

A Holistic CPS for Smart Precision Livestock Farming: Multi-Actor Collaborative Decision-Making Across Ecosystem Domains

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Abstract—Precision Livestock Farming (PLF) increasingly relies on integrated technologies to improve animal health, welfare, reproduction, and productivity within a complex ecosystem. However, current approaches often deal with specific use cases, single domain, and remain fragmented, relying on siloed analytics tools and unilateral decision-making. This paper proposes a holistic Cyber-Physical System (CPS) for smart PLF that enables seamless end-to-end processes, spanning several stakeholders' perspectives and farm domains: animals, environment, production, and logistics. The proposed layered and modular architecture leverages adaptive AI capabilities enabling intelligence-driven functionalities within an integrated farm workflow, and supports automated, human-in-the-loop and hybrid modes. Both domain-specific and shared views are provided to foster collaborative decision-making, and control across operations. The CPS capabilities are illustrated through various use cases, highlighting their relevance across different operational settings. By integrating sensing, data, analytics, human perspectives, and collaborative decision-making, the proposed CPS enhances visibility, transparency, and efficiency in livestock management and monitoring.

I. INTRODUCTION

PRECISION Livestock Farming (PLF) increasingly relies on integrated technologies to support farm management and monitoring in order to enhance animal health, welfare, reproduction, and production [1], [2]. In fact, modern PLF systems collect and analyze data from sensors and environmental monitors to provide actionable insights and support real-time decision-making [3], [4]. Despite these developments, PLF systems still face significant challenges among them, the limited collaborative decision support among multiple stakeholders since data access and alert sharing are typically controlled by the farmer or herd manager [5]. Only a few initiatives, such as ClearFarm [6], integrate external stakeholders at the value-chain level, but not at the operational level where

the decision-making remains unilateral and primarily farmer-centered. Although differences in actor perspectives are recognized, existing approaches partially address role-specific views and lack structured processes enabling stakeholders the opportunity to interact, express their viewpoints, validate outcomes, and co-construct decisions [7], [8], [9], [6]. In addition, the PLF ecosystem is addressed partially, and most systems focus on isolated aspects of a specific domain rather than covering multiple domains including animals, environment, infrastructure, production, logistics and supply chain [11]. Furthermore, AI capabilities remain task-specific, addressing particular and fragmented prediction or optimization problems instead of providing scalable and adaptive support for intelligence-driven functionalities [12]. Finally, many initiatives focus narrowly on a single decision-making or control mode while neglecting multilevel autonomy embedding automated, human-in-the-loop and hybrid modes. The coordination between decision-making and command execution processes for the implementation of approved recommendations into concrete tasks also remains largely absent [3], [5]. The fragmented structures of existing PLF systems hinder end-to-end visibility and transparency, restrict the autonomy of specialized actors, and may delay timely responses to health, welfare, reproduction or production issues. To address these challenges, this paper presents a holistic Cyber-Physical System (CPS) for smart PLF ecosystems. Our main contributions include:

- The integration of multiple PLF domains including animals, environment, infrastructure, production, processes and logistics, ensuring comprehensive integration.
- The integration of several stakeholder with various perspectives through domain-specific views, enabling coordinated decision-making across roles.

- A modular and adaptive AI capabilities, tailored to processes' needs in perception, diagnosis, prediction, decision-making and adaptive control, to support system-wide observation, reasoning, action and collaboration functionalities within an integrated farm-scale workflow.
- A modular, multi-level architecture integrating flexible end-to-end workflows supporting automated, human-in-the-loop, and hybrid modes of control and monitoring, while fostering visibility, transparency, and collaboration among stakeholders.

This CPS provides an integrated solution addressing identified challenges in current PLF implementations.

The remainder of this paper is organized as follows. Section II reviews related work on PLF systems and highlights existing challenges. Section III presents the functional and non-functional requirements for smart PLF environments. Section IV describes the proposed holistic CPS architecture, including its layers, modules, and workflows. Section V details the proposed Intelligent and collaborative decision support modules. Section VI presents the compliance with the requirements and illustrative use-cases. Finally, Section VII concludes the paper, summarizes key findings, and outlines insights and directions for future research.

