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AI-SUPPORTED PROCESS MANAGEMENT TOOLS FOR HANDLING DISTURBANCES IN INDUSTRY 4.0 PRODUCTION SYSTEMS

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Abstract:
Production systems operating in Industry 4.0 environments are increasingly exposed to disturbances that affect process stability, performance, and managerial decision-making. The growing complexity and digital integration of production processes require structured approaches that go beyond reactive disturbance handling and support process-oriented management. In this context, artificial intelligence (AI) is increasingly used as a decision-support mechanism to enhance data interpretation and managerial responses. This article aims to examine how AI-supported process management tools can be used to handle disturbances in Industry 4.0 production systems. A structured qualitative coding methodology is proposed and applied to systematically identify disturbances, corresponding management actions, and disturbance-related process signals. Disturbances are classified using D-codes, management responses using A-codes, and observable indicators using signal codes, forming an integrated analytical framework for process-level analysis. Empirical data collected from real production systems were analyzed using the proposed coding approach. AI-supported data processing was used to assist pattern recognition, signal interpretation, and the linking of disturbances with management actions, without replacing human judgment in decision-making. The results provide an empirically grounded classification of disturbances and process management tools relevant to digitally integrated production environments. The study contributes to production engineering and management literature by offering a transferable methodological framework for analyzing disturbance handling in Industry 4.0 production systems. From a practical perspective, the findings demonstrate how basic process management tools, supported by AI-based decision-support, can enhance managers' ability to identify, interpret, and respond to disturbances in complex production processes.

Key words: process management, industry 4.0, production systems, artificial intelligence (AI), disturbance management, decision-support systems

INTRODUCTION

Industry 4.0 and complexity of modern production systems

The development of Industry 4.0 has fundamentally transformed production systems through the integration of digital technologies, cyber–physical systems, advanced automation, and real-time data exchange. Contemporary production environments, particularly in sectors such as automotive manufacturing, metal processing, electronics, and process industries, increasingly operate as tightly coupled socio-technical systems in which machines, information systems, and human operators interact continuously [1, 2, 3, 4, 5, 6].

Production engineering research emphasizes that the growing level of digital integration has led to a significant increase in system complexity. While Industry 4.0 technologies enable higher levels of productivity, flexibility, and customization, they also intensify interdependencies between production processes [7, 8, 9, 10, 11, 12, 13, 14]. In highly automated assembly lines, flexible manufacturing systems, and digitally controlled process industries, even minor deviations in one process stage may propagate across the system, resulting in disturbances affecting overall process stability and performance [4, 15, 16, 17, 18].

Empirical studies published in production engineering and management journals indicate that Industry 4.0 environments are particularly vulnerable to disturbances related to information flow, system integration, and coordination between technical and organizational subsystems. These challenges are frequently observed in multi-stage production processes, distributed manufacturing networks, and production systems operating under high variability and short product life cycles. As a result, disturbance handling has become a critical issue not only at the operational level, but also from a strategic process management perspective [1, 2, 4, 5, 17, 19].

Process management approaches and disturbance handling in production engineering

Disturbance handling has long been addressed within production engineering through established management approaches such as Lean Manufacturing, Total Productive Maintenance (TPM), Statistical Process Control (SPC), and production scheduling and control systems. These approaches provide structured tools for identifying deviations, stabilizing processes, and improving operational performance. However, their application in Industry 4.0 environments presents new challenges [20, 21].

Lean-based methods focus on waste reduction and process standardization, yet in highly digitalized production systems disturbances often emerge from dynamic interactions between processes rather than from isolated inefficiencies. Similarly, TPM emphasizes equipment reliability, but does not fully address disturbances arising from information inconsistencies or cross-process integration. SPC and process control techniques enable detection of process variability, but their effectiveness depends on timely interpretation of large volumes of real-time data [18, 21, 22, 23] .

