Research on the Framework of Safety Production Supervision System for Bulk Cargo Terminals Based on Intelligent Collaboration

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Abstract. In response to the challenges faced in Safety Production Supervision during the digital and intelligent transformation of dry bulk terminals—such as data silos, reactive responses, inflexible systems, and poor coordination—this paper proposes and constructs a framework for an "Intelligent and Collaborative Safety Production Supervision System for Dry Bulk Terminals." Supported by artificial intelligence, the Internet of Things, and big data technologies, this framework adopts a four-layer architecture of "Perception-Data-Intelligence-Application." It aims to integrate multi-source, heterogeneous data encompassing all elements of the terminal—including people, machinery, materials, methods, and the environment—and break down the barriers between traditional, isolated business systems. It innovatively introduces multi-agents with autonomous decision-making and collaborative capabilities, designing specialized agents for hazard identification, compliance verification, risk early warning, emergency command, and intelligent Q&A. Together, these agents form the system's "intelligent brain," driving a paradigm shift in supervision from "reactive response" to "proactive prevention and intelligent collaboration." This paper elaborates on the system's six-layer architecture and the functional design of its four core subsystems. Using the safety education subsystem as an example, it analyzes the internal coordination among multi-agents as well as the cross-system business coordination mechanisms between them and other subsystems. This research provides a systematic solution for dry bulk terminals to achieve intelligent collaborative supervision covering "process monitoring, safety control, environmental monitoring, and compliance verification."

Keywords: Keyword: Intelligent collaboration; safety production supervision; bulk cargo terminals; multi-agent systems; system framework

1 Introduction

Dry bulk terminals serve as hubs in the global supply chain, handling the loading, unloading, storage, and transshipment of bulk commodities such as coal and iron ore. They constitute critical infrastructure that underpins national energy security and the development of industry and agriculture. Safety supervision at these terminals covers

N. Malik et al. (eds.), *Proceedings of the 6th International Conference on Public Management and Intelligent Society (PMIS 2026)*, Advances in Engineering Research 301,
https://doi.org/10.2991/978-94-6239-721-7_19

all operational scenarios, including berths, storage yards, loading and unloading operations, access points, environmental protection, and equipment[1]. However, current practices still rely on traditional methods such as manual inspections and certification, making it difficult to completely eliminate human error and management blind spots. With the integration of global trade and the development of smart ports, operational scales are expanding, cargo types are becoming more complex, and processes are growing increasingly sophisticated, placing higher demands on intelligent, efficient, and collaborative supervision.

Currently, safety supervision at dry bulk terminals is at a critical juncture of transformation and faces multiple challenges[2-4]. Although some terminals have introduced digital tools, shortcomings remain: First, significant data silos exist, with modules operating independently and information failing to synchronize. For example, it is difficult to link data from stacker-reclaimers with conveyor belt video feeds for fault analysis, and monitoring of hold cleaning operations is disconnected from personnel tracking and gas detection systems. Second, supervision is primarily reactive, lacking the ability for proactive sensing and prediction, making it difficult to address dynamic scenarios. Third, system flexibility is poor; traditional systems have been in service for a long time and struggle to adapt to multiple cargo types, diverse processes, and the integration of new technologies. Fourth, the capacity to process multi-source data is insufficient, making it impossible to uncover data correlations, which leads to inefficient resource allocation and redundant processes.

Dry bulk terminals are characterized by dynamic cargo flow, dusty, high-humidity, and corrosive environments, the complexity of large-scale machinery coordination, and risks associated with multi-interface handoffs, all of which place higher demands on supervision. There is an urgent need to integrate a real-time perception, early warning, traceability, and control system covering the entire process and all elements (people, machinery, materials, methods, and environment). This will break down information silos, improve the efficiency of hazard identification and rectification, strengthen equipment lifecycle management, and drive the transition from "reactive response" to "proactive prevention."

Technologies such as artificial intelligence, the Internet of Things, and big data offer potential solutions to the pain points in work safety management[5-8]. As a closed-loop system with perception, decision-making, execution, and learning capabilities, the intelligent agent achieves a leap from passive response to active problem-solving through a "perception—belief—desire—intention—action" framework. Its characteristics—including autonomy, responsiveness, foresight, interactivity, and iterativeness—can effectively address issues such as poor coordination and decision-making delays in traditional systems. In the field of port supervision, intelligent agents align closely with the needs of dry bulk terminals[9-11]. This study adapts the existing platform architecture to build an enterprise-level intelligent service hub. By adopting an integration approach similar to that of the WeCom Open Platform, it positions the work safety management platform as the host system. This enables seamless integration across multiple systems and collaborative operation with intelligent agents, achieving automated data synchronization and intelligent processing. It consolidates access points and constructs an intelligent interactive interface, laying a solid foundation for data value extraction.