II. RELATED WORKS

A. Multi-Actor Collaboration Limitations

In PLF, multiple actors must collaborate to ensure effective farm management and monitoring efficiency [5]. Some existing approaches enable the sharing of sensor-derived data and welfare indicators, but the collaboration remains informal and lacks structured mechanisms and decision support architectures, limiting coordinated decision-making [9]. ClearFarm Project [6] emphasizes multi-actor co-design at the value-chain level, but operational roles such as veterinarians, nutritionists, and maintenance staff are not formally integrated, and some interactions still rely on the farmer as intermediary and unilateral decision-maker. Consequently, stakeholders' key expertise is not taken into account and their proposals are not coordinated, leading to delayed, inconsistent, or conflicting on-farm decisions [7].

B. Multi-View and Multi-Perspective Integration

Current PLF systems provide dashboards for monitoring farm indicators, allowing actors to interpret situations according to their roles. However, these views are generally isolated, limiting sharing of variety of perspectives and experiences [9]. The ClearFarm Project [6] illustrates harmonized data sharing at the value-chain level and emphasizes combining perspectives for decision-making. Nevertheless, the operational multi-view integration on the farm has not been addressed yet. The involved actors have distinct perceptions and priorities regarding the same situation, depending on a variety of factors such as risk and trust in technology [7], [13]. Different users assume distinct roles in collaborative decision-support systems, which require both role specific and shared interfaces to ensure expertise, visibility, transparency and coordination [14]. Thus,

capturing and managing multi-views and multi-perspectives remains a challenge for informed decision-making.

C. Partial Integration Across Farm Domains

Most existing decision-support systems in PLF focus on isolated domains, such as animal health, welfare, or production, without integrating data across animals, environment, infrastructure, production, logistics, and supply chain processes [11]. This siloed approach can lead to conflicting and/or non-actionable decisions, thus limiting holistic coordination, management and monitoring efficiently livestock operations. For example, a PLF alert detects a health problem in a cow. The veterinarian validates an immediate change in treatment. When logistics providers receive the order, they report that they cannot fulfill the request. Effective coordination between actors in the animal and the logistics domains could have reduced delays and enabled a single, consistent, and immediately applicable decision. Although IoT-based sensing systems enable domain-level data collection in livestock environments, these solutions remain fragmented and are deployed separately within each domain [26], [27], [28].

D. AI Capabilities in Precision Livestock Farming

AI techniques have been widely applied for behavior recognition [15], [16], health monitoring [9], [10], lameness detection [23], estrus detection [24], disease and stress discrimination [25] and welfare assessment [17]. In [12], the authors present a comprehensive overview of AI approaches. In this context, AI applications are typically developed for each emerging need as isolated, task-specific solutions that are not designed as modular and adaptive components integrated into a farm-wide workflow. Furthermore, adaptive control and learning, whereby outcomes are fed back to refine models, remain largely unexplored, particularly in terms of mechanisms and continuous workflow.

E. Multi-Level Autonomy and Command Execution

Some PLF systems enable automated actions, such as feeding or environmental control adjustments, but these are generally confined to isolated subsystems [3], [5]. Existing work rarely considers multi-level autonomy across automated, human-in-the-loop and hybrid decision-making and control modes, and often overlooks execution, leading to a gap between recommendations and their implementation.

F. Cyber-Physical System Integration

Research on cyber-physical systems in PLF has mainly addressed the integration of sensing, computation, and control to support decision-making [18]. However, related CPS are often limited to isolated applications or subsystems related to a single domain, and comprehensive workflows spanning all farm operations are still largely absent [9], [19]. Prototype systems combining AI and modular sensors have been developed for applications such as rumen monitoring in dairy cows. Unfortunately, multi-actor collaboration and human-in-the-loop integration remain rare [20]. Overall, these studies

illustrate that current CPS are fragmented and that holistic, end-to-end workflows across PLF domains have not yet been implemented [9], [19].

