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| RESEARCH ARTICLE

A Human-Centric AI Governance Framework for Smart Manufacturing Systems

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| ABSTRACT

Increased usage of AI in smart manufacturing allows predicting equipment failures, performing automated quality checks, optimizing processes, implementing intelligent robotics, and making decisions based on data. At the same time, increased AI autonomy creates a number of issues related to the transparency, accountability, data reliability, safety, and decision-making ability of humans. This paper presents the Human-Centric AI Governance Framework for Smart Manufacturing Systems that helps to adopt AI in a responsible way but still retains the possibility for humans to retain control over operations. The framework comprises five layers that are interconnected with each other. These layers include: AI and data governance, risk and decision classification, human oversight and decision authority, operational monitoring and control, and accountability with continuous improvement. One of the distinguishing features of the framework is that it uses the risk-based approach where the amount of human involvement increases with respect to the risks associated with the potential consequences of the decision made by means of AI. The practical use of the proposed framework is demonstrated by means of an example related to the use of AI in the process of predictive maintenance of equipment. The integration of data validation, risk classification, human involvement, performance monitoring, and feedback in the process of using AI is illustrated on the given example.

| KEYWORDS

Human-Centric AI; AI Governance; Smart Manufacturing; Industry 5.0; Responsible AI; Human Oversight; Artificial Intelligence; Intelligent Manufacturing

| ARTICLE INFORMATION

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1. Introduction

The fast-paced development of AI technology is bringing changes to the modern manufacturing industry, making production systems smarter, connected, flexible, and autonomous. Technologies such as machine learning, computer vision, the Industrial Internet of Things, digital twins, intelligent robotics, and big data analytics are increasingly used across manufacturing processes in order to facilitate maintenance, inspections, process control, production planning, resource management, and decision making. The described features are core characteristics of smart manufacturing, which involves collecting and analyzing vast amounts of data in order to increase efficiency, quality, flexibility, and use of equipment. With the development of AI technology from a tool for analysis into a system that facilitates decision making, the impact on the physical processes of manufacturing becomes even stronger [1].

However, increased autonomy in AI presents difficulties that go beyond the established standards of accuracy and efficiency of the system itself. AI can give an accurate prediction without much information about how the decision was made in the first place. In addition, decisions about shutting down devices, changing process parameters, choosing what maintenance to conduct, what to reject in terms of quality control, and robotics can have consequences for the safety of workers, productivity of processes, quality of products, and performance of the company. Too much reliance on automated predictions can create an automation bias, and lack of clarity in the division of responsibility can prevent proper attribution of accountability in case of negative consequences from such decisions [2].

This shows the need to shift from a technological perspective on AI governance to a human one. Human-centered governance does not mean restricting automation or insisting that humans always confirm all decisions made through algorithms. It involves ensuring that human control remains an important part of the process in cases where decisions made by AI may have operational, safety, ethical, or organizational implications. Such a perspective is in close agreement with those being developed through the Industry 5.0 concept, where human-centeredness is complemented with technological effectiveness, sustainability, and resilience. In manufacturing industries, the experienced people who run the machines may have some context-specific information that cannot be learned from data or AI [3][4].

While there has been increasing focus on trustworthy and responsible AI, current methods have been defined at higher organizational and technology levels. Similarly, in the domain of smart manufacturing, most efforts have concentrated on the applications of AI, prediction, performance, automation, and optimization. An actual problem in this context is how to align principles of AI governance with the specific aspects of manufacturing contexts in which digital decision-making may impact machines, processes, products, and people. Also, different applications of AI do not pose the same level of risk; for example, AI that is used to predict energy consumption requires a different amount of control compared to one that can change critical process parameters [5][6].

This research paper fills a known void in literature through the development of a Human-Centric AI Governance Framework for Smart Manufacturing Systems. The framework takes into consideration several key aspects like AI and data governance, decision making risk categorization, human supervision and empowerment, monitoring and accountability with continuous improvement. The fundamental idea behind this framework is that the level of human supervision needed depends on the possible outcomes of an AI decision in terms of operational risk, safety and effects on humans. This framework can help promote responsible AI adoption and at the same time retain the flexibility of smart manufacturing systems.