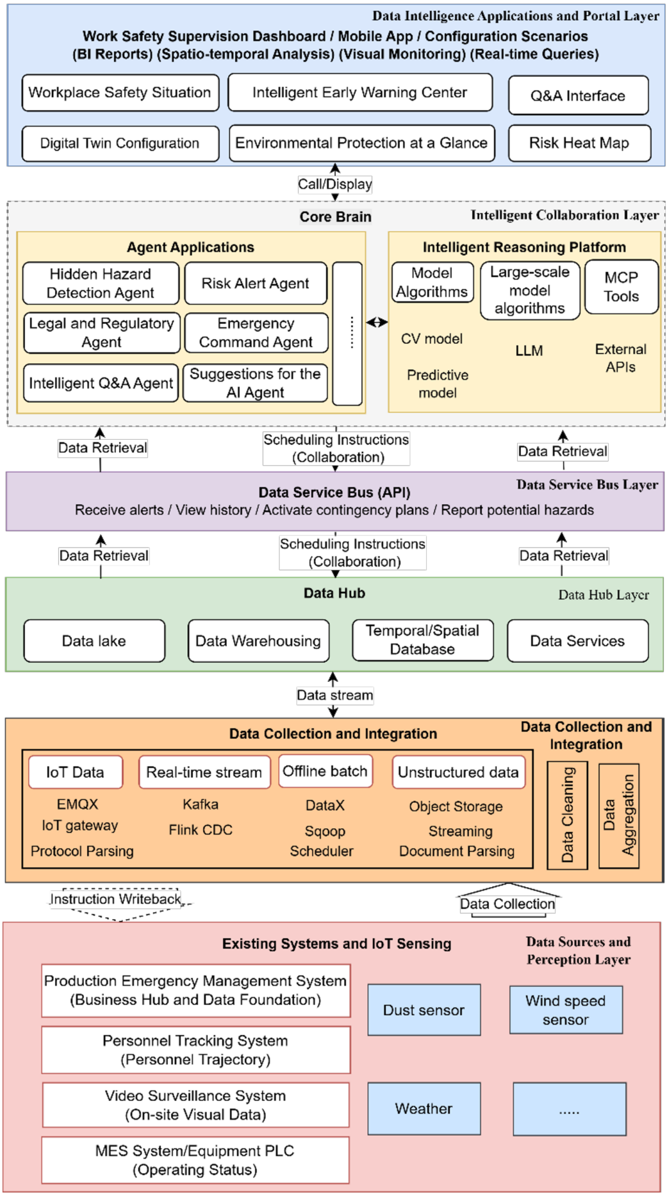

Fig. 1. Overall System Framework of Safety Production Supervision System for Bulk Cargo Terminals Based on Intelligent Collaboration

2 Overall System Framework

The system framework generally adopts a four-layer logical architecture comprising "Sensing-Data-Intelligence-Application". In terms of specific implementation, it is divided into the following six layers, as show in Fig 1: Data Sources and Perception Layer, Data Collection and Integration Layer, Data Hub Layer, Data Service Bus Layer, Intelligent Collaboration Layer, and Data Intelligence Applications and Portal Layer. Leveraging IoT, big data, and artificial intelligence technologies, it integrates existing systems—such as production emergency management, personnel tracking, and video surveillance—along with IoT sensing devices to build a unified data foundation. Through the collaboration of an intelligent inference platform and multi-agent systems, it delivers core capabilities including hazard identification, compliance verification, and emergency command. A data service bus connects the business closed-loop, driving application scenarios such as the work safety cockpit and mobile apps, ultimately forming a comprehensive, end-to-end intelligent collaborative supervision system covering the four core areas of "process monitoring, safety control, environmental monitoring, and compliance verification." The system architecture is as follows:

(1) Data Sources and Perception Layer

As the foundational source of data, this layer integrates the production emergency management system (which provides core operational data such as risk classification and hazard identification), video surveillance systems, personnel location systems, MES, and equipment PLCs (which provide feedback on equipment status and operational progress), as well as environmental sensing devices such as dust sensors and weather stations, to comprehensively collect operational, visual, location, equipment, and environmental data.