III. CPS REQUIREMENTS FOR SMART PLF ENVIRONMENTS

This section presents the functional (**RQ1** to **RQ14**) and non-functional (**RQ15** to **RQ17**) requirements of the CPS architecture for smart PLF environments. These requirements are derived from Section II, with traceability to the corresponding subsections (§) and references in the related work.

RQ1 The system shall integrate several domains within a smart PLF ecosystem (§ II-C [11], § II-F [19]).

RQ2 The system shall support cross-domain stakeholders with diverse roles and expertise through human-in-the-loop and bidirectional interactions for action execution and system feedback (§ II-A [5], [7], [8], § II-B [14]).

RQ3 Users will be able to interact with a dedicated dashboard to support continuous performance monitoring through KPI-based visualizations and feedback loops (§ II-B [9], [14]).

RQ4 Users will be able to interact with a dedicated dashboard to manage, monitor and track system alerts in real time (§ II-B [9], [10]).

RQ5 The system shall provide a dedicated dashboard enabling stakeholders to access specific and shared interfaces to express viewpoints, share recommendations, and collaboratively validate decisions under operational constraints (§ II-A [7], § II-B [6], [14]).

RQ6 The system shall provide a configuration dashboard enabling actors to manage system-wide parameters and interact bidirectionally with system feedback (§ II-A [5], § II-B [9], § II-D [12], § II-F [18]).

RQ7 The system shall generate alerts related to performance, real-time system status, AI, execution, and human/decision-related dimensions (§ II-D [10], [23], [24], [25]).

RQ8 The system shall provide a data acquisition capability across all ecosystem domains with real-time transmission of collected data and/or information (§ II-C [26], [27], [28]).

RQ9 The system shall support transforming raw data, storing results for historical tracking and traceability, accessing AI models, and distributing processed data to relevant system modules (§ II-D [12], § II-F [19]).

RQ10 The system shall provide AI-driven perception, diagnosis, prediction, decision optimization, and adaptive control and learning using data-driven methods, supporting performance monitoring, alert generation, decision-making, and AI agent functions as needed (§ II-D [15], [16], [17]).

RQ11 The system shall provide decision support using contextual analysis and multi-source data fusion, generating consistent decision proposals and shared views, triggered by alerts or user requests (§ II-A [5], § II-B [13]).

RQ12 The system shall support decision-making and control processes in automated, AI-assisted, human-operated, and hybrid modes, triggered by system alerts or user requests (§ II-E [3], § II-E [20]).

RQ13 The system shall support multi-level autonomy in

command execution, enabling automated, manual, and hybrid execution of system commands depending on operational constraints (§ II-E [3], § II-F [19]).

RQ14 The system shall incorporate execution feedback to ensure consistency, alignment, and continuous improvement across system operations, with feedback propagated to the originating components (§ II-C [2], [3], [9], § II-D [12]).

RQ15 The system shall ensure end-to-end traceability and consistency across data, decision, control, execution, and human interaction flows (§ II-C [11], § II-F [19]).

RQ16 The system shall adopt a modular architecture to support flexibility and scalability, with clearly defined interactions between components (§ II-C [4], [28], § II-F [19]).

RQ17 The system architecture shall support applicability across different PLF systems without being constrained to a specific operational setting (§ II-C [11], § II-F [19]).

IV. PROPOSED CPS ARCHITECTURE

The proposed CPS architecture consists of a human layer, a physical layer, a communication layer, and three cyber layers.

A. Human Layer

It represents stakeholders interacting with the CPS through dashboards and the PLF ecosystem, contributing to collaborative decision-making. Key actors include veterinarians (animal health and welfare), farm managers (farm operations and resource coordination), nutritionists (animal nutrition), reproduction specialists (animal reproduction), technicians (CPS infrastructure and maintenance), data analysts (AI and data analytics), agricultural consultants (technical expertise and innovation support), regulatory inspectors (compliance and certification), and supply chain representatives (quality and logistics). Each actor accesses role-specific information to contribute to, validate, and refine system decisions.

