatively impact bird health, causing airway irritation and exacerbating long-term health issues (Nääs et al., 2007).

2.6.1 Monitoring Ammonia and Other Gases

The presence of ammonia (NH_3) constitutes a primary challenge in the environmental control of poultry houses. Elevated levels of ammonia can irritate the respiratory tract of chickens, resulting in reduced feed efficiency, decreased growth rates, and increased susceptibility to respiratory illness. These factors not only compromise bird welfare but also diminish productivity and increase operating costs due to the necessity for increased veterinary medications and interventions. Furthermore, carbon dioxide (CO_2), although present in lower concentrations, can adversely affect bird well-being, particularly in environments with inadequate ventilation, by reducing air quality and contributing to physiological stress.

2.6.2 Air Quality Technology

The utilization of gas sensors has proven effective for monitoring ammonia and CO_2 levels in poultry houses. Specialized sensors are capable of accurately measuring the concentration of these gases, enabling producers to adjust ventilation systems and control airflow with greater efficiency. The installation of these sensors at strategic points within the poultry house, specifically at bird level, ensures that measurements are representative of the actual environmental conditions experienced by the flock. Moreover, continuous monitoring allows for the detection of fluctuations in gas levels, aiding in the prevention of respiratory issues before they reach critical stages. However, the challenge lies in maintaining measurement accuracy and ensuring a rapid response to critical gas concentrations to prevent the exposure of birds to harmful conditions.

2.6.3 The Application of Logic Eτ in Gas Monitoring

Logic Eτ can be applied to enhance air quality monitoring, particularly regarding ammonia and carbon dioxide. By analyzing data from gas sensors, Logic Eτ is able to process uncertainty and rapid fluctuations in gas levels, such as the temporary variations that occur in poultry houses with variable ventilation or less efficient control systems. Logic Eτ can analyze the data to quickly identify oscillations in ammonia or CO_2 concentrations that may approach critical thresholds.

2.6.4 Generate Immediate Alerts

By identifying these peaks or variations, Logic Eτ can generate automatic alerts for poultry farmers, allowing adjustments to be made immediately to ventilation systems or other environmental control systems, such as humidification or air replacement.

On the other hand, improving data reliability: by dealing with contradictory or inaccurate data, Logic Eτ ensures that decisions are made with greater confidence, even in environments with partially inconsistent data.

By integrating Logic Eτ into air quality monitoring, poultry farmers can significantly improve environmental management, preventing respiratory problems in birds, reducing the risk of disease, and increasing production efficiency, while ensuring a healthier and more controlled environment.

2.7 Monitoring and Maintenance System Failures

The sensor and automation systems utilized in poultry houses depend on a robust and reliable infrastructure to ensure continuous and effective environmental monitoring. However, failures in these systems, such as loss of network connectivity, sensor malfunctions, or human error during maintenance, can compromise the collection of essential data and impede decision-making. These failures can have severe consequences, negatively affecting environmental control and bird health.

2.7.1 Sensor Reliability Challenges

The degradation of sensors over time, due to operational wear or technical faults, constitutes one of the primary challenges in environmental monitoring. Inaccurate or outdated sensors can yield erroneous data, directly affecting the performance of the environmental control system. Furthermore, improper maintenance of systems and sensors can lead to complete monitoring failure, compromising both the data collection process and the accuracy of subsequent decisions. For instance, temperature or relative humidity sensors may fail to detect a critical variation, resulting in an unsuitable environment for birds, thereby increasing the risk of heat stress and disease.

2.7.2 Impact on Operation

Frequent failures in monitoring systems can disrupt environmental control and compromise bird welfare. If ventilation or heating systems are improperly adjusted based on erroneous data, extreme fluctuations in temperature and humidity can occur, negatively affecting bird health and productivity. Additionally, data collection failures prevent poultry farmers from making rapid, accurate decisions, thereby increasing operational inefficiencies and incurring additional costs for veterinary interventions and treatments.

2.8 Challenges in the environmental management of poultry houses

Effective environmental management in poultry houses is crucial for ensuring the optimal health, productivity, and well-being of the birds. Key challenges include controlling temperature, humidity, and air quality within the facilities, as well as managing waste and minimizing environmental pollution.

Temperature control is essential to prevent heat stress, which can negatively affect broiler performance and welfare. Modern poultry houses are equipped with ventilation systems, evaporative coolers, and other climate control technologies to maintain optimal thermal conditions. However, these systems require proper maintenance and management to function effectively, and energy costs remain a significant concern (Deaton et al., 1978; Damasceno et al., 2010; Abreu; Abreu, 2011; Baxevanou et al., 2017).

Moisture management is another critical aspect, as high humidity levels can exacerbate the effects of heat stress and promote pathogen growth. Proper ventilation and litter management practices are necessary to control humidity levels and maintain a healthy environment for the birds.

Air quality is influenced by factors such as dust, airborne particles, and ammonia emissions from manure. High levels of ammonia can impair respiratory health and immune function in broilers, leading to reduced performance and increased susceptibility to disease. Strategies to mitigate ammonia emissions include regular litter removal, the use of air purifiers, and dietary adjustments to reduce nitrogen excretion (Blake; Hess, 2001; Banhazi et al., 2008; Wei et al., 2015).

Finally, waste management presents a significant challenge in poultry production, as substantial volumes of manure must be handled and disposed of properly. If managed correctly, manure serves as a valuable resource, functioning as a fertilizer or a renewable energy source through biogas production. However, inadequate management can lead to environmental pollution and public health concerns.

Implementing effective environmental management practices requires a comprehensive approach that considers the specific needs and operational conditions of each poultry house. Continuous research and technological innovation are essential to develop sustainable solutions that balance productivity, animal welfare, and environmental stewardship (Yahav, S.; Hurwitz, 1996; Williams; Barker; Sims, 1999).

CHAPTER III

3 THEORETICAL FRAMEWORK

In this chapter, the theoretical framework that underlies the study is presented.

3.1 Broiler Production Chain

The broiler production chain encompasses all stages, from rearing to processing and distribution, with each stage playing a crucial role in ensuring the quality and efficiency of poultry production. The chain begins with the management of breeder flocks, followed by hatcheries where eggs are incubated and hatched. Day-old chicks are then transferred to broiler farms, where they are reared until they reach market weight. The final stages involve processing plants where chickens are slaughtered, processed, and packaged for distribution to retailers and consumers (Nääs et al., 2015).

Key elements in the broiler production chain include feed mills, which provide diets specially formulated to meet the nutritional needs of broilers at different growth stages, and veterinary services, which ensure the health and welfare of the birds. Efficient management practices and advanced technologies are crucial to optimize production, reduce costs, and maintain high standards of food safety and animal welfare (Branco, et al. 2020).

Environmental factors such as temperature, humidity, and ventilation significantly impact the performance and welfare of broilers. Modern broiler houses are equipped with climate control systems to maintain optimal conditions, minimizing heat stress and promoting efficient growth (Sartor, R. et al., 2001; Barbosa, et al., 2012). Proper litter and waste management are also essential to control ammonia levels and reduce environmental pollution (Bjerg, et al., 2002).

Furthermore, the vertical integration of the broiler production chain ensures traceability and quality control from farm to table. This integration is achieved through close collaboration between growers, processors, and retailers, supported by comprehensive data management systems that monitor and analyze production parameters to improve efficiency and sustainability (Nääs et al., 2015).

3.2 Brazilian Poultry Production

Brazil is indisputably one of the world's leading poultry producers and exporters, boasting a highly developed and competitive industry. The country's favorable climate, abundant natural resources, and advanced production technologies contribute to its dominance in the global market (Oliveira et al., 2021).

The Brazilian poultry industry is characterized by large-scale, vertically integrated operations that cover all stages of production, from breeding and incubation to grow-out farms and processing plants. This vertical integration ensures efficiency, cost control, and consistent product quality, allowing Brazilian producers to compete effectively in international markets (Marmelstein et al., 2024).

In recent years, the industry has focused on improving sustainability and environmental management practices. Efforts include adopting renewable energy sources, such as biogas and solar power, and implementing advanced waste management systems to reduce environmental impact (Choi, 2025). Moreover, ongoing research and development in genetics, nutrition, and health management continue to drive improvements in productivity and animal welfare (Zhang et al., 2023).

The Brazilian poultry sector also benefits significantly from the strong support of industry associations and government agencies, which provide technical assistance, market intelligence, and advocacy. These organizations play a key role in promoting best practices, ensuring compliance with regulatory standards, and facilitating access to export markets (Atti et al., 2022).

Despite its successes, the Brazilian poultry industry faces challenges such as fluctuating feed costs, disease outbreaks, and trade barriers. Addressing these challenges requires continuous innovation, investment in biosecurity measures, and strategic market diversification to sustain growth and competitiveness in the global arena (Yahav et al., 2004).

3.3 Precision Poultry Farming

Precision Poultry Farming (PPF) refers to the use of advanced technologies and data-driven approaches to improve the management and productivity of poultry farms. PPF technologies include sensors, automation systems, and data analysis tools that monitor and control various aspects of the production environment, such as temperature, humidity, feed intake, and poultry health (Rowe, et al., 2019).

One of the main goals of PPF is to optimize the use of resources and improve animal welfare by providing insights into the production process. For example, sensors can detect deviations in environmental conditions or bird behavior, allowing for immediate corrective action to prevent stress and disease. Automation systems, such as automated feeders and drinkers, ensure accurate delivery of feed and water, reduce waste, and improve efficiency.

Data analytics and machine learning algorithms play a fundamental role in PPF by analyzing large volumes of data to identify patterns and predict outcomes. These insights enable farmers to make informed decisions, such as adjusting feeding schedules, optimizing stocking densities, and implementing preventive health measures. Additionally, mobile apps and cloud-based platforms facilitate remote monitoring and management, providing farmers with greater flexibility and control over their operations (Liakos et al., 2018; Benos et al., 2021; Araújo et al., 2021).

The adoption of PPF technologies has the potential to significantly increase the sustainability of poultry production by reducing resource consumption, minimizing environmental impact, and improving animal welfare. However, the implementation of these technologies requires substantial investment and technical expertise, presenting challenges for small-scale farmers with limited resources (Van Hertem et al., 2017; Lovarelli et al., 2020).

Despite these challenges, the future of PPF appears promising, with continued advancements in technology and growing awareness of the benefits of precision agriculture. Collaborative efforts among researchers, industry stakeholders, and policymakers are essential to promote PPF adoption and support the development of scalable and cost-effective solutions (Barbosa Filho et al., 2009; Wang et al., 2009).

3.4 Internet of Things (IoT)

IoT refers to the interconnection of devices through the internet, allowing for the collection and exchange of data. Equipped with sensors and software, these devices communicate with each other and with central systems, offering insights and automating processes. In poultry farming, IoT has provided precise control over various aspects of production (Porter; Heppelmann, 2014). The application of IoT in animal production systems, including poultry farming, improves the monitoring and control of environmental conditions in poultry houses (García; Martínez, 2019).

Sensors and monitoring are essential components for the application of IoT in poultry farming, offering efficiency in controlling environmental conditions within poultry houses

(Martinez et al., 2021). Their main functions are the detection of critical variations and the transmission of immediate alerts, allowing adjustments to maintain an ideal environment for bird development (García; Martínez, 2019). Thus, temperature, humidity, and air quality sensors, which monitor parameters such as ammonia and carbon dioxide levels, prevent issues related to heat stress and respiratory problems, thereby improving productivity and reducing mortality. Furthermore, sensors installed in drinkers and feeders detect changes in consumption patterns, indicating possible health problems or stress, helping to optimize the feeding and management of birds (Porter; Heppelmann, 2014).

While the benefits of IoT in poultry farming are widely recognized, its implementation faces significant challenges. In rural areas, the lack of adequate communication infrastructure and harsh environmental conditions complicate the installation and efficient operation of these systems. Distance from urban centers also hinders quick and efficient equipment maintenance, potentially affecting bird welfare. Additionally, reliance on a consistent electrical power supply in remote areas constitutes a significant obstacle to the continuous operation of automated systems. Device connectivity also increases vulnerability to cyberattacks, compromising sensitive data and farm operations. Therefore, the adoption of IoT for monitoring requires high upfront investments, making implementation difficult for smallholders.

Ultimately, IoT offers significant potential to optimize poultry production through monitoring and control, improving operational efficiency and animal welfare. However, for these benefits to be fully realized, it is imperative to overcome infrastructure-related challenges and high upfront costs (Friha et al., 2021; Balaji; Rao; Ranganathan, 2023).

3.5 Fundamentals of Paraconsistent Logic

Classical logic is founded on two mutually exclusive states, true and false, which limits its capacity to represent situations where uncertainties, contradictions, or incomplete information coexist. However, a large portion of real-world phenomena does not fit into this rigid dichotomy, as they present varying degrees of imprecision and conflicting evidence. In this context, annotated paraconsistent logics emerge as a family of non-classical logics developed to allow the formal treatment of inconsistencies without leading to inferential collapse, thereby expanding the possibilities for representation and reasoning in computational systems (SUBRAHMANIAN, 1987).

Paraconsistent Annotated Evidential Logic Eτ was structured based on studies conducted by various authors, including da Costa, Abe, and Akama. The formal foundations of this logic include contributions to predicate logic, model theory, annotated set theory, and modal systems. Among the most significant advancements are the meta-theorems of strong and weak completeness for a subclass of first-order annotated logic, as well as the systematization of an annotated model theory capable of generalizing classical results to evidential structures (Abe, 1992).

Beginning in the 1990s, different computational applications began to be developed based on Logic Eτ. Abe and his collaborators implemented the paraconsistent programming language Paralog, conceived independently of previous work on annotated programming (Da Costa et al., 1999). The formalism of Logic Eτ was also applied to the construction of complex computational architectures, including manufacturing cells integrated by planners, databases, and vision systems, as well as in *frame-based* knowledge representation models, allowing for the explicit treatment of inconsistencies and exceptions (Prado, 1996; Ávila, 1996).

In the field of hardware, Da Silva Filho developed digital circuits based on Logic Eτ, including the implementation of Complement, AND, and OR logic gates capable of processing conflicting signals in a structured manner (Da Silva Filho, 1999). This advancement opened new perspectives for the use of paraconsistent logics in electronics, culminating in the creation of logic analyzers (*Para-analyzer*), controllers (*Paracontrol*), simulators (*Parasim*), and signal processing systems (*Parasonic*). As a practical demonstration of the potential of this field, paraconsistent robots were constructed, such as *Emmy*, equipped with hardware grounded in Logic Eτ, and *Sofya*, developed with software based on Logic Eτ, followed by other subsequent prototypes (Da Silva Filho; Abe, 2001).

Beyond computational and engineering applications, annotated logics also encompass aspects associated with non-monotonic, defeasible, deontic, and default reasoning. The relationship between Logic Eτ and Fuzzy logic is also significant. Specifically, annotated set theory generalizes fuzzy set theory, enabling hybrid interpretations and combined controllers, such as those developed by da Costa and collaborators (Abe, 1992; Da Costa et al., 1999).

3.5.1 Annotated Propositions and Evidential Pairs (μ, λ)

In Logic Eτ, a proposition is represented in the form $p_{(\mu, \lambda)}$, where μ and λ, belonging to the interval [0,1], indicate the degree of favorable evidence and the degree of contrary evidence associated with the proposition, respectively. This structure expands the possibilities of classical logic by allowing favorable and unfavorable information to coexist simultaneously. Consequently, this enables the formal analysis of situations involving uncertainty, conflict, or incompleteness without compromising the inferential process. The evidential pair (μ, λ) constitutes the basic unit of representation in Logic Eτ and can assume different interpretations depending on the application context, such as degrees of confidence, measurement intensities, or levels of certainty.

Each annotated proposition corresponds to a point on the unit square [0,1] × [0,1], This space serves as the foundation for defining the degrees of certainty, contradiction, and paracompleteness, as well as for classifying propositions into extreme and non-extreme states. Thus, annotated propositions establish the mathematical framework necessary for utilizing Logic Eτ in monitoring, inference, and decision-making systems that operate under conditions of uncertainty and informational conflict (Abe, 1992).

3.5.2 Negation in Logic Eτ

Negation in Logic Eτ exhibits behavior distinct from that found in classical logic. Rather than simply inverting the logical value of a proposition, Logic Eτ performs negation by inverting the degrees of evidence that constitute the annotation. Thus, given an annotated proposition $p(\mu, \lambda)$, its negation is represented by:

$$\neg p_{(\mu, \lambda)} = p_{(\lambda, \mu)}.$$

This implies that the degree of favorable evidence for the proposition assumes the position of the degree of contrary evidence, and vice-versa. This operation is fundamental because it enables the formal representation of situations where the negation of a proposition does not eliminate the possibility of existing conflicting evidence.

An illustrative example is the case where the evidential values are identical, such as p(0,5, 0,5). In this scenario, both the proposition and its negation exhibit the same evidential pair, implying that both are simultaneously supported by equivalent quantities of favorable and contrary evidence. This behavior expresses one of the primary characteristics of Logic Eτ the possibility of coexistence between affirmation and negation without the system suffering inferential collapse, a condition that would be inadmissible in classical logic.

Defining negation as the inversion of evidential pairs grants Logic Eτ the capacity to operate in environments characterized by uncertainty, imprecision, and contradiction, offering a robust mechanism for the formal processing of inconsistent information. This property is essential for applications in monitoring, diagnostic, control, and decision-making systems, where contradictions are frequently inevitable (Abe, 1992).

3.5.3 Logical Connectives in Logic Eτ

The logical connectives of Paraconsistent Annotated Evidential Logic Eτ play an essential role in the processing of inconsistent and incomplete information. They permit the combination of annotated propositions without the system suffering inferential collapse, as would occur in classical logic. Similar to traditional formalism, the connectives of conjunction, disjunction, implication, and bi-implication are utilized. However, in Logic Eτ, each operation is applied directly to propositions of the type $p_{(\mu, \lambda)}$ e $q_{(\theta, \rho)}$, preserving the evidential pairs that constitute each annotation.

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Table 1 - Connectors

Connectors	Read
$p_{(m, \lambda)} \wedge q_{(\theta, \rho)}$	a conjunction of $p_{(\mu, \lambda)}$ and $q_{(\theta, \rho)}$
$p_{(m, \lambda)} \vee q_{(\theta, \rho)}$	a disjunction of $p_{(\mu, \lambda)}$ and $q_{(\theta, \rho)}$
$p_{(m, \lambda)} \rightarrow q_{(\theta, \rho)}$	an implication of $q_{(\theta, \rho)}$ by $p_{(\mu, \lambda)}$

Source: Abe (2010).

Conjunction combines two propositions such that the result simultaneously reflects their favorable and contrary evidence. It is expressed as:

$$p_{(\mu, \lambda)} \wedge q_{(\theta, \rho)}.$$

Disjunction represents the informational union between the propositions and is written as:

$$p_{(\mu, \lambda)} \vee q_{(\theta, \rho)}.$$

Implication establishes a directional relationship between the evidential pairs of p and q, enabling the evaluation of the extent to which the evidence of one proposition contributes to supporting the other. Its general form is given by:

$$p_{(\mu, \lambda)} \rightarrow q_{(\theta, \rho)}.$$

Bi-implication reflects logical equivalence between the propositions and is defined as the conjunction of two implications:

$$p_{(\mu, \lambda)} \leftrightarrow q_{(\theta, \rho)} = (p_{(\mu, \lambda)} \rightarrow q_{(\theta, \rho)}) \wedge (q_{(\theta, \rho)} \rightarrow p_{(\mu, \lambda)}).$$

These connectives operate by preserving the degrees of evidence associated with each proposition, allowing for the construction of robust inference systems even when facing contradictory or insufficient data. In practice, their utilization provides the formal foundation for decision-making algorithms, paraconsistent classifiers, and computational models that depend on flexible, inconsistency-tolerant logical relations. (Abe, 1992)

3.5.4 The Unit Square in the Cartesian Plane (USCP)

The Unit Square in the Cartesian Plane (USCP) constitutes the fundamental geometric structure of Paraconsistent Annotated Evidential Logic Eτ. Each annotated proposition $p_{(\mu, \lambda)}$ is represented as a point in the two-dimensional space defined by the Cartesian product [0, 1] × [0, 1], where μ e λ correspond, respectively, to the degrees of favorable and unfavorable evidence.

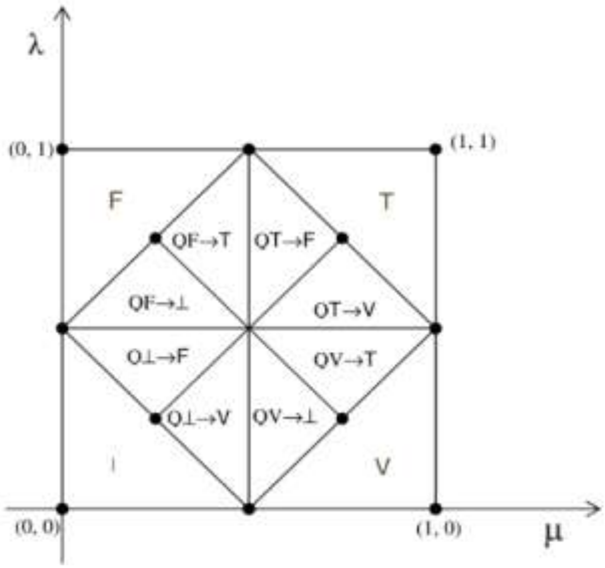
Table 2 – Lattice Properties

Expression	Property
$\forall \mu, \lambda \in \tau, (\mu, \lambda) \leq (\mu, \lambda)$	Reflexivity
$\forall \mu_1, \lambda_1, \mu_2, \lambda_2 \in \tau, (\mu_1, \lambda_1) \leq (\mu_2, \lambda_2)$ and $(\mu_2, \lambda_2) \leq (\mu_1, \lambda_1)$, imply $(\mu_1, \lambda_1) = (\mu_2, \lambda_2)$	Antisymmetry
$\forall \mu_1, \lambda_1, \mu_2, \lambda_2, \mu_3, \lambda_3 \in \tau, (\mu_1, \lambda_1) \leq (\mu_2, \lambda_2)$ and $(\mu_2, \lambda_2) \leq (\mu_3, \lambda_3)$, imply $(\mu_1, \lambda_1) \leq (\mu_3, \lambda_3)$	Transitivity
$\forall \mu_1, \lambda_1, \mu_2, \lambda_2 \in \tau$, the supremum of $\{(\mu_1, \lambda_1), (\mu_2, \lambda_2)\}$ exists, denoted by $(\mu_1, \lambda_1) \vee (\mu_2, \lambda_2) = (\mathrm{Max}\{\mu_1, \lambda_2\}, \mathrm{Min}\{\lambda_1, \lambda_2\})$	
$\forall \mu_1, \lambda_1, \mu_2, \lambda_2 \in \tau$, the infimum of $\{(\mu_1, \lambda_1), (\mu_2, \lambda_2)\}$ exists, denoted by $(\mu_1, \lambda_1) \wedge (\mu_2, \lambda_2) = (\mathrm{Min}\{\mu_1, \lambda_2\}, \mathrm{Max}\{\lambda_1, \lambda_2\})$	

Source: Abe (2010).