2. AI in Smart Manufacturing: Opportunities and Governance Challenges

AI is now playing an important role in intelligent manufacturing as it enables the conversion of large-scale manufacturing data into predictive and prescriptive insights. Modern manufacturing processes use a combination of data gathered from machines, sensors, production lines, quality control mechanisms, and enterprise applications in order to make quick and well-informed decisions. Machine learning algorithms enable the identification of patterns which are often difficult to identify through traditional methods of monitoring, allowing manufacturers to forecast equipment failure, process irregularities, optimize process parameters, and make dynamic adjustments to changing production needs. Therefore, AI is becoming an active participant in the decision-making process in manufacturing [7][8].

Another application that has been well-established is that of predictive maintenance, which involves AI analyzing parameters such as vibrations, temperatures, pressures, acoustic waves, and past maintenance histories of machines in order to determine the current status of the machine and predict any probable failures. This early identification of deterioration will help prevent downtime as well as plan for maintenance depending on the actual state of the machine. On the same note, another application of AI is in computer vision for automated quality control, where images of manufactured items are analyzed to identify defects and any variations in shape, assembly, or other aspects that deviate from the required quality standards [9].

Not only in the context of particular machinery, but also outside of it, artificial intelligence can improve the planning process of manufacturing through scheduling, allocating resources, predicting demand, creating digital twins, and using intelligent robots. The combination of digital twins and AI results in the creation of constantly updated models of the manufacturing processes and assets, thus allowing for the evaluation of possible scenarios before making any changes in the actual process. Intelligent robots also change their behavior depending on the circumstances of production and interaction with human operators. However, increased levels of autonomy mean that the decisions made by AI have an impact on both physical processes and people involved in them [10].

One of the key governance issues involves the transparency problem with AI decision making. The complicated machine learning algorithms may produce outputs that lack sufficient explanation for operators and engineers. For example, an AI could suggest the replacement of a certain part of the machine, reject a produced item, modify a process variable or stop production; however, the system will not provide enough information on why this output was produced. In the absence of sufficient explanation for the outputs, human oversight is very difficult. On the other hand, continuous interaction with seemingly correct AI outputs may lead to automation bias [11][12].

Accountability is yet another important issue that has to be dealt with. The more decisions are made by manufacturing industries using AI technologies, the more interactions there will be between different parties, including AI system developers, data scientists, process engineers, operators, maintenance staff, equipment vendors, and plant managers. In case something goes wrong because of an AI-based decision-making, namely when an accident or some other event occurs as a result of such a decision, it may be hard to identify who is responsible for what [13].

It should be noted that the reliability of decisions made with the help of artificial intelligence is dependent on the quality of the data collected within the manufacturing industry. Problems related to sensors' breakdowns, insufficient information for historical analysis, changing circumstances, inaccuracies in labeling, cybersecurity problems, or the problem of drift in models could affect model performance once it becomes operational. It should be emphasized that this issue acquires special importance in the manufacturing industry since the digital prediction leads to the physical action [14][15].

The issues outlined above reveal that AI governance in manufacturing cannot be based only on the technical aspects, such as accuracy of the models. The governance framework should take into account the environment and implications associated with each individual decision made by the AI. The decisions related to workers' safety, critical equipment, the integrity of the product, or significant process variables require much more control from the humans and well-articulated procedures of intervention. The risk-based approach forms the foundation of human-focused governance, in which the level of human involvement directly correlates with the implications of AI decisions. The key principles of governance are analyzed further below.

3. Human-Centric AI Governance Principles

Human-oriented governance of artificial intelligence in intelligent manufacturing involves striking a balance between the operational efficiency of intelligent machines and the role of human beings in decision-making procedures that carry considerable weight. The goal is not to limit the freedom of artificial intelligence systems but to ensure that the level of their freedom corresponds to the level of risks, complexity, and consequences associated with the decisions. In this regard, there are five principles that human-oriented governance may be based on [16].

Human monitoring forms the core principle of the governance model that is suggested in this paper. The appropriate level of human involvement would depend on the possible impact of the decision made through the use of artificial intelligence. There are three types of human interaction that have been traditionally used: human-in-the-loop, human-on-the-loop, and human-out-of-the-loop. In the case of human-in-the-loop, an operator, an engineer, or another agent is able to examine and approve the recommendation of the AI prior to implementing it [17]. This type of monitoring is especially relevant for critical decisions related to safety-critical equipment or processes, human-robot interaction, or significant changes in procedures. Human-on-the-loop means that AI is able to independently complete certain actions, while people are able to monitor their performance and interfere if necessary. Human-out-of-the-loop monitoring might be appropriate in the case of low-risk repetitive operations when the consequences of any mistakes would not be very severe [18].