B. Physical Layer

It encompasses animals, sensors, actuators, physical environments, infrastructure, production, and logistics within the PLF ecosystem. It includes four main domains[9]:

- *Animals*: focuses on health, welfare, growth, and reproduction using wearable sensors (heart rate, accelerometers, rumination), biosensors (temperature, pH), computer vision [24], [25], and RFID for identification and tracking. Actuators support automated feeding and precision treatment delivery, enabling closed-loop decision-making.
- *Environment & Infrastructure*: covers housing and operational conditions monitored via temperature and humidity sensors, with actuators for ventilation, heating, and lighting control to ensure welfare and efficiency [26].
- *Production & Processes*: includes sensors for milking (yield, conductivity), feed intake, motion, and weighing [27], with actuators such as robotic milking, precision feeding, automated sorting, and herd routing for workflow automation.
- *Logistics & Supply Chain*: relies on GPS, RFID/barcodes, and cold-chain sensors, with actuators for automated

refrigeration and smart routing to ensure traceability and optimized logistics.

C. Communication Layer

Positioned between the Physical and Data Treatment & Storage Layers, it connects sensing/actuation components to data processing modules via networks, IoT protocols, and transmission infrastructures [28]. It transmits: (i) Sensor data from the Physical Layer to the Data Treatment & Storage Layer. (ii) Control commands/feedback in the opposite direction to actuators. This bidirectional exchange enables continuous interaction between the physical and cyber systems. It ensures reliable, secure transmission using standardized protocols (MQTT, CoAP, HTTP), maintaining synchronization and data integrity for real-time decision-making and system coordination.

D. Cyber Layer

It consists of three layers. The Data Treatment & Storage Layer handles data collection, preprocessing, and storage of structured and historical data, including AI models. The Intelligent Decision and Control Layer provides AI-driven analytics, generating alerts, decisions, and control commands for both automated and human-in-the-loop operation. The Application Layer offers dashboards for monitoring, visualization, KPI tracking, alerts, and collaborative decision-making. Table I summarizes the modules and their functions across these layers.

E. CPS layers, modules and flows

Figure 1a illustrates the proposed layered CPS architecture, its modules, and the exchanged flows between components, while Figure 1b details these interactions. The architecture integrates perception, data processing, decision-making, and execution within a generic framework supporting human-in-the-loop collaboration and AI deployment across multiple application domains. Its generic, extensible design ensures coherent cross-layer information flows while remaining independent of any specific application context.

V. INTELLIGENT AND COLLABORATIVE DECISION SUPPORT MODULES AND WORKFLOWS

A. AI Core Module: Capabilities and Macro-Functions

We propose an AI Core Module that provides modular, adaptive, and context-aware AI capabilities for anomaly detection, alert generation, information aggregation and analysis, decision support, collaboration, operational control, decision-to-command translation, and system performance monitoring. These capabilities enable system-wide observation, reasoning, and action across multiple use cases, including key AI macro-functions such as:

- *Perception*: infers animal behavior, physiological indicators, and environmental conditions from multimodal sensor and system data.
- *Diagnosis*: identifies anomalies, deviations, and root causes.

- *Prediction*: anticipates risks, events, and performance degradation.
- *Decision & Optimization*: generates recommendations and constructs actor views, while fusing information, resolving conflicts, and prioritizing optimal actions.
- *Adaptive Control & Learning*: continuously updates models and control strategies to address data drift, model decay, and performance degradation.

B. Alert generation

The CPS generates multi-source alerts indicating abnormal or anticipated conditions derived from raw and processed data, AI inferences, operational decisions, and manual observations. Alerts are defined across domains, including animal health and welfare (e.g., lameness, estrus, disease detection [23], [25]), environment and infrastructure (e.g., thermal stress, air quality, ventilation issues [26]), production and processes (e.g., milk quality changes, production drops, feeding or milking disruptions [27]), logistics and supply chain (e.g., delivery delays, stock shortages), and system-level issues (e.g., sensor failures, communication loss, AI degradation). AI can be used for alert generation, such as predictive risk detection, early warning signals, cross-domain correlation, operational optimization, and strategic or economic impact assessment [29]. The alert life cycle begins when an issue is detected through sensors, KPIs, system events, or AI outputs. It is then validated against historical data and domain rules to reduce false positives, before triggering AI-driven or rule-based actions. The cycle ends with resolution once normal conditions are restored, while persistent or worsening issues may be escalated for further analysis.

