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A Study on the Structural Characteristics of AI-Based Industrial Safety Information Systems

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Abstract

Purpose: The purpose of this study is to compare and analyze the structural characteristics of AI-based industrial safety information systems with those of conventional industrial safety management systems, and to identify a paradigm shift in industrial safety management from an information systems perspective. **Research design, data and methodology:** The analytical framework is a risk-aware, information-flow–based decision-making structure, which enables a comparative analysis of conventional industrial safety management systems and AI-based systems. **Results:** The analysis reveals that conventional systems are characterized by reactive post-incident management that focuses on documentation and inspections. In contrast, AI-based industrial safety information systems exhibit a cyclical structure that integrates real-time data collection, AI-driven analysis, immediate alerts and responses, and continuous feedback and organizational learning. This structural distinction indicates a transformation in which industrial safety management has shifted from regulation-compliance–oriented post-incident management to a data-driven prediction and proactive management system. **Conclusions:** This research conceptualizes the AI-based safety information system as a fundamental paradigm shift in industrial safety management structures. The findings elucidate a transition from compliance-oriented reactive protocols to data-driven proactive systems. Consequently, this study suggests that future safety frameworks must prioritize optimized information flows and structural management to ensure sustainable organizational safety.

Keywords : Artificial Intelligence, Industrial Safety Management, Safety Information Systems, Structural Analysis

JEL Classification Code : D81, M10, M15, M19

1. Introduction

The traditional industrial safety management paradigm has evolved around regulation compliance and post-incident analysis. While this approach has contributed to a certain level of risk control, it reveals clear limitations in modern industrial environments characterized by high complexity and uncertainty. Leveson (2011) argued that conventional industrial safety management systems are rooted in unilinear thinking models and post-incident–analysis–centered structures, which are inadequate for explaining interactive risks arising from complex systems. This perspective

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suggests that industrial safety issues are closely related to the structural characteristics of the overall system, rather than to human error by individual workers or failures of single facilities. The contemporary industrial landscape has been increasingly exposed to persistent risk factors, including the expansion of automated facilities, the unstructured coexistence of workers from multiple subcontractors, and the continuous operation of high-risk processes. Consequently, safety management is required to undergo a transition from inspection- and reporting-centered systems to a management paradigm capable of real-time risk awareness and proactive prevention. Hale and Borys (2013) emphasized the need to redesign safety management structures, arguing that while conventional systems focus on procedural and rule compliance, actual risks emerge from dynamic changes in the workplace.

Driven by this problem consciousness, the field of industrial safety has begun to adopt information and communication technologies (ICT) and data-driven approaches. Research on industrial site safety management utilizing IoT sensors by Ding et al (2014) demonstrated that real-time environmental data collection can complement the limitations of existing document-centric management methods.

Even these studies primarily employed sensor data as monitoring tools, while risk assessment and decision-making often remained within a manager-centric structure. This indicates that, despite the availability of data, the ways in which information is interpreted and acted upon do not substantially differ from those of conventional safety management systems. Subsequently, advancements in artificial intelligence (AI) technologies created opportunities for structural transformation in industrial safety management systems. Fang et al. (2018) empirically demonstrated, in their study on construction site safety using deep learning–based computer vision technologies, that the wearing of personal protective equipment and hazardous worker behaviors can be automatically recognized. These findings suggest that risk awareness—one of the core functions of safety management—can be shifted from human observation and experience to algorithm-based judgment.

The AI- and IoT-integrated industrial safety information system exhibits fundamental differences in information flow and decision-making structure compared to existing safety management systems. The conventional system features a unilinear structure, in which on-site data are accumulated in documents or reports, and managers make judgments and take actions based on these data. In contrast, AI-based industrial safety information systems integrate data collection, analysis, judgment, and feedback into a single cyclical structure. Rasmussen (1997) argued that safety should be viewed as a dynamic control problem, continuously adjustable rather than a static rule-compliance issue. His perspective provides an important theoretical foundation for understanding the structural characteristics of AI-based safety information systems.