Within the USCP, four special points, designated as *cardinal points*, play a central role in the interpretation of evidential logic: point (1, 0) represents the *True* state; (0, 1) represents the *False* state; (1, 1) corresponds to the *Inconsistent* state; and (0, 0) corresponds to the *Paracomplete* state. These points define the extremities of logical behavior and serve as a reference for the positioning of annotated propositions within the plane.

Figure 1 - Unit Square in the Cartesian Plane



Source: ABE (2010).

In addition to the cardinal points, two notable segments structure the dynamics of the USCP. The *perfectly defined segment*, described by the equation $\mu + \lambda = 1$, characterizes situations where favorable evidence is exactly complementary to unfavorable evidence, approximating the binary behavior of classical logic. Conversely, the *perfectly undefined segment*, defined by the relation $\mu = \lambda$, groups propositions where favorable and unfavorable evidence possess the same intensity, representing states of indefiniteness that vary continuously between paracompleteness and inconsistency.

Based on this geometric configuration, it becomes possible to calculate numerical measures that express the degree of certainty, contradiction, or indefiniteness associated with each annotation. These degrees, in turn, allow for the classification of propositions into extreme or non-extreme logical states, constituting the basis for the inference mechanisms employed by Logic Eτ. Thus, the USCP provides a visual and mathematical representation that facilitates the analysis of situations characterized by uncertainty, information conflict, and evidence variability (Abe, 2010).

3.5.5 Degrees of Logic Eτ

The degrees defined in Paraconsistent Annotated Evidential Logic Eτ epresent numerical measures that allow for the interpretation of the intensity of the evidence associated with an annotated proposition $p(\mu, \lambda)$. These degrees are fundamental for analysis and decision-making, as they enable the structured quantification of aspects such as certainty, contradiction, inconsistency, and paracompleteness. Based on the position of the evidential pair within the USCP, it is possible to derive indicators that express the logical behavior of the proposition.

The degree of certainty, represented by G_{ce}, is calculated by the difference between favorable and unfavorable evidence:

$$G_{ce} = \mu - \lambda.$$

This degree reflects the extent to which a proposition approximates the True or False states within the USCP. Positive values indicate a predominance of favorable evidence, whereas negative values reveal a higher intensity of contrary evidence.

The degree of contradiction, denoted by Gct, is obtained by summing the evidence values minus one:

$$Gct = \mu + \lambda - 1.$$

This degree expresses the deviation of the proposition relative to the perfectly defined segment. When both evidence values are high, the degree of contradiction approaches 1, representing strong informational conflict typical of the Inconsistent state. Conversely, when both values are low, it approaches –1, characterizing the *Paracomplete* state.

From these two primary degrees, it is possible to derive further measures of truth, falsity, inconsistency, and paracompleteness, which represent intermediate regions within the USCP. Truth is related to the predominance of μ over λ; conversely, falsity reflects the inverse relationship. Inconsistency and paracompleteness reflect situations where μ and λ are simultaneously high or low, indicating extreme uncertainty or a significant absence of evidence, respectively.

These degrees provide a quantitative foundation for classifying propositions into extreme and non-extreme states, which will be discussed in the next section. Their utilization enables Logic Eτ to operate robustly even when facing contradictory, incomplete, or uncertain information. This characteristic is essential for applications in computational systems that rely on decisions based on imprecise data (Abe, 2010).

3.5.6 Decision States: Extreme and Non-Extreme

Decision states in Paraconsistent Annotated Evidential Logic Eτ represent qualitative interpretations of the evidential pairs associated with an annotated proposition $p_{(\mu, \lambda)}$. These states are determined based on the degrees of certainty and contradiction, as well as the position of the point (μ, λ) at the Unit Square in the Cartesian Plane (USCP). Classification into extreme and non-extreme states allows for a more precise understanding of the logical behavior of the proposition, especially in situations involving conflict, indefiniteness, or the absence of evidence.

The extreme states correspond to the four cardinal points of the USCP and express well-defined logical behaviors. The point (1, 0) represents the True state, where there is a total predominance of favorable evidence. The point (0, 1) characterizes the False state, marked by a complete prevalence of contrary evidence. The point (1, 1) indicates the Inconsistent state, where favorable and contrary evidences are simultaneously at maximum intensity. Finally, the point (0, 0) corresponds to the Paracomplete state, characterized by the absence or significant insufficiency of evidence to support any conclusion.

Table 3 - Symbology of Extreme States.

Extreme States	Symbol
True	V
False	F
Inconsistent	T
Paracomplete	⊥

Source: Abe (2011).

In addition to these extreme states, Logic Eτ contemplates non-extreme states, which represent intermediate regions within the USCP. These states express nuances that are not captured by the cardinal points, allowing for a refinement of logical interpretation. Among the non-extreme states are, for instance, those describing situations of quasi-true tending toward inconsistency, quasi-true tending toward paracompleteness, quasi-false tending toward inconsistency or paracompleteness, and states near inconsistency or paracompleteness that approximate the poles of truth or falsity. These intermediate states provide greater flexibility to the inferential process, enabling the evaluation of propositions in a manner compatible with phenomena that exhibit gradual variation of evidence and transitional behaviors.

Table 4 - Symbology of Non-Extreme States.

Non-Extreme States	Symbol
Quasi-true tending to Inconsistent	QV→T
Quasi-true tending to Paracomplete	QV→⊥
Quasi-false tending to Inconsistent	QF→T
Quasi-false tending to Paracomplete	QF→⊥
Quasi-inconsistent tending to the True	QT→V
Quasi-Inconsistent tending to False	QT→F
Quasi-paracomplete tending to the True	Q⊥→V
Quasi-paracomplete tending to False	Q⊥→F

Source: Abe (2010).

The distinction between extreme and non-extreme states is fundamental to Logic Eτ, as it provides the semantic foundation for decision-making in environments with imperfect information. This structure enables a system based on Logic Eτ to differentiate between situations of strong certainty, high uncertainty, explicit contradiction, or data insufficiency, allowing for the adequate evaluation of scenarios where classical logic would be unable to provide consistent answers (Abe, 2010).

CHAPTER IV

4 METHODOLOGY

This section presents the methodological procedures adopted in the research, ranging from the definition of the study design and approach to the development and validation of the proposed artifact. The methodological path was structured according to Design Science Research (DSR), a methodology that guides the development of scientific and technological artifacts aimed at solving complex problems.

In this dissertation, DSR served as a structuring reference, aligning the research stages with the specific objectives and the generated products, including scientific articles and the developed computational artifact. This approach ensures coherence between theory, method, and practical application, consolidating an investigative process of a constructive and empirically validated nature.

Finally, the communication phase of the DSR cycle was completed through the publication of three scientific articles derived from this research: a bibliometric review accepted for presentation at KES 2025; a logical-model paper based on Logic Eτ; and a full paper accepted for presentation and publication at AISS 2025.

4.1 Type and Approach of Research

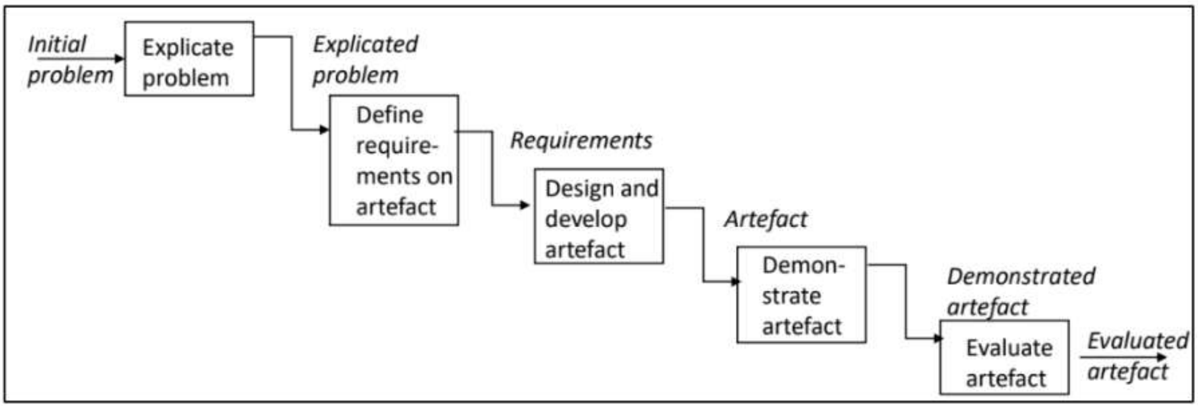
This thesis is characterized as applied research with a qualitative-quantitative approach, focused on the development of a computational artifact. The adopted methodological framework is Design Science Research (DSR) due to its suitability for studies aiming to propose, build, and evaluate innovative solutions to real and complex problems through the creation of models, methods, or systems. The DSR methodology grounds the investigation process in scientific evidence and provides a systematic framework for identifying the problem, defining requirements, developing the artifact, illustrating its applicability, and evaluating its effectiveness. This approach was selected as it aligns with the nature of this research, which aims to develop an intelligent environmental classification system for poultry farming based on Logic Eτ.

4.2 Methodological reference: Design Science Research

This research was conducted based on Design Science Research (DSR), an approach initially proposed and later consolidated through updates (Peffers et al., 2020). DSR guides researchers in the development of innovative artifacts, such as models, methods, or systems, aimed at solving complex real-world problems through a systematic and iterative process of construction and evaluation.

Figure 6 (based on Peffers et al., 2007) presents the conceptual structure of the DSR method, illustrating the flow from the initial problem to the evaluated artifact. The process begins with the identification of the problem and the definition of requirements, followed by the design, development, demonstration, and evaluation of the resulting artifact.

Figure 2 – Theoretical stages of Design Science Research (DSR)



Fonte: Adapted from Peffers et al. (2007; 2020)

The application of Design Science Research (DSR) in this dissertation was organized into three main stages, structured to integrate the theory, development, and validation of the proposed artifact. This methodological structure aimed to ensure coherence between the research objectives, the methods adopted, and the results obtained, allowing each stage to contribute progressively to the construction of knowledge and the consolidation of the proposed solution.

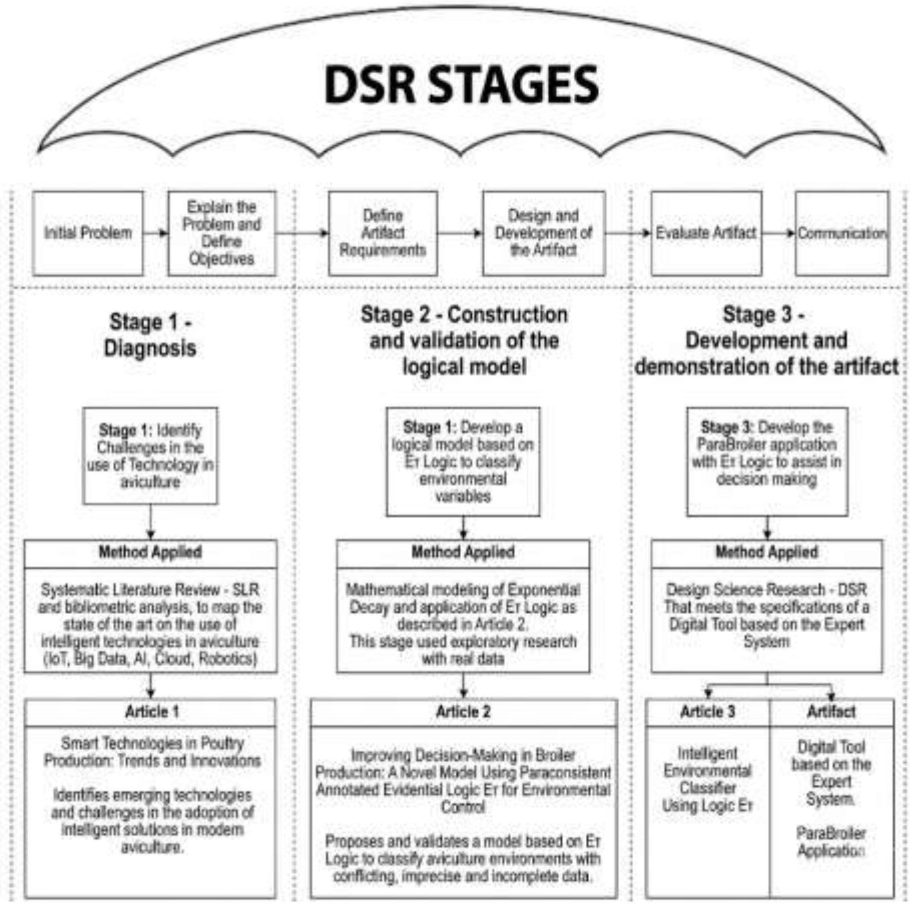
Stage 1 focused on identifying the problem and analyzing the technological landscape of poultry farming through a Systematic Literature Review (SLR) carried out in international databases, specifically Scopus and Web of Science, covering the period from 2018 to 2024. This review made it possible to map emerging technologies, adoption barriers, and scientific gaps related to the use of intelligent systems in poultry farming, highlighting the need for methods capable of managing conflicting, inaccurate, and incomplete data.

Subsequently, Stage 2 consisted of the construction and validation of a logical model based on Paraconsistent Annotated Evidential Logic Eτ, designed to interpret environmental variables under conditions of uncertainty and contradiction. This phase involved the development of a mathematical-logical model and its validation through simulations and tests with real data, ensuring robustness and applicability to the proposal.

Finally, Stage 3 corresponded to the development and demonstration of the computational artifact, resulting in the Parabroiler application, which operationalizes the logical model developed in the previous stage. This phase involved implementation, testing, and usability evaluation, culminating in the registration of the software and the consolidation of a functional technological product aimed at decision-making in precision poultry farming.

Figure 3 presents the integration between the theoretical framework of Design Science Research (DSR) and the practical steps developed in this dissertation.

Figure 3 – Integration between DSR activities and research stages



Source: author, 2025

The diagram illustrates the alignment between the six activities of DSR, as established by Peffers et al. (2007; 2020), and the three empirical phases of the research: diagnosis, construction of the logical model, and development of the computational artifact.

This graphic representation demonstrates the coherence between the specific objectives, the methods applied, and the products generated, facilitating an understanding of the study's methodological progression, from problem identification to the validation of the final artifact.

4.3 Stages of the Application of DSR in the Dissertation

In the context of this dissertation, the DSR method was adapted and aligned with the three empirical stages presented, mapping each stage to a specific set of the six theoretical activities proposed by Peffers et al. (2007). This integration ensures the methodological coherence of the research process, where each step results in a scientific or technical product, forming a complete cycle of construction, demonstration, and evaluation of the artifact.

4.3.1 Stage 1 - Diagnosis and Problem Definition

Stage 1, diagnosis, corresponds to activities 1 and 2 of Design Science Research (DSR), which involve identifying the problem and defining the solution requirements. This phase aligns with Specific Objective 1 (SO1) of the dissertation: "To identify the challenges faced by broiler producers in the use of smart technologies in precision poultry farming."

The main purpose of this stage was to identify the problem and understand the technological landscape of poultry farming through a Systematic Literature Review (SLR). The survey was carried out in the Scopus and Web of Science databases, covering the period from 2018 to 2024, using the descriptors: "Precision Poultry Farming," "IoT," "Smart Farming," "Environmental Control," and "Decision Support Systems".

The SLR enabled the mapping of emerging technologies applied to poultry farming and the identification of main adoption barriers, such as infrastructure limitations, high sensor costs, connectivity restrictions, lack of standardization, and lack of technical qualification. The studies also revealed recurring gaps related to the inconsistency and incompleteness of environmental data, as well as the poor interpretability of conventional decision support systems.

These findings supported the need for a logical model capable of managing contradictions and uncertainties, justifying the adoption of Paraconsistent Annotated Evidential Logic Eτ as the conceptual basis of this work.

This stage resulted in Article 1, "Smart Technologies in Poultry Production: Trends and Innovations," which presented the main technological trends, challenges, and gaps identified, in addition to defining the theoretical and practical requirements for the development of the proposed artifact.

4.3.2 Stage 2 – Construction and Validation of the Logical Model Based on

The Stage 2 is about the Construction and validation of the logical model that corresponds to activities 3 and 4 of Design Science Research (DSR), which involve designing, developing and proposing an artifact. This stage is aligned with Specific Objective 2 (OE2) of the dissertation: "*To develop an expert system using the Paraconsistent Annotated Evidential Logic Eτ, capable of qualitatively classifying the analyzed environmental parameters — temperature, relative humidity, air velocity, carbon dioxide and ammonia*."

In this phase, a mathematical-logical model based on Logic Eτ was developed and validated, designed to classify the environmental conditions of poultry houses in the face of conflicting, imprecise and incomplete data. The model was developed from the principles of Logic Eτ, allowing to simultaneously represent degrees of evidence favorable (μ) and unfavorable (λ) to a proposition, in order to maintain inferential coherence even under contradiction.

Conversion of variables into paraconsistent evidence: The environmental variables — temperature (T), relative humidity (H), air velocity (V), carbon dioxide (CO_2) and ammonia (NH_3) — were converted into pairs of evidence (μ, λ) based on the ideal ranges of thermal comfort defined for each age of the birds. When necessary, an exponential decay function was applied to weigh the reliability of old measurements, ensuring temporal coherence in the inferences.

Operators and logical indicators: From the evidence (μ, λ), the model calculates the indicators of Degree of Certainty (G_{ce}) and Degree of Uncertainty (G_{in}), used to determine the logical state of each elementary proposition. The variables were combined according to Logic Eτ, resulting in the compound proposition:

$$P = T \wedge H \wedge V \wedge CO2 \wedge NH3$$

The position of this proposition in the Unit Square of the Cartesian Plane (USCP) defines the inferred environmental state. This logical structure allows for explainable, transparent and reproducible interpretations, an essential feature for intelligent systems applied to precision poultry farming.

Classification and Inference in USCP: The model classifies the environment into two categories — Excellent or Critical — based on the position of the pairs (μ, λ) in the USCP and the values obtained for G_{ce} and G_{in}. This approach provides explicit logical justifications for each classification, making the inference process auditable and interpretable.

Model Validation: The validation was conducted through controlled simulations and experiments with real data, with the objective of evaluating the logical robustness, inferential stability and consistency of the classifications in scenarios with noise, contradiction or sensor failures. The results showed that the model have maintained coherence and accuracy even in the face of uncertainties, proving its effectiveness and practical applicability.

This stage resulted in the publication of Article 2 – "Improving Decision-Making in Broiler Production Using Paraconsistent Annotated Evidential Logic Eτ", in which the developed model, the validation procedure and the results obtained are described in detail.

4.3.3 Stage 3 – Development, Demonstration and Registration of the Computational Artifact

Stage 3 – Development, demonstration and registration of the computational artifact correspond to activities 5 and 6 of Design Science Research (DSR), which involve demonstrating, evaluating and communicating the developed artifact. This step is aligned with Specific Objective 3 (SO3) of the dissertation: "To develop the Parabroiler application with Logic Eτ to assist in poultry farmers' decision-making."

This phase comprised the development, demonstration and registration of the computational artifact called Parabroiler, elaborated based on the logical model developed in Stage 2. The app is designed to classify the environmental conditions of poultry houses and support the decision-making of precision poultry producers and researchers.

4.3.4 System Architecture

The Parabroiler artifact is built with multi-layered functional architecture, integrating accessible and open-source technologies:

Mobile frontend: responsible for the user interaction interface, allowing to insert environmental variables and view classification results, history and management recommendations, this layer uses Thunkable as the low-code development platform (Thunkable, 2025).

Backend: performs the logical processing based on Logic Eτ, applying the developed model and performing the environmental inferences. This layer was developed using Python/Flask in PythonAnywhere (Grinberg, 2018; Pythonanywhere, 2025).

Persistence: performs the automatic storage of inputs and outputs, ensuring traceability of the data and results processed.

Each version of the application generates a cryptographic hash for integrity control, according to digital traceability best practices (Li et al., 2025), and has been registered with the National Institute of Industrial Property (INPI, 2025), ensuring authenticity and intellectual protection.

4.3.5 Data and Application Context

The artifact validation was conducted with real data from commercial farms and simulated scenarios. The measurements were carried out in three types of sheds — Blue House, Dark House and Solid Wall — at four different ages of the production cycle (21, 28, 35 and 42 days), at two daily times (9 am and 2 pm).

The monitored variables included: Temperature (°C), Relative Humidity (%), Air Velocity (m/s), Carbon Dioxide (CO_2, ppm) and Ammonia (NH_3, ppm).

This data was used to test and validate the logical model implemented in the application, ensuring compatibility with real operating conditions.

4.3.6 Parabroiler Operation Flow

The system works in four sequential steps, as described below:

The user enters the environmental variables and metadata (type of aviary, age of the birds, date and time of collection). The backend processes the information using Logic Eτ, performing environmental classification. The application returns the result of the inference, indicating the classification category (Excellent or Critical) and management recommendations. Finally, all data and results are stored automatically, ensuring complete history and traceability of operations.

4.4 Parabroiler Application Usability Evaluation

The usability evaluation stage of the Parabroiler – Intelligent Environmental Classifier application was conducted through a structured form developed on the Google Forms platform, based on consolidated methodologies of Usability Engineering and Human-Computer Interaction (HCI). Recent studies reinforce the importance of systematic and methodological approaches to evaluating the usability of digital applications, highlighting updated frameworks and methods for testing on mobile devices and web interfaces (Weichbroth et al., 2024; Drungilas; Ramašauskas; Kurmis, 2024).

