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Smart In-Process Inspection with Human-Automation Symbiosis for Industry 5.0 Manufacturing Systems

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Abstract

Since the advent of Industry 4.0, manufacturing industries have been continually integrating cutting-edge technologies into manufacturing systems, creating a more complex and dynamic production environment. To maintain high product quality throughout the manufacturing processes, in-process inspection (IPI) becomes an efficient strategy, enabling prompt identification of defective parts and real-time process control through defect mitigation. Consequently, smart in-process inspection (s-IPI) has emerged as a critical research area in manufacturing. Furthermore, as manufacturing technologies advance, the relationship between humans and automation agents evolves. Industry 5.0, as the next phase in manufacturing, differs from Industry 4.0 by shifting its focus from economic gains to human social value and well-being, emphasizing a human-centric philosophy. This underscores the importance of implementing human-automation symbiosis (HAS), which fosters closer partnership and mutually beneficial collaboration between humans and automation agents. In this regard, this paper envisions s-IPI with HAS in Industry 5.0 manufacturing systems (I5MS) as an emergent research paradigm. This paper explores the integration of s-IPI into manufacturing systems and the implementation of HAS for I5MS from the task allocation and task execution perspectives. This research sets the stage for future innovations in manufacturing, ultimately contributing to the development of human-centric environments.

Keywords
Industry 5.0, Human-automation symbiosis, Human-automation interaction, In-process inspection, Advanced manufacturing systems

Introduction
Since the revolution of Industry 4.0, manufacturing industries have kept integrating innovative and cutting-edge technologies into different application scenarios of manufacturing systems to improve production performance. Radical changes take place not only in single workstations but also in operations at the system level, which are driven by multiple factors, such as increased data availability, real-time data analysis, and decision-making, advances in robotics and automation, and so on (Arinez et al. 2020). In this evolving context, the manufacturing environment becomes more dynamic and complex, introducing new characteristics such as high-precision manufacturing, self-optimization and self-configuration, digitalized operations management, high-mix low-volume manufacturing, human-automation collaboration, and so on. To fit in this dynamic, complex, and connected working environment,

manufacturers must reexamine and adjust their current operations and strategies, with a significant emphasis on the role of human operators. In this regard, this paper proposes smart in-process inspection with human-automation symbiosis in Industry 5.0 Manufacturing systems. Section 2 presents the literature review. Section 3 shows the research framework. Sections 4 to 7 introduce research tasks and solutions for each identified fundamental issue. Finally, conclusions are provided in Section 8.

2. Literature Review

2.1 Industry 5.0 Manufacturing Systems

Industry 4.0 emphasizes the digitalization of manufacturing, where smart factories utilize advanced data analytics and automation to enhance efficiency, flexibility, and productivity. The core technologies driving Industry 4.0 include Internet of Things (IoT), big data, AI, and machine learning, which collectively enable real-time monitoring and decision-making in manufacturing environments (Lasi et al. 2014). The advent of Industry 4.0 has led to significant transformations in production methods, supply chain management, and product lifecycle management, promoting a more interconnected and intelligent manufacturing landscape (Hermann et al. 2016). Furthermore, the human workforce's role is evolving, requiring new skill sets to interact with advanced technologies and manage automated systems effectively (Buer et al. 2018).

In contrast, Industry 5.0 represents a human-centric approach to industrial development, focusing on the collaboration between humans and machines. While Industry 4.0 emphasizes automation and data exchange, Industry 5.0 seeks to enhance the synergy between human intelligence and cognitive computing. This evolution aims to create a more sustainable, resilient, and socially responsible industrial ecosystem (Nahavandi 2019). It emphasizes personalized production, where human and customization play a significant role, supported by collaborative robots and AI (Xu et al.2018). Compared to the age where humans and machines work independently, humans and automation agents are more engaged and form a synergetic team (Romero et al.2016). The performance of this system is the product of the quality of both the automation support and the manner in which humans use this support (Sanchez 2009). Industry 5.0 thus represents a paradigm shift towards a more inclusive and human-friendly production environment.

2.2 Manufacturing Inspection

In manufacturing industries, inspection is an essential part of maintaining product quality. Inspection can be defined as an activity that measures, examines, tests, or gauges one or more characteristics of a product or service and compares the results with specifications to understand if conformity is achieved for each characteristic (Genta et al. 2020). If a product or a part is identified as a defect, there will be several actions before the next stage: it can be sent back to the station for rework modification, it can be replaced by a new defect-free one, or it can be scrapped. Inspection can be categorized into online inspection and offline inspection based on the timing of the operation.

Online inspection involves real-time monitoring and examination of a manufacturing process and inspects process, while offline inspection happens after the process is completed. Online inspection can be more effective than offline inspection, but it has more challenges in data acquisition and control algorithms (Shi 2023). Inspection can be conducted with destructive and non-destructive methods. For non-destructive methods, conventional approaches include vision-based approaches, radiography, acoustic or ultrasonic testing, and so on. Visual inspection is one primary approach in manufacturing inspection, and prevailing approaches include manual inspection, machine vision, statistical methods, deep learning, and so on (Wang et al. 2024). Manual inspection relies on operators' observations and experience for judgment decision-making, and the performance can be influenced by human fatigue and subjectivity. To conduct a fast and reliable inspection for productivity improvement, advanced vision techniques are needed, such as machine vision and deep learning algorithms.