C. Decision-Making Module: Intelligent Operational Support

We propose a Decision-Making Module (DMM) including the following key functionalities:

- *Contextual Analysis and Recommendation Generation*: produces contextual recommendations from predictive models and analytics, enabling actor review and validation.
- *System-wide and Actor-specific Fusion*: fuses CPS and actor inputs to generate coherent, actionable proposals. Fusion occurs at three levels: automatic fusion for rule-based routine events; AI-assisted fusion for complex cases using ML, ensembles, or consensus methods; and hybrid fusion, where actors refine or adjust outputs using contextual knowledge and constraints. Methods to support information fusion include rule-based aggregation, MCDA (AHP, TOPSIS, VIKOR), outranking (ELECTRE), and fuzzy/probabilistic approaches [22].
- *Multi-Actor, Multi-Perspective, and Shared Views Generation*: generates actor-specific and shared views by integrating CPS and actor inputs into a coherent system-wide representation, supporting coordinated decision-making through aggregated recommendations, fused inputs, and proposed actions. It interprets events, scores, and recom-

TABLE I: Functional overview of Cyber Layer modules in the proposed CPS architecture.

Cyber Layer	Modules	Function(s)
Data Treatment & Storage Layer	Data Processing & Integration	Collects, cleans, and integrates data from multiple sources (sensors, systems, actors).
	Data Storage (Databases)	Stores structured, historical, and contextual data for analysis, traceability, and learning.
	AI Models Repository	Stores trained AI models and makes them available for inference and updates.
Intelligent Decision & Control Layer	AI Core Module	Provides adaptive, data-driven intelligence that supports perception, diagnosis, prediction, decision-making, optimization, and learning processes. Delivers actionable insights to enable intelligence and advanced functionalities across intelligent modules.
	Alert Generator	Detects anomalies or threshold violations and generates alerts. Classifies alerts into automatic or decision-required.
	Decision-Making Module	Serves as the core component for making decisions by analyzing heterogeneous data from users and other modules, providing recommendations, and preparing validated decisions for execution to the Command Generator.
	Automated Systems/AI Agents	Translates validated decisions or automatic alerts into executable commands for actuators or operational actions. Manages execution logic.
	Command Generator	Translates validated decisions or automatic alerts into executable commands for actuators or operational actions. Manages execution logic.
Application Layer	Performance & KPI Dashboard	Calculates performance indicators for system monitoring and performance tracking, and supports two-way interaction with actors to adjust views, filter data, or provide feedback.
	Alerts Dashboard	Displays alerts, allows actors to create, acknowledge, deactivate, or prioritize alerts, and provides situational awareness. Supports two-way interaction between actors and the dashboard for alert management and response.
	Collaborative Decision Dashboard	Provides actors with personalized views of system recommendations and a shared space to view peers' proposals, submit, validate, or adjust decisions, enabling two-way interaction between actors and the system.
	Configuration & Roles Dashboard	Allows actors to define system parameters (thresholds, AI models, rules, priorities) applied across all modules, and supports two-way interaction to view current settings, adjust parameters, and receive system feedback.

mendations from multiple actor perspectives to produce coherent, domain-informed proposals.

- *Decision Consolidation and Prioritization*: consolidates validated recommendations into final decisions and supports automatic, human, or hybrid decision-making, while prioritizing actions under operational constraints for command execution.
- *AI-Driven Intelligence*: the DMM interacts with the AI Core Module to enable adaptive, context-aware reasoning, improving information integration and decision support. It also enables predictive analytics and machine learning to enhance decision quality and responsiveness.

D. Alert-Driven Collaborative Decision Workflow

This section presents the Collaborative Decision Dashboard through an alert-driven workflow, illustrating how multiple actors interact and how shared decision support facilitates coordination and prioritization. The workflow represents a specific decision scenario, while additional use case-driven workflows are presented in the following section.