Existing studies have tended to focus primarily on the implementation of individual functions or the evaluation of system performance using AI or IoT technologies, while relatively little research has addressed structural changes in overall industrial safety management. In particular, systematic comparative analyses examining differences between conventional safety management systems and AI-based industrial safety information systems in terms of risk awareness, information flow, and decision-making mechanisms have been limited.

This study aims to elucidate the paradigm shift in industrial safety management from an information system perspective by comparatively analyzing the structural characteristics of AI-based industrial safety information systems and conventional systems. Specifically, it seeks to theoretically examine how AI-based systems reorganize industrial safety management structures beyond mere technology adoption, and to provide implications for the future design of safety management systems in industrial sites as well as for academic research.

2. Literature Review

2.1. AI-Based Industrial Safety Information System

Industrial Safety Information System can be defined as an information system designed to systematically collect and analyze diverse risk-related data at industrial sites and to utilize such data for safety-related decision-making. While traditional industrial safety management systems have largely focused on documenting accident records and inspection results, Industrial Safety Information System aims to integrate safety-related data as a core organizational management asset. In this regard, Leveson (1997) argued that safety should be viewed not as the result of isolated events, but as an emergent property arising from interactions within the entire system. Safety management system should be conceptualized as a comprehensive framework that encompasses information flows and control structures.

AI-Based Industrial Safety Information System is defined as a system that automates risk recognition and decision-making functions by integrating artificial intelligence technology into existing Industrial Safety

Information System. Rasmussen (1997) explained that in the modern industrial environment, the risk is not static but continuously shifts in response to changes in technology, organizational structures, regulatory conditions, and the surrounding environment. He argued that managing such dynamic risks requires a control structure based on real-time data and feedback mechanisms. From this perspective, the AI-based Industrial Safety Information System can be understood as a technological realization of these theoretical requirements.

The AI-Based Industrial Safety Information System collects environmental information and worker behavior data from industrial sites in real time through sensors and video equipment and automatically identifies hazardous situations using machine learning and deep learning algorithms. Fang et al. (2018) empirically demonstrated that a computer vision-based deep learning model can detect the use of personal protective equipment and hazardous worker behaviors in real time Their findings indicate that risk awareness no longer relies solely on human observation and experience.

The AI-Based Industrial Safety Information System goes beyond functioning as a mere monitoring tool and exhibits the characteristics of a decision support system. Endsley explained that effective decision-making becomes possible when the stages of information perception, comprehension, and projection are organically interconnected through her theory of Situation Awareness. From this perspective, the AI-Based Industrial Safety Information System not only detects risk signals but also interprets their significance and predicts the likelihood of future hazardous events.

2.2. Necessity of Establishing the AI-Based Industrial Safety Information System

The necessity of establishing the AI-Based Industrial Safety Information System arises from the structural limitations of the existing industrial safety management system. Hale and Borys (2013) pointed out that a safety management system centered on regulations and procedures risks tend to remain at the level of formal compliance. They also argued that such systems are not capable of adequately reflecting the complexity and variability of actual workplace environments. Under these conditions, risks are often recognized only after an accident occurs, rather than being identified in advance. Modern industrial sites have evolved into environments in which risk factors interact in increasingly complex ways due to the expansion of automated facilities, the unstructured coexistence of multiple workers, and the growing interdependence among processes. Leveson (2011) explained that in such complex systems, accidents cannot be effectively prevented through single-cause analysis or post-incident measures alone, emphasizing the need for a system-wide approach to risk management. This implies that the industrial safety management system must be structurally redesigned.

The advancement of information technology presented a possibility of overcoming these limitations. Ding et al. (2014) suggested that IoT-based data collection technology can complement the shortcomings of existing document-centric safety management methods by visualizing risk information on industrial sites in real time. However, even in these studies, risk judgment and response often still relied on the interpretation of managers, indicating a structural limitation in data utilization.

The AI-Based Industrial Safety Information System is required not as a means of transforming the management structure, rather than merely supplementing existing technologies. Reason (2000) emphasized that the fundamental cause of accidents lies more in organizational and system failures than in individual human errors, arguing that risk management should be addressed at the level of system design and control rather than individual control. The AI-Based Industrial Safety Information System aligns with this theoretical requirement by providing a structure in which risks are identified and shared by the system, rather than being reduced to an individual's duty of care.
The AI-Based Industrial Safety Information System contributes to the sustainability and consistency of safety management. From the perspective of dynamic risk management proposed by Rasmussen (1997), risk information must be collected and analyzed in real time, shared across the organization, and accumulated through a repetitive learning process. The AI-Based system enables organizational learning for accident prevention by systematically accumulating and analyzing risk-related data.