The instrument was developed with the objective of collecting perceptions of specialists and potential users about the efficiency, effectiveness and satisfaction in the use of the application, and fundamental dimensions of usability. The questionnaire was adapted from consolidated models for evaluating human-computer interaction and complemented with indicators from the *System Usability Scale* (SUS), widely applied in usability analysis of digital systems and technological applications (Setiyawati; Bangkalang, 2022).

The digital form was structured in eight interdependent sections. The first section corresponded to the identification of the evaluator, addressing profile, training and experience in technology. The second section contemplated the initial tasks, allowing free exploration of the application before the formal evaluation. In the third section, the usability evaluation was carried out, using a Likert scale from 0 to 5, which analyzed aspects such as ease of use, clarity, consistency and visual organization. The fourth section presented open questions for collecting qualitative impressions about difficulties and suggestions for improvement. Next, the fifth section used a simplified version of the SUS Scale, composed of ten adapted items, aimed at measuring the general perception of use and confidence of the participants. After that, the sixth section dealt with general satisfaction, with an indication of the level of approval of the application. Subsequently, the seventh section presented the Informed Consent Form, ensuring the ethical and voluntary participation of respondents (Weichbroth et al., 2024).

The SUS Scale was used due to its validity and reliability in measuring subjective perceptions of usability, even in small samples. The overall structure of the instrument was based on an empirical model that combines qualitative and quantitative data to identify interaction problems and support interface improvements (De Dios López et al., 2024).

Usability testing aims to observe real users using the product to identify problems and possibilities for improvement, configuring itself as an essential technique in the validation stages of prototypes and digital systems. Thus, the instrument was applied after the completion of the functional development of the application in the *low-code* environment, and the access link was made available to the participants for remote completion.

4.5 Ethical aspects, reproducibility and availability

The research was conducted in accordance with ethical principles and responsible use of data, with all records obtained exclusively for academic purposes and treated anonymously. The reproducibility protocol describes the backend versions, the structure of the data sheets (column names) and examples of requests, ensuring the transparency of the process and the traceability of the development stages.

The technical documentation of the Parabroiler application, including the *validation hash*, the software registration with the National Institute of Industrial Property (INPI).

CHAPTER V

5 RESULTS AND DISCUSSIONS

The results of this dissertation are presented in the format of scientific articles, elaborated in line with the specific objectives and methodological steps described in Chapter 4. Each article represents a distinct phase of the research process, articulating the theoretical basis, the development of the logical model and the practical application of the computational artifact.

5.1 Article 1 – KES 2025 Bibliometric Review

As a key result of this stage, the article entitled "Smart Technologies in Poultry Production: Trends and Innovations" is presented. It has been approved for publication in the international journal *Procedia Computer Science* (May 2025), a highly indexed publication recognized for its academic rigor. The manuscript was prepared according to the journal's editorial guidelines and submitted to a rigorous peer review process, ensuring the methodological quality and scientific relevance of the study for the areas of Production Engineering and Computer Science.

The article presents a bibliometric and systematic analysis of the use of emerging technologies in modern poultry farming, focusing on the Internet of Things (IoT), Big Data, and Artificial Intelligence (AI). The adopted methodology included the mapping of relevant publications between 2018 and 2023 in international scientific databases, with inclusion criteria aimed at studies applying digital solutions for environmental monitoring, animal health, and production management.

The results revealed a significant gap in the literature regarding the integration of these technologies with non-classical logical approaches capable of processing conflicting, inaccurate, and incomplete data, particularly in small and medium-sized rural properties.

The study concludes that, although technologies such as IoT and AI are expanding within the poultry sector, challenges persist related to practical implementation and the efficient analysis of generated data. Thus, the findings reinforce the need for robust logical decision-making models, such as the one proposed in Article 2, which continues the development of the mathematical-logical model based on Paraconsistent Annotated Evidential Logic Eτ.

The full version of this report in is found bellow, as published in the proceedings of the 29th International Conference on Knowledge-Based and Intelligent Information & Engineering Systems (KES 2025):

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Procedia Computer Science 270 (2025) 4451–4460

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29th International Conference on Knowledge-Based and Intelligent Information & Engineering Systems (KES 2025)

Smart Technologies in Poultry Production: Trends and Innovations

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Abstract

Poultry farming faces significant challenges, including increasing productivity, improving animal welfare, and promoting sustainability. Smart technologies, such as the Internet of Things (IoT), Artificial Intelligence (AI), Big Data, cloud computing, and robotics, offer transformative potential for this sector. However, implementing these technologies involves challenges, such as high initial costs, proper infrastructure, and adaptation to adverse environmental conditions. Innovative approaches, including government subsidies, cooperative models, and adaptive technologies, are being explored to reduce costs and improve accessibility. Furthermore, there is a lack of comprehensive research on the applicability of these technologies in poultry farming. This study aims to provide an overview of the applications of smart technologies in optimizing productivity, improving animal welfare, and promoting sustainability across various stages of poultry production, including feeding, health monitoring, and environmental control. The study details key use cases and challenges encountered using methods such as systematic literature review and bibliometric analysis in databases like Web of Science and Scopus. The results highlight a significant increase in global interest in research. The study offers a global overview of scientific production and significant contributions to the advancement of scientific research, specifically in integrating smart technologies across different stages of poultry farming and introducing new approaches, such as non-classical logic, to handle inconsistent and incomplete data. The study provides a better understanding of the potential of smart technologies in poultry farming and critically evaluates their impact on productivity, animal welfare, and sustainability.

Keywords: Smart Poultry Farming, Artificial Intelligence, Internet of Things, Big Data, Robotics

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10.1016/j.procs.2025.09.570

1. Introduction

The poultry industry faces complex challenges in meeting the growing demand for meat, eggs, and other poultry products sustainably, with strict quality control standards and increasing ethical concerns. To address these pressures, the sector is undergoing a digital transformation marked by the adoption of data-driven technologies that are reshaping production practices. From precision monitoring to automated decision-making, these innovations are redefining efficiency, sustainability, and animal welfare in poultry farming [1].

Smart Technologies are high-impact innovations in various economic sectors, encompassing IoT, AI, Big Data, Cloud Computing, Automation, and Robotics. With advanced capabilities, these technologies quickly adapt to ever-changing production environments, processing large volumes of information in real- time. Data collected by IoT sensors is distributed via Cloud Computing and analyzed by AI systems in Big Data applications to support decision-making [2]. In poultry farming, the adoption of these technologies is rapidly expanding, with applications at all stages of the production process aimed at increasing efficiency, productivity, and sustainability [3]. However, scientific production on the topic tends to focus on specific technologies, and there is a lack of comprehensive and integrated studies on specific applications and the identification of the most suitable technologies for different stages of production [4].

This paper aims to provide an overview of the applications of Smart Technologies in optimizing productivity, improving animal welfare, and promoting sustainability in poultry production. The aim is to discuss the benefits of these implementations, highlighting their potential to increase efficiency, productivity, and sustainability. Finally, the paper seeks to identify the challenges and opportunities for wider adoption [5]. This paper conducts a systematic literature review using scientific and technical databases from Web of Science and Scopus to achieve this. Relevant scientific papers related to the topic are collected and subjected to bibliometric analysis for a better understanding of the field's current state.

The study is structured into four sections: "Development," which presents the theoretical framework; "Methodology," which discusses the research methods and procedures; "Results and Discussions," which present and analyzes the main findings; and "Conclusions," which consolidate the results and provides recommendations for future research.

Thus, this paper offers a comprehensive view of the applications of Smart Technology in Poultry Farming, identifying promising technologies for each stage of production and discussing the benefits and challenges of their implementation, contributing to the advancement of scientific research and a better understanding of the use of these technologies in poultry farming.

2. Background

This section presents a theoretical framework related to the use of Smart Technology in Poultry Farming. The applications of IoT, AI, Big Data, Cloud Computing, and Robotics in poultry farming are discussed. Trends and innovations, use cases, and the challenges of implementation are analyzed.

2.1. Internet das Coisas (IoT)

IoT interconnects devices via the internet, enabling real-time data collection and exchange. These devices communicate with each other and central systems, optimizing processes and providing insights. In poultry farming, IoT allows precise control of conditions within poultry houses. Its application enhances environmental monitoring and control, benefiting the well-being of the birds [6].

Real-time sensors and monitoring are essential, detecting critical variations and sending alerts, facilitating adjustments to maintain an ideal environment [8]. Temperature, humidity, and air quality sensors help prevent heat stress and respiratory issues, improving productivity and reducing mortality [9]. Sensors in drinkers and feeders detect changes in consumption, assisting in optimizing feeding and management [8].

Despite the benefits, the implementation of IoT faces challenges, such as the lack of communication infrastructure in rural areas and adverse environmental conditions, which hinder the operation of systems. The distance from urban centers and unreliable electricity supply also impact device maintenance, affecting the well-being of the birds [11].

Additionally, increased connectivity raises vulnerability to cyberattacks, compromising data and farm operations [12]. The high initial cost is another obstacle, especially for small producers [13].

IoT has great potential to optimize poultry production and improve animal welfare, but overcoming challenges related to infrastructure and high initial costs is crucial.

2.2. Artificial Intelligence (AI) and Machine Learning (ML)

AI refers to the ability of systems to perform tasks that require human intelligence, such as pattern recognition and decision-making. ML, a subfield of AI, involves algorithms that allow computers to learn from data and improve their performance without explicit programming for each task. In poultry farming, AI and ML can optimize feeding, health monitoring, and environmental control processes, improving animal welfare and productivity [14, 33].

Despite the benefits, the implementation of these technologies faces challenges. The need for large volumes of high-quality data can be an obstacle for small producers. Additionally, the lack of infrastructure and high initial costs limit large-scale adoption. Establishing clear regulations to ensure responsible use, protect data privacy, and operational security is also crucial [15]. While AI and ML have great potential to optimize poultry production, overcoming obstacles related to data, infrastructure, and regulation is necessary to realize these benefits, especially for small producers. Future studies should focus on making these technologies more accessible and secure.

2.3. Big Data and Advanced Analytics

Big Data refers to the large volume of rapidly generated data in various forms, requiring specific capture, storage, and analysis technologies. This data comes from environmental sensors, health monitoring, and productivity records in poultry farming. Advanced Analytics, using machine learning and predictive algorithms, extracts insights from this data, optimizing management and productivity and improving the birds' genetic selection [16].

However, the implementation of Big Data faces challenges such as poor communication infrastructure and the lack of connectivity in rural areas, hindering the capture and transmission of data. Additionally, the reliability of the power supply and the need for advanced technical skills limit adoption, especially among small producers. Inaccurate or inconsistent data can also lead to erroneous analyses, requiring methods to handle incomplete and ambiguous information [17,18].

In summary, Big Data can improve efficiency and accuracy in poultry farming, promoting more informed and sustainable management. However, it is necessary to overcome technical and infrastructure challenges and create clear policies to ensure the ethical use of data. Future studies should focus on making these technologies more accessible, especially for small producers [19].

2.4. Cloud Computing

Cloud computing refers to delivering computing services over the internet, enabling on-demand access, scalability, and pay-as-you-go pricing. Smart poultry farming provides a robust infrastructure for processing large volumes of data from sensors, cameras, and other sources, enabling secure storage and data analysis through intuitive dashboards [20]. Despite its advantages, it faces obstacles such as connectivity and infrastructure issues, particularly in rural areas, and high initial and operational costs, making adoption difficult [19]. Cloud computing holds promise for optimizing data processing in poultry farming, but overcoming technical and financial challenges is crucial to making its benefits accessible to all producers [21].

2.5. Automation and Robotics

Automation and robotics involve the design, construction, operation, and use of robots for automated tasks in poultry farming, such as feeding, cleaning, egg collection, and bird monitoring, enabling more efficient farm management and reducing manual labor [22]. This strategy improves the birds' nutrition and reduces feed waste, contributing to sustainability [23].

Additionally, the automation of repetitive tasks improves working conditions, reducing the risk of worker injuries. However, challenges related to high initial costs and the need for specialized skills hinder the adoption of these technologies [24].

3. Methodology

This research was based on a theoretical analysis investigating Smart Technologies' impact on Poultry Farming. A systematic literature review initially focused on the leading Smart Technologies, following research lines from [23,25]. We agree that these technologies relate to poultry farming. The technologies analyzed include IoT, AI, Big Data, Cloud Computing, Automation, and Robotics. This combined approach is widely recognized as a modern and robust methodology to capture both conceptual developments and emerging research trends in rapidly evolving fields. Subsequently, a bibliometric analysis was performed to quantify and examine scientific publications discussing the use of these technologies in poultry farming. By integrating these complementary methods, the study ensures both analytical depth and methodological reliability. The methods applied in this study provided an in-depth understanding of current and emerging trends related to the topic [1,23].

This research was based on a theoretical analysis of the impact of Smart Technologies in Poultry Farming, starting with a systematic literature review of the main technologies and relating these technologies to poultry farming [14,26]. The technologies analyzed include IoT, AI, Big Data, Cloud Computing, Automation, and Robotics. Then, a bibliometric analysis was conducted to quantify publications on the use of these technologies in poultry farming, providing an understanding of current and emerging trends [27].

3.1. Bibliometric Analysis

The bibliometric analysis was conducted to understand the current landscape of Smart Technologies applications in Poultry Farming, using the Scopus database, operated by Elsevier, and Web of Science (WoS), operated by Clarivate Analytics, due to their academic recognition and reliability. Both databases are recognized for including high-quality, peer-reviewed publications, which is essential for ensuring the validity of the analyzed data. The continuous update with the latest scientific publications and the extensive coverage of literature were key factors in choosing these platforms. The user interfaces and advanced search and citation analysis features enabled detailed searches per the proposed methodology. Two searches were conducted: the first, more restricted, using only the terms "Poultry Farming" and "Smart Technologies," and the second, with specific terms for each of the technologies involved (Table 1).

Table 1 – Full search terms for WoS and Scopus databases

Search	Base	Full search term
Restricted	WoS	ALL= ("poultry farming") AND (ALL= ("smart technology") OR ALL= ("intelligent technology"))
	Scopus	ALL ("poultry farming") AND (ALL ("smart technology") OR ALL ("intelligent technology"))
Broad	WoS	ALL= ("poultry farming") AND ((ALL= ("smart technology") OR ALL= ("intelligent technology")) OR (ALL=("IoT") OR ALL= ("Internet of things") OR ALL=("sensor")) OR ALL= ("Big Data") OR ALL= ("artificial intelligence") OR (ALL=("robotics") or ALL=("automation")) OR ALL= ("cloud computing"))
	Scopus	ALL ("poultry farming") AND ((ALL ("smart technology") OR ALL ("intelligent technology")) OR (ALL("IoT") OR ALL ("Internet of things") OR ALL("sensor")) OR ALL ("Big Data") OR ALL ("artificial intelligence") OR (ALL("robotics") or ALL("automation")) OR ALL ("cloud computing"))

The searches were conducted on July 26, 2024, and the results, exported in CSV format, were consolidated into a unified dataset. Duplicates were removed, and author names were adjusted to avoid incorrect analyses due to different spellings. With the cleaned data, bibliometric analysis began by visualizing co-authorship networks, citations, and keywords.

The VOSviewer software, developed by Leiden University, was chosen due to its wide acceptance and recognized ability to handle large datasets, providing interactive and detailed visualizations [28]. These techniques provided a structured approach to identify search trends, technology adoption dynamics, and interdisciplinary connections—elements that are crucial for mapping innovation trajectories in smart poultry farming.

4. Results and Discussion

This section presents the results of the research conducted in the scientific and technical literature databases and the bibliometric analyses carried out based on these results. The search date was June 26, 2024.

4.1. Growing interest in the topic of Smart Technologies and Poultry Farming

The research confirmed the scarcity of comprehensive studies on the topic, as evidenced by the small number of documents found in the restricted search compared to the broad search (Table 2).

Table 2 – Results of restricted and broad searches in WoS and Scopus databases

Type of Research	Documents Found Exclusively in WoS	Documents Found in Both Databases	Documents Found Exclusively in Scopus	Total
Restricted	0	0	33	33
Broad	13	57	693	763

The research confirmed the scarcity of comprehensive studies on the topic, as evidenced by the limited number of documents in the restricted search. The research also revealed a notable increase in interest in the topic in recent years (Figure 1), as reflected by the growing number of publications, especially since 2020, with an average year-over-year growth of 60% in the number of publications.

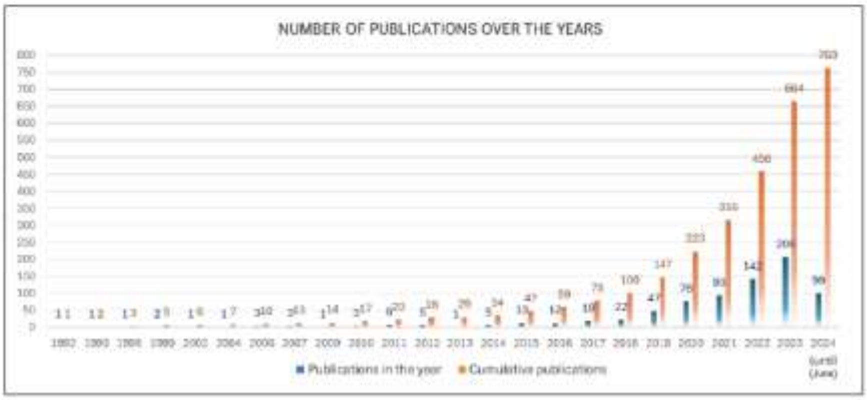

Figure 1 – Annual Growth: Publications on Poultry Farming and Smart Technologies

4.2. Leading Researchers on Smart Technologies and Poultry Farming

The analysis revealed that the countries leading research on Smart Technologies for Poultry Farming are China, India, the United States, the United Kingdom, and Brazil, accounting for about 50% of all publications on the topic.

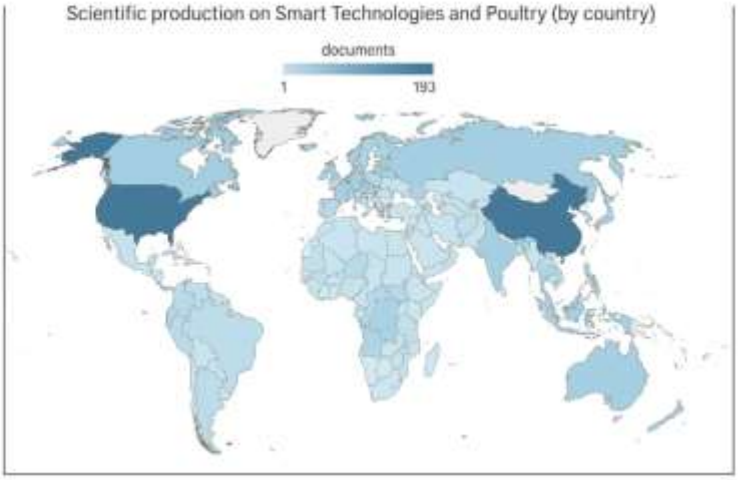

Figure 2 – Leading Countries in Scientific Research on Smart Technologies and Poultry Farming

The analysis also showed that although this group of five countries leads research on the subject, it is a globally discussed topic, with 90 countries across all continents having significant contributions. Globally, Asia stands out with about 51% of the total scientific production on the topic, followed by Europe with 27%, North America with 10%, South America and Africa with 5%, and Oceania with 2% of the published articles (Figure 2).

Table 3 – Ranking of the Top 10 Publishers

Publisher	Number of Publications
Institute of Electrical and Electronics Engineers Inc.	120
Elsevier B.V.	65
MDPI	58
Elsevier Ltd	43
Multidisciplinary Digital Publishing Institute (MDPI)	40
Springer Science and Business Media Deutschland GmbH	30
Springer	26
MDPI AG	18
Elsevier Inc.	13
John Wiley and Sons Inc	12

Table 4 – Ranking of the Top 10 Journals

Journal	Number of Publications
Animals	38
Computers and Electronics in Agriculture	25
Sensors	12
Sustainability (Switzerland)	11
IEEE Access	9
Poultry Science	9
Agriculture (Switzerland)	8
IOP Conference Series: Earth and Environmental Science	8
Transactions of the Chinese Society of Agricultural Engineering	8
Transactions of the Chinese Society for Agricultural Machinery	7

From the perspective of research organizations, the study revealed 177 publishers involved, with 7 of them responsible for more than 50% of the publications. Regarding journals, a total of 478 were identified, with 20% responsible for 50% of the publications. Tables 3 and 4 highlight the main contributors to the published articles.

4.3. Search trends identified in the main associated keywords

The bibliometric analysis revealed the predominance of research in the field of Internet of Things applications, emphasizing the crucial role of data collection automation and real-time monitoring in poultry farming. Also notable is the interest in research on AI and its subdivisions, including machine learning, deep learning, and artificial neural networks (Figure 3).

Figure 3 – Keywords clusters - Number of articles per technology group

The analysis of keyword co-occurrences revealed five clusters, highlighting the interdisciplinary nature of research on Smart Technologies in Poultry Farming, involving AI, machine learning, computer vision, IoT, and cloud computing. The first cluster (Figure 4) red focuses on technologies such as IoT and Cloud Computing applied to poultry farming, emphasizing sustainability. The second (green) addresses computer vision and image processing using deep learning and convolutional neural networks. The third cluster (blue) focuses on animal welfare and environmental monitoring, utilizing AI and Robotics, with references to "broiler" and "PLF" for poultry farming and livestock breeding.

The fourth cluster (yellow) highlights food safety and antimicrobial resistance, employing techniques such as "random forest," Big Data, and cloud computing, focusing on public health and productive efficiency. The fifth cluster (purple) is related to environmental monitoring, including ammonia and temperature, aiming to maintain optimal animal welfare and productivity conditions.

The research revealed a strong interconnection between poultry farming and the Internet of Things (IoT), highlighting the growing adoption of IoT technologies in poultry practices and signaling a trend toward connected and data-driven poultry farming. Additionally, it highlighted the increasing application of Smart Technologies in poultry farming, indicating a rise in demand for operational efficiency using predictive monitoring, pattern recognition, and anomaly detection in the supply chain.