2.3 Human-automation Interaction

In recent years, many new concepts have emerged or are advocated in manufacturing industries, bringing new technologies into manufacturing activities for system performance improvement. These new technologies have gradually changed the role of operators in manufacturing activities (Holm 2018). Meanwhile, the relationship between humans and technologies has been continuously evolving during the integration (Nahavandi 2019; Wang et al. 2023a.). HAS has gained consensus as a vision for the future of human-automation research in both industry and academia. HAS is a concept stemming from "man-computer symbiosis", in which symbiosis emphasizes the coexistence and mutual benefits from it (Licklider1960). Similarly, HAS distinguishes itself from other human-automation relations because of the partnership and mutual benefits (Gerber et al.2020). HAS entails several objectives, including developing an effective system that augments human capabilities and coordinate both agents to work towards a common goal, optimal and dynamic use of resources, human-like communication, and so on (Jacucci et al. 2014).

These objectives depict a dynamic human-automation system where human and automation agents are interdependent, and their collaborative performance is better than the sum of individual performance. Meanwhile, there are some reasons why HAS is identified as one primary study after HAI. Firstly, it is expected that the joint power of human and automation agents goes beyond physical power enhancement and intelligence amplification (Wilson and Daugherty 2018). Secondly, accepting automated agents as crew members is a better direction than building a fully automated system (Marquez et al. 2018). This is not only due to the loss of situation awareness in a highly automated system but also because human errors are inevitable and can be passed from the design stage to the operating stage. Thirdly, a fully automated system in which humans only monitor the system and intervene has high risks that operators cannot take over manual control when the system fails, and proper engagement is needed to maintain operator situation awareness (Endsley 2017). Therefore, seeking a symbiotic relationship is beneficial and effective for a human-automation system.

3. Research Framework

Advanced manufacturing is envisioned to be fulfilled by various cutting-edge technologies, making the production environment more complex and dynamic. To maintain high product quality all along the manufacturing processes and enable in-time feedback of process issues, in-process inspection is an efficient strategy that manufacturers usually adopt. In this regard, this section envisions smart in-process inspection as an emergent research paradigm for manufacturing in Industry 5.0, elaborating on the efforts of implementation and integration of smart inspection in Industry 5.0 manufacturing systems. By examining this issue from three levels of a manufacturing system (workstation level, process level, and system level), this study identifies four fundamental issues of s-IPI with human-automation symbiosis in I5MS. A holistic framework is proposed to illustrate the fundamental issues.

As a quality control strategy, IPI conducts inspection operations within the manufacturing stage, which identifies defective parts immediately when or after they are processed. This approach is expected to enhance overall product quality and yield by enabling prompt defect handling and real-time process control. Advanced manufacturing environments are characterized by their dynamic, complex, and fast-paced production nature. Integrating IPI into such manufacturing systems requires seamless collaboration between human operators and automation systems. This section examines how s-IPI influences manufacturing from a system hierarchy perspective and proposes a holistic framework for achieving s-IPI in I5MS.

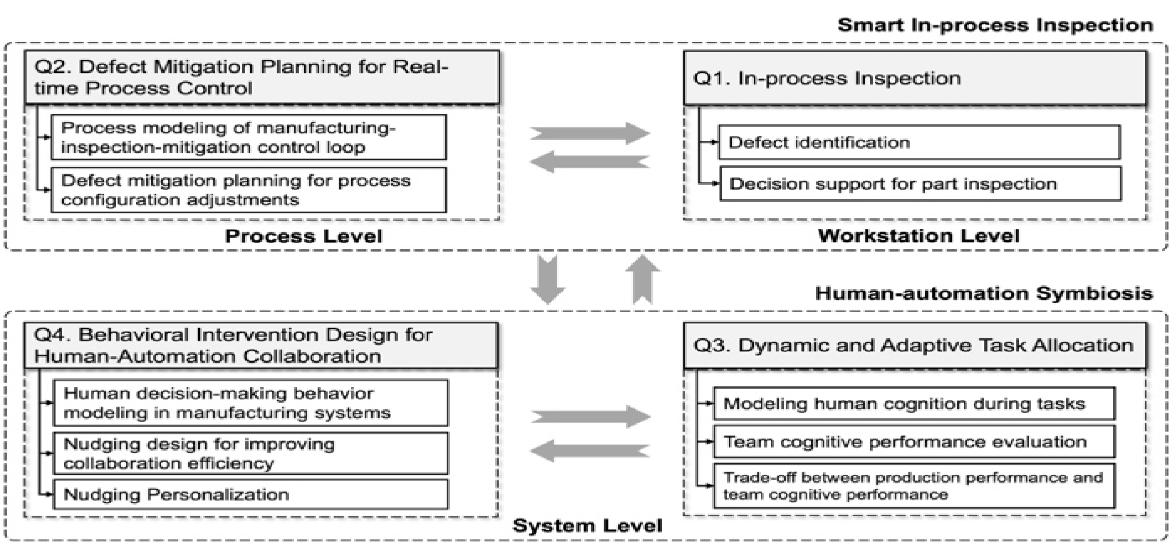

Figure 1. A Holistic framework for s-IPI in I5MS

(1) Workstation level. The workstation level executes manufacturing tasks, where human operators and machines work individually or collaboratively to complete tasks with inspection operations performed within the workstation.