Recent research highlights that disturbances in Industry 4.0 production systems increasingly stem from organizational coordination issues, scheduling conflicts, and information flow disruptions rather than purely technical failures [2, 4]. This shift is particularly evident in industries characterized by high product variability, complex logistics, and distributed decision-making, such as automotive supply chains, customized manufacturing, and process industries operating under continuous production regimes [1, 2, 19, 24].

From a process management perspective, these observations indicate that traditional tools must be complemented by approaches that support cross-process coordination, integrated decision-making, and adaptive responses to disturbances. However, despite the widespread application of process management methods in production engineering, there is still limited empirical research that systematically links specific disturbance types with corresponding management actions across different production contexts [25, 26].

AI-supported decision-support in production process management

The increasing availability of production data in Industry 4.0 environments has accelerated the use of artificial intelligence as a decision-support mechanism in production process management. AI-based analytics are applied to support tasks such as anomaly detection, predictive maintenance, production scheduling, and performance monitoring. In practice, these applications are particularly relevant in data-intensive production environments, including automated assembly lines, flexible manufacturing systems, and continuous production processes. The growing availability of real-time production data has stimulated the application of artificial intelligence tools in production management, particularly as decision-support mechanisms [22, 24].

However, existing research often treats AI as a technological solution rather than as an integral component of management systems. Many studies focus on algorithmic performance or automation potential, while relatively little attention is paid to how AI-supported tools interact with established process man-

agement practices. In industrial settings, AI is rarely implemented as a fully autonomous decision-maker; instead, it supports engineers and managers by aggregating information, identifying patterns, and highlighting potential response options. AI solutions are increasingly used to support data analysis, pattern recognition, anomaly detection, and predictive functions within production systems [23, 27]. Importantly, AI in production management is typically implemented as a support for managerial decision-making rather than as a fully autonomous control mechanism [28, 29]. Despite the growing interest in AI applications, there remains a lack of integrated analytical frameworks that link disturbances, management actions, and process-level signals in production systems [3, 23, 29]
Production engineering literature increasingly emphasizes the importance of hybrid management approaches that combine human expertise with intelligent decision-support. AI-supported tools can enhance the effectiveness of traditional process management methods by improving signal interpretation, supporting early detection of disturbances, and reducing decision-making uncertainty in complex production systems. Nevertheless, there remains a lack of structured analytical frameworks that integrate qualitative analysis of disturbances with AI-supported signal interpretation at the process level [20, 30].

Research aim and contribution

In response to the identified research gaps, this article aims to examine how AI-supported process management tools can be used to handle disturbances in Industry 4.0 production systems. The study proposes and applies a structured qualitative coding methodology that links disturbances, management actions, and disturbance-related process signals within a coherent analytical framework.
The contribution of this study lies in integrating established production management approaches with AI-supported decision-support from a process-oriented perspective. By focusing on recurring disturbance–response patterns across different production contexts, the article advances research in production engineering and process management and provides practical insights applicable to a wide range of industrial sectors.

RESEARCH METHODOLOGY

The study adopts a qualitative research design aimed at systematically analyzing disturbances in production systems and their handling through process management tools in the context of Industry 4.0. The research focuses on process-level analysis, emphasizing the relationships between disturbances, managerial actions, and observable process signals within digitally integrated production environments. Artificial intelligence is treated as a decision-support mechanism that enhances data processing, pattern recognition, and signal interpretation rather than as an autonomous decision-making system.
Empirical data were collected from production systems operating under real industrial conditions. The data sources included production documentation, process records, incident and deviation reports, and observational data related to process performance and disturbances. In addition, expert inputs from production managers and process engineers were used to support the interpretation of identified disturbances and management actions. The collected data reflect typical characteristics of Industry 4.0 production systems, including high process interconnectivity, extensive digital data availability, and real-time monitoring. Based on the research aim, the following research questions were formulated:
RQ1: What types of disturbances can be identified in production systems operating in Industry 4.0 environments?
RQ2: What process management actions are applied to handle disturbances in production systems?
RQ3: How can disturbances and corresponding management actions be systematically linked using a structured coding approach?
RQ4: How can AI-supported data processing enhance the identification and interpretation of disturbance-related signals in production processes?
The core of the methodology is a structured qualitative coding procedure developed to analyze disturbances and their handling in production systems. Disturbances were coded using D-codes, management