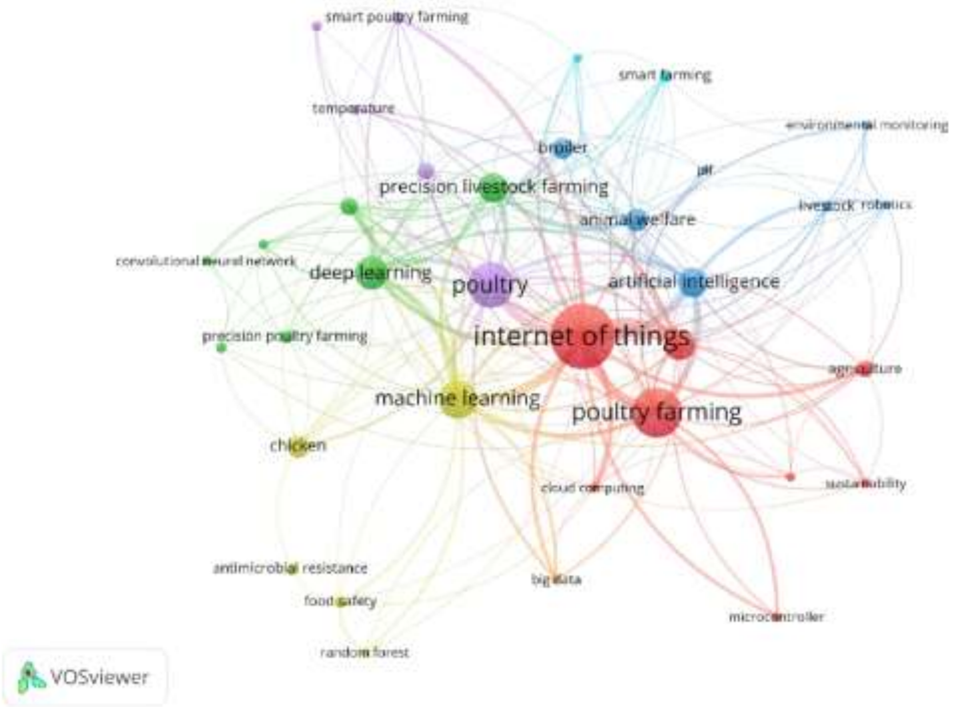

Figure 4 – Keywords Co-occurrence Network

5. Conclusions

This research provided a comprehensive overview of the impact of Smart Technologies in Poultry Farming, detailing innovations, benefits, and challenges, with a focus on optimizing productivity, animal welfare, and sustainability. Beyond offering a descriptive analysis, the study provides a theoretical foundation for understanding how digital technologies can reshape production models, while also highlighting concrete implications for producers, researchers, and policymakers.

Although Smart Technologies brings significant benefits, it faces considerable challenges. Using sensors and real-time monitoring can be costly and prone to connectivity and accuracy issues, especially in rural areas. IoT requires high initial investments, making it difficult for small producers to adopt [29]. Big Data analysis deals with data quality and consistency issues and requires advanced technical skills and robust infrastructure. AI and ML require large volumes of high-quality data and substantial investments, limiting their adoption [19,30,33]. Cloud computing faces challenges related to connectivity, security, and high costs, particularly in rural areas. Automation and robotics, while effective, require high initial investments and specialized maintenance [19,30].

The bibliometric analysis revealed that IoT and AI are the leading technologies in research, highlighting their role in automation and real-time monitoring in poultry farming, with Asia's leading scientific production. The growing interconnection between Smart Technologies and their applications in poultry farming indicates a rising demand for operational efficiency, predictive monitoring, pattern recognition, and anomaly detection, emphasizing the importance of automation.

The keyword co-occurrence analysis showed clusters focused on IoT and Cloud Computing with an emphasis on sustainability; computer vision and image processing with deep learning; animal welfare and environmental monitoring with AI and Robotics; food safety and antimicrobial resistance with Machine Learning; and environmental condition monitoring with IoT. These clusters highlight that the scientific production of Smart Technologies in Poultry Farming is highly interdisciplinary, suggesting a growing trend toward connected and data-driven poultry farming.

This study provides insights into Smart Technologies in Poultry Farming but presents limitations. The bibliometric analysis, with data up to June 26, 2024, may not reflect more recent publications, and the search strings in the WoS and Scopus databases, focused on the most common terms, may not cover relevant variations.

Future studies could explore solutions to enable the adoption of Smart Technologies by small producers at reduced costs, including designing applications to optimize real-time environmental monitoring, considering infrastructure limitations. Non-classical logic, such as fuzzy logic and annotated evidential paraconsistent logic, is recommended to handle incomplete and conflicting data [31,32]. New business models, government subsidies, and cooperatives could address the reduction of Smart Technology costs.

This study achieved its objectives by providing a comprehensive view of Smart Technologies in Poultry Farming, highlighting innovations, benefits, and challenges, and contributing to future research and developments in the field. As the sector evolves toward data-driven and automated production models, the integration of Smart Technologies is no longer optional—it is essential to meet the demands of scalability, welfare, and resilience. This transformation reflects a broader shift in agriculture, where digital tools redefine how value is created and sustained across the production chain.

Acknowledgements

This study was partially financed and supported by CAPES – grant 88887.940472/2024-00

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5.2 Article 2 – KES - The Model Based on Logic Eτ

As part of the results of this dissertation, the article entitled "Improving Decision-Making in Broiler Production: A Novel Model Using Paraconsistent Annotated Evidential Logic Eτ for Environmental Control" is presented, approved for publication in the international journal Procedia Computer Science (May 2025), a journal widely indexed and recognized for its academic rigor. The manuscript was prepared according to the journal's editorial guidelines and submitted to a rigorous peer review process, ensuring the methodological quality and scientific relevance of the study for the areas of Production Engineering and Computer Science.

The article proposes an innovative model for environmental control in broiler production, based on the application of the Evidential Annotated Paraconsistent Logic Eτ. The model seeks to improve the monitoring of commercial aviaries, directly addressing the challenges arising from conflicting, inaccurate, incomplete data, often present in conventional control systems.

The methodology was structured in three main steps:

(i) Data collection — carried out through IoT sensors, covering critical environmental variables such as temperature, relative humidity, air velocity, carbon dioxide and ammonia;

(ii) Logical processing — using Logic Eτ to assign favorable and unfavorable degrees of evidence (μ and λ) to each variable, allowing inferences under conditions of uncertainty;

(iii) Model validation — conducted with simulations and robustness tests under controlled disturbances, evaluating the stability and logical performance of the system in the face of contradictory and noisy data.

The results indicated that the model based on Logic Eτ maintains high inferential reliability even in the face of inconsistent information, overcoming the limitations of traditional methods of environmental monitoring. It is concluded that the application of Logic Eτ represents an innovative and effective approach to environmental control in poultry production systems, contributing to more accurate decisions, improved animal welfare conditions and greater operational efficiency in precision poultry farming.

The full article is presented below, as published in the proceedings of the 29th International Conference on Knowledge-Based and Intelligent Information & Engineering Systems (KES 2025).

Available online at www.sciencedirect.com

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Procedia Computer Science 270 (2025) 2463–2472

Procedia Computer Science

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29th International Conference on Knowledge-Based and Intelligent Information & Engineering Systems (KES 2025)

Improving Decision-Making in Broiler Production: A Novel Model Using Paraconsistent Annotated Evidential Logic Eτ for Environmental Control

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Abstract

As the poultry industry grows, maintaining effective environmental control presents increasing challenges, particularly in tropical climates where variability undermines data reliability. Temperature, relative humidity, air velocity, and gas concentrations directly affect broiler health, productivity, and welfare. Although IoT-based monitoring technologies have enhanced data collection, conventional systems remain limited in managing inconsistent, incomplete, or contradictory sensor readings caused by abrupt fluctuations, equipment failures, or animal interference. This study presents a novel, mathematically grounded model for environmental monitoring in broiler production, leveraging Paraconsistent Annotated Evidential Logic Eτ to process conflicting data without discarding potentially valuable information. The model assigns dynamic degrees of favorable and unfavorable evidence to each reading and integrates a temporal decay function to reduce the influence of outdated data. This approach enables consistent inference even when faced with contradictory or delayed sensor data inputs. The results demonstrate that the proposed model effectively manages inconsistent sensor data, enhancing decision-making in dynamic and uncertainty-prone production environments. The approach improves the robustness and accuracy of environmental assessments, supports timely interventions, and contributes to better animal welfare, productivity, and operational efficiency. Beyond its practical contributions, the model illustrates the applicability of non-classical logic in smart agriculture, offering a flexible framework for decision support in farming contexts. The research also supports SDGs 3, 9, and 12, promoting sustainable, innovative, and welfare-focused poultry production.

Keywords: Paraconsistent Annotated Evidential Logic Eτ, Environmental Control, Poultry Houses, IoT Sensors, Inconsistent Data, Smart Agriculture

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10.1016/j.procs.2025.09.368

1. Introduction

Economic growth and changing diets—especially in developing countries across Asia and South America—have driven a global rise in animal protein consumption, with poultry meat projected to grow by up to 70% by 2050. In this scenario, broiler production has become central to Brazilian agribusiness, making the country the top global exporter [1]. Maintaining this performance requires effective environmental control in poultry houses, particularly in tropical climates where variability demands precise, technology-driven management to optimize feed conversion, reduce losses, and improve competitiveness [2].

Environmental variables such as temperature, relative humidity, and air velocity directly impact broiler performance and welfare, especially under tropical conditions. Their complex interactions and rapid fluctuations challenge interpretation and control, even with the adoption of automated systems for ventilation and evaporative cooling [3,14,19]. Although IoT-based monitoring has improved the tracking of environmental variables, issues such as sensor failures, wear, dust accumulation, desynchronization, and bird behavior (e.g., clustering), combined with external factors like climate variability and power outages, still frequently lead to inconsistent or missing data and further compromise data quality [4,17]. Conventional systems cannot handle incomplete or contradictory inputs, which limits dynamic adaptation and leads to suboptimal conditions [5]. Various techniques have been proposed to mitigate data inconsistencies—such as outlier removal, interpolation, cross-calibration, and noise filtering—but each has limitations: they may discard relevant information, smooth over critical events, require significant resources, or delay response times [6]. In this context, restoring data reliability under such adverse conditions becomes essential for maintaining control precision in animal production systems. Given these challenges, adaptive control systems that account for environmental dynamics and the birds' physiological needs are increasingly necessary [7,18].

In this context, Paraconsistent Annotated Evidential Logic Eτ (Logic Eτ) offers a practical approach for managing inconsistencies in sensor data—especially in highly variable environments like poultry houses. Its strength lies in integrating contradictory inputs without invalidating inferences, supporting reliable decisions even amid failures or imprecise data. By allowing contradictions to coexist in a controlled way, Logic Eτ enables more accurate environmental control, benefiting both productivity and welfare. While its application is still emerging, it has shown promise in complex agricultural contexts, including some poultry production cases [15,16].

The main objective of this study is to propose a model—based on Logic Eτ and supported by a formal mathematical framework—for inferring the adequacy of environmental conditions in poultry houses and identifying the need for corrective adjustments, even when sensor data is inconsistent or incomplete.

By incorporating Logic Eτ, we aim to address the limitations of conventional systems, which cannot unable to adequately handle inconsistent, incomplete, or contradictory information—a recurring challenge in dynamic environments such as poultry houses, where unstable data is frequently generated. Through this model, we seek to mitigate these inconsistencies, enhance environmental monitoring, and ultimately improve the conditions that directly influence animal welfare and productivity [9,13].

We hypothesize that the proposed model enhances the reliability of sensor data in poultry houses, even in the presence of inconsistencies and missing information, thereby strengthening decision-making processes. The solution is designed to process contradictory information and generate more accurate assessments of environmental conditions. This, in turn, enables more efficient adjustments in control systems, positively impacting on productivity and bird health [10].

This study contributes to scientific progress by applying Logic Eτ to environmental control in tropical poultry houses, offering a model that addresses data inconsistencies, improves productivity, and reduces costs. Its non-classical logic foundation enhances flexibility for automation and control, opening avenues for future research in smart agriculture. The results also support sustainable practices and public policies aligned with UN SDGs 9, 12, and 3.

The article is structured into four sections: Background introduces Logic Eτ and environmental control challenges in poultry houses; Materials and Methods details our approach and mathematical application of Logic Eτ to IoT data; Results and Discussion presents model outcomes; and Conclusion summarizes findings, contributions, and future research directions [11].

2. Background

This section outlines the theoretical basis for the model, introducing the Logic Eτ as a tool for handling inconsistent sensor data.

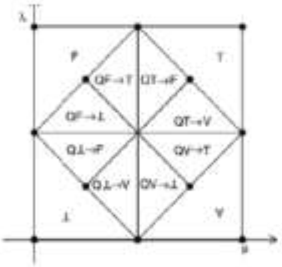
2.1. Paraconsistent Annotated Evidential Logic Eτ

Non-classical logic is a field of formal logic that seeks to overcome the limitations of traditional classical logic, particularly in contexts where conventional rules of truth and falsity are insufficient to describe the complexity of specific systems. Different approaches within non-classical logic have been developed to handle uncertainty, ambiguity, and contradiction in dynamic environments with imperfect information [8].

In this context, Paraconsistent Logic (PL) was developed to handle contradictions without leading to triviality—a condition in which all propositions are considered true, rendering the system useless [4,5]. The ability to tolerate and process inconsistencies in a controlled manner allows systems based on PL to operate effectively even with conflicting information. This makes it particularly valuable in domains where data inconsistencies are inevitable, such as artificial intelligence, robotics, and environmental monitoring. Unlike classical logic, which fails to process contradictory information, PL offers a robust foundation for complex systems that rely on uncertain or conflicting data sources [4].

The Paraconsistent Annotated Evidential Logic (Logic Eτ) extends the capabilities of Paraconsistent Logic by introducing annotations that represent levels of evidence—both favorable (μ) and unfavorable (λ)—associated with each piece of information. The resulting logical states tend to converge toward four extreme states: True, False, Inconsistent, and Paracomplete [5,8].

This process can be visually interpreted through a two-dimensional graph that illustrates the resulting propositions, as shown in Figure 1. The vertices of the lattice correspond to the four extreme logical states. Logical states located within the internal regions of the lattice—those that do not match the extreme states—are referred to as non-extreme logical states.



Symbol	Non-Extreme States
QV→T	Quasi true tending to Inconsistent
QV→⊥	Quasi true tending to Paracomplete
QF→T	Quasi false tending to Inconsistent
QF→⊥	Quasi false tending to Paracomplete
QT→V	Quasi Inconsistent tending to True
QT→F	Quasi Inconsistent tending to False
Q⊥→V	Quasi Paracomplete tending to True
Q⊥→F	Quasi Paracomplete tending to False

Fig. 1. Latice of decision-making

This evidential approach enables refined decision-making in systems where data are inconsistent and vary in reliability and precision. Logic Eτ can prioritize data quality even in the presence of contradictions by assigning degrees of certainty to each input, which is particularly valuable for decision-making in dynamic environments [6].

3. Materials and Methods

This research is applied in nature, follows a quantitative approach, and adopts an experimental design, focusing on the technological validation of a model for environmental control in poultry houses. This section presents the proposed model as well as the experimental procedures used to evaluate its performance.

3.1. Description of the Proposed Model

The proposed model applies Logic Eτ to data collected by IoT sensors in broiler production, enabling inference on whether environmental conditions in the poultry house support bird welfare and productivity—even under inconsistent or missing data. It evaluates a central proposition of environmental adequacy by analyzing five variables—temperature, humidity, air velocity, carbon dioxide, and ammonia—whose favorable and unfavorable evidential degrees are computed using exponential decay. These values are compared with animal welfare standards and aggregated to support the final inference. The model operates in four stages: Data Acquisition, Evidence Annotation, Processing, and Inference. It was implemented in Python (3.13.2) using NumPy (1.26.0), Pandas (2.2.3), Matplotlib (3.10.1), and Seaborn (0.13.2) for data handling and visualization.

3.1.1. Data Acquisition.

In the data acquisition stage, the model receives as input a set of measurements obtained from IoT sensors installed in poultry houses, which monitor critical variables for environmental control. These measurements are collected as time series, with variable update rates depending on sensor characteristics and without synchronization across sources. As a result, data gaps or inconsistencies may occur—scenarios for which the model is specifically designed.

The model thus enables the acquisition and processing of environmental variables over time: temperature (*T*), relative humidity (*H*), air velocity (*V*), carbon dioxide concentration (CCO_2), and ammonia concentration (CNH_3). Each variable is recorded as an annotated time series according to Logic Eτ, in which each measurement Xi is represented by the quadruple (ti, xi, μi, λi). In this representation, ti denotes the timestamp of the observation, xi is the measured value, μi is the degree of favorable evidence, and λi is the degree of unfavorable evidence associated with the measurement [2].

The raw data sets are defined as follows: *T*: Ambient temperature, *H*: Relative humidity, *V*: Air velocity, CCO_2C: Carbon dioxide concentration, CNH_3C: Ammonia concentration

Each data set $X \in \{T, H, V, CCO_2, CNH_3\}$ is formally defined as:

$$X = \langle (t_1, x_1, \mu_1, \lambda_1),\ (t_2, x_2, \mu_2, \lambda_2),\ \dots,\ (t_n, x_n, \mu_n, \lambda_n) \rangle \qquad (1)$$

These annotations enable the identification and handling of contradictions and inconsistencies within the time series.

3.1.2. Evidence Annotation: Applying Logic Eτ to Handle Inconsistencies in Sensor Measurements.

One of the key strengths of the proposed model is its robustness against IoT sensor limitations in poultry houses, where irregular update rates and lack of synchronization hinder accurate readings. The model assumes measurement reliability is highest at the time of collection but gradually decreases due to environmental dynamics such as thermal fluctuations, gas emissions, and bird metabolism.

The model applies an exponential decay mechanism that adjusts the degrees of favorable (μ) and unfavorable (λ) evidence based on temporal lag to address this. This process penalizes older data and prioritizes more recent information, ensuring that inferences more accurately reflect real conditions. The decay equation is parameterized by Δt (the time elapsed since collection), a sensitivity factor α, and a minimum reliability threshold C_{min}, ensuring that measurements do not completely lose their relevance.

$$C(\Delta t) = C_{min} + (1 - C_{min})\, e^{-\alpha \Delta t} \qquad \alpha = \frac{\ln(2)}{t_{1/2}} \qquad (2)$$

The sensitivity factor α represents the decay rate and can be adjusted according to the characteristics of the environment and the sensors. This parameter may be defined based on historical data or by using the half-life ($t_{1/2}$), which represents the time required for reliability to be reduced by half. In poultry houses, this half-life depends on factors such as ventilation, animal density, and gas release dynamics, which determine how quickly a measurement loses its representativeness. Since the model assumes asymptotic decay, reliability never reaches zero but decreases progressively, preserving traces of relevance even in older data [12].

Finally, each measurement is annotated with μi and λi, which are calculated based on the exponential decay equation for reliability, as follows:

$$\mu_i = C(\Delta t) \qquad \lambda_i = 1 - \mu_i \tag{3}$$

This approach effectively models natural phenomena in which time plays a critical role, allowing for a smooth transition from full reliability to minimum reliability. It continuously assigns greater weight to recent measurements and progressively reduces the relevance of older ones, without abrupt changes.

3.1.3. Model Parameterization

Since the model allows for the definition of a minimum reliability threshold—ensuring that a measurement never becomes completely irrelevant—a minimum reliability of 10% was adopted for the experiments ($Cmin = 0.1$). In addition, considering that the parameter $t_{1/2}$ can be configured to reflect the impact of structural features that directly influence the internal environmental behavior in different types of poultry houses, the experimental tests included three main configurations: Blue House (BH), Dark House (DH), and Solid Wall (SW). Table 1 describes each poultry house type and its corresponding influence on environmental control, highlighting the values used for $t_{1/2}$ and α [7].

Table 1. Poultry House Types and Parameter Configuration for Environmental Control Modeling

Poultry House	Description & Impact on Environmental Control	Sensitivity	$t_{1/2}$	α
BH	Uses positive-pressure ventilation with cooling pads and blue plastic curtains, offering moderate insulation and intermediate environmental control—common in mild climates.	High	15 min	0.0462
DH	Fully enclosed, with ventilation, temperature, and lighting controlled by mechanical exhaust and evaporative cooling. Creates a stable microclimate and enables precise light cycle management to optimize feed conversion and weight gain.	Medium	30 min	0.0231
SW	Built with solid masonry or insulating walls, offering high thermal stability and sound insulation. Like Dark Houses, they use mechanical ventilation and evaporative cooling, with superior protection from external climate variations.	Low	45 min	0.0154

This yields a decay equation with a 10% minimum reliability threshold, used to calculate μi and λi for each measurement. The decay rate α varies by poultry house type, as shown in Table 1.

$$\mu_1 = 0.1 + 0.9\, e^{-\alpha \Delta t} \qquad \lambda_1 = 1 - \mu_1 \tag{4}$$

3.1.4. Processing: Applying Logic Eτ to Analyze Evidence in Sensor Measurements

In the processing stage, the model evaluates the environmental conditions of the poultry house based on the annotated sets *T, H, V,* CCO_2, and CNH_3. Table 2 presents the inferential thresholds used as proposed by [9]. In this case, *Xmin* and *Xmax* generally represents the set of acceptable environmental conditions for:

Table 2. Inferential Thresholds for Environmental Variables [3]

Variable	*Xmin*	*Xmax*
Temperature (°C)	*Tmin*=19	*Tmax*=25
Relative Humidity (%)	*Hmin*=40	*Hmax* =69
Air Velocity (m/s)	*Vmin*=0.80	*Vmax*=3
Carbon Dioxide Concentration (ppm)	CCO_2min=0	CCO_2max =3000
Ammonia Concentration (ppm)	CNH_3min=0	CNH_3max=150

Thus, the model assesses whether its value falls within the predefined minimum and maximum thresholds for each annotated measurement in the environmental variable sets. Measurements that fall within these inferential limits are counted as favorable evidence μ_X in the group total. Conversely, those that exceed the thresholds are counted as unfavorable evidence λ_X.

$$\mu_X = \frac{\sum_{i=1}^{n_X} \mu_i^X . 1_{[x_{min}, x_{max}]}(X_i)}{n_X} \qquad \lambda_X = \frac{\sum_{i=1}^{n_X} \mu_i^X . (1 - 1_{[x_{min}, x_{max}]}(X_i))}{n_X} \tag{5}$$

The flexibility of these parameters, combined with their adaptability to different poultry house types and structural characteristics, allows the model to be applied across various production contexts, ensuring a more accurate assessment of environmental conditions.

3.1.5. Inference: Deriving Environmental Conditions from Evidential Data

In this stage, the model evaluates the logical status of a central proposition using Logic Eτ, based on the aggregated evidential values (μ, λ).