- 1) *Alert Generation*: The system generates and distributes alerts to the DMM and relevant actors.
- 2) *Collaborative interaction and validation*:
 - The Collaborative Dashboard displays actor-specific and shared views from the DMM, providing system recommendations and aggregated proposals;

- Actors provide recommendations, feedback, and adjustments based on their domain perspective;
- The dashboard enables requests for additional analyses, scenario exploration, and alternative evaluations;
- The dashboard supports coordination, integration of perspectives, and validation of recommendations to produce coherent decisions.

- 3) *Decision preparation & Command execution*: The DMM prepares validated decisions and transmits them to the Command Generator or automated CPS systems for execution.
- 4) *Feedback loop*: Feedback from execution is processed to update system modules (command generator, AI agents, decision-making module, alert generator, and dashboards) and stored as system state data.

VI. REQUIREMENT COMPLIANCE & USE CASE-DRIVEN WORKFLOWS

This section presents the compliance of the proposed holistic CPS architecture with the requirements defined in Section III. Use case-driven workflows are introduced to illustrate its application in different operational scenarios, highlighting the end-to-end system behavior. The satisfaction of all requirements is demonstrated through the illustrations and details provided in Table II.

TABLE II: Requirement compliance & use case-driven workflows.

Requirement Compliance and use cases	
RQ1	The Physical Layer corresponds to the PLF ecosystem, composed of four domains (see Section IV-B). · [Ecosystem - Sensors] → (1) → [Communication Layer] · [Ecosystem] → (25) → [Human Layer-Actors] → (24) → [Ecosystem] · [Command Generator] → (13) → [Communication Layer] → (13) → [Actuators-Ecosystem] → (14) → [Communication Layer] → (14) → [Command Generator]
RQ2	The Human Layer integrates multiple stakeholders. Their roles, domains, and actions are defined in Section IV-A Bidirectional interactions: (5; 5b), (10;11), (18;19) and (24;25).
RQ3	[Human Layer-Actors] → (21) → [Performance & KPI Dashboard] → (22) → [Human Layer-Actors]
RQ4	[Human Layer-Actors] → (5b) → [Alerts Dashboard] → (5) → [Human Layer-Actors]
RQ5	[Human Layer-Actors] → (11) → [Collaborative Decision Dashboard] → (10) → [Human Layer-Actors]
RQ6	[Human Layer-Actors] → (19) → [Configuration & Roles Dashboard] → (18) → [Human Layer-Actors]
RQ7	The Alert Generator module processes multi-source data originating from various system modules and actors (see Section V-B). · [Human Layer-Actors] → (5b) → [Alert Generator] · [Performance & KPI Dashboard] → (5c) → [Alert Generator] · [Data Treatment & Storage Layer (real-time event streams)] → (5a) → [Alert Generator] · [Data Treatment & Storage Layer (complex events)] → (3) → [Alert Generator] · [AI Core Module] → (7) → [Alert Generator] · [DMM] → (16) → [Alert Generator]
RQ8	· Sensor-based: [Ecosystem - Sensors] → (1) → [Communication Layer] → (2) → [Data Treatment & Storage Layer] · Human-based: [Ecosystem] → (25) → [Human Layer-Actors] → (11) → [DMM] · Human-based: [Ecosystem] → (25) → [Human Layer-Actors] → (5b) → [Alerts Dashboards]