responses were coded using A-codes, and observable indicators were captured using disturbance-related signal codes. Together, these code sets form an integrated analytical framework enabling systematic identification, categorization, and interpretation of disturbance–response relationships at the process level.

The coding procedure consisted of three main stages. First, observed disturbances were identified and classified using D-codes representing deviations from expected process behavior affecting process flow, stability, or performance. Second, corresponding management responses were coded using A-codes, reflecting basic process management tools applied to mitigate, correct, or adapt to disturbances. Third, disturbance-related signals were identified based on observable changes in process parameters, system states, information flows, and human, process interactions.

Artificial intelligence was incorporated into the analysis as a supporting analytical tool. AI-based data processing facilitated the handling of large and heterogeneous data sets, supported the identification of recurring patterns, and assisted in linking disturbances with corresponding management actions and signals. In particular, AI-supported tools were primarily associated with A-P5 management actions and S-P3 information system signals, enabling enhanced pattern recognition, predictive assessment, and interpretation of disturbance-related data without replacing human judgment in the decision-making process.

The reliability of the coding procedure was ensured through predefined coding rules and consistent application of the coding framework across the data set. Iterative refinement of codes was conducted to improve clarity and internal coherence. Validation was supported through expert review and cross-checking of coded disturbance, action relationships with practitioners involved in production process management. The structured nature of the methodology enhances transparency and reproducibility, providing a robust foundation for examining disturbance handling in Industry 4.0 production systems.

An overview of the applied D-codes, A-codes, and disturbance-related signal codes is presented in Tables 1-3.

Table 1
Overview of disturbance codes (D-codes)

Code type	D-code	Code category	Description
D-code	D-P1	Technical disturbances	Disturbances related to machines, equipment, tools, or technological infrastructure affecting process continuity or stability.
D-code	D-P2	Organizational disturbances	Disturbances resulting from work organization, scheduling, coordination, or allocation of tasks and resources.
D-code	D-P3	Human-related disturbances	Disturbances associated with human factors, including skills, experience, decision-making, and communication issues.
D-code	D-P4	Information flow disturbances	Disturbances caused by delayed, incomplete, inconsistent, or incorrect information within production processes, including digitally generated and system-integrated data.
D-code	D-P5	Process integration disturbances	Disturbances arising from interdependencies between processes, systems, or production stages in interconnected and digitally integrated production environments.

Table 2
Overview of management action codes (A-codes)

Code type	A-code	Code category	Description	Code type	A-code
A-code	A-P1	Process adjustment actions	Management actions involving modifications of process parameters, sequences, or operating conditions to mitigate disturbances.	A-code	A-P1
A-code	A-P2	Resource management actions	Actions related to reallocation or adjustment of human, material, or technical resources in response to disturbances.	A-code	A-P2
A-code	A-P3	Organizational coordination actions	Actions aimed at improving coordination, communication, and task alignment across process actors or organizational units.	A-code	A-P3
A-code	A-P4	Information management actions	Actions focused on improving data availability, quality, and flow to support disturbance handling.	A-code	A-P4
A-code	A-P5	AI-supported decision-support actions	Management actions involving the use of digital and AI-supported tools to support managerial decision-making, including pattern recognition, signal interpretation, predictive assessment, and recommendation of response options during disturbance handling.	A-code	A-P5

Table 3
Overview of disturbance-related signal codes

Code type	Signal code	Code category	Description
Signal	S-P1	Process performance signals	Observable changes in process indicators such as cycle time, throughput, variability, or output stability.
Signal	S-P2	Operational system signals	Signals related to machine states, alarms, downtime, or deviations from standard operating conditions.
Signal	S-P3	Information system signals	Signals generated by production information systems, dashboards, monitoring tools, and AI-supported analytics indicating anomalies, trends, or deviations in process behavior.
Signal	S-P4	Human–process interaction signals	Signals reflecting changes in operator behavior, communication patterns, or decision-making activities within production processes.