(2) Data Collection and Integration Layer

This layer is responsible for efficiently aggregating multi-source data into the data middle platform. It employs differentiated collection strategies for IoT sensing data, real-time business streams, offline batch data, and unstructured video documents. Through data cleansing and standardization, it provides unified, reliable data inputs for upper-level systems.

(3) Data Hub Layer

Constructs a unified storage system integrating a data lake, data warehouse, and time-series/spatial databases. The data lake enables low-cost, massive-scale data retention; the data warehouse forms thematic analytical datasets; and the time-series/spatial databases optimize the storage of spatio-temporal data such as trajectories and states. Based on this, unified data service interfaces are encapsulated to eliminate data silos and enable asset reuse and sharing.

(4) Data Service Bus Layer

Serving as a bridge between the middle platform and the intelligent collaboration layer, this layer provides standardized RESTful API interfaces and implements routing, authentication, and monitoring through an API gateway. Intelligent agents use the bus to retrieve data in real time and write decisions back to existing systems (such as automatically creating work orders for potential hazards), forming a bidirectional closed-loop from perception to response, while also supporting third-party system integration.

(5) Intelligent Collaboration Layer

Serving as the system's core brain, this layer consists of dedicated intelligent agents and an intelligent inference platform. Intelligent agents cover functions such as hazard identification (addressing typical risks like spontaneous combustion in stockpiles, conveyor belt misalignment, and non-compliant bin cleaning), risk early warning, and emergency command; the intelligent inference platform integrates model algorithms and large language models to provide algorithmic support and knowledge expansion. These intelligent agents work in concert to achieve an automated closed-loop of "perception-analysis-decision-execution."

(6) Data Intelligence Applications and Portal Layer

This layer provides multi-device application access points for different users. The safety production cockpit displays the overall operational situation, while the mobile app supports on-site task management and hazard reporting. Digital twin configuration enables the mapping of virtual and physical environments. The intelligent application layer transforms analytical results into intuitive alerts and operational instructions, enabling rapid response; user operation feedback is simultaneously transmitted back to the data middleware, forming a continuous learning loop for ongoing optimization.

3 Design of Key Subsystems

3.1 IoT Sensing and Data Integration Subsystem and Functions

The IoT Sensing and Data Integration Subsystem serves as the "nerve endings" of the system. It is responsible for the unified access, protocol adaptation, and preprocessing of multi-source data across the entire domain, ensuring that heterogeneous data from existing business systems, IoT sensing devices, and external data sources can be efficiently and reliably aggregated into the data middle platform. This subsystem abstracts the complexity and heterogeneity of underlying systems, providing standardized, real-time, high-quality data inputs to upper layers, and serves as the data foundation for building an intelligent collaborative supervision system. The IoT Sensing and Data Integration Subsystem includes the following primary functional modules:

IoT Sensing Access Module: Manages the registration, configuration, and status monitoring of various sensors, supporting high-concurrency connections for massive numbers of devices. It enables access via lightweight protocols such as MQTT and CoAP through IoT gateways (e.g., EMQX) and provides a framework for proprietary protocol parsing plugins to adapt to sensor devices from different manufacturers (e.g., dust, wind speed, meteorological sensors), ensuring the real-time nature and integrity of IoT data. Given the characteristics of large mobile machinery at dry bulk terminals, this module can be extended to adapt to onboard sensors on equipment such as ship unloaders and stacker-reclaimers.

Existing System Integration Module: For existing systems such as production emergency management, personnel tracking, video surveillance, and MES, this module provides standardized interface adapters supporting various integration methods, including direct database connections, API calls, and file transfers. It manages authentication, rate limiting, and retry mechanisms for interfaces, ensuring the stable extraction and incremental synchronization of business data (hazard inspections, incident reports, personnel trajectories, and equipment status).

Real-time Stream Processing Module: Based on the Kafka message queue and the Flink computing engine, this module performs data cleansing, format conversion, and lightweight aggregation on real-time data streams. It supports dynamic adjustment of data processing topologies, custom data filtering rules, and field mapping to meet real-time requirements across various scenarios.