RQ9	· Raw data transformation: [Ecosystem - Sensors] → (1) → [Communication Layer] → (2) → [Data Processing & Integration] · Results storage: [Intelligent Decision & Control Layer] → (22) → [Data Storage (Databases)] · Results storage: [Performance & KPI Dashboard] → (23) → [Data Storage (Databases)] · AI models access: [AI Models Repository] → (3a) → [AI Core Module] · Processed data distribution: 3b, 3, 5a
RQ10	The AI Core Module, supported by AI models stored in the Data Layer, consists of five components covering perception, diagnosis, prediction, decision-making/optimization, and adaptive control/learning (see Section V-A). · AI performance requests and responses: [Performance & KPI Dashboard] → (6a) → [AI Core Module] → (7a) → [Performance & KPI Dashboard] · Alert requests and responses: [Alert Generator] → (6) → [AI Core Module] → (7) → [Alert Generator] · AI Decision requests and responses: [DMM] → (6) → [AI Core Module] → (7) → [DMM] · AI Agents requests: [Automated Systems/AI Agents] → (6) → [AI Core Module] → (7) → [Automated Systems/AI Agents]
RQ11	· [Alert Generator] → (9) → [DMM] → (10) → ([Collaborative Decision Dashboard],[Actors]) → (11) → [DMM] · [Actors] → [Collaborative Decision Dashboard] → (11) → [DMM] → (10) → ([Collaborative Decision Dashboard],[Actors]) → (11) → [DMM] The loop (10-11) is repeated iteratively until validation is achieved.
RQ12	· Automatic mode : [Alert Generator] → (9) → [DMM] · AI-assisted mode : [Alert Generator] → (9) → [DMM] → (6) → [AI Core Module] → (7) → [DMM] · Human mode : [Alert Generator] → (9) → [DMM] → (10) → ([Collaborative Decision Dashboard],[Actors]) → (11) → [DMM] · Hybrid mode : [Alert Generator] → (9) → [DMM] → (6) → [AI Core Module] → (7) → [DMM] → (10) → [Collaborative Decision Dashboard] → [Actors] → (11) → [DMM]
RQ13	· Automated Command Execution: [Alert Generator] → (8) → [Automated systems] → (13) → [Actuators] · Human Command Execution: [Alert Generator] → (9) → [DMM] → (10) → ([Collaborative Decision Dashboard],[Actors]) → (11) → [DMM] → (10) → ([Collaborative Decision Dashboard],[Actors]) → (24) → [Ecosystem] · Code-generated Command Execution: [Alert Generator] → (9) → [DMM] → (10) → ([Collaborative Decision Dashboard],[Actors]) → (11) → [DMM] → (12) → [Command Generator] → (13) → [Actuators] · Hybrid Command Execution: [Alert Generator] → (9) → [DMM] → (10) → ([Collaborative Decision Dashboard],[Actors]) → (11) → [DMM] → (12) → ([Command Generator], [Automated systems]) → (13) → [Actuators]
RQ14	[Ecosystem] → (14) → [Command Generator] → (15) → [DMM] → (16) → [Alert Generator] → (5) → ([Alerts Dashboard],[Actors])
RQ15	Raw data transformation: [Ecosystem - Sensors] → (1) → [Communication Layer] → (2) → [Data Processing & Integration] → (5a) → [Alert Generator] → (9) → [DMM] → (6) → [AI Core Module] → (7) → [DMM] → (10) → ([Collaborative Decision Dashboard],[Actors]) → (11) → [DMM] → (12) → [Command Generator] → (13) → [Ecosystem-Actuators] → (14) → [Command Generator] → ((15) → [DMM] → (16) → [Alert Generator] → (5) → ([Alerts Dashboard],[Actors])) and ((22) → [Data Storage (Databases)])
RQ16	This requirement has been addressed. The system adopts a modular architecture ensuring flexibility and scalability, with clear interactions between components and well-defined data flows (see Figure 1a and Figure 1b).
RQ17	This requirement has been addressed. The system adopts a generic layered CPS architecture not tied to any specific operational setting, ensuring adaptability across diverse PLF environments.