RESULTS AND DISCUSSION

The application of the proposed qualitative coding methodology enabled the systematic identification of disturbances, corresponding management actions, and disturbance-related signals in Industry 4.0 production systems. The results are presented from a process management perspective, emphasizing structured relationships between D-codes, A-codes, and signal codes, as well as the supporting role of AI-based decision-support mechanisms.

Process management actions and disturbance-response relationships

The analysis revealed that disturbances in production systems are multidimensional and originate from diverse sources. All five categories of D-codes were identified in the empirical material, confirming the complex and interconnected nature of disturbance phenomena in Industry 4.0 production environments.

Technical disturbances (D-P1) were associated with machine malfunctions, equipment instability, and technological infrastructure issues affecting process continuity. Organizational disturbances (D-P2) reflected challenges related to scheduling, coordination, and resource allocation across interconnected processes. Human-related disturbances (D-P3) included skill gaps, decision-making delays, and communication issues, which were often intensified by increasing system complexity.

Information flow disturbances (D-P4) and process integration disturbances (D-P5) were particularly prominent. These disturbance types were closely linked to digitally generated data, system interoperability, and cascading effects across processes. As illustrated in Table 4, these disturbance categories were associated with a broad range of management actions, indicating their systemic character and their relevance for process-oriented management in Industry 4.0 environments.

Table 4
Relationships between disturbance codes (D-codes) and management action codes (A-codes)

D-code	Description	Dominant A-codes applied	Interpretation from a process management perspective
D-P1	Technical disturbances	A-P1, A-P2, A-P5	Technical disturbances are primarily addressed through process adjustments and resource reallocation. AI-supported tools assist in diagnosing root causes and selecting optimal adjustment options.
D-P2	Organizational disturbances	A-P2, A-P3, A-P4	Organizational disturbances require coordination and resource management actions supported by improved information flow and data transparency.
D-P3	Human-related disturbances	A-P3, A-P4, A-P5	Human-related disturbances are mitigated through coordination and information management, with AI-support enhancing decision consistency and reducing cognitive load.
D-P4	Information flow disturbances	A-P4, A-P5	Information flow disturbances are primarily addressed through information management actions, strongly supported by AI-based data analysis and anomaly detection.
D-P5	Process integration disturbances	A-P1, A-P3, A-P5	Integration-related disturbances require coordinated process adjustments across interconnected systems, with AI-support facilitating pattern recognition and cross-process impact assessment.

The identified disturbances were linked with a range of process management actions coded using A-codes. The disturbance-response relationships are synthesized in Table 4, which presents a structured overview of how specific disturbance categories are addressed through different management actions.

Process adjustment actions (A-P1) and resource management actions (A-P2) were predominantly applied in response to technical and organizational disturbances. Organizational coordination actions (A-P3) were frequently associated with organizational and human-related disturbances, highlighting the importance of communication and coordination mechanisms in complex production systems. Information management actions (A-P4) played a key role in addressing information flow disturbances by improving data quality, accessibility, and transparency.

AI-supported decision-support actions (A-P5) emerged as a cross-cutting category in Table 4, supporting the handling of multiple disturbance types. These actions were most frequently linked to information flow disturbances (D-P4) and process integration disturbances (D-P5), where large volumes of data, interdependencies, and dynamic process behavior require advanced analytical support. The results indicate that AI-supported tools enhance the effectiveness of existing process management actions rather than replacing them.