Offline Batch Collection Module: Periodically extracts historical data using tools such as DataX and Sqoop, supporting resume-from-breakpoint and task scheduling. The module provides a visual configuration interface for data synchronization tasks, allowing flexible definition of data sources, target tables, and synchronization frequencies to ensure seamless integration between offline and real-time data.

Unstructured Data Processing Module: Designed for unstructured data such as videos and documents, this module provides streaming media parsing services and object storage management. It extracts key frames from videos, invokes OCR to recognize document content, and associates the processed metadata with structured data, providing richer input for intelligent analysis.

3.2 Data Hub and Data Governance Subsystem

The Data Hub and Data Governance Subsystem serve as the system's "data hub," responsible for the centralized storage, asset-based governance, and unified service provision of multi-source, heterogeneous data. By constructing data lakes, data warehouses, and time-series/spatial databases, it establishes a multi-tier storage system covering raw data, thematic data, and spatio-temporal data. This is complemented by governance capabilities such as metadata management, data quality monitoring, and data lifecycle management. Ultimately, it provides high-quality, easily accessible data assets to intelligent analytics and business applications via API services. The Data Hub and Data Governance Subsystem comprises the following primary functional modules:

(1)Multi-model Data Storage Module: Unified management of three types of storage engines—the data lake stores raw logs, video clips, and sensor time-series data, supporting low-cost, massive-scale retention and time-travel queries; the data warehouse performs dimensional modeling on business data, forming star/snowflake models oriented toward analytical themes; Time-Series/Spatial Database (e.g., InfluxDB + PostGIS): Optimizes the storage of spatiotemporal sequence data such as personnel trajectories, device status, and environmental monitoring, supporting efficient range queries and geographic analysis.

(2)Metadata Management Module: Maintains technical metadata (table structures, field types, storage locations) and business metadata (data meanings, data sources, quality rules), providing data lineage tracking capabilities and supporting data traceability from the application layer back to the source.

(3)Data Quality Management Module: Embedded with quality rules for integrity, accuracy, timeliness, and uniqueness; generates quality reports and triggers alerts through periodic audits of critical data fields. The module supports custom rule definition and quality remediation workflow management.

(4)Data Lifecycle Management Module: Establishes data hot/cold tiering strategies (e.g., retaining recently accessed, high-frequency data in high-speed storage, while migrating historical, low-frequency data to low-cost storage or archives). It automatically executes data migration and expiration cleanup to balance storage costs with query performance.

(5)Data Service Encapsulation Module: Based on API gateway technology, this module encapsulates data storage capabilities into RESTful APIs, providing standard service interfaces for data read/write operations, metric calculation, multidimensional retrieval, and spatio-temporal queries. The module supports service registration, traffic control, and call auditing, and can rapidly deploy new data services according to upper-layer requirements.

3.3 Analysis and Decision Support Subsystem

The Intelligent Analysis and Decision Support Subsystem serves as the system's "brain," performing core functions such as multi-source data fusion and analysis, intelligent risk identification, and the generation of collaborative decision-making instructions. It integrates artificial intelligence technologies such as computer vision, time-series forecasting, and large language models. Through a multi-agent collaboration mechanism, it analyzes the comprehensive data provided by the data platform in real time, generating decision-making information such as hazard alerts, compliance checks, and emergency command instructions. These instructions are then transmitted back to existing systems via the data service bus, achieving an automated closed-loop process of "perception-analysis-decision-execution." The Intelligent Analysis and Decision Support Subsystem includes the following functional modules:

Agent Management Module: Unifies the management of the full lifecycle of various specialized agents, including the Hazard Identification Agent (which uses computer vision models to detect issues such as workers not wearing safety helmets, open flames, and spontaneous combustion in stockpiles), the Equipment Health Agent (which uses time-series forecasting models to predict failures in equipment such as feeders and tippers), Environmental Monitoring Agents (fusing dust and meteorological data to assess environmental risks), Compliance Verification Agents (using large language models to compare operational behaviors against regulatory requirements), Emergency Command Agents (matching contingency plans and dispatching resources), Intelligent Q&A Agents (natural language interaction to query the knowledge base), and Recommendation Agents (generating optimization suggestions based on comprehensive situational analysis). The module supports agent registration, scheduling, status monitoring, and logging to ensure the stability of collaborative agent operations.