3. Research Methods and Materials

3.1. Structural Characteristics of the Conventional Industrial Safety Management System

The conventional industrial safety management system has primarily focused on post-incident response and regulatory compliance. Under this system, industrial safety tends to be perceived as an issue of analyzing causes and implementing preventive measures after an incident, rather than proactively predicting risks. Reason (2000) argued that traditional approaches to industrial safety management tend to attribute accidents to individual human errors, which leads accident analysis and responses to concentrate heavily on ex-post measures. This approach structurally confines industrial safety management to the realm of control and supervision.

In terms of information flow, the conventional industrial safety management system possesses a unilinear structure. Accidents or hazards occurring on site are recorded in documents such as checklists, incident reports, and work logs, which are then reviewed and assessed by managers who take subsequent measures. Hale and Borys (2013) pointed out that such a regulation-centric safety management system may be effective in verifying formal compliance but often fails to adequately capture the complexity and variability of the actual work environment. Consequently, risk information tends to be managed in organized formats after a certain period, rather than being shared immediately as it arises on the site.

The decision-making structure is also designed to be manager-centered. In the existing system, most risk awareness, judgment, and action-taking are managed by managers, while workers are often positioned as passive subjects who follow regulations. Reason (2000) noted that this structure may lead to focusing more on the clarification of responsibility than on accident prevention. This implies a structural limitation, as it culminates in individual control and strengthened discipline, rather than promoting organizational learning or structural improvement.

The conventional industrial safety management system also exhibits a characteristic of being focused on post-incident responses from a temporal perspective. Rasmussen (1997) explained that in industrial society, risks are not static but continuously shift in response to changes in technology, organizational structures, regulatory conditions, and surrounding environment. However, the traditional safety management system finds it difficult to reflect these dynamic risks in real time. In a structure that relies on periodic inspections and evaluations, most risks are often controlled and managed only after they occur.

In the existing system, safety-related data tends to be managed in a fragmented manner. Leveson (2011) argued that industrial safety problems arise from the interactions of the entire system rather than from individual equipment or work unit issues. However, facility safety, work safety, and environmental safety issues are often managed separately in traditional safety management systems. This fragmentation leads to a failure to interpret risk information comprehensively and to identify the fundamental causes of accidents.

These structural characteristics culminate in industrial safety management being conducted in a static manner. Hale and Borys (2013) pointed out that a safety management system focused on rules and procedures can actually weaken the adaptive response capability at the site, and they emphasized the need to redesign the information flow and decision-making structure for safety management to function properly. The existing industrial safety management system perceives safety as something that must be managed and controlled, and its systemic capability to learn from and adjust to risks in real time has been implemented only to a limited extent.

3.2. Structural Characteristics of AI-Based Industrial Safety Information Systems

Unlike the conventional industrial safety management system, the AI-Based Industrial Safety Information System collects and analyzes risk information in real time and directly links it to decision-making and actions. This system views industrial safety not as something to be managed only after an accident occurs, but as a dynamic state that must be continuously monitored and adjusted. From the perspective of dynamic risk management proposed by Rasmussen (1997) the AI-Based Industrial Safety Information System provides the structural foundation for reflecting changes in working environments and risk factors in real time.

In terms of the Input Structure, the AI-Based Industrial Safety Information System is based on the collection of pluralistic data. While the conventional industrial safety management system relied mainly on single-source records such as checklists and accident reports, the AI-based system collects environmental information and worker behavior data simultaneously through diverse channels such as IoT sensors, video equipment, and wearable devices. Ding et al (2014) explained that this pluralistic data collection structure enables risks in industrial worksites to be perceived in a more multidimensional manner. This represents a structural difference in that risk information is managed as a continuous flow of data rather than as records limited to a specific point in time.