Let P be the proposition:

P = "The environmental conditions of the poultry house are adequate for bird welfare and productivity."

This proposition is constructed through the paraconsistent conjunction of the monitored environmental variables, enabling the combination of multiple pieces of evidence—even in the presence of uncertainty or contradiction in the sensor data [9].

$$P = T \wedge H \wedge V \wedge CCO_2 \wedge CNH_3 \tag{6}$$

Each variable $X \in \{T, H, V, CCO_2, CNH_3\}$ already has its respective annotations derived from the processing of sensor measurements. To determine the inference regarding proposition P, the model applies Logic Eτ operators to compute the degrees of evidence μ_P, λ_P, which are given by:

$$\mu_P = \min_{1 \le i \le n} \mu_i \qquad \lambda_P = \max_{1 \le i \le n} \lambda_i \tag{7}$$

The model performs inference based on the favorable (μ_P) and unfavorable (λ_P) degrees of evidence for proposition P, positioning them within the Logic Eτ lattice to classify the environmental condition into one of the four logical states: True, False, Inconsistent, or Paracomplete.

This framework enables paraconsistent reasoning under uncertainty, ensuring logical interpretation of environmental data. It supports management, assesses animal welfare impacts, and validates robustness. Proposition P is only classified as True when all variables show strong favorable evidence.

3.2. Model Validation

We validated the model through robustness tests to assess its stability under variations in environmental data. The goal was to determine whether the Logic Eτ-based system preserves inferential consistency under subtle changes, without abrupt oscillations. Sensor data from a test dataset—real poultry house monitoring records—were first processed to establish a reference benchmark [11]. The test set was then generated from this original dataset, reflecting typical poultry house conditions.

The dataset used for model validation was collected in 2013 from three commercial broiler poultry houses (BH, DH and SW) in Amparo, São Paulo, Brazil (22°42'04" S, 46°45'52" W, 674 m), under a Cwa climate with hot, humid summers and dry winters. The houses varied in ventilation, insulation, and lighting, offering environmental diversity for evaluation. Mobile sensors measured temperature, humidity, air velocity, ammonia, and CO_2 at 21 equidistant points, 0.30 m above the floor, across four production stages (21, 28, 35, and 42 days). The dataset includes real inconsistencies, such as faults and contradictions, ideal for testing model robustness [1,10].

Since the dataset lacked labeled data, supervised validation was not feasible. We therefore adopted a robustness test to assess model reliability under controlled perturbations [11]. A modified dataset introduced small random variations to simulate natural fluctuations (e.g., diurnal cycles, bird movement, ventilation, air quality), with magnitudes based on IoT sensor accuracy and real poultry house conditions: ±0.5 °C (T), ±2% (H), ±0.1 m/s (V), ±20 ppm (CCO_2), and ±1 ppm (CNH_3) [32,33,34]. A 50% perturbation rate per group balanced statistical representation and computational feasibility [35]. Rather than induce significant changes, the goal was to verify whether the model maintained inferential consistency under minor variations [11]. Comparing (μ_P, λ_P) vectors between original (N) and perturbed (P) data confirmed system stability.

Robustness was assessed by computing Euclidean distances in the $[0,1]^2$ evidential space of Logic Eτ between inferences before and after perturbation, across combinations of poultry house, bird age, time, and variable. Aggregated averages enabled the creation of a heatmap highlighting sensitivity regions. We also generated (μ, λ) vector plots connecting original and perturbed inferences, with variable-specific color coding to reveal displacement patterns within each poultry house.

4. Results and Discussion

This section presents the results obtained from applying the proposed model to the test dataset. We first analyze the outputs generated under the original environmental conditions (N), followed by a comparison with the perturbed dataset (P) to assess the model's robustness.

Applying the model to the original dataset (N), without perturbations, allowed us to evaluate its inferential capability under real environmental conditions. The results reflect the system's response to the monitored variables across different poultry house types, bird ages, and times of day throughout the production cycle [1].

Table 3 summarizes the model's paraconsistent inferences for BH, DH, and SW at 21 days of age, evaluated at 9 a.m. and 2 p.m. Although most environmental indicators present favorable evidence, their values remain near the boundary of logical indefiniteness, trending toward the paracomplete region. This pattern suggests that, while conditions are not explicitly contradictory, the evidence is weak or incomplete—limiting confidence in decision-making. Air velocity stands out as the most critical variable, consistently operating far from the ideal range. This may indicate either mechanical deficiencies in the ventilation systems or the need to revisit the current reference thresholds [2].

Table 3. Paraconsistent Inference Results for Environmental Conditions in Poultry Houses

Poultry House	(μ_P, λ_P)	Paraconsistent Inference	Reasoning
BH-9h	(0.00, 0.55)	F	The model infers that the conditions are inadequate for welfare and productivity
BH-14h	(0.13, 0.44)	Q⊥→F	Available evidence is insufficient for a confident judgment, but suggests conditions tend to be inadequate for welfare and productivity
DH-9h	(0.26, 0.34)	Q⊥→F	The evidence is insufficient for a confident judgment on environmental adequacy, but it suggests conditions likely fall short for welfare and productivity
DH-14h	(0.38, 0.19)	Q⊥→T	The evidence is insufficient for a confident judgment, but it suggests conditions are likely adequate for welfare and productivity
SW-9h	(0.09, 0.48)	Q⊥→F	The evidence is insufficient for a confident judgment, but it strongly suggests conditions are likely inadequate for welfare and productivity
SW-14h	(0.08, 0.46)	Q⊥→F	The evidence is insufficient for a confident judgment, but strongly suggests conditions tend to be inadequate for welfare and productivity

Notably, applying the temporal decay function was essential in revealing a structural trend: under the current configuration, all poultry houses tend to be inferred as environmentally unsuitable, reinforcing the importance of timely and high-reliability sensor data for maintaining animal welfare.

Figure 2 illustrates the use of Logic Eτ in analyzing of environmental data collected from the poultry houses. The lattices display the evidential positions of each environmental variable and the resulting inference for proposition *P* for BH, DH, and SW, considering broilers at 21 days of age, with data collected at 9:00 and 14:00 [4].

In the different poultry house types, environmental control was most effective in SW, which showed greater stability in the monitored variables and lower uncertainty in the measurements. BH performed reasonably well but exhibited some fluctuations in temperature and humidity, along with a lack of data on carbon dioxide concentration, suggesting that its positive-pressure ventilation system could be improved. DH demonstrated efficient environmental control overall, except for temperature, where a lack of reliable evidence may hinder informed decision-making. Air velocity was the most critical variable, with elevated uncertainty levels, indicating that ventilation systems could benefit from further optimization [5].

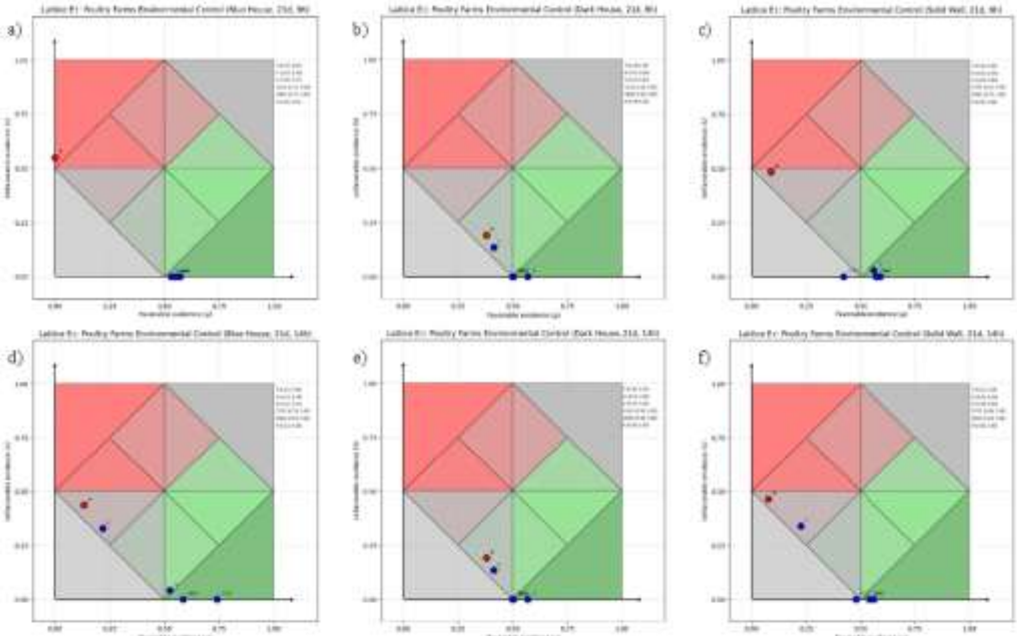


Fig. 2. Logic Eτ inference for (a) BH 21d, 9h, (b) DH 21d, 9h, (c) SW 21d, 9h, (d) BH 21d, 14h, (e) DH 21d, 14h, (f) SW 21d, 14h.

The resulting heatmap (Fig. 3a) introduces the robustness test results (N vs. P) and provides a concise visualization of the model's response to subtle variations in input data. Particular poultry house and variable pairs—such as DH-V, BH-V, and SW-V—exhibited more pronounced distances between the original and perturbed scenarios, suggesting greater local sensitivity of the model. This local sensitivity refers to the model's capacity to react significantly to small changes in observational data, shifting its favorable (μ) or unfavorable (λ) evidence levels. On the other hand, areas with lower distance values—such as SW-H, DH-CCO_2, and BH-T—indicate more stable inferences, even in the presence of input perturbations. This uneven sensitivity distribution may reflect both intrinsic characteristics of the environmental variables and specific aspects of how the model operates within the evidential space of Logic Eτ [6].

The observed behavior suggests that, although the model demonstrates robustness in most cases, it is selectively sensitive to specific variables—particularly to air velocity (V), which accounts for the largest displacements in the evidential plane. This sensitivity may be related to the strict inferential thresholds defined for this variable during the inference process. However, such selectivity may represent a desirable feature in applications where variations in certain variables are more critical than others [7].

In Figure 3b, each arrow in the plots represents the transition of an instance before (N) and after (P) the application of perturbations, indicating the model's sensitivity (through vector length) and the predominance of favorable evidence (μ), unfavorable evidence (λ), or both (through direction). Variables V and T exhibited more intense displacements in λ, while H, CCO_2, and CNH_3 showed more subtle changes—suggesting that the model responds differently depending on the type and range of variation. The pronounced sensitivity of V and T may be linked to stricter inferential thresholds, which amplify the model's response even under small changes—consistent with the sensitivity patterns observed in the heatmaps, especially for V [8]. In this context, the heatmaps and vector plots offer an intuitive yet technically grounded visualization of local sensitivities, enabling informed operational adjustments based on the evidential dynamics of each environmental factor.

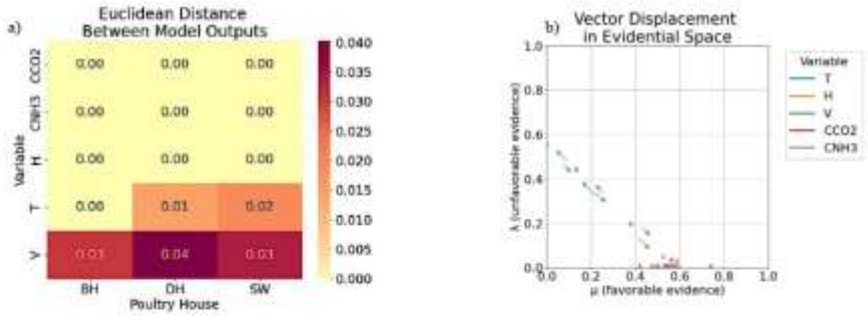


Fig. 3 (a) Sensibility Heatmap – Euclidean Distance Between Model Outputs (Shift After Data Perturbations); (b) Vector Displacement in Evidential Space by Aviary - shift after data perturbation in (μ, λ)

The results demonstrate that the model based on Logic Eτ responds coherently and predictably to the introduction of perturbations in the data, particularly for variables with more restrictive operational ranges. No erratic or disconnected behaviors were observed between the original and perturbed scenarios; on the contrary, the displacement vectors followed directions consistent with the type of alteration applied, preserving the system's internal logic.

Despite perturbations, most transitions remained within stable or logically valid regions, underscoring the model's resilience. However, selective response patterns indicate that the calibration of inferential parameters strongly influences the model's robustness. This factor should be carefully considered in operational deployments [9].

Overall, the robustness test confirms the model's logical stability and selective responsiveness, supporting its suitability for real-world applications subject to variability and uncertainty. Among its main advantages, the model offers logical resilience, adaptability to various poultry house types, and clear interpretability through evidential visualizations. However, its performance remains sensitive to the calibration of inferential thresholds and may vary depending on the operational significance of each variable, which should be considered in deployment.

5. Conclusions

This study proposed a model based on Paraconsistent Annotated Evidential Logic Eτ — logically driven and mathematically grounded — to classify and analyze environmental conditions in poultry houses, using data collected by IoT sensors that are often subject to inconsistencies, contradictions, and inaccuracies, especially in tropical environments. Its use demonstrates the viability of non-classical logic as a foundation for adaptive, decision-making in complex agricultural systems.

The results confirm our initial hypothesis: the proposed model, grounded in Logic Eτ, improves inferential reliability even with conflicting data, maintaining logical stability under uncertainty and controlled variation. This supports more accurate environmental control decisions. The model produced stable, coherent inferences by processing contradictions without discarding data — even with inconsistent or incomplete inputs. Robustness tests confirmed its logical consistency, selective responsiveness, and resilience, reinforcing applicability to real-world scenarios with variability and sensor faults. A key observation is that model response depends on inferential threshold calibration, which may require adjustment across contexts. Still, the Logic Eτ-based model proved robust, interpretable, and effective in handling inconsistencies in poultry house data, enabling reliable inferences under uncertainty.

The main scientific contribution of this work lies in the innovative application of Logic Eτ to environmental control in poultry farming, with particular emphasis on the use of decay functions to adjust reliability, the construction of a replicable robustness test, and the integration of logical inference with graphical representation in the evidential space.

By tolerating asynchronous data streams, contradictory readings, and sensor imperfections, the model demonstrates resilience under practical limitations commonly found in field applications. The proposed approach aligns with smart agriculture and the United Nations Sustainable Development Goals —particularly SDGs 9, 12, and 3 — by promoting more accurate, sustainable, and technologically grounded decision-making.

This study has limitations, including the lack of labeled data, which prevented supervised validation, and the use of controlled perturbations that do not simulate severe faults or extreme events. The dataset is also not recent, potentially limiting its relevance to current conditions. Furthermore, limited technical literature constrained the rigorous calibration of inferential thresholds, requiring reliance on partial or adapted references.

For future research, we propose: (i) implementing the model in real-time control systems; (ii) adapting it to other agricultural or industrial environments with uncertain data; and (iii) developing visual interfaces that translate logical states into accessible operational recommendations.

Acknowledgements

This study was partially financed and supported by CAPES – grant 88887.940472/2024-00

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5.3 Article 3 - Full Paper Accepted at AISS 2025

As a direct outcome of this dissertation, a full paper derived from the Parabroiler logical-computational model, entitled "Parabroiler: An Intelligent Environmental Classifier powered by Paraconsistent Annotated Evidential Logic Eτ”, was accepted for presentation at the *1st International Conference on Artificial Intelligence for Sustainable Society (AISS 2025)*, to be held in Kobe, Japan. The paper will be published in the Springer conference proceedings and indexed in major scientific databases such as Scopus and EI Compendex. This acceptance provides strong international validation of the scientific relevance, originality, and methodological rigor of the proposed model, reinforcing the dissertation’s contribution to the fields of Artificial Intelligence, sustainable technologies, and precision livestock farming.

To formalize the development of the artifact, the Parabroiler system was officially registered as a computer program at the *Brazilian National Institute of Industrial Property (INPI)*, under process number BR512025005223-5. This certification validates the originality, authenticity, and intellectual property of the system, reinforcing its status as a technological product derived from this dissertation. The registration strengthens the scientific, technical, and legal integrity of the artifact and establishes formal recognition of its innovative contribution. The official INPI registration certificate is provided in Appendix A as supporting documentation for verification and archival purposes.

Parabroiler: An Intelligent Environmental Classifier powered by Paraconsistent Annotated Evidential Logic Eτ

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Abstract. Broiler chicken production is an essential segment of the agriculture and food production sector, responsible for providing animal protein to the global market in a widely accessible manner. The productive performance and welfare of the poultry flocks depend on continuous monitoring and effective control of critical environmental variables in the poultry houses, such as temperature, humidity, gas concentration, and ventilation. However, conventional data-analysis systems face limitations when faced with conflicting, imprecise, and incomplete information generated by IoT devices, particularly due to the adverse conditions typically found in poultry environments, which compromises assertiveness in decision-making.

In this context, this study presents Parabroiler , an expert system developed as an intelligent environmental classifier powered by Paraconsistent Annotated Evidential Logic Eτ, designed to support the evaluation of environmental conditions in poultry houses. The system integrates sensor-based evidence and maps it into favorable and unfavorable degrees of evidence, enabling consistent inferences even in the presence of incomplete or contradictory data.

The results obtained from real poultry-house data demonstrated higher resilience, coherence, and interpretability compared to traditional threshold-based approaches.

This study contributes to the scientific field by applying and validating a logical-evidential framework capable of enhancing automated reasoning under uncertainty and contradiction. For the productive sector, it provides more reliable support for environmental management decisions, reducing losses and optimizing zootechnical performance. From a social perspective, it contributes to the achievement of the UN Sustainable Development Goals, including SDG 2 (Zero Hunger), SDG 9 (Industry, Innovation and Infrastructure), and SDG 12 (Responsible Consumption and Production).

Keywords: Smart Poultry Farming · Expert Systems · Decision Support Systems · Environmental Monitoring · IoT Sensor Data · Paraconsistent Annotated Evidential Logic Eτ · Broiler Production.

1 Introduction

Broiler production constitutes one of the main segments of the global food chain, playing a strategic role in the supply of low-cost animal protein and contributing significantly to food security and the global economy. However, technological advances and an increase in the production scale have intensified environmental challenges within poultry houses, particularly with respect to microclimate control, the mitigation of noxious gasses and the adequacy of ventilation, which are factors directly associated with bird health, welfare and productive performance. This scenario highlights the need for intelligent monitoring systems capable of optimizing internal facility conditions and reducing losses in intensive systems [20, 30, 8].

The variables of temperature, relative humidity, air velocity, ammonia, and carbon dioxide exert a direct influence on bird welfare and zootechnical indicators, serving as determinants for maintaining adequate conditions of thermal comfort and health. Fluctuations in these parameters can generate heat stress, respiratory problems, and a reduction in the feed conversion ratio, compromising animal health, productivity, and the final quality of the product. Thus, environmental control has become an essential element for reconciling productive efficiency, sustainability, and animal welfare [14, 23, 32].

With the advancement of digital technologies and Industry 4.0 principles, poultry farming has begun to incorporate automated environmental monitoring and control systems. Sensors, wireless networks, Internet of Things (IoT) based applications, and Artificial Intelligence techniques have enabled real-time data collection, integration, and analysis, allowing for automatic adjustments of internal poultry house conditions. These mechanisms constitute what is known as Precision Poultry Farming (PPF), the purpose of which is to reduce losses, optimize energy use, and improve the thermal comfort of the birds [29].

Despite these advances, technical and operational challenges persist that hinder the widespread adoption of these technologies. Many producers face barriers related to high implementation costs, connectivity instability in rural areas, and a lack of standardization among different digital platforms. Small and medium-sized producers, who represent a significant portion of poultry production, encounter additional difficulties in implementing complex and high-cost solutions. Furthermore, even in more developed systems, data captured by sensors may present failures, gaps, or contradictions resulting from dust, thermal variations, humidity, and electrical interference, compromising measurement reliability and the quality of environmental decisions [16, 10, 29].

Most control systems utilize classical Boolean logic models, based on dichotomous relationships of true or false, or fixed statistical averages. Although simple, these approaches are inadequate in contexts where data is incomplete, contradictory, or imprecise, which is a common situation in animal breeding environments [18]. Faced with inconsistent measurements, such systems tend to generate incorrect alerts or discard relevant information without offering the operator a logical and reliable explanation of the environmental situation.

To overcome these limitations, it becomes necessary to use more flexible logical models capable of representing uncertainty and contradiction without invalidating the reasoning process. In this context, Paraconsistent Annotated Evidential Logic $E\tau$ (Logic $E\tau$) presents itself as a robust alternative. Unlike classical logic, Logic $E\tau$ allows for the simultaneous processing of favorable and unfavorable evidence, generating inferences that reflect degrees of confidence and doubt. This characteristic makes it especially suitable for applications in environmental decision support systems, where variables change rapidly and data may contain noise [3, 2].

The application of this logic in computational systems enables more consistent results, allowing the manager to better comprehend the state of the environment, identify risks, and adopt corrective measures with greater safety and efficiency [9, 21].

The environmental data in poultry houses are collected continuously, which entails a gradual loss of reliability over time. Readings are subject to oscillations caused by internal and external factors, such as dust, heat, humidity, gases, and bird movement, that affect sensor performance. In rural regions, internet instability and communication failures also affect data flow, resulting in outdated or contradictory measurements [28, 27].

Conventional environmental control models, based on fixed rules or averages, do not contemplate this complexity. When divergent data arises, these systems either disregard the information or generate erroneous diagnoses, compromising decision reliability [18]. Although Logic $E\tau$ has already been applied in areas such as electrical engineering, medicine, and industrial automation, its utilization in intelligent environmental systems aimed at poultry farming is still incipient.

Despite advances in environmental modeling and the use of digital technologies in poultry farming, there are currently no systems capable of integrating a paraconsistent logical model, mechanisms for handling contradictory data, and accessible computational resources into a single operational solution. The literature lacks tools that reconcile logical robustness, interpretability, low cost, and practical applicability in intensive production environments. This gap becomes even more relevant given the growing need for systems resilient to noise, sensor failures, and data inconsistencies, which are characteristics common in modern poultry houses. Thus, there is an explicit demand for innovative approaches that offer more reliable and explainable environmental analyses, especially for small and medium-sized producers.

This scientific gap highlights the need for new approaches capable of integrating paraconsistent logical modeling, environmental analysis, and accessible digital technologies. This research seeks to fill this gap through the development of an intelligent environmental classifier application, named Parabroiler, founded on Logic $E\tau$ [3].