Model Inference and Training Module: Features a built-in model algorithm repository containing CV models, time-series prediction models (LSTM/Transformer), and large language models, and provides model version management, online inference service deployment, A/B testing, and performance evaluation capabilities. The module supports hot updates and rollbacks for models, and can integrate with external model training platforms to enable continuous iterative optimization of models.

Multi-Agent Collaboration Engine: Facilitates information exchange and task coordination among agents via a distributed message bus. The engine incorporates a rule engine and a reinforcement learning decision-maker, enabling dynamic combination of agent capabilities based on scenario requirements to complete complex tasks (e.g., hazard identification triggering emergency command, and emergency command invoking video and location data). The collaboration engine also resolves conflicts and prioritizes agent outputs to ensure the consistency and rationality of decisions.

External Knowledge Expansion Module: Based on the MCP (Model-Controller-Processor) tool framework, agents can call external APIs to obtain real-time meteorological data, query regulatory databases, and access geographic information services, thereby expanding their knowledge boundaries and enhancing the comprehensiveness and accuracy of decisions. The module manages authentication, rate limiting, and result caching for external APIs, thereby reducing the risk of dependency on external services.

Decision Command Generation and Routing Module: This module encapsulates the decision results generated through agent collaboration into a standard command format and distributes them via the data service bus to business collaboration subsystems or writes them directly back to existing systems (e.g., automatically creating hazard work orders in the production emergency management system). The module supports command priority management, retry mechanisms, and execution status tracking to ensure reliable delivery of commands.

3.4 Business Collaboration and Application Services Subsystem

The Business Collaboration and Application Services Subsystem serves as the system's "interaction interface," providing multi-device, scenario-based application services tailored to different user roles (management, security specialists, and frontline operators), thereby translating intelligent analysis and decision-making capabilities into intuitive, actionable business functions. This subsystem not only enables visual interactions such as the Safety Production Cockpit, mobile applications, and digital twin configurations, but also drives business closed-loop operations by seamlessly integrating decision directives with business processes, ensuring a complete chain from early warning to response. The main functional modules of the Business Collaboration and Application Services Subsystem are as follows:

Safety Production Cockpit Module: Designed for management, this module integrates BI reports, risk heatmaps, spatiotemporal analysis (trajectory playback), and equipment health dashboards to present the overall safety status of the terminal via a large visual display. It supports multi-dimensional data drilling and customizable dashboards, offering trend alerts and metric monitoring to help managers quickly grasp the big picture and make informed decisions.

Mobile Application Service Module: Designed for on-site personnel, this module provides a lightweight mobile app featuring task assignment and feedback, on-the-spot hazard reporting, real-time queries (equipment status, personnel qualifications), alert notifications, and geofence alarms. The module supports offline mode, allowing on-site data to be cached and automatically synchronized once network connectivity is restored.

Digital Twin Configuration Module: Constructs 3D digital twin scenarios for berth operations, stockpile loading/unloading, and cargo handling processes, providing real-time mapping of equipment status, personnel locations, material flow, and environmental parameters. The module supports configuration of display screens and simulation exercises, enabling the modeling of emergency response strategies under extreme conditions to support training and contingency plan validation.

Emergency Command and Coordination Module: During emergencies, this module provides a unified map of emergency resources (including firefighting equipment and rescue team locations), step-by-step guidance for contingency plans, real-time video feeds from the scene, and heatmaps of personnel distribution. It supports one-click issuance of instructions to relevant personnel's mobile devices and tracks the progress of emergency tasks, enabling visual command and dispatch.

Business Closure Loop Engine: This engine is responsible for translating decision directives issued by the intelligent analysis subsystem into specific business process operations. It includes built-in workflow templates (such as hazard remediation and emergency response processes) and can invoke APIs from existing systems to automatically create work orders, initiate approvals, and assign tasks, while tracking the closure loop status in real time (pending, in progress, completed). The closure loop results are fed back to the data middle platform for model effectiveness evaluation and rule optimization.

4 Subsystem and Agent Collaboration: Examples

4.1 Agent Collaboration Architecture

Advances in large-scale model technology have endowed agents with autonomous planning and decision-making capabilities, enabling them to independently formulate reasonable action plans based on complex and dynamic environments and objectives. At the same time, they possess outstanding tool invocation and execution capabilities, allowing them to precisely manipulate various tools to complete specific tasks. Furthermore, their continuous learning and self-optimization capabilities enable them to continually improve during practical application, resulting in ever-increasing performance and efficiency. Human-machine collaboration and multi-agent cooperation capabilities further break down the boundaries between different entities, achieving complementary strengths and efficient coordination.