In terms of the Processing Structure, the AI-Based Industrial Safety Information System is built around artificial intelligence algorithms. Fang et al. (2018) empirically demonstrated that Deep Learning-based computer vision technology can automatically recognize whether workers are wearing personal protective equipment and their hazardous behaviors. In this processing structure, risk judgment is made through algorithm-based analysis rather than relying on the experience or subjective interpretation of managers. Leveson (2011) pointed out that the cognitive limitations of humans can be a major cause of accidents in complex systems, and the AI-based analysis structure serves to compensate for these limitations.

The Output Structure also demonstrates a fundamental difference from the conventional system. In the traditional industrial safety management system, risk information is reported to the manager, who subsequently determines the appropriate actions. In contrast, in the AI-Based Industrial Safety Information System, the outcomes of risk assessment are delivered simultaneously to both workers and managers. Endsley argued that effective decision-making requires situation awareness information to be provided in a timely manner and at an appropriate level. The AI-based system institutionalizes this requirement through features such as warnings, notifications, and dashboard visualizations. Consequently, the risk response is no longer confined to the individual judgment of managers but is extended to the immediate actions of all on-site personnel.

The Feedback Structure is one of the most crucial structural characteristics of the AI-Based Industrial Safety Information System. In conventional industrial safety management systems, the results of post-incident measures are often not sufficiently accumulated as organizational learning. But the AI-based system re-accumulates data on risk occurrences, responses, outcomes, and the implementation of corrective actions are continuously fed back into the system. As emphasized by Rasmussen and Leveson, the safety is a system property sustained through learning and adjustment, and the AI-Based Industrial Safety Information System technically provides a technical infrastructure that institutionalizes such a learning structure (Rasmussen, 1997; Leveson, 2011).

The AI-Based Industrial Safety Information System transforms the decision-making structure from a centralized model to a distributed and collaborative one. Reason (2000) argued that system design is more important than individual control for accident prevention, and the AI-based system aligns with this theoretical requirement by performing risk awareness and information sharing at the system level. Risk information is provided simultaneously not only to managers but also to workers, thereby enabling immediate on-site response. 2011).

3.3. Structural Comparison of the Conventional System and the AI-Based System

The most fundamental difference between the conventional industrial safety management system and the AI-Based Industrial Safety Information System lies in the structural method of perceiving and managing risk. The conventional system focuses on managing risk through post-accident records and reports, whereas the AI-based system detects risk in real time and responds proactively. In terms of Rasmussen's (1997) dynamic risk management perspective, the conventional system assumes risk to be static, while the AI-based system views risk as continuously shifting in response to temporal and environmental changes.

In the Information Flow Structure, the conventional industrial safety management system operates in a unilinear manner. Risk information generated on-site is recorded in the form of checklists or incident reports, and actions are taken based on the manager's judgment. Hale and Borys (2013) pointed out that while this regulation-centric structure may be effective for formal compliance, it cannot immediately reflect the dynamic risks that arise in the actual work environment. In contrast, in the AI-Based Industrial Safety Information System, data collected through sensors and video equipment forms a cyclical structure where it is analyzed, judged, and immediately connected to warnings and actions. This means that risk information functions as a real-time management resource rather than a recorded document.

The Decision-Making Structure also shows a clear distinction between the two systems. In the conventional industrial safety management system, risk perception and response decisions are concentrated in the hands of managers, resulting in a highly centralized structure. Reason (2000) pointed out that such a structure carries the risk of reducing the causes of accidents to individual human errors and of leading to responsibility-centered management. By contrast, in the AI-based Industrial Safety Information System, the system itself identifies risks and simultaneously provides this information to both managers and workers, thereby transforming the decision-making structure into a distributed and collaborative model. This represents a structural shift in industrial safety management from a paradigm of supervision and control to one of joint response and organizational learning.

Structural differences are also evident from a temporal perspective. The conventional system operates primarily through regular inspections and ex-post analyses, meaning that risk is managed on a fixed cycle. Leveson (2011) pointed out that this approach is insufficient to prevent accidents arising in complex socio-technical systems, emphasizing the importance of real-time control and feedback. The AI-Based Industrial Safety Information System manages risk constantly through ongoing data collection and analysis, which transforms industrial safety management a series of one-off inspections into a continuous management process.