Disturbance-related signals and AI-supported interpretation

The analysis of disturbance-related signals provides additional insight into how disturbances are detected and interpreted in Industry 4.0 production systems. The relationships between AI-supported management actions (A-P5) and signal codes are summarized in Table 5.

Table 5

Relationships between AI-supported management actions (A-P5) and disturbance-related signals

Signal code	Signal category	Role of signal in disturbance handling	AI-supported contribution (A-P5)
S-P1	Process performance signals	Indicate deviations in process stability, efficiency, and output parameters.	AI-supported trend analysis and predictive assessment support early detection of performance degradation.
S-P2	Operational system signals	Reflect machine states, alarms, and deviations from standard operating conditions.	AI assists in correlating operational signals with disturbance patterns and recommending response actions.
S-P3	Information system signals	Provide integrated data from production systems, dashboards, and analytics platforms.	AI-based analytics enable anomaly detection, pattern recognition, and integration of heterogeneous data sources.
S-P4	Human–process interaction signals	Capture changes in operator behavior, communication patterns, and decision-making activities.	AI-supported analysis helps identify emerging coordination issues and supports adaptive managerial interventions.

Process performance signals (S-P1) and operational system signals (S-P2) provided direct information about deviations in process behavior and system states. Information system signals (S-P3), often generated or enhanced through AI-supported analytics, played a particularly important role in early disturbance detection and pattern recognition. As shown in Table 5, these signals were most strongly associated with AI-supported decision-support actions (A-P5).

Human-process interaction signals (S-P4) complemented system-generated data by capturing changes in operator behavior, communication patterns, and decision-making activities. The integration of AI-supported analytics with multiple signal types enabled a more comprehensive interpretation of disturbance situations, supporting proactive and informed management responses.

Overall, the results demonstrate that effective disturbance handling in Industry 4.0 production systems depends on the structured integration of disturbances, management actions, and signals, with AI acting as an enabling decision-support mechanism.

The results provide important insights into the role of AI-supported process management tools in handling disturbances in Industry 4.0 production systems. By explicitly linking disturbance categories with management actions (Table 4) and AI-supported signal interpretation (Table 5), the study advances a process-oriented understanding of disturbance handling in digitally integrated production environments.

Table 6 provides a synthesized overview of the dominant relationships between disturbance types and applied management actions. The dot-based representation highlights recurring disturbance–response patterns, showing that AI-supported decision-support actions (A-P5) are most strongly associated with information-intensive and integration-related disturbances (D-P4 and D-P5), while traditional process management actions remain central for handling technical and organizational disturbances.

Table 6

Relationships between disturbance codes (D-codes) and management action codes (A-codes)

D-codes/A-codes	A-P1	A-P2	A-P3	A-P4	A-P5
D-P1	●	●			●
D-P2		●	●	●	
D-P3			●	●	●
D-P4				●	●
D-P5	●		●		●

● *indicates the presence of a dominant or recurring relationship identified in the empirical analysis*

The discussion focuses on interpreting the identified disturbance-response patterns from a process management perspective, with particular attention to the role of AI-supported decision-support tools in Industry 4.0 production systems. Rather than reiterating the empirical findings, this section seeks to explain *why* specific patterns emerge and *how* they contribute to improved disturbance handling in digitally integrated production environments.

Process-oriented disturbance-response patterns

The results confirm that disturbance handling in Industry 4.0 production systems cannot be understood as a set of isolated corrective actions. Instead, it represents a system of recurring disturbance-response patterns embedded in interconnected production processes. The dot-based representation presented in Table 6 provides a condensed visualization of these patterns and highlights the dominant links between disturbance types and management actions.