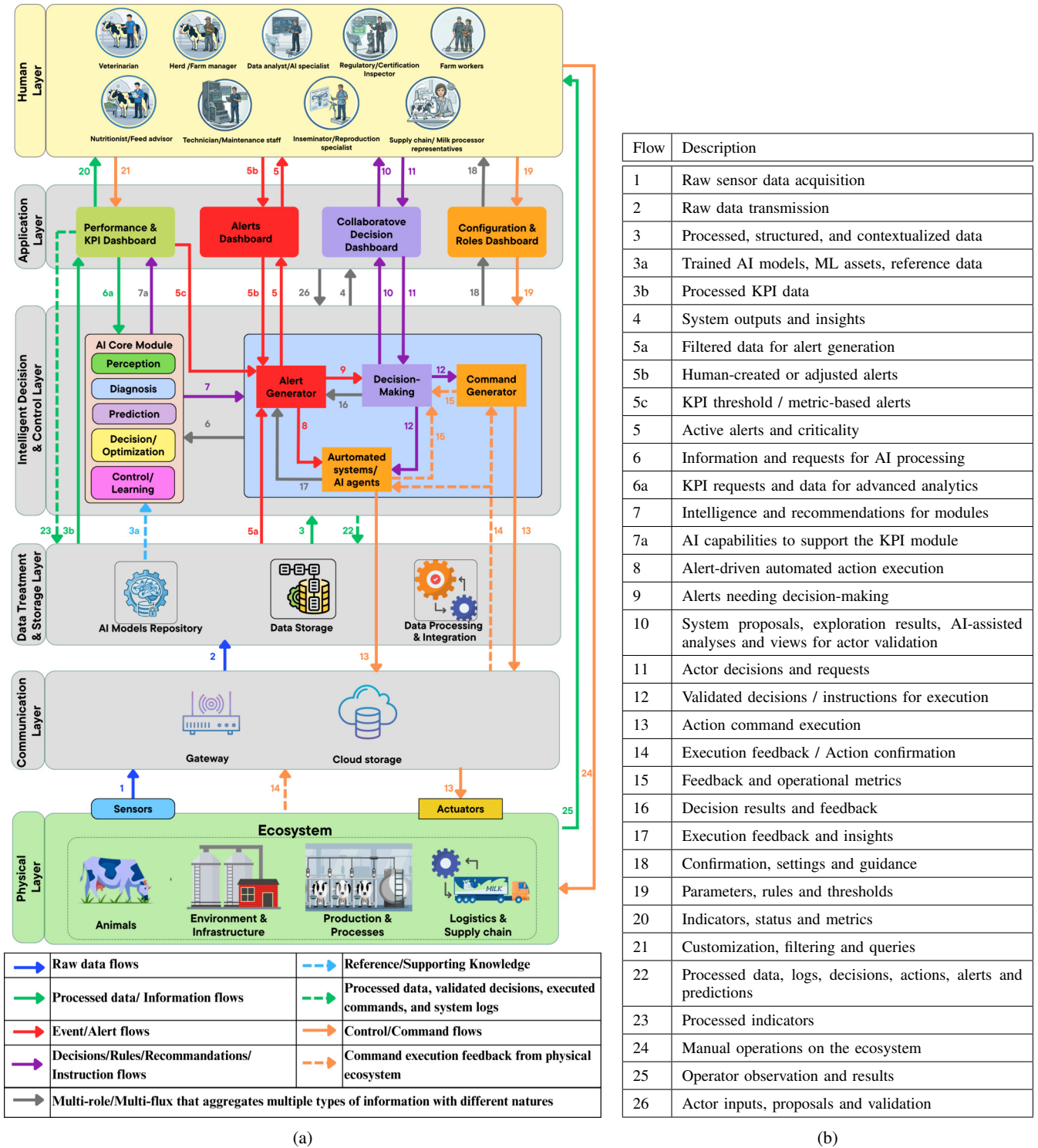


Fig. 1: (a): Proposed holistic CPS architecture, (b): Module interactions and flow descriptions in the CPS architecture.

VII. CONCLUSION

This paper presents a holistic Cyber-Physical System (CPS) architecture for Smart Precision Livestock Farming, bridging existing gaps in cross-domain integration, AI capabilities, and multi-stakeholder coordination. By adopting a multi-level, modular design, the framework structures perception, data transmission, decision-making, execution, and feedback into clearly defined components, enabling flexible end-to-end workflows and human-in-the-loop interactions across system operations. In contrast to traditional farmer-centric or centrally driven approaches, we introduced a shared collaborative dashboard and workflows that enable diverse stakeholders to interact, coordinate, and collectively validate through multi-view and multi-perspective views tailored to their roles. While this enhances visibility, transparency, and efficiency in livestock management, future work requires the further refinement of collaboration mechanisms, including role-based interactions, approval sequences, and coordination rules. Additionally, addressing interoperability challenges stemming from the heterogeneity of IoT devices, sensor networks, and software services remains a key priority, motivating the need for standardized mechanisms for data exchange, alignment, and system compatibility to ensure consistent implementation and reuse.

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