The Data Management Structure is also fundamentally different in the two systems. In the conventional industrial safety management system, data related to equipment safety, operational safety, and environmental safety are often managed fragmentarily. Leveson (2011) explained that this fragmented management approach imposes limitations in identifying the structural causes of accidents. In contrast, in the AI-Based Industrial Safety Information System, diverse types of safety data are managed on an integrated platform and utilized as the basis for risk judgment and learning. Ding et al. (2014) analyzed that the integrated data structure contributes to a more three-dimensional understanding of risks on the industrial site.

This structural comparison suggests that the AI-based Industrial Safety Information System does not merely upgrade the existing industrial safety management system, but instead transforms its underlying management logic. While the conventional system regarded safety as the outcome of regulatory compliance and accident prevention, the AI-based system views the safety as a state that must be continuously maintained and adjusted in real time. From the perspective of systems thinking, this transition is an inevitable change within increasingly complex industrial environments (Rasmussen, 1997; Leveson, 2011).

Previous research has mainly focused on the performance and feasibility of AI or IoT technologies. In contrast, this study contributes by analyzing the structural transition of the industrial safety management system from an information-systems perspective. The AI-based Industrial Safety Information System should be understood not simply as a matter of technology adoption, but as a management system that reorganizes risk perception, information flow, decision-making structures, and organizational learning mechanisms. In this regard, future research should move beyond technology-centered approaches and be extended to the level of management structures and system design.

4. Results and Discussion

This study seeks to identify the paradigm shift in industrial safety management from an information-systems perspective by comparing the structural characteristics of the AI-based Industrial Safety Information System with those of the conventional industrial safety management system. The conventional system has developed around a regulation- and document-centered management structure, accompanied by a temporal characteristic that emphasizes post-incident responses. Within this structure, risk perception and decision-making have been primarily concentrated in managers. As pointed out by Hale and Borys (2013), although such characteristics may contribute to formal compliance, they also reveal structural limitations in today’s industrial environments, which are increasingly complex and uncertain.

In contrast, the AI-Based Industrial Safety Information System has a cyclical structure that detects and analyzes risk in real time and links them directly to immediate responses. From the dynamic risk management perspective proposed by Rasmussen (1997), does not treat risk as a static condition, but as something that continuously changes. It therefore follows a management logic fundamentally different from that of conventional systems, in which safety is maintained through continuous data collection and feedback. This study structurally analyzes that this difference does not simply represent technological advancement, but instead entails a transformation in the overall framework of industrial safety management, including information flow, decision-making structures, and organizational learning mechanism.

The AI-Based Industrial Safety Information System moves beyond the conventional structure in which risk perception depended primarily on human observation and experience, and incorporates algorithm-based analysis and prediction as core elements of the management structure. From the perspective of system thinking emphasized by Leveson (2011), this can be understood as a shift from reducing accident causes to the failure of individual components, to expanding the object of management to the interactions and control structures of the system as a whole. Furthermore, in light of Reason's (2000) organizational accident theory, the AI-based system enables a shift from a responsibility-centered, ex-post management structure to a prevention-oriented structure in which risk information is shared across the organization.

5. Conclusions

The academic implications of this study are as follows: First, it is differentiated from prior research, which focused primarily on the performance or feasibility of AI or IoT technology, by taking the structural change of the industrial safety management system itself as the object of analysis. This suggests the need for industrial safety research to expand beyond individual technology-centric approaches to the level of management frameworks and information system structure. Second, by interpreting the AI-Based Industrial Safety Information System from the perspective of dynamic risk management and system control—drawing on the theories of Rasmussen (1997) and Leveson (2011)—this study attempts a theoretical expansion that connects existing safety management theory with the modern information technology environment.

The practical implications are also clear. The AI-Based Industrial Safety Information System should not be understood simply as the introduction of sensors or AI technologies, but as a process of redesigning the decision-making structure and information flow of industrial safety management. This implies that when companies establish safety management systems, they should prioritize the structure for data integration, real-time decision-making frameworks, and feedback-based learning systems over the adoption of individual technologies. To overcome the limitations of regulation-centric safety management pointed out by Hale and Borys (2013), it is necessary to design the technical and managerial structures together.

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