The principles of transparency and explainability are necessary to provide effective oversight by humans. The operators and engineers have to be informed about enough information to understand the underlying reasons for the significant AI decisions, especially if these decisions involve physical manufacturing procedures. Transparency implies knowledge about the used data, limitations of the model, levels of certainty and operational boundaries. The explainability should also focus on the needs of the manufacturing professionals and not on the technical data designed only for the developers of AI. For example, a failure prediction becomes much clearer when there are known factors that contributed to the failure, such as unusual vibrations or overheating [19].

Accountability ensures that accountability is maintained in environments where there is partial automation of the decisions. It is imperative to ensure that there is a clear assignment of roles relating to ownership of the AI systems, data management, model verification, authorization, performance and monitoring as well as incident management. Hence, it is important to ensure that AI systems are not accountable independently between the software developers and manufacturing staffs. Instead, accountability should be clearly assigned to all the stakeholders such as AI developers, process engineers, operators, maintenance staff, IT and management staff [20].

In cases where artificial intelligence comes into contact with physical machines in manufacturing environments, safety and reliability become issues of paramount importance. AI should be designed to operate within safe parameters, as well as to detect abnormal operation, declining model accuracy, and untrusted data. Any high-stakes operations conducted by artificial intelligence should incorporate a fail-safe that allows humans to step in before the onset of danger. It is important to monitor such systems, since, although a model may have proven itself to be reliable initially, this will likely decline as machine conditions change [21].

Last but not least, worker engagement and empowerment are key ingredients of human-focused governance. The contribution of workers in manufacturing environments, such as operators, technicians, and engineers, includes information that is not necessarily captured in data sets and algorithms. Involving these workers in the development, verification, deployment, and assessment of the AI system can improve the reliability of the system as well as its acceptance among users. Therefore, human feedback, such as the decision to reject an AI recommendation, should be treated as useful information [22][23].

All these principles collectively form the basis of a governance approach wherein AI technology is an amplifier to human expertise and not a replacement. Human oversight provides the decision-making power, transparency provides the scope to intervene, accountability provides the responsibility, while safety and reliability ensure the physical processes are secure. Further, involvement of workers provides the practical insights into the AI process life cycle. Based on these principles, the next section forms the Human-Centric AI Governance Framework.

4. Proposed Human-Centric AI Governance Framework

Borrowing from the human-centric considerations introduced earlier, this research presents a five-level governance architecture to be adopted for the adoption of artificial intelligence in smart manufacturing environments. The proposed governance architecture aims at connecting the technology-related aspects of AI management with operational risks, human decision-making authority, monitoring, and accountability. Breaking away from the monolithic governance architecture that applies to all types of situations, the proposed framework adopts the risk-oriented perspective where control is strengthened in line with the possible consequences of the decision made through AI. The five interdependent levels include: (1) AI and Data Governance, (2) Risk and Decision Classification, (3) Human Supervision and Decision Authority, (4) Operational Monitoring and Control, and (5) Accountability and Continuous Improvement.

4.1 Layer 1: AI and Data Governance

This first layer explains the technical foundation upon which trustworthy AI operation rests. The performance of the system is very dependent on the quality, relevancy, and reliability of data utilized when training the system as well as during real-time decision making. Data used in manufacturing can come from sensors, machines, quality assurance systems, maintenance data, enterprise software systems, or operators. For this reason, there needs to be provisions made for data verification, traceability, data ownership, data access control, cybersecurity, and data management. Information about the AI model needs to be provided about its purpose, the data used for training it, limitations, operating parameters, and its versioning history.

4.2 Layer 2: Risk and Decision Classification

Once the validation of the AI system and its data is done, then in the second tier, the potential consequences of the decision made by the system are analyzed. The framework that has been proposed divides the AI-driven manufacturing decisions in three types of risks, namely low risk, medium risk, and high risk. The low-risk applications would include activities like energy forecast, production reports, and other analytical recommendations. The medium risk applications would include activities like predictive maintenance, production schedule, and quality recommendations, which might not create a direct danger of safety or cost but can adversely affect the productivity and cost.