Defect analysis, such as scrap or rework decisions, is also performed to support defect disposition. (2) Process level. The process level controls the process configurations of a production line, focusing on process self-configuration through defect mitigation planning. Defect mitigation planning addresses how to adjust process configuration to eliminate or reduce defects based on defect information collected from the workstation level. (3) System level. The system level manages and plans production operations for the human automation team, coordinating collaboration between human operators and automation agents to maintain production performance. This level aims to achieve a symbiotic relationship for the human automation team through dynamic task allocation and the design and personalization of manufacturing nudges. Nudge is used to indirectly encourage individuals to act or believe in a certain way (Kahneman and Tversky 2013), and manufacturing nudging aims to alter or influence operators' behavior during their interaction with automation systems by presenting certain information at the proper time, which can be in different forms, such as visual cues via Augmented Reality glasses or auditory prompts via earphones. Under this proposed hierarchy, the workstation level provides defect information to the process level for defect mitigation planning, which then adjusts machine configurations accordingly. Concurrently, data from production lines, such as machine status, operator status, and process cycle time, are utilized by the system level to dynamically assign tasks and configure manufacturing nudges for team synergy. This feedback loop ensures continuous improvement and alignment across all levels, enhancing HAS and overall production efficiency.

To further understand the underlying requirements, the fundamentals of s-IPI in I5MS and the corresponding technical issues are examined and summarized into a holistic framework, as shown in Figure 1. The proposed framework addresses two primary objectives of three levels within the system hierarchy: smart in-process inspection and human-automation symbiosis. Smart in-process inspection involves two fundamental issues: in-process inspection, and defect mitigation planning for real-time process control. Human-automation symbiosis also involves two fundamental issues: dynamic and adaptive task allocation, and behavioral intervention design for human-automation collaboration. These four fundamental issues are detailed with their underlying technical aspects in the framework, providing a comprehensive approach to achieving s-IPI with HAS in I5MS.

3.1 In-process Inspection

Implementing inspection within the same process as the manufacturing operation is a crucial and fundamental issue. The integration of inspection into the manufacturing process requires modifying the existing procedures to accommodate an additional inspection task during or immediately after the manufacturing operation. One example is 3D printing inspection, which uses infrared cameras during the printing process to monitor part quality (Gradl et al., 2020). In-process inspection involves two primary technical issues. Firstly, defect identification is to detect and classify defects using selected vision equipment and inspection algorithms. Challenges in this area include ensuring that both hardware and software are capable of performing accurate and reliable defect inspection in an Industry 5.0 manufacturing environment. Secondly, decision support for part inspection aims to automate decision-making activities partially or fully during the inspection process. Activities include defect disposition (deciding whether to scrap or rework a part), assigning rework operations, and so on. These automated decisions help streamline the inspection process.

3.2 Real-time Process Control through Inspection Feedback

The objective of s-IPI extends beyond merely identifying defective parts, it also aims to mitigate defect generation from a process control perspective. Achieving this requires addressing two key technical issues: process modeling of the manufacturing-inspection-mitigation control loop and defect mitigation planning for process configuration adjustments. The control loop refers to a self-configuration process that uses mitigation planning to correct process configurations that lead to defects, based on inspection results. The loop ensures that the manufacturing process is continuously adjusted to reduce or eliminate defects, enhancing overall product quality. Defect mitigation planning involves the cognitive processes required to determine how to adjust process configurations. Effective mitigation planning leverages real-time data from inspection, ensuring the potential issues are addressed promptly and efficiently.

3.3 Dynamic and Adaptive Task Allocation

Given the cognitive complexity of inspection and other manufacturing tasks, collaboration between human operators and automation systems is essential and inevitable. This study proposes two approaches to enhance HAI and facilitate HAS: task allocation during the planning stage and behavioral interventions during the execution stage. Therefore, dynamic and adaptive task allocation is identified as one fundamental issue, which aims to achieve mutual adaptation between human operators and automation agents with human-centered allocation while maintaining production performance. Unlike conventional human-automation task allocation which focuses solely on production performance and employs static allocation, the proposed method introduces human cognition to task allocation and utilizes real-time agent status, allowing agents to adjust themselves to better align with the status of other team members. To achieve dynamic and adaptive task allocation, several technical issues need to be addressed, including (i) modeling human cognition during tasks, which involves identifying factors that can represent human cognition and formulating them mathematically; (ii) team cognitive performance evaluation, which enable a new team performance measure that can reflect human cognition at the team level; and (iii) trade-off between production performance and team cognitive performance, which aims to balance the two performance and is crucial for optimal task allocation. By addressing these issues, the proposed method can create a more adaptive and efficient collaboration between humans and automation, ultimately enhancing