The central objective of this study is to develop the Parabroiler application, an environmental decision support tool for broiler poultry farming capable of interpreting inconsistent, contradictory, and imprecise data. The system was designed to simultaneously analyze the variables of temperature, relative humidity, air velocity, ammonia, and carbon dioxide, classifying the environment as excellent or critical according to the Logic Eτ model [9, 21].

Considering this context, the present study adopts a Proof of Concept (PoC) approach, focusing on demonstrating the logical, computational, and operational viability of the proposed model. The objective is not to perform comparative analyses with other platforms or present large-scale empirical metrics, but to establish formal foundations and experiment with the practical application of paraconsistent reasoning in a controlled environment. This approach is consistent with exploratory Design Science research aimed at introducing new theoretical-computational models.

The choice of this approach is justified by its potential to translate complex data into practical and understandable information, promoting safer and more sustainable decisions. Furthermore, the application was developed on a no-code/low-code platform with cloud hosting, ensuring low cost and broad accessibility, even for properties with limited infrastructure [25]. In this way, Parabroiler contributes to democratizing the use of digital technologies in the field and strengthening the productive sustainability of the poultry chain.

The research was conducted according to the Design Science Research (DSR) paradigm, oriented toward the creation and demonstration of technological artifacts. The process involved three main stages: (i) theoretical review and survey of environmental thermal comfort parameters; (ii) logical modeling based on Logic Eτ, incorporating the exponential decay of measurement confidence; and (iii) construction and testing of the computational prototype [15]. Simulations were performed in a controlled environment, considering different poultry house types (Blue House, Dark House, and Solid Wall) and different combinations of environmental variables.

This approach ensured coherence between theory, mathematical modeling, and practical application, uniting scientific rigor and technical applicability. Based on this set of objectives and identified gaps, this study presents four original contributions to the field of precision poultry farming and the development of intelligent environmental decision support systems:

Scientific Contribution: Expands knowledge on the use of non-classical logics in environmental classification systems and proposes the unprecedented application of Logic Eτ in the context of precision poultry farming.

Technological Contribution: Presents a functional, accessible, and intuitive application, integrating data collection, logical processing, and result visualization on mobile devices and browsers.

Methodological Contribution: Proposes a logical-computational model capable of handling incomplete, contradictory, or uncertain data, ensuring greater robustness in inference.

Social Contribution: Expands access for rural producers to simple and low-cost digital technologies, fostering sustainable practices aligned with the Sustainable Development Goals (SDGs 2, 9, and 12).

The remainder of this article is organized as follows: Section 2 presents the theoretical foundation on poultry ambience, logical uncertainty, and applications of Logic Eτ. Section 3 describes the methodology adopted and the development process of the computational artifact. Section 4 discusses the demonstration, potential impact, and application scenarios of the system. Finally, Section 5 gathers conclusions, limitations, and recommendations for future research.

2 Related Work

2.1 Poultry Farming and Environmental Control

Poultry farming represents one of the pillars of animal protein production in Brazil and worldwide, playing a strategic role in food security and the global economy. The productive success of the sector is intimately linked to the control of environmental conditions, which directly influence welfare, zootechnical performance, and the sustainability of the breeding system. Temperature, relative humidity, air velocity, and the concentrations of carbon dioxide (CO_2) and ammonia (NH_3) are determinant variables in bird productive efficiency. Fluctuations in these factors can cause heat stress, a reduction in the feed conversion ratio, and an increase in mortality, compromising profitability and the quality of the final product. Furthermore, the avian microclimate is highly dynamic and depends on the age, density, and strain of the birds, making environmental management a complex and variable task throughout the production cycle [23].

Among the environmental variables, temperature is considered the most critical. It affects metabolism, growth, and feed consumption, serving as a determinant for thermal comfort. Temperatures above ideal limits provoke heat stress, leading to hyperthermia and a drop in productivity. On the other hand, values below the recommended range reduce weight gain and elevate energy expenditure for the maintenance of body temperature. In broiler chickens, the ideal thermal range varies according to age, starting at 32–34 °C on the first day of life and reducing gradually to 22–24 °C in the final phase. Ventilation acts as a complementary variable, as moderate temperatures can become stressful when associated with low air movement. Classical studies demonstrate that adequate temperature control promotes a better feed conversion ratio and lower production costs, evidencing that the microclimate is a decisive factor for zootechnical efficiency [19].

The relative humidity of the air assumes a critical role in the thermal comfort of the birds, given that it directly affects their capacity to dissipate heat through evaporation. When humidity exceeds 70 percent, the efficiency of thermal exchange is compromised, exacerbating heat stress. Conversely, levels below 50 percent foster dust accumulation and favor the emergence of respiratory problems. Consequently, maintaining humidity within an ideal range (approximately between 50 percent and 70 percent) reveals itself to be fundamental not only for ensuring the physiological welfare of the birds but also for preventing the proliferation of pathogenic microorganisms in the poultry litter. High humidity reduces the rate of body heat evaporation, intensifying heat stress, while also favoring moisture accumulation in the litter, which elevates ammonia production and predisposes birds to respiratory problems [13].

Air velocity plays a fundamental role in thermal regulation in broiler production houses by promoting convection and assisting in the removal of both residual heat from the birds and produced humidity. In conditions of heat stress, studies indicate that air velocities around 1.5 to 2.0 m/s provide significant gains in weight and feed conversion compared to lower velocities (0.8 or 1.0 m/s) or environments without adequate ventilation [32]. The absence of efficient ventilation can lead to gas accumulation, increased thermal load, and a drop in productive performance. In the final stages of the cycle, when birds present greater body mass and lower heat dissipation capacity, adequate ventilation becomes even more crucial to avoid hyperthermia.

In addition to these physical variables, the concentration of gases, especially ammonia (NH_3) and carbon dioxide (CO_2), constitutes an essential parameter for evaluating air quality in poultry houses. Levels of NH_3 above 15–20 ppm provoke irritation in the respiratory tract, increased susceptibility to infections, and a decline in productive performance. Similarly, high concentrations of CO_2, often exceeding 3,000 ppm, compromise tissue oxygenation, affect metabolism, and indicate insufficient ventilation [14]. Thus, the efficient control of ventilation and air renewal is indispensable for maintaining environmental comfort and bird health.

The set of these variables defines the so-called ideal thermal environment, characterized by conditions that allow birds to express their maximum genetic potential without energy waste on physiological adaptation. Thermal comfort is achieved when the balance between temperature, humidity, and ventilation maintains the birds' body temperature within physiological limits, promoting optimal performance and a low mortality rate. It is important to highlight that environmental variables do not act independently; temperature increases can be partially compensated by greater air velocity, while high humidity potentiates the impact of heat. This interdependence reinforces the need for integrated microclimate analyses [19].

The interaction between temperature, humidity, and air velocity forms the basis of microclimatic management and must be constantly adjusted according to the age and development phase of the birds. In the first days of life, birds require higher temperatures (32–34 °C) and little air movement, whereas in the final phases (36–42 days), they require cooler environments (22–24 °C) and more intense ventilation. This dynamic adjustment guarantees homeothermy, reduces energy losses, and ensures balanced growth [11].

Based on these principles, automated environmental control has been gaining prominence in modern poultry farming, enabling the continuous monitoring of critical variables and the automatic activation of ventilation, heating, and cooling systems. However, the effectiveness of these systems depends on the quality and consistency of the collected data, which is a frequent challenge in rural environments where physical interference and sensor failures can generate incomplete or contradictory information [27].

Therefore, understanding the interactions between environmental variables and maintaining the balance among temperature, humidity, ventilation, and gases is essential for the welfare and productive performance of broiler chickens. This understanding serves as the basis for the development of logical models and decision support systems, such as Parabroiler, which are capable of interpreting environmental data and assisting the producer in the efficient management of the avian environment, even in the face of imperfect information. This complexity reinforces the need for models capable of interpreting contradictions and uncertainties, since conventional approaches often fail when confronted with divergent measurements [33].

2.2 Precision Poultry Farming and Digital Technologies

The advancement of digital technologies has driven a profound transformation in how productive systems are managed, inaugurating the era of Industry 4.0, which is marked by the integration of the physical and digital worlds through sensors, intelligent devices, communication networks, and artificial intelligence algorithms. In the agricultural sector, this evolution gave rise to the concept of **Agriculture 4.0**, the purpose of which is to connect machines, processes, and people, thereby optimizing resource utilization and improving decision-making [33].

In poultry farming, the incorporation of these principles gave rise to Precision Poultry Farming (PPF), a branch of modern animal science that utilizes digital technologies to monitor, assess, and control in real time the factors affecting bird productive performance and welfare. This approach allows for the continuous collection of data regarding temperature, humidity, ventilation, lighting, feed consumption, and animal behavior, enabling automatic adjustments and evidence-based decisions. Consequently, the producer ceases to act reactively and begins to manage the environment in a predictive and intelligent manner, aligning economic efficiency, sustainability, and animal welfare [24].

Among the main enabling technologies of precision poultry farming, the Internet of Things (IoT), Artificial Intelligence (AI), and Big Data Analytics stand out. IoT connects sensors and actuators installed at different points in the poultry house to digital platforms that store and process the collected data. This continuous connection permits real-time reading of environmental variables and the sending of automatic commands to ventilation, heating, or cooling systems. AI, in turn, acts on the interpretation of data and the generation of predictive patterns, identifying correlations between environmental conditions and the productive behavior of the birds. Meanwhile, Big Data contributes to organizing large volumes of historical data, offering support for the formulation of more precise and individualized management policies [24].

These technologies enable the development of Decision Support Systems (DSS), which integrate data coming from environmental sensors, production histories, and computational models to assist the manager in choosing the best action to take. In poultry farming, DSS allow for the identification of environmental anomalies, the prediction of equipment failures, and the recommendation of operational adjustments that reduce heat stress and improve zootechnical performance. The integration of machine learning algorithms and logical reasoning techniques makes it possible not only to monitor the environment but also to interpret the meaning of observed variations in an intelligent and contextualized manner, contributing to more efficient and predictive management [33, 25].

Despite its potential, the full adoption of these technologies faces structural and operational barriers. The first challenge refers to the high cost of implementing automated systems, especially for small and medium-sized properties, which comprise the majority of Brazilian poultry production. The second is the limitation of connectivity in rural areas, which hinders the continuous transmission of data between sensors and servers. Interoperability between devices from different manufacturers also constitutes an obstacle, given that many pieces of equipment do not follow unified communication standards. Furthermore, data inconsistency and incompleteness (resulting from sensor failures, environmental interference, and interruptions in information flow) can compromise the reliability of decisions based on conventional systems [27, 24].

Faced with these limitations, there is a clear need for flexible, accessible, and robust solutions capable of offering analytical intelligence even in contexts of limited infrastructure. In this scenario, **no-code** and **low-code** platforms emerge as promising alternatives for the development of applications aimed at the field. These technologies allow professionals without advanced training in programming to create and maintain digital systems through graphical interfaces and pre-configured modules. Such a characteristic reduces development cost and time, in addition to facilitating the adaptation of solutions to the local needs of producers [17].

The combined use of no-code/low-code platforms with cloud computing services enhances the portability and scalability of digital solutions. The cloud provides remote storage and processing infrastructure, dispensing with the need for local server installation and allowing access to data via mobile devices or web browsers. This architecture is particularly relevant for poultry farming, as it guarantees that environmental data is stored securely and is available for analysis at any time and place. Additionally, cloud services favor integration with APIs and logical intelligence systems, expanding the possibilities for using advanced computational models, such as Logic Eτ, employed in this study [27, 28].

Thus, precision poultry farming is in a process of consolidation as an interconnected digital ecosystem, in which sensors, algorithms, and interfaces converge to generate high-value information for environmental and productive management. However, for these technologies to reach the entire sector, it is indispensable to invest in solutions that are adaptable, accessible, and resistant to data imperfections. In this context, the development of decision support systems based on robust logical models, such as the one proposed by the Parabroiler application, represents a relevant step toward democratizing access to technology, reducing digital inequalities, and promoting smarter, more efficient, and sustainable production [29, 33].

2.3 Fundamentals of Paraconsistent Annotated Evidential Logic Eτ

Non-classical logics emerged to formally represent situations involving uncertainty, incompleteness, or contradiction. Classical logic is incapable of handling these scenarios without collapsing due to the principle of explosion. The paraconsistent tradition, initiated by Newton da Costa, breaks this limitation by allowing the presence of contradictions without rendering the system trivial. This advancement enabled the development of applications in artificial intelligence, control, and intelligent systems that require models capable of reasoning even in the face of conflicts or data gaps. Unlike Fuzzy Logic, which smooths uncertainties by assigning continuous degrees of membership, Logic Eτ explicitly preserves contradictions and the absence of information, allowing for the treatment of inconsistent measurements without discarding them. This aspect is essential in environments where sensors present noise, divergence, or signal loss [3].

The graphical representation of these ordered pairs is fundamental for understanding the dynamics of Logic Eτ. In the Unit Square of the Cartesian Plane (USCP), each point defined by the pair (μ, λ) occupies a specific position that indicates the logical state of the analyzed proposition. Figure 1 illustrates this geometric structure, highlighting the four extreme states at the vertices of the square and the internal regions corresponding to non-extreme states. The spatial arrangement shown in the figure demonstrates how small variations in the values of μ and λ shift the point between regions of truth, falsity, inconsistency, and paracompleteness, in addition to the gradual transitions represented by quasi-logical states. This visualization facilitates the interpretation of the logical results produced by the system and demonstrates the capacity of Logic Eτ to operate even in the face of contradictory or incomplete data. In the context of the present study, this geometric structure is essential, as it enables the graphical representation of the environmental classification performed by Parabroiler, offering the user an intuitive visualization of the logical states resulting from environmental measurements [3].

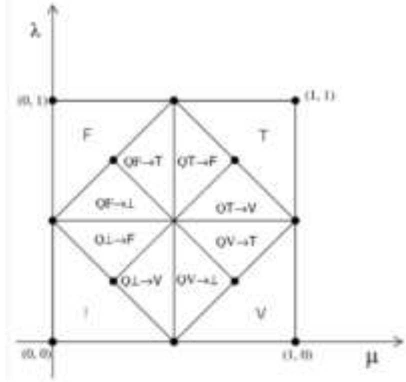

Fig. 1. Unit Square of the Cartesian Plane (USCP).

When the Degree of Uncertainty is positive, the system recognizes that there is a contradiction between the evidences, yet it is still capable of producing valid inferences. When the Degree of Uncertainty is negative, the available information is insufficient, characterizing the paracomplete state. In this way, Logic Eτ preserves deductive capacity in environments with imperfect data and avoids the logical collapse present in traditional systems. In a poultry house, this occurs, for instance, when different sensors simultaneously register 26 °C and 30 °C due to failures or interference; even so, Logic Eτ is capable of producing a valid inference regarding the global thermal state [5, 2].

The structure of the USCP distinguishes two main sets of logical states: the extreme states and the non-extreme states. The extreme states correspond to the vertices of the square and represent fully defined situations. For example, when $\mu = 0.92$ and $\lambda = 0.05$, the point is located very close to the True state, indicating high favorable evidence and low contrary evidence. The True state occurs when μ approaches 1 and λ approaches 0; the False state when μ tends to 0 and λ tends to 1; the Inconsistent state when both values are high; and the Paracomplete state when both are low. These four fundamental states are synthesized in Table 1, which presents the symbology utilized for each logical condition. Situated between these vertices are the intermediate regions that characterize the non-extreme states, which are responsible for expressing graduations, tendencies, and approximations toward the extreme states, such as quasi-true, quasi-false, quasi-inconsistent, and quasi-paracomplete [5].

Table 1. Symbology of the Extreme States

Extreme states	Symbol
True	V
False	F
Inconsistent	T
Paracomplete	⊥

Fonte: Abe (2015)

Following the characterization of the extreme states, it is also necessary to consider the intermediate regions of the USCP, which represent non-extreme states. These states describe situations where the values of μ and λ are not sufficiently high or low to define an absolute logical condition. They indicate tendencies and approximations toward the extreme states and contribute to a more refined interpretation of the evidence. This detailed classification is presented in Table 2, which gathers the main non-extreme states and their respective symbols, allowing for analyses that are more sensitive to the informational nuances present in the data [7].

Table 2. Symbology of the Non-Extreme States

Non-extreme states	Symbol
Quasi-true tending to Inconsistent	$QV \to T$
Quasi-true tending to Paracomplete	$QV \to \perp$
Quasi-false tending to Inconsistent	$QF \to T$
Quasi-false tending to Paracomplete	$QF \to \perp$
Quasi-inconsistent tending to True	$QT \to V$
Quasi-inconsistent tending to False	$QT \to F$
Quasi-paracomplete tending to True	$Q\perp \to V$
Quasi-paracomplete tending to False	$Q\perp \to F$

Fonte: Abe (2015)

In summary, Logic $E\tau$ constitutes a solid formulation among non-classical logics. By integrating qualitative and quantitative dimensions of reasoning, it offers a robust model for the treatment of contradiction, uncertainty, and incompleteness in real systems. Its structure based on the USCP makes inference transparent and coherent, allowing for applications in intelligent systems, decision-making, and technologies that need to interpret imprecise data in an explainable and reliable manner [5].

2.4 Decision Support Systems in Agriculture

Decision Support Systems (DSS) are computational tools designed to assist managers and producers in the analysis of complex information and the selection of alternatives most suitable to production conditions. In agriculture, DSS have established themselves as essential instruments for the intelligent management of natural resources, crop planning, and environmental control, favoring data-driven and evidence-based decisions rather than isolated experiences [33, 6].

These systems combine mathematical models, databases, and user interfaces, allowing the interpretation of environmental, economic, and productive variables in an integrated manner. For example, in poultry farming, a DSS can correlate data on temperature, humidity and ventilation with growth rates and feed conversion ratios, recommending automatic adjustments to optimize the thermal comfort of birds and reduce losses. Thus, the DSS acts as a bridge between data collection and strategic decision-making, translating technical information into practical actions [32].

With the spread of the Internet of Things (IoT) and Artificial Intelligence (AI), decision support systems have evolved into connected digital environments capable of processing large volumes of data (Big Data) and generating real-time predictions. These systems are applied not only to animal production but also to smart irrigation, crop management, and climate risk forecasting. However, challenges remain regarding data quality and consistency, interoperability between platforms, and the intuitive comprehension of information by rural users [4, 12].

To overcome these limitations, recent research has sought to incorporate more robust and transparent logical models capable of handling uncertainties and contradictions in environmental data. In this context, the integration of non-classical logics, such as Logic Eτ, represents a conceptual advance by allowing the rational interpretation of incomplete or contradictory information. The adoption of this approach in decision support systems can enhance the reliability of analyses and offer the producer clear, interpretable, and contextualized information, thereby strengthening precision agriculture and productive sustainability [3, 7].

3 Materials and Methods

3.1 Research Design and Logical-Computational Structure

This is applied research developed under the Design Science Research (DSR) paradigm, the purpose of which is the development and demonstration of a computational artifact named Parabroiler, aimed at environmental classification in broiler poultry houses. This methodological approach was chosen because it integrates scientific rigor and technological relevance, favoring the creation of innovative systems founded on theoretical and empirical knowledge [15, 26]. The choice of the DSR paradigm is justified by the nature of the problem, which involves informational uncertainty and the need to construct a decision support artifact, characteristics that align with the scope of this methodology.

The decision core of the artifact utilizes mathematical modeling based on Logic Eτ, incorporating the exponential confidence decay model to weight the temporal validity of environmental readings. This formulation allows for the processing of inconsistent, incomplete, or contradictory data while preserving the logical coherence of the generated inferences. The use of the temporal decay coefficient is essential because it ensures that old measurements lose influence over the inference, preventing outdated data from harming the consistency of the environmental classification.

In this phase, there was no participation of end-users, such as poultry farmers or specialists, nor were usability tests performed. The focus was concentrated exclusively on the logical and computational validation of the model; thus, the study is characterized as a proof of concept, prioritizing the demonstration of the technical consistency and theoretical viability of the artifact. This methodological decision characterizes the artifact as being at an early stage of technological maturity (proof of concept level), focused on logical consistency before advancing to empirical evaluations and validation with specialists.

Figure 2 presents the methodological structure adopted for the development of the application, founded on the Design Science Research (DSR) cycle. To guide the construction of the artifact and ensure alignment among problem, solution, and evaluation, the DSR methodological cycle was adopted as presented below.

Fig. 2. Development process of Parabroiler based on Design Science Research (DSR).

As illustrated in Figure 2, the study was organized into four main stages: the first consisted of problem identification and the definition of the objectives of the proposed solution. The second involved the design and construction of the computational artifact. The third stage corresponded to the demonstration of the system's functionality in a simulated environment. Finally, the fourth stage dealt with the evaluation of the logical robustness of the model in the face of inconsistent data, ensuring its operational capacity even in scenarios of informational uncertainty. In the context of this artifact, these stages allowed for the operationalization of Logic Eτ modeling, the structuring of the computational architecture, and the simulation of environmental readings under different combinations of critical variables [26].

The study is therefore configured as a computational Proof of Concept (PoC), intended to demonstrate the logical, mathematical, and operational viability of the model based on Paraconsistent Annotated Evidential Logic Eτ in environmental classification. The scope does not contemplate empirical validation in poultry farms, statistical performance analyses, or direct comparisons with commercial systems, which generally utilize proprietary architectures and do not make equivalent databases available for evaluation. Thus, the emphasis falls on the formal coherence of the model, the inferential robustness regarding contradiction, and the potential for application in the environmental management of precision poultry farming. Future studies should incorporate field experimentation, specialist evaluation, and comparisons with technologies already utilized in the sector [22].

3.2 Application Context and Critical Environmental Variables

The Parabroiler application was designed for the monitoring and classification of environmental conditions in different types of broiler rearing facilities, covering three productive configurations with distinct levels of insulation and climate control: Blue House, Dark House, and Solid Wall.

Each type of poultry house presents its own thermal and structural behavior, requiring specific parameters for the interpretation of environmental variables. Thus, the system was configured to adapt the confidence decay factors according to the type of facility, ensuring greater precision in classification.

The age range considered was from 21 to 42 days, which is the phase in which environmental conditions exert the greatest influence on bird welfare and zootechnical performance. During this period, variations in temperature, humidity, air velocity, and gases (NH_3 and CO_2) directly impact the feed conversion ratio and growth, justifying the focus of the model on this developmental range.