AI risk categorization must include both the probability of the AI's incorrect output as well as the consequences that it entails. In this context, the risk categorization becomes the bridge between AI autonomy and human control.

4.3 Layer 3: Human Oversight and Decision Authority

The third layer determines the right level of human intervention based on the risk assessment made in the second layer. Low-risk tasks with sufficient validation might operate with significant autonomy and be subject to occasional human evaluation. Medium-risk tasks can be taken care of by operating in a human-on-the-loop setup, whereby the AI system takes action or recommends an action and the human monitors the system with the ability to override its recommendations. High-risk tasks ought to follow the human-in-the-loop setup.

The following example of a scenario includes the automatic generation of a warning by the AI regarding abnormal vibrations in machinery. In case the system then recommends the stopping of an important manufacturing line or any process variable outside the set operation parameters, the decision needs to be escalated to a human. A sample high-risk decision-making process could be:

AI Identification → Risk Analysis → Human Review → Decision Making → Implementation

The above structure preserves the benefits of fast AI processing as well as ensuring that the decision-maker is known for risky decisions.

4.4 Layer 4: Operational Monitoring and Control

AI governance is not limited to deployment, since the manufacturing setting and the way models operate might change through time. Therefore, the fourth layer includes monitoring. Examples of important metrics can include predictions' precision, false positives, process deviations, model drift, data quality problems, operator intervention, overrides, and safety incidents.

It is important that human overrides be systematically recorded. Constant override of an individual's suggestion from the AI system could be indicative of inefficient performance of the system, changes in production circumstances, and other considerations that the model does not account for. Therefore, monitoring needs to involve both performance measures and human feedback. Once pre-set performance/safety standards are exceeded, the system should automatically escalate its operations.

4.5 Layer 5: Accountability and Continuous Improvement

The final layer identifies the accountability of the organization and builds in the feedback process to improve AI governance in the future. There must be defined responsibility in each area of the AI implementation process, including ownership of the AI system, data handling, validation of the model, operations, decision-making authority, and investigation of any incidents. The decision logs will ensure that the AI recommendations and subsequent actions are recorded.

The framework takes the approach that governance is a process in a lifecycle rather than one-off decision-making exercise. Operational experience should form part of continuous model and governance improvement by way of the following cycle:

Monitor → Audit → Learn → Update → Validate → Redeploy

For example, false alarms due to maintenance may require retraining the model, while repeated override actions from operators may require changing the decision logic or risk classification. Also, changes in machinery, materials, manufacturing environment, and safety standards would require a re-examination of the artificial intelligence system.

On the whole, the five-stage model is a governance cycle rather than controls that are separate from each other. AI and Data Governance ensure trusted inputs; Risk Classification analyzes the impact that the decisions made by AI can have; Human Oversight identifies the scope of decision-making power for human beings; Operational Monitoring evaluates actual performance; and Accountability turns the experience gained at the operational level into improvement. Human safety, transparency, and accountability are present in all five stages. Hence, the offered framework allows manufacturing companies to empower AI appropriately and leave humans in charge where it matters.