The observed patterns indicate that traditional process management actions remain fundamental for handling technical and organizational disturbances. For example, technical disturbances (D-P1) are predominantly associated with process adjustment (A-P1) and resource management actions (A-P2), reflecting the continued importance of classical production engineering interventions. However, the presence of AI-supported decision-support actions (A-P5) alongside these traditional responses suggests a shift toward more informed and data-driven decision-making even in technically oriented disturbance situations.

Organizational and human-related disturbances (D-P2 and D-P3) show strong associations with coordination- and information-oriented actions (A-P3 and A-P4). This pattern underscores the role of process transparency, communication, and information flow as critical enablers of effective disturbance handling in complex production systems. Importantly, the co-occurrence of A-P5 in human-related disturbances suggests that AI-supported tools can support managerial consistency and reduce cognitive load in decision-intensive situations.

The role of AI in pattern stabilization rather than automation

One of the most significant insights derived from Table 6 is the selective and non-universal role of AI-supported decision-support actions. AI does not appear as a dominant response across all disturbance categories; instead, its strongest associations are observed for information flow disturbances (D-P4) and process integration disturbances (D-P5). This finding suggests that AI contributes most effectively in situations characterized by high data intensity, system interdependencies, and limited human observability.

Rather than automating disturbance handling, AI-supported actions contribute to *pattern stabilization* by enabling managers to recognize recurring disturbance configurations and select appropriate response strategies. In this sense, AI functions as a cognitive extension of process management rather than as a replacement for managerial judgment. This interpretation aligns with the conceptual positioning of AI as a decision-support mechanism and addresses common concerns related to excessive automation in Industry 4.0 environments.

The absence of AI-supported actions as a dominant response to certain disturbance types further reinforces the argument that effective Industry 4.0 implementation does not require universal AI deployment. Instead, targeted integration of AI into specific process management actions appears to be both sufficient and desirable.

Implications for production engineering and management systems

From a production engineering perspective, the identified disturbance-response patterns highlight the need to design management systems that explicitly account for process interdependencies and information dynamics. The structured relationships illustrated in Table 6 provide a practical reference for configuring process management tools in Industry 4.0 production systems.

From a management systems perspective, the findings suggest that AI-supported tools should be embedded within existing process management frameworks rather than introduced as standalone solutions. The coexistence of traditional actions (A-P1 – A-P4) with AI-supported decision-support (A-P5) indicates that hybrid management systems, combining established practices with intelligent support, offer a balanced and scalable approach to disturbance handling.

More broadly, the results contribute to ongoing discussions on resilience and adaptability in production systems by demonstrating that resilience emerges not from technological sophistication alone, but from the structured alignment of disturbances, management actions, and decision-support mechanisms. The analytical framework proposed in this study, and particularly the pattern-based insights derived from Table 6, provide a foundation for future research on process-oriented and AI-supported production management.

CONCLUSION

This study examined the use of AI-supported process management tools for handling disturbances in Industry 4.0 production systems. The findings confirm that disturbances remain an inherent feature of digitally integrated production environments and require structured, process-oriented management approaches rather than reactive interventions.

The results show that basic process management tools, including process adjustments, resource management, organizational coordination, and information management, form the core of effective disturbance handling. Artificial intelligence enhances these tools by supporting pattern recognition, signal interpretation, and managerial decision-making, particularly in information-intensive and highly interconnected disturbance situations. Importantly, AI functions as a decision-support mechanism and does not replace human judgment in the management process.

Based on the findings, the following key highlights can be identified:

- **Disturbance handling in Industry 4.0 production systems is primarily process-oriented**, relying on coordinated management actions rather than isolated corrective measures.
- **AI-supported tools strengthen existing process management practices,** especially in situations characterized by complex data flows and system interdependencies.
- **Effective integration of AI does not require full automation,** but targeted decision-support embedded within established management frameworks.
- **Structured linking of disturbances, management actions, and process signals enhances managerial consistency and process resilience.**

Overall, the results highlight the importance of combining established management tools with intelligent support systems to improve process stability, responsiveness, and resilience in modern production systems.

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