This study employs a hierarchical agent architecture to enable collaboration among different agents. Its core design philosophy involves utilizing multiple large models to undertake distinct tasks, thereby achieving specialized division of labor and efficient collaboration. The system designed based on this hierarchical architecture establishes a cross-system collaboration framework involving multiple models and agents, addressing two key dimensions: vertical resource integration and horizontal collaborative services. Regarding vertical resource integration, specialized agents can deeply interface with specific resources in vertical domains, such as risk classification and control, hazard identification and remediation, operational process management, safety education and training, stakeholder management, facility risk management, institutionalized management, emergency management, incident management, team management, fire safety management, and safety investment management. This enables deep integration and efficient utilization of information; In terms of horizontal collaborative services, different agents achieve seamless integration and collaborative work through a layered architecture, enabling rapid response to complex task requirements. This architecture also supports flexible scalability and maintainability; when a specific functional module requires upgrading or optimization, adjustments need only be made to the agents at the corresponding level, without the need to reconstruct the entire system. Additionally, by incorporating reinforcement learning and multi-agent collaboration mechanisms, more efficient coordination is achieved across all levels, further enhancing the system's adaptability and intelligence.

Agents utilize the MCP tool to call external APIs (weather, regulatory databases, geographic information), integrating external knowledge into the analysis process to compensate for the limitations of internal models.

4.2 Overall Mechanism for Subsystem Collaboration

The system adopts a "data-driven + event-triggered" collaboration model, with each subsystem interconnected via standard interfaces and message middleware:

(1) The IoT Sensing and Data Integration Subsystem continuously collects data from multiple sources, cleanses it, and pushes it to the Data Hub and Data Governance Subsystem;(2) The Data Hub uniformly stores data and provides external data services, while simultaneously publishing real-time data changes (such as sensor threshold exceedances or equipment status changes) via message queues like Kafka;(3) The Intelligent Analysis and Decision Support Subsystem subscribes to relevant data topics. The Multi-Agent Collaboration Engine schedules various agents to perform real-time analysis, generating alerts, instructions, or decision recommendations;(4) Decision outcomes are distributed via the data service bus as APIs to the business collaboration and application service subsystem, or directly written back to existing systems (such as the production emergency management system);(5) The business collaboration subsystem converts instructions into specific business processes, driving on-site personnel or equipment to execute them, with execution results fed back to the data hub to form a closed-loop system. This mechanism ensures the efficient coordination of data flows, model flows, and decision flows, thereby establishing a closed-loop system from perception to response.

4.3 Case Study of Intelligent Collaboration Mechanisms for Key Subsystems: The Safety Education Subsystem as an Example

A comprehensive Safety Production Supervision system typically consists of multiple functional modules, including risk classification and control, hazard identification and rectification, operational process management, safety education and training, stakeholder management, facility risk management, institutionalized management, emergency management, accident and incident management, team management, fire safety management, and work safety investment management. To achieve a systematic and intelligent closed-loop business process, it is essential to decouple the various functional modules at the architectural level and design a series of highly specialized, clearly defined intelligent agents. These agents communicate and coordinate through standardized data interfaces and API calls, forming an orderly collaborative mechanism to collectively accomplish complex business objectives ranging from risk identification and process control to training and improvement.

Building a truly intelligent and collaborative Safety Production Supervision system requires not only covering various business scenarios at the functional level but also constructing corresponding agent subsystems around core business processes at the architectural level, while ensuring effective coordination among them at the logical, data, and execution levels. The safety education subsystem is one of the primary subsystems constituting the intelligent and collaborative Safety Production Supervision system. The effective operation of its intelligent collaboration processes relies deeply on and connects the data and logical support of multiple core functional modules within the platform, serving as a representative example of cross-module, multi-agent collaboration. As shown in the Fig 2, this chapter presents the construction of the safety education subsystem.