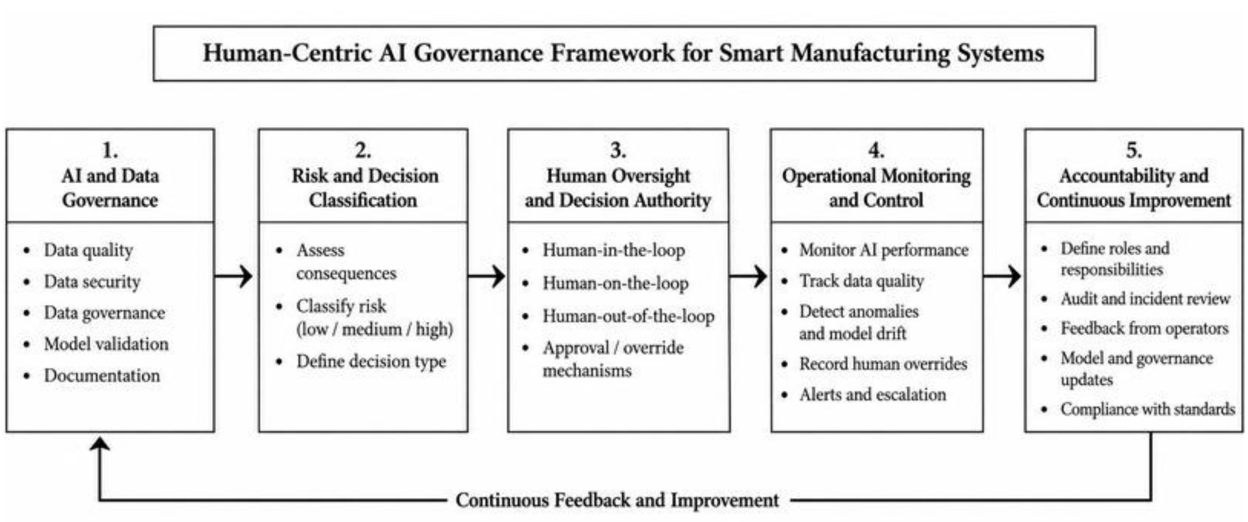

Fig 1. Human-Centric AI Governance Framework for Smart Manufacturing Systems

The Human-Centric AI Governance Framework for Smart Manufacturing Systems will follow a five-step governance process cycle, which aims at ensuring reliability, transparency, and proper human oversight of manufacturing decisions made through AI systems. First comes AI and Data Governance, which includes quality of data, data security, model validation, and documentation. Next is the process of Risk and Decision Classification, whereby AI decisions are classified into low, medium, or high risk based on the severity of the possible consequences that might arise from the decision. This is followed by Human Oversight and Decision Authority, which classifies the operation of the AI systems depending on whether the AI can be operated independently, requires continual human intervention, or requires approval from humans. Operational Monitoring and Control will involve continual analysis of AI performance, quality of data, drift of model, human overrides, and abnormal behavior of AI during the implementation process. Accountability and Continuous Improvement will establish who is responsible, conduct auditing of outcomes, incorporate feedback from operators, and update the AI model and governance framework.

5. Framework Application in Smart Manufacturing

The pragmatic usability of the proposed Human-Centric AI Governance Framework could be proved by an AI-powered prediction maintenance system used in the context of smart manufacturing. Imagine a factory where all of the critical equipment is being constantly monitored using the data about vibration, temperature, sound, current and other operating parameters. The machine learning algorithm analyzes the data and predicts anomalies and failures in the future. While the use of this system could increase maintenance efficiency, at the same time the decisions made by the system could influence the availability of equipment, schedules of production, expenses on maintenance and even the safety of the workers. The use of the proposed framework will ensure that the decision making process takes into account the possible outcomes of those decisions.

At Layer 1: AI and Data Governance, the readings obtained from sensors and the records from past maintenance processes get validated before being used for prediction. The documents involve data completeness, data quality in terms of reliability of the sensors, access controls, version of the model, and history of prediction. For example, when a vibration sensor gives different data, then there should be a detection of the problem with the data.

At Layer 2: Risk and Decision Classification, the output from AI is evaluated depending on its consequence. A decision for regular check-up can be termed as low-risk, while a prediction of impending failure of crucial production machinery will fall under medium to high-risk. Similarly, a decision by AI which requires shutting down of the machinery immediately will be of a higher risk category since any error in decision-making can cause disruption of production or create further operational consequences.

The decision-making system provides the necessary level of human intervention in Layer 3-Human Oversight and Control. In the case of low-risk alerts, they can be automatically registered and included in the maintenance planning process. In the case of medium-risk forecasts, they have to be analyzed by the maintenance staff during the period when the AI system is supervised. For the high-risk decisions like the shutdown of important devices, the system has to provide relevant data like unusual trends in the sensors, forecasted failure scenario, and reliability metrics to the appropriate engineer or supervisor before implementing any action.

Post-implementation, Layer 4: Operational Monitoring and Control monitors the continuous reliability of the predictions made by the AI system. Data on prediction accuracy, false alarms, prediction of no failure where there is one, number of overrides by operators, results of maintenance, and change in behavior of the equipment are collected. For example, if maintenance technicians keep on overriding the AI prediction of failures and inspections show that there was nothing wrong with the equipment, then the human feedback may serve as a valuable data source regarding AI performance.