3.3 System Development and Operational Architecture

Parabroiler was developed according to the principles of precision poultry farming and Logic Eτ, within the methodological paradigm of Design Science Research (DSR), which guides the creation of technological artifacts aimed at solving real problems.

The development utilized no-code/low-code visual programming platforms, allowing for the implementation of computational solutions with minimal need for manual coding. The system possesses a mobile interface and business rules integrated directly into the application, dispensing with complex intermediate servers.

The architecture of **Parabroiler** is composed of three main layers:

(a) Frontend: responsible for the data entry of environmental variables (air temperature, relative humidity, air velocity, ammonia (NH_3), and carbon dioxide (CO_2)), allowing the operator to register sensor readings manually to ensure system accessibility even in facilities without integrated IoT telemetry, in addition to metadata such as bird age and poultry house type;

(b) Logic: executes information processing using Logic $E\tau$ and the exponential confidence decay model, implemented in a REST API (requests and responses in JSON format);

(c) Data: performs the tabular storage of collections and classifications in cloud computing infrastructure, composing the environmental history of the poultry house.

The operational flow follows the sequence: Input → Logic $E\tau$ Processing → Classification → JSON Response → Display.

The parameters of thermal comfort and bird welfare, such as temperature, relative humidity, air velocity, and gas concentration, are widely established in technical literature. These ideal ranges were incorporated into the model as reference limits, serving as the basis for the automatic evaluation of the poultry house environmental conditions and for the classification performed by the system [13, 32].

During development, these variables were integrated into the logical model as system inputs, allowing for the automatic comparison between collected values and ideal ranges. Logical reasoning based on Logic Eτ interprets measurements under different levels of consistency and contradiction, generating an automatic environmental classification interpretable by the user, without the need for complex calculations.

The application was implemented in a Low Code platform (responsible for the interface and data collection) and the Python/Flask framework (logic engine and server communication). Information is stored in Google Sheets, which enables the recording and historical consultation of measurements, ensuring portability, transparency, and ease of use, even in rural properties with limited internet access.

The adopted methodology combines a solid theoretical basis, applied logical structure, and practical implementation, resulting in an accessible and robust digital tool that contributes to intelligent environmental management and the strengthening of sustainability in broiler production (**Banhazi et al., 2018**).

Figure 3 illustrates the general system architecture, composed of four main modules: Cloud Infrastructure, No-Code/Low-Code Platforms, Mobile Interface, and Logic Model $E\tau$. Each module plays an essential role in the application's operation: the cloud infrastructure guarantees portability and scalability; the no-code/low-code platforms allow rapid implementation with minimal coding; the mobile interface performs manual data collection and automatic classification; and the Logic Eτ model processes favorable and unfavorable evidence for environmental inference.

Fig. 3. Architecture and functionalities of the Parabroiler application.

3.4 Integration of Components and Database

Integration among Parabroiler components was structured in a three-tier architecture, composed of the interface (front end), logic service (back end), and cloud storage (datastore). This structure guarantee interoperability, scalability, and consistency in the exchange of information between modules, maintaining simplicity and low operational cost.

Communication between the interface layer and the logic engine occurs via a REST API, developed in Python with the Flask framework, utilizing requests and responses in JSON format. This architecture allows for direct and lightweight interaction between the mobile application and the logical processing service, ensuring dynamic response and system stability.

The collected data (temperature, relative humidity, air velocity, ammonia (NH_3), and carbon dioxide (CO_2)) are sent via the interface and processed by the model based on Logic Eτ, which applies temporal weighting via exponential confidence decay and performs paraconsistent inference to determine the environmental state.

Storage is performed on the cloud computing infrastructure using a simplified tabular structure, which is sufficient to record, track, and consult measurements without the need for a complex relational database. Each entry is recorded with the date, time, poultry house type, and classification result, making a history of environmental conditions accessible to the user.

This design characterizes Parabroiler as a frugal application, as it combines low cost, accessibility, and computational efficiency with practical relevance for environmental management in poultry houses. The use of no-code/low-code platforms, low-cost cloud storage, and optimized mathematical modeling translates the principle of frugal innovation, that is, creating technological solutions of high functional impact and low resource consumption [31].

Thus, the system adopts a sustainable, scalable, and replicable technological integration capable of functioning even in rural environments with limited connectivity, reinforcing its alignment with the Sustainable Development Goals (SDGs 9 and 12).

3.5 Tools and Documentation

The development of the system was conducted entirely in a no-code/low-code environment, which eliminated the need for external tools for prototyping, documentation, or version control. The platforms utilized automatically generated the documentation of the execution flow and application interfaces. Data collections and results were stored in tabular format in the cloud, with timestamping (date and time) to ensure traceability and transparency in all stages of the process. Since the study did not involve empirical data, animals, or human subjects, approval by an ethics committee or institutional authorization was not required.

3.6 Computational Logic and Modeling

The core of **Parabroiler's** decision implements the operations of Logic Eτ, employing the exponential confidence decay model to weight the temporal validity of environmental readings. **Parabroiler** receives as input a structured set of environmental and operational variables, including: poultry house type (Blue House, Dark House, or Solid Wall), bird age, date and time of collection, temporal interval between collection and classification (Δt), decay model parameters (α and $C(\Delta t)$), and the environmental variables themselves: air temperature (T), relative humidity (H), air velocity (V), carbon dioxide (CO_2), and ammonia (NH_3). For each environmental variable, the system automatically calculates the degrees of favorable (μ) and unfavorable (λ) evidence, weighted by the temporal reliability derived from the exponential decay function. Based on these values, the model applies the operators of Logic Eτ, inferring logical states that can vary between the extreme regions (True and False) and the non-extreme regions (Paracomplete and Inconsistent) of the Unit Square of the Cartesian Plane (USCP). The global logical result (μ_P, λ_P) combines the evidence from all monitored variables, allowing the system to classify the environment as excellent, adequate, quasi-critical, or critical, in an explainable and consistent manner even in the face of incomplete, imprecise, or contradictory data.

This modeling allows the system to interpret contradictory, incomplete, or uncertain values, while maintaining logical coherence in the final classification of the environment.

The environmental variables: temperature (T), relative humidity (H), air velocity (V), carbon dioxide concentration (CO_2), and ammonia (NH_3); are treated as evidence inputs. Each dataset is represented by time series annotated according to Logic Eτ, in which each measurement is expressed by the quadruple $(t_i, x_i, \mu_i, \lambda_i)$. In this format, t_i indicates the instant of measurement, x_i

the observed value, μ_i the degree of favorable evidence, and λ_i the degree of unfavorable evidence.

During processing, the logic engine applies temporal weighting via exponential decay, where the decay factor (α) and the half-life time ($t_{1/2}$) are adjusted according to the type of poultry house type. This stage reduces the influence of old measurements and prioritizes recent data, making the system's reasoning more stable and representative of current conditions [9].

$$X = \langle (t_1, x_1, \mu_1, \lambda_1), (t_2, x_2, \mu_2, \lambda_2), \ldots, (t_n, x_n, \mu_n, \lambda_n) \rangle \tag{1}$$

T hese annotations allow the identification and treatment of the contradictions and inconsistencies present in the time series of environmental variables. One of the main advantages of the use of this model is its robustness regarding the limitations of measurements obtained by IoT sensors, which are common in poultry houses where readings may occur at irregular intervals and without synchronization between devices.

The model considers that the reliability of measurements is maximum at the instant of collection but decreases progressively over time due to environmental factors such as thermal fluctuations, gas emissions, and bird metabolism. To deal with this informational obsolescence, an exponential decay mechanism is applied, which adjusts the degrees of favorable (μ) and unfavorable (λ) evidence according to the elapsed time interval (Δt).

This process penalizes old data and prioritizes recent information, ensuring that inferences reflect the real state of the environment with greater precision. The decay equation is parameterized by Δt (time since collection), a sensitivity factor α, and a minimum reliability threshold (C_{min}), ensuring that measurements never completely lose their relevance [9].

$$C(\Delta t) = C_{min} + (1 - C_{min})e^{-\alpha \Delta t} \tag{2}$$

$$\alpha = \frac{\ln(2)}{t_{1/2}} \tag{3}$$

F or each annotation (μ_i, λ_i), the conjunction aggregates favorable and unfavorable evidence, producing (μ_P, λ_P) for the proposition. The resulting pair is then mapped to the Unit Square of the Cartesian Plane, classifying the global logical state (true, false, paracomplete, inconsistent). This compositional coupling makes Logic Eτ suitable for decision support systems with multiple indicators, as local conflict does not invalidate the global decision.

The innovation introduced by the operator E_τ consists in weighting the temporal validity of the evidence, assigning a lower weight to the old information and a greater weight to the more recent information. This temporal weighting is necessary in dynamic systems, such as poultry environments, where conditions vary continuously and sensor readings rapidly become obsolete [10].

The exponential decay function is utilized to model the gradual loss of confidence in information over time:

$$\tau(t) = e^{-\alpha \Delta t} \tag{4}$$

Where $\tau(t)$ represents the temporal confidence coefficient, t is the time interval elapsed since the last measurement, and α is the decay factor, adjusted according to the sensitivity of the variable and the stability of the environment. Larger values of α indicate more unstable environments, where data lose validity quickly; smaller values of α correspond to more stable environments, in which measurements remain reliable for longer [9].

Based on this principle, the model updates the degrees of favorable evidence (μ) and unfavorable evidence (λ) for each piece of evidence through the expressions:

$$\mu_1 = 0.1 + 0.9e^{-\alpha \Delta t} \tag{5}$$

$$\lambda_1 = 1 - \mu_1 \tag{6}$$

The computational reasoning of **Parabroiler** was developed based on Logic $E\tau$, applied to the classification of environmental conditions in broiler poultry houses. This logic allows for consistent inferences even in the face of imprecise, incomplete, or contradictory information, preserving the coherence of the final decision.

The model simultaneously analyzes the variables of air temperature, relative humidity, air velocity, ammonia concentration (NH_3), and carbon dioxide (CO_2), determining the general state of the environment according to the degree of bird thermal comfort.

The first step of processing consists of evaluating the temporal reliability of measurements. For this, an exponential decay equation is applied, which calculates the gradual loss of validity of readings over time. This temporal confidence coefficient guarantees that inferences are based primarily on recent data, reducing the influence of outdated measurements. Figure 3 illustrates the behavior of this decay function for different poultry house types, evidencing how confidence decreases at distinct rates according to the α value adopted in each environment.

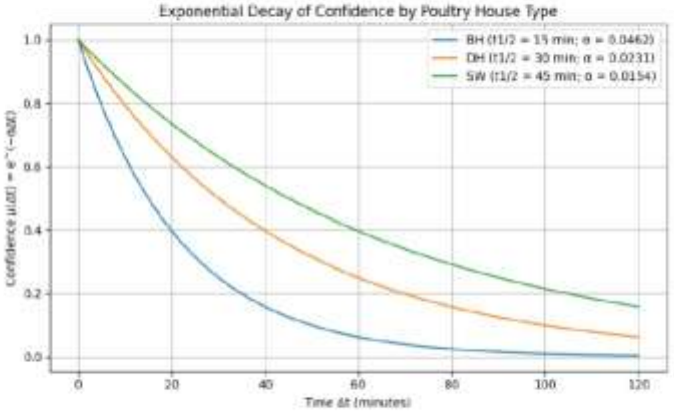

Fig. 4. Behavior of the exponential temporal confidence decay equation.

The decay equation incorporates two parameters: the half-life ($t_{1/2}$) and the decay factor (α), both adjusted according to the type of poultry house. Each structure presents a distinct thermal behavior: more insulated environments (such as Solid Wall Houses) possess higher $t_{1/2}$ and lower α, reflecting greater thermal stability; conversely, less protected environments present lower $t_{1/2}$ and higher α, indicating greater environmental variability.

Table 3 presents the parameters adopted for each type of poultry house, relating the half-life ($t_{1/2}$) and the decay factor (α) used in system modeling.

Table 3. Poultry House Types and Parameter Configuration for Environmental Control Modeling

Type	Description & Impact on Environmental Control	Sensitivity	$t_{1/2}$	α
BH	Uses positive-pressure ventilation with cooling pads and blue plastic curtains, offering moderate insulation and intermediate environmental control (common in mild climates).	High	15 min	0.0462
DH	Fully enclosed, with ventilation, temperature, and lighting controlled by mechanical exhaust and evaporative cooling. Creates a stable microclimate and enables precise light cycle management to optimize feed conversion and weight gain.	Medium	30 min	0.0231
SW	Built with solid masonry or insulating walls, offering high thermal stability and sound insulation. Like Dark Houses, they use mechanical ventilation and evaporative cooling, with superior protection from external climate variations.	Low	45 min	0.0154

Source: De Souza Thomas (2025)

After calculating the temporal reliability, the system verifies whether each environmental variable is within or outside the thermal comfort range corresponding to the age of the birds. This verification is performed individually, comparing the collected values with the ideal intervals. For each variable, the model assigns a degree of adequacy, indicating how closely the environment approaches the recommended conditions for bird welfare.

These equations describe the evolution of the reliability of a reading over time Δt. When the interval between measurements (Δt) is small, the exponential term $e^{-\alpha\Delta t}$ approaches 1, and the value of μ_1 tends to 1, indicating high confidence in the information. As time passes and Δt increases, the value of $e^{-\alpha\Delta t}$ decreases, causing μ_1 to gradually decrease toward 0.1, while λ_1 increases in the opposite direction, expressing the increase of unfavorable evidence.

In operational terms, the system applies this temporal weighting in each data update cycle, so that older evidence begins to exert reduced influence on the calculations of the degrees of favorable (μ) and unfavorable (λ) evidence. This technique of exponential confidence decay stabilizes the logical behavior of the model, reduces the impact of inconsistent, delayed, or noisy measurements, and improves the coherence of the inferences produced by the application, reflecting informational obsolescence.

During processing, the model evaluates the environmental conditions of the poultry house based on the annotated sets T, H, V, CO_2, and NH_3, verifying if the measured values are within the limits of thermal comfort defined for each growth phase. Table 4 presents the ideal ranges for each environmental variable according to the age of the birds and the recommendations of the technical literature.

Table 4. Ideal Ranges of Environmental Variables in Broiler Poultry Houses

Variable	Unit	0–14 days	15–28 days	29–42 days	Technical Source
Temperature	°C	33–29	28–24	23–19	[13, 32]
Relative Humidity	%	40–70	40–70	40–70	[1]
Air Velocity	m/s	0.0–1.2	1.0–2.5	1.0–2.5	**Fidaros et al. (2018)**
Ammonia (NH_3)	ppm	< 15	< 15	< 15	**Oliveira et al. (2021)**
Carbon Dioxide (CO_2)	ppm	< 3000	< 3000	< 3000	[13]; **Costa et al. (2020)**

Source: Martinez et al. (2024)

Thus, the model evaluates whether each measured value is within the predefined minimum and maximum limits for each annotated environmental variable. Measurements that remain within these limits are recorded as favorable evidence (μ_x), while those that exceed the comfort intervals are recorded as unfavorable evidence (λ_x) [9].

$$\mu_X = \frac{\sum_{i=1}^{n_X} \mu_{x_i} \cdot \mathbf{1}[X_{\min}, X_{max}](X_i)}{n_X} \tag{7}$$

$$\lambda_X = \frac{\sum_{i=1}^{n_X} \mu_{x_i} \cdot (1 - \mathbf{1}[X_{\min}, X_{\max}](X_i))}{n_X} \tag{8}$$

The flexibility of the model parameters, combined with its adaptability to different types of poultry house and structures, allows its application in varied production contexts, ensuring more precise environmental evaluations. In this stage, the system utilizes Logic $E\tau$ to evaluate the central proposition: "*The environmental conditions of the poultry house are adequate for bird welfare and productivity*", which is constructed by the paraconsistent conjunction of the monitored variables. This formulation makes it possible to combine multiple pieces of evidence, even in the face of uncertainties or contradictions in the environmental data.

Each variable $X \in \{T, H, V, CO_2, NH_3\}$ possesses its respective annotations derived from the processing of environmental measurements. To determine the inference associated with the proposition P, the model applies the operators of Logic $E\tau$, calculating the corresponding degrees of favorable (μ_P) and unfavorable (λ_P) evidence [9].

$$\mu_P = \min_{1 \leq i \leq n} \mu_i \tag{9}$$

$$\lambda_P = \max_{1 \leq i \leq n} \lambda_i \tag{10}$$

The model performs paraconsistent inference based on the degrees of favorable (μ_P) and unfavorable (λ_P) evidence associated with the proposition (P), which integrates all environmental variables into a unique representation of the poultry house state. These values are positioned within the Logic E_τ structure, on the Unit Square of the Cartesian Plane (USCP), whose axes correspond to the degrees of belief (μ) and disbelief (λ) [9].

$$P = T \wedge H \wedge V \wedge C_{CO_2} \wedge C_{NH_3} \tag{11}$$

B ased on the location of the point (μ_P, λ_P) in the USCP, the system classifies the environment into one of the four fundamental logical states: True, False, Inconsistent, or Paracomplete, or into intermediate regions that express transitional situations between environmental conditions. This approach allows for reasoning under uncertainty, ensuring coherent interpretations even in the face of contradictory data.

Finally, the application converts the logical result into an interpretable environmental classification, informing whether the environment is excellent or critical, and indicating which variables are outside the comfort range. In this way, **Parabroiler** transforms complex data into practical and actionable information, allowing the producer to make rapid, well-founded, and safe decisions.

3.7 Frontend Development (User Interface)

The **Parabroiler** interface was designed according to the principles of accessibility, clarity, and simplicity, prioritizing intuitive use on mobile devices and environments with varying levels of technological infrastructure.

The design allows for the rapid and organized collection of environmental variables, such as temperature, humidity, air velocity, ammonia, and carbon dioxide, in addition to complementary information such as bird age and type of poultry house.

The application structure features screens for data collection, result visualization, and data history, presented directly and in a language that is understandable to the user. The results of environmental classification are displayed in an interpretable format, accompanied by automatic management recommendations.

This approach ensures usability, traceability, and operational practicality, integrating with the system's logical environmental classification process.

Figure 7 presents the Home Screen and the Final Result screen of the **Parabroiler** application, where the user can start a new collection, view previous data, finalize collections, and access the history. This screen synthesizes the accessibility and simplicity principles adopted in the interface design.

Fig. 5. Home Screen and Final Result screen of the Parabroiler application.

3.8 Backend Development

The backend of the **Parabroiler** application was developed in Python, utilizing the Flask microframework to manage communication between the application and the logic engine, which is based on Logic $E\tau$. This layer is responsible for processing the environmental variables sent by the application and generating the poultry house environmental classification.

Requests are transmitted via HTTP POST in JSON format, containing readings for temperature, relative humidity, air velocity, ammonia (NH_3), and carbon dioxide (CO_2), in addition to complementary information such as poultry house type and bird age. The server interprets the data, applies the exponential confidence decay model, and performs the paraconsistent inference, resulting in the degrees of favorable (μ) and unfavorable (λ) evidence.

Based on these values, the system determines the global logical state of the environment—true, false, inconsistent, or paracomplete, and returns a response in JSON format, which is displayed in the application with interpretable messages, such as "*Excellent environment*" or "*Critical situation*".

The server was hosted on the PythonAnywhere platform, ensuring stable execution, secure communication (HTTPS), and low resource consumption, which allows for adequate functioning even in environments with limited connectivity. Thus, the backend constitutes the intelligent core of **Parabroiler**, responsible for converting environmental data into useful and accessible information for management in poultry systems. Figure 8 illustrates this processing flow, highlighting how data collected in the frontend are submitted to the logical model, treated by the decay mechanism, and transformed into explainable outputs that ground the environmental classification.

3.9 Tests and Validation

Logical robustness and functional tests were performed in a simulated environment, conducted by the developers themselves. The objective was to verify the model's capacity to deal with inconsistent and incomplete data, ensuring the stability of responses and the coherence of the classifications produced [9].

Quantitative performance metrics, such as response time or comparative accuracy, were not applied, since the focus of the present study was the conceptual and functional proof of the artifact.

It is important to highlight that, as this is a proof of concept structured within the Design Science Research paradigm, the validation performed in this study concentrates on logical robustness and the functional demonstration of the artifact, not requiring the use of real large-scale data. The explanatory nature of Logic $E\tau$ and its independence from statistical samples make this approach adequate in this phase. Quantitative evaluations, comparative studies, and field tests will be incorporated in future research phases.

3.10 Validation Protocol

The validation of **Parabroiler** was conducted in a simulated environment, with the objective of verifying the logical robustness and computational consistency of the model based on Logic $E\tau$. In this stage, the system was submitted to different combinations of environmental values, including scenarios with inconsistent, incomplete, and contradictory data, to evaluate its ability to maintain coherence in inferences.

Variations in environmental variables (temperature, humidity, air velocity, ammonia and carbon dioxide) were simulated, considering the ideal ranges for broiler chickens between 21 and 42 days of age. The system responded as expected, generating classifications compatible with the logical behavior defined in the model.

The validation was conceptual and technical in nature, not involving empirical data or user tests. The results of the model based on Logic $E\tau$ confirmed the stability of the logic engine, the adequacy of the confidence decay modeling and the consistency of the generated environmental classifications, demonstrating the viability of the application as an environmental decision support tool in poultry systems.

4 Operational Impact and Scientific Contribution

Parabroiler represents a lightweight solution based on formal evidence to mitigate operational risks associated with environmental management in poultry houses. The system translates the technical literature and the thermal comfort parameters into logical judgments, supported by Logic $E\tau$, allowing for the interpretation of incomplete, contradictory or noisy data without loss of inferential coherence. This mechanism reduces incorrect diagnoses, which are common in systems based exclusively on fixed thresholds, and favors more rational and transparent environmental decisions.

As an early-stage conceptual artifact, the present study prioritizes the presentation of logical reasoning and operational architecture, highlighting its transformative potential for the productive sector. The absence of empirical data does not limit the scientific contribution, as the objective of this phase is to establish a new explainable and theoretically sound model for environmental classification, capable of subsidizing future applications on a commercial scale.

By synthesizing multiple critical variables, such as temperature, humidity, ventilation, NH_3, and CO_2, into degrees of evidence (μ, λ) and logical states, Parabroiler provides a clear, interpretable, and actionable environmental classification. This allows rapid identification of risk situations, minimization of interventions based on trial and error, and reduction of losses resulting from heat stress, contributing to bird welfare and productive stability.