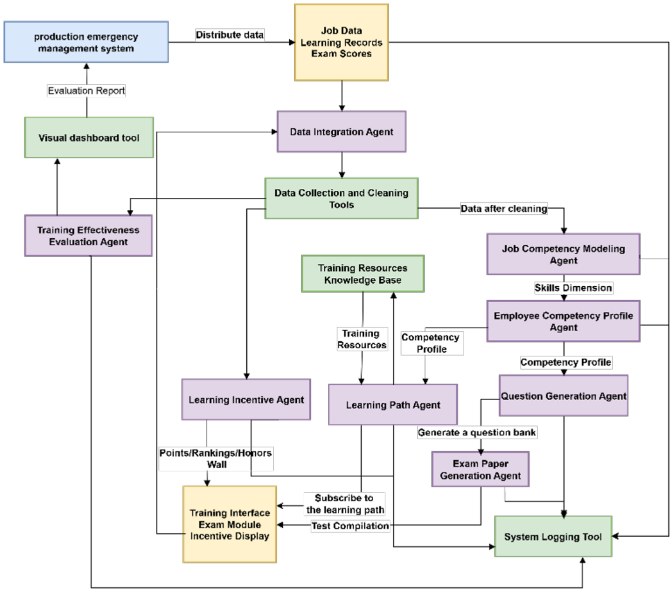

Fig. 2. The Safety Education Subsystem of Safety Production Supervision System for Bulk Cargo Terminals Based on Intelligent Collaboration

(1) Collaborative Process Among Agents Within the Subsystem

The safety education subsystem achieves intelligent management of the entire training process through a closed-loop workflow of "data-driven—intelligent decision-making—task execution—effectiveness feedback," relying primarily on the collaborative work of the following agents:① Data Integration Agent: Serving as the starting point of the process, this agent retrieves raw data (such as position data, employee learning records, and exam scores) from the "Work Safety Emergency Management System" and completes data integration via standardized interfaces, providing foundational input for subsequent analysis.② Data Collection and Cleaning Tool: Raw data transmitted by the integration agent enters the cleaning phase, where operations such as deduplication, data completion, and format conversion are performed to output "cleaned data," ensuring data quality meets analytical requirements.③ Job Competency Modeling Agent: Based on the cleaned job data and combined with job skill standards from the "Training Resource Knowledge Base," this agent constructs job competency models (e.g., skill dimensions, competency indicators) and outputs "skill dimension" data to provide a benchmark for employee competency profiling.④ Employee Competency Profile Agent: Integrates employee learning records, exam scores (derived from the cleaned data), and the job competency model (skill dimensions). Using machine learning algorithms, it generates an employee "competency profile" (e.g., skill proficiency levels, areas of weakness), enabling the precise identification of training needs.⑤ Learning Path Agent: Receives employee competency profiles, matches corresponding training resources (courseware, videos, practice questions) from the "Training Resource Knowledge Base," and combines them with the skill requirements from "Job Competency Modeling" to generate personalized learning paths, which are then pushed to the "Training Interface, Exam Module, and Incentive Display" terminals.⑥ Question Generation Agent: Based on the skill gaps identified in employee competency profiles, this agent extracts relevant knowledge points from the "Training Resource Knowledge Base." Using large language model algorithms, it automatically generates targeted exam questions (multiple-choice, true/false, case studies, etc.) and outputs a "Generated Question Bank."⑦ Exam Paper Generation Agent: Receives the "generated question bank" and, based on exam scenarios (e.g., job role, difficulty level, knowledge point coverage), rapidly generates personalized exam papers using intelligent paper-generation algorithms, then pushes them to the exam module for execution.⑧ Learning Incentive Agent: Tracks employee learning progress and exam scores (from cleaned data), generates incentive content through mechanisms such as points, rankings, and honor boards, and synchronizes this to the "training interface" for display to boost employee engagement.⑨ Training Effectiveness Evaluation Agent: Integrates data on employee learning behavior (e.g., completion rates, distribution of incorrect answers), exam scores, and changes in competency profiles. Utilizes analytical models to generate "Evaluation Reports," which are presented via "Visualization Dashboard Tools." The reports are also fed back into the "Work Safety Emergency Management System" to support subsequent training optimization.⑩ System Logging Tool: Continuously records the operational activities of each agent, data flow paths, and task execution statuses to generate system logs, providing data evidence for troubleshooting and process auditing.