Finally, the fifth layer, Accountability and Continuous Improvement, uses operational records to improve both the AI model itself and its governance processes. The responsibility of managing the model, its maintenance, the quality of the data, and updates of the model are assigned to certain organizational roles. Frequent false predictions might lead to model re-training and/or re-validation, and changes in the equipment or operations will require re-evaluation of the initial risk assessment.

This governing principle can be easily extended to other applications in the smart manufacturing domain such as automated quality inspections, intelligent robotics, digital twins, production scheduling, and intelligent process controls. Critically, the required amount of human involvement depends on the significance of the decision that needs to be made. While an AI system can optimize a non-safety critical production schedule independently, any changes to a critical machining, welding, thermal, or robotic process parameters will require human confirmation. Thus, this framework does not call for a single approach to human involvement, but provides a scalable governing model where the higher significance of the AI autonomy leads to greater human involvement.

6. Discussion and Implications

The suggested Human-Centric AI Governance Framework suggests that adopting AI responsibly in smart manufacturing involves much more than accuracy and automation. As the involvement of AI into decision-making becomes ever greater, it is important to find a proper balance between the autonomy of machines and human control. This is precisely what is accomplished by the suggested framework, which links the extent of human control to the level of risk of the AI-assisted decision being made. This solution is necessary to avoid the following two extremes: human involvement that undercuts the advantages of automation and the uncontrolled autonomy of AI.

In an organizational sense, the architecture allows for more accountable, understandable, trustworthy decisions, as well as greater preparedness for governance. The defined roles of system owners, validators, approvers, and handlers limit uncertainties about who is responsible for the decisions made using the AI algorithms. On the other hand, the involvement of the operators and engineers in the system monitoring provides recognition of the importance of their knowledge about manufacturing processes. Human override can provide useful feedback on process changes, data quality, and potential performance problems with the models.

The proposed framework has important implications regarding the transition from Industry 4.0 to Industry 5.0 in which technology will be gradually merged with the values of human centrism, resilience, and sustainability. In such a case, artificial intelligence will retain its ability to quickly process data and make decisions while humans will retain control in situations that require understanding, evaluation, or analysis. Such cooperation may result in creation of highly developed manufacturing processes that would take into account human and organizational needs as well.

However, there could be difficulties in implementing the framework. Development of governance processes could increase the costs at the outset and could require collaboration among the manufacturing, engineering, IT, data science, safety, and management domains. Setting up the right risk threshold might be challenging due to varying complexities and implications of manufacturing processes. In addition, the lack of interpretability in some types of AI, aversion to new decision-making structures, a lack of AI governance knowledge, and ever-changing manufacturing environment might hinder implementation of the framework. This implies that the framework needs to be kept flexible.

As a whole, the model treats human-centered governance as enabler of responsible AI autonomy, rather than inhibitor of automation. Through granting more autonomy to lower-risk systems and keeping humans at the center of important choices, manufacturing companies will be able to enjoy all the benefits of AI in an ethical manner.

7. Conclusion and Future Research

The integration of artificial intelligence in smart manufacturing is revolutionizing the ways through which production systems are being monitored, optimized and controlled. While there is no doubt that the adoption of AI offers great possibilities in terms of improving productivity, quality, flexibility, predictive maintenance and efficiency, higher levels of autonomy pose issues related to issues such as transparency, accountability, reliability of data, worker safety, and human involvement in decision making processes.

This paper develops a Human-Centric AI Governance Framework for Smart Manufacturing Systems that consists of five interconnected layers of: (1) AI and data governance, (2) risk and decision classification, (3) human supervision and decision-making authority, (4) monitoring and control of operations, and (5) accountability and continuous improvement. This framework defines the risk-dependent linkage between AI autonomy and human involvement, which allows more autonomy in the low-risk cases and stricter human supervision of decisions having high operational and safety impacts. As a result, human knowledge and AI technologies are viewed as complementary components of intelligent manufacturing, not conflicting decision-making tools.

Future research can focus on validating the suggested framework using industrial applications and evaluation by experts who are manufacturing engineers, operators, artificial intelligence experts, and safety experts. It is suggested to develop some quantitative governance measures that can be used for measuring parameters like frequency of overrides, model validity, decision traceability, human reaction, and governance efficiency. Further, some studies can look at the use of the suggested framework in digital twins, collaborative robotics, autonomous quality inspection, AI-enabled welding and additive manufacturing, and other such manufacturing operations where there is an associated safety risk.

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