Its frugal architecture, built with no-code/low-code platforms and cloud infrastructure, ensures low implementation and maintenance costs. This combination expands access to technology for small and medium-sized producers, who generally face infrastructure limitations and high costs regarding automation equipment [31]. In this way, **Parabroiler** democratizes the use of intelligent decision support tools, promoting greater operational efficiency, environmental sustainability, and alignment with the Sustainable Development Goals (SDGs 2, 9 and 12).

4.1 Technical Innovation

Environmental management routines based solely on fixed limits, simple averages, or manual inspections face several challenges: (i) lack of integration among critical variables; (ii) low decision transparency in the face of conflicting readings; (iii) dependence on connectivity and infrastructure for heavy automation; and (iv) implementation and maintenance costs that hinder adoption by smaller farms.

Existing digital platforms frequently present "raw" data to the operator (tables and graphs) and require technical interpretation under time pressure. Furthermore, sensor inconsistencies (delay, failure, noise) tend to generate spurious alarms or conceal relevant situations. The result is a decision space with low explainability and a risk of delayed or erroneous actions.

Table 5 synthesizes the main differences between conventional environmental monitoring approaches and the solution proposed by **Parabroiler**, highlighting advances in variable integration, contradiction handling, explainability, and operational cost.

Table 5. Comparison between current approaches and Parabroiler

Criterion	Current Approaches	Parabroiler
Variable Integration	Low	High (T, H, V, CO_2, NH_3 combined)
Contradiction Handling	Does not support	Supports via Logic $E\tau$
Time Sensitivity	Does not consider	Exponential decay $\tau(t)$
Decision Transparency	Low	High (USCP explainability)
Implementation Cost	High	Low (no-code/low-code)
Infrastructure Dependence	High	Low (frugal architecture)
Productive Profile Coverage	Limited	Blue House / Dark House / Solid Wall

Source: Author (2025)

Parabroiler addresses these limitations with a logic engine based on Logic $E\tau$, which:

Reasons in contradiction: Combines favorable and unfavorable evidence without trivializing the decision, positioning (μ, λ).

Weights time: Apply exponential decay to reduce the influence of obsolete readings and stabilize the classification.

Explains the result: Presents the final classification of the environment (e.g., "excellent" or "critical") accompanied by an indication of the variables that directly influenced this decision.

4.2 Data Protection

Architecturally, the application utilizes a REST API with minimal payloads (containing no sensitive personal data), tabular cloud storage, and no-code/low-code components, which simplifies deployment, reduces costs, and facilitates auditing. There is no need for user accounts; the solution avoids collecting unnecessary identifiers, concentrating only on environmental measurements and strictly useful operational metadata.

4.3 Implications, Future Directions, and Limitations

As a proof of concept, **Parabroiler** demonstrates the viability of a frugal and explainable DSS for poultry ambience. Promising paths include: (i) external validation studies comparing classifications with specialist decisions and zootechnical indicators; (ii) integration with IoT networks and interoperability protocols; (iii) usability tests with different producer profiles (digital literacy); and (iv) terminological localizations and contextual recommendations by poultry house type/climate. The current version does not cover all exception scenarios nor perform automatic equipment control; in complex situations, a complementary technical evaluation is recommended. Even so, by complementing existing systems with a robust and transparent logic core, **Parabroiler** has the potential to elevate decision quality in the field, expand the adoption of digital tools, and contribute to sustainability and animal welfare goals.

A direct comparison with other digital platforms was not performed, since there are no equivalent systems that integrate Logic $E\tau$, temporal confidence decay, and low-cost frugal architecture for poultry ambience. Thus, Parabroiler inaugurates a new category of explainable systems based on logical-evidential reasoning. This absence of benchmarking does not compromise the validity of the study, as the focus of this phase lies in establishing the theoretical, computational, and conceptual foundations that will allow for broader empirical evaluations in future works.

5 Conclusions

This study presented **Parabroiler**, a decision support system for environmental control in poultry farming based on Logic $E\tau$, incorporating temporal confidence decay to interpret environmental measurements under uncertainty, noise, and contradiction. The results demonstrate that the approach allows for the integration of multiple critical variables (T, H, V, NH_3, CO_2) into a coherent and interpretable judgment, overcoming the recurrent limitations of statistical, and fixed-threshold models, especially in contexts where sensors present latency, intermittent failures, or divergence among measurements.

The system represents a relevant scientific contribution by explicitly formalizing a robust reasoning mechanism for inconsistent, contradictory, and imprecise data, which is an essential characteristic in connected agricultural systems. By applying temporal weighting mechanisms, the system offers stable and explainable inferences, an aspect that is still little explored in decision systems aimed at agriculture/livestock, which traditionally lack logical transparency and remain vulnerable when confronted with contradictions.

From a technological point of view, the artifact has consolidated itself as a frugal, scalable, and low-cost solution. The simplified architecture reduces access barriers and favors adoption by small and medium-sized producers, a demographic that is frequently excluded from more complex and costly automation technologies. Furthermore, the system makes the environmental classification explicit and identifies the variables responsible for the result, expanding operational reliability and favoring more precise preventive decisions regarding heat stress control and the reduction of productive losses.

The research, however, presents limitations. The validation focused on simulated environments, covering neither real microclimatic variability nor quantitative comparisons with existing solutions. Furthermore, manual data entry may introduce operational variability, and the absence of native integration with IoT restricts the capacity for continuous monitoring. Such limitations do not compromise the conceptual soundness of the model but indicate that its maturation requires applied studies, dynamic calibration, and performance evaluations under real field conditions.

As future directions, the following are recommended: (i) the integration of Parabroiler with on line IoT sensors for automatic collection; (ii) the evaluation of the model in commercial farms, comparing its inferences with specialists and zootechnical performance indicators; (iii) the expansion of the logic for automated or semi-automated recommendations, moving the system closer to an intelligent controller; and (iv) the extension of the logical framework to other productive chains, such as swine farming, dairy farming, fish farming, and environmental monitoring in agricultural greenhouses. (v) Additional research may also explore integration with physical ventilation models, expanding the robustness and autonomy of the system.

Therefore, **Parabroiler** demonstrates that Logic $E\tau$ models constitute a consistent alternative for the development of efficient, resilient, and accessible environmental classifiers in precision agriculture. The integration between mathematical rigor and operational simplicity positions the system strategically, paving the way for future applications of Logic $E\tau$ in intelligent technologies for agribusiness.

6 Acknowledgements

This study was partially financed and supported by CAPES – Grant 88887.940472/2024-00

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5.4 Cross-Study Discussion

This dissertation established the primary objective of developing a Paraconsistent Expert System for environmental monitoring in poultry houses using Logic Eτ. The central justification for this objective is grounded in the limitation of conventional analysis methods, based on binary classical logic, to address the complexity and imperfect nature of environmental data collected by sensors in poultry houses. These data frequently present inconsistencies, inaccuracies, and instances of incompleteness. Logic Eτ is considered well-suited for this scenario as it allows the formal processing of contradictory evidence without compromising inferential coherence and enables the attribution of degrees of confidence to decisions.

The first stage of the research, presented in the article "Smart Technologies in Poultry Production: Trends and Innovations" and corresponding to SO1, conducted a systematic literature review and a bibliometric analysis. This study identified the main trends in Precision Poultry Farming and confirmed that technologies such as IoT and Artificial Intelligence, including Machine Learning and Deep Learning, are fundamental to the sector. However, it was found that the low quality of data generated by sensors, influenced by abrupt fluctuations, equipment failures, dust accumulation, and synchronization mismatches, compromises the direct applicability of these technologies. Obstacles related to high implementation costs and the need for robust infrastructure were also identified, factors that hinder the adoption of advanced solutions by small and medium-sized producers. Furthermore, the study revealed a gap in the literature regarding the use of non-classical logics, such as Logic Eτ, to handle environmental data inconsistencies in a structured manner. This result reinforced the relevance of developing a model based on Logic Eτ, which aligned with SO2, since traditional statistical approaches and classical logic do not adequately address this type of problem.

The second article addressed SO2 and presented the development of the system's logical model. This model introduces the possibility of simultaneously representing favorable and contrary evidence through annotations and incorporates an exponential confidence decay function that adjusts the temporal validity of measurements. This mechanism considers that, in environments with rapidly changing dynamics, older measurements should carry lower inferential weight, thereby allowing for a more accurate representation of the current state of the environment. Robustness tests with controlled perturbations demonstrated that the model maintains logical coherence even under noise. A relevant result was the identification of differentiated sensitivity among environmental variables. Experiments showed that certain variables exhibited a greater impact on inferences when perturbed, indicating the necessity of calibrating specific thresholds according to the zootechnical importance of each variable.

The analysis of the position of inferences within the USCP demonstrated that, under normal operating conditions, conclusions frequently cluster in the quasi-paracomplete region, particularly in poultry houses BH and DH. This indicates that, even without explicit contradictions, many situations present insufficient evidence for highly reliable decisions.

This behavior highlights the relevance of Logic Eτ by enabling the identification and quantification of uncertainties that would be disregarded by classical logic, which tends to reduce the absence of evidence to a condition of falsehood.

The third article, corresponding to SO3, presented the development and practical demonstration of the functional artifact, the Parabroiler application. The system was implemented using a low-cost, scalable architecture compatible with no-code platforms and cloud services, directly addressing the limitations identified in SO1. This approach enables expanded access to decision support technologies in farms with limited technological resources.

Parabroiler stands out for its capability to process inconsistent, incomplete, and contradictory data. In addition to classifying the environment into categories such as "Excellent" or "Critical," the system indicates which variables influenced the decision and to what intensity.

This transparency allows the user to understand the origin of each classification and facilitates precise interventions in environmental management.

The integration of results obtained across the three studies confirms the suitability of the approaches and methodology adopted to address the problem proposed in this dissertation. Each stage of the process fulfilled a specific and complementary role: the first study characterized the context and highlighted real challenges in poultry environmental monitoring; the second presented the logical structure capable of responding to these limitations; and the third demonstrated the practical viability of the solution by implementing it in a functional artifact.

This progressive articulation evidences that the model based on Logic Eτ offers a consistent alternative for managing uncertainties and variations in environmental data, while the implementation of the artifact demonstrates that this approach can be applied in a simple and accessible manner. The convergence between diagnosis, logical foundation, and practical application reinforces that the proposed solution meets the general objective of the research and presents itself as a promising path for decision support systems in rural environments operating under infrastructure constraints.

In general, the implications of this integration point to the potential of Logic Eτ as a foundation for intelligent technologies in agribusiness and show that formal methods, when allied with accessible architectures, can significantly expand the reach and utility of environmental monitoring systems.

5.5 Contributions

From a scientific perspective, this dissertation proposes and validates a novel theoretical-methodological model for environmental control in productive environments, grounded in Paraconsistent Annotated Evidential Logic Eτ and applied to Precision Poultry Farming. This application expands the field of study of non-classical logics in decision support systems and fills a gap in the literature regarding the use of logical-evidential structures to treat environmental information subject to uncertainty. Logic Eτ proves capable of formally handling contradictory, incomplete, and imprecise data, allowing for the controlled coexistence of favorable (μ) and unfavorable (λ) evidence without logical collapse. This results in more consistent environmental assessments compared to approaches based on fixed thresholds or statistical averages, especially in scenarios with noise, sensor failures, or reading desynchronization. Additionally, the incorporation of a temporal confidence decay mechanism, modeled by an exponential decay function, updates the validity of measurements according to environmental dynamics and prioritizes more recent information in contexts of rapid data obsolescence, such as poultry houses. Finally, the use of the Unit Square of the Cartesian Plane as an instrument for representing inferences confers transparency and explainability to the model, allowing each classification to be accompanied by explicit logical justifications and consolidating an explainable approach to logical-evidential reasoning in the agricultural sector.

In the practical and technological realm, the primary materialization of these contributions is the development and registration, with the *National Institute of Industrial Property* (INPI), of *Parabroiler*, a functional decision support system aimed at environmental monitoring in poultry houses. This artifact converts complex environmental variables, such as temperature, humidity, ventilation, and concentrations of CO_2 and NH_3, into operational information synthesized in classifications such as "Excellent" or "Critical," accompanied by management recommendations that support rapid and well-founded interventions. The system was conceived with a frugal architecture based on no-code/low-code platforms and simplified cloud infrastructure, reducing implementation and maintenance costs and making the solution accessible to producers facing connectivity and financial resource limitations. The research further demonstrates the logical, mathematical, and operational viability of the model in different types of poultry houses, such as *Blue House*, *Dark House*, and *Solid Wall*, evidencing its potential for adaptation to distinct productive contexts and its replicability for other precision agriculture chains, such as fish farming, swine farming, or agricultural greenhouses. By providing robust inferences in a timely manner, Parabroiler contributes directly to optimizing operational efficiency, reducing losses associated with heat stress and respiratory problems, and improving bird welfare, thereby bridging the gap between paraconsistent logic and daily field management practices.

From a social, socioeconomic, and sustainability perspective, the proposed solution reinforces the strategic role of poultry farming in food security by promoting more stable, efficient, and safe production, mitigating losses resulting from inadequate environmental conditions, and strengthening the resilience of the production chain. The model aligns with several UN Sustainable Development Goals (SDGs), notably SDG 2, by favoring more productive and sustainable agriculture; SDG 9, by encouraging the incorporation of intelligent and digital systems in a traditional sector; and SDG 12, by contributing to responsible consumption and production through the optimized use of natural resources, such as energy and water, in poultry management. The adoption of a low-cost, highly accessible architecture favors the democratization of access to technology, expanding digital inclusion in rural areas and empowering small and medium-sized producers to adopt smarter management practices based on data and more rigorous environmental criteria. By combining logical rigor, technological applicability, and social impact, this dissertation offers an integrated contribution to responsible innovation in Precision Poultry Farming.

5.6 Limitations

The limitations of this research stem primarily from the exploratory nature and proof-of-concept status of Parabroiler in applying Logic Eτ to environmental monitoring in poultry houses. The validation focused on the logical robustness and functional demonstration of the model, seeking to establish its theoretical, computational, and conceptual foundations.

However, it does not yet include large-scale empirical tests in commercial farms or systematic performance analyses, such as response time metrics or accuracy comparisons with statistical systems or existing commercial platforms.

The dataset utilized for validation was collected in 2013 and does not encompass extreme events, which limits the evaluation of the model's behavior in critical situations, such as severe equipment failures, extreme climatic variations, or sudden environmental shifts resulting from disease outbreak.

Another relevant limitation is associated with the absence of labeled data, which precluded supervised validation and restricted the direct comparison of Parabroiler's predictive performance relative to other models.

Environmental classification thresholds were defined based on preliminary studies and available technical literature without finer calibration anchored in large annotated databases. This suggests a need for contextual adjustments according to the type of poultry house and the operational relevance of each environmental variable.

On the operational level, the current version of the system requires manual data entry, lacks native integration with sensors and IoT networks, and does not perform automatic equipment control. This limits continuous monitoring and fully autonomous field operation. In more complex scenarios, the utilization of the system must therefore be complemented by specialized technical evaluation. These limitations, typical of studies in the proof-of-concept phase within the scope of Design Science Research, indicate clear paths for future work. These include expanding databases, obtaining reference labels, refining the calibration of inferential parameters, integrating with IoT infrastructure, and evolving toward more automated modes of operation.

CHAPTER VI

6 FINAL CONSIDERATIONS

This dissertation investigated how an expert system based on Paraconsistent Annotated Evidential Logic Eτ can support environmental monitoring and decision-making in broiler production. The starting point was the problem of high variability in environmental conditions within poultry houses and the low quality of sensor data, which is often inconsistent, incomplete, or imprecise. In such situations, classical logic proves limited in adequately representing reality and supporting reliable decisions.

Based on the Design Science Research methodology, the work was structured into three integrated stages. Initially, a diagnosis of the state of the art regarding intelligent technologies in poultry farming was conducted through a systematic and bibliometric review, allowing for the mapping of trends, challenges, and gaps. Subsequently, a logical model based on Logic Eτ, was developed, aimed at the qualitative classification of environmental conditions under uncertainty. Finally, this model was operationalized in the computational artifact Parabroiler, a functional decision support system for Precision Poultry Farming.

In response to the research question, the results indicate that an expert system based on Logic Eτ can contribute to the optimization of broiler production by formally processing conflicting, incomplete, and imprecise data without logical collapse, maintaining inferential coherence even in the presence of divergent information. Furthermore, the model produces environmental classifications grounded in degrees of evidence and their position in the Unit Square of the Cartesian Plane, which enables the tracking of each decision back to the informational configuration that originated it. By translating complex environmental information into simple operational categories accompanied by management recommendations, the system facilitates faster and well-founded interventions in the production environment, with positive reflections on animal welfare and productive efficiency.

The general objective of developing a Paraconsistent Expert System for environmental monitoring in poultry houses was achieved through the construction of the Logic Eτ model and its implementation in Parabroiler. The specific objectives were also addressed: the systematic and bibliometric review enabled the identification of trends, challenges, and the absence of non-classical logical approaches applied to Precision Poultry Farming; the proposed logical model proved capable of qualitatively classifying variables such as temperature, humidity, air velocity, CO_2 and NH_3 in uncertainty scenarios; and the development, demonstration, and

registration of Parabroiler consolidated these results into a functional system accessible to producers and researchers.
The contributions of this research can be synthesized into three main dimensions. On the scientific level, the dissertation expands the application of Logic Eτ in decision support systems for productive environments, demonstrating its viability in the environmental control of poultry houses and its capacity to provide consistent classifications even in the face of uncertainties.

On the technological level, Parabroiler materializes this model in a low-cost architecture based on accessible technologies, bridging advanced logical models with daily environmental management practices. On the socioeconomic and sustainability level, the proposed solution favors more efficient resource use, contributes to reducing losses associated with heat stress and respiratory problems, and supports the improvement of bird welfare, with significant adoption potential for small and medium-sized producers.

The limitations of the study stem primarily from its proof-of-concept nature. The validation of the model and system utilized a finite and unlabeled dataset without coverage of extreme environmental events. Additionally, classification thresholds were defined based on literature and preliminary analyses, which restricts the generalization of results. Furthermore, the current version of Parabroiler requires manual entry of measurements and is not yet integrated into IoT infrastructures or automatic equipment control, limiting its operation in a fully autonomous mode. Such limitations do not compromise the logical and conceptual validity of the model, but they delimit the scope of application and point to the need for additional studies to expand and deepen the proposal.

6.1 Future Works

Based on the identified limitations and the viability demonstrated by Logic Eτ, future works aim to advance Parabroiler from a proof-of-concept to a robust and automated operational system. The priorities are to integrate the model with IoT sensors for automatic collection and continuous monitoring, eliminate manual data entry, and connect it to embedded systems, mobile applications, and cloud platforms. This will enable not only real-time environmental classification but also support for automated or semi-automated actions regarding equipment, in addition to centralizing and comparing data from different production units. In this process, it is anticipated that the set of monitored variables will be expanded (including luminosity, noise, and suspended particles) and that integration with physical ventilation models will be explored to enhance the robustness of environmental control.

Another important axis involves methodological refinement and validation under real production conditions. Studies in commercial farms are necessary to compare Parabroiler classifications with expert decisions and zootechnical indicators, as well as to utilize new databases that encompass extreme events. Classification thresholds and inferential parameters must be refined and adjusted to different poultry house types, climates, and management practices, ensuring recommendations that are more suitable to each producer's context. The logical framework can also be replicated in other precision agriculture chains, such as swine farming, fish farming, and greenhouse horticulture, provided that more intuitive dashboards and interfaces are developed and validated with producers possessing varying levels of technological familiarity. In a subsequent stage, integration with generative Artificial Intelligence models could support automatic and personalized corrective recommendations, expanding the system's role from an essentially diagnostic tool to a more prescriptive support for decision-making.

6.2 Final Thoughts

It is concluded that this research achieved its main objectives with consistency, originality, and scientific relevance by proposing and validating an innovative logical approach for environmental monitoring in poultry production systems. The application of Paraconsistent Annotated Evidential Logic Eτ proved not only viable but particularly suitable for contexts of high informational complexity, favoring safer, more efficient, and sustainable decisions.

The developed model and the artifact derived from it contribute significantly to the United Nations Sustainable Development Goals (SDGs), especially SDG 2 (Zero Hunger and Sustainable Agriculture), SDG 9 (Industry, Innovation, and Infrastructure), and SDG 12 (Responsible Consumption and Production). Thus, this dissertation consolidates a consistent theoretical-methodological foundation for the advancement of applied research in Paraconsistent Logic and Agriculture 4.0, establishing itself as a relevant milestone in the development of digital solutions aimed at sustainability, innovation, and animal welfare.

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ANNEXES

Appendix A – INPI Software Registration Certificate

REPÚBLICA FEDERATIVA DO BRASIL
MINISTÉRIO DO DESENVOLVIMENTO, INDÚSTRIA, COMÉRCIO E SERVIÇOS
INSTITUTO NACIONAL DA PROPRIEDADE INDUSTRIAL
DIRETORIA DE PATENTES, PROGRAMAS DE COMPUTADOR E TOPOGRAFIAS DE CIRCUITOS

Certificado de Registro de Programa de Computador

Processo Nº: **BR512025005223-5**

O Instituto Nacional da Propriedade Industrial expede o presente certificado de registro de programa de computador, válido por 50 anos a partir de 1° de janeiro subsequente à data de 28/09/2025, em conformidade com o §2°, art. 2° da Lei 9.609, de 19 de Fevereiro de 1998.

Título: ParaBroiler SISTEMA INTELIGENTE DE CLASSIFICAÇÃO AMBIENTAL PARA AVICULTURA BASEADO NA LÓGICA PARACONSISTENTE ANOTADA EVIDENCIAL Et

Data de publicação: 28/09/2025

Data de criação: 28/05/2025

Titular(es): ASSUPERO ENSINO SUPERIOR LTDA.

Autor(es): JAIR MINORO ABE; LEANDRO CIGANO DE SOUZA THOMAS

Linguagem: PYTHON

Campo de aplicação: AG-10

Tipo de programa: IA-02

Algoritmo hash: OUTROS

Resumo digital hash: 6ad5c4e8cddd034de0a037f269ae5ec3

Expedido em: 28/10/2025

Aprovado por:
Alexandre Gomes Ciancio
Coordenador Geral da COGTI