(2) Cross-Subsystem Business Collaboration Mechanism

The full realization of the safety education subsystem's potential relies on deep collaboration with other core subsystems within the system, forming a three-tiered integration of "data-capabilities-services":

①Collaboration with the data middleware and data governance subsystems: All training-related data (job role data, learning records, exam scores, training resources, etc.) undergoes standardized governance, storage, and integration through the data middleware, forming a unified data asset focused on education. For example, the tagging of resources in the "Training Resource Knowledge Base" and the standardization of dimensions in the "Employee Competency Profile" both rely on the governance capabilities of the Data Hub to ensure data consistency across all intelligent agents.②Synergy with the Intelligent Analysis and Decision Support Subsystem: The Safety Education Subsystem delegates complex analytical tasks (such as competency profile generation and training effectiveness evaluation) to the "Intelligent Analysis and Decision Support Subsystem," leveraging its algorithmic models (such as machine learning and big data analytics) to achieve precise analysis. For instance, the "Employee Competency Profile Agent" invokes the clustering algorithms of the analysis subsystem to rapidly identify employees' skill gaps; the "Training Effectiveness Evaluation Agent" invokes predictive models to forecast the impact of training on safety performance.③Synergy with the Business Collaboration and Application Services Subsystem: "Training Interface, Exam Module, and Incentive Display" serve as a unified service entry point, integrated into the portal of the "Business Collaboration and Application Services Subsystem," providing personalized operation interfaces for different roles (such as employees, administrators, and training specialists). For example, employees use the portal to view learning paths, take exams, and check points; administrators use the portal to monitor training progress and export evaluation reports, thereby achieving unified delivery of business services.④Integration with the IoT Sensing and Data Integration Subsystem: When organizing in-person training or exams, data such as personnel location and access control from the "IoT Sensing and Data Integration Subsystem" can be utilized to facilitate on-site check-in and identity verification, ensuring the authenticity and compliance of training participants.

(3) The Closed-Loop Value of Collaborative Workflows

The intelligent collaborative workflow of the safety education subsystem forms a complete closed loop: "data input → competency modeling → pathway planning → training delivery → effectiveness evaluation → data feedback." Through the division of labor and collaboration among intelligent agents, as well as the integration of resources across subsystems, this workflow facilitates a transformation in training from "experience-driven" to "data-driven" and from "standardized instruction" to "personalized empowerment," thereby providing precise talent and competency support for safety production oversight at dry bulk terminals.

5 Conclusion

To address the systemic challenges currently facing safety production supervision at dry bulk terminals, this study has established an overall framework for a safety production supervision system centered on the core principles of "data-driven and intelligent collaboration." Through a layered design comprising "sensing, data, intelligence, and application," this framework systematically integrates IoT sensing, data integration, data governance, intelligent analysis, and business applications, forming a complete technical closed-loop that spans from data collection to intelligent decision-making and ultimately to application services. Its core value lies in:

(1) Architectural Advancement: By introducing a multi-agent collaboration system and deeply integrating agent technology into the core business processes of safety

production supervision, the framework enables proactive sensing, intelligent analysis, and collaborative decision-making in complex scenarios, effectively overcoming the limitations of traditional information systems—namely, "information silos" and "passive response."

(2) Collaborative Efficiency: Through a data service bus and standardized collaboration mechanisms, seamless coordination is achieved among subsystems and functional agents. Taking the safety education subsystem as an example, this demonstrates how the division of labor and collaboration among multiple specialized agents, combined with deep integration with the data middleware and intelligent analysis subsystems, enables the full-process intelligent and personalized management of training—from needs identification and path planning to effectiveness evaluation. This provides a model for the collaborative operation of other business closed-loop systems within the framework (such as hazard identification and emergency command).

(3) Practical Guidance: The system framework proposed in this study fully considers integration with the terminal's existing information systems (such as the production emergency management system and MES). By adopting an "add-on" and interface-based integration approach, it ensures the solution's feasibility and a phased implementation path. The system can significantly improve the accuracy of hazard identification and the efficiency of corrective actions, strengthen equipment lifecycle management capabilities, and provide scientific data support for management decisions, ultimately driving a fundamental shift in the work safety management model toward preemptive prevention, real-time control, and continuous optimization.

Due to the scope of this study, this paper does not provide an in-depth analysis of multi-agent collaborative conflict resolution, the issues of hallucination and reliability in large models within specialized industrial scenarios, or the data governance challenges associated with integrating heterogeneous systems. These topics are all core technologies that will influence the practical implementation of such systems in the future and warrant further in-depth research.

Acknowledgments

This study supported by the Guangxi Major Science and Technology Special Project (Gui Ke AA23062021); Central Basic Research Operating Funds (WTI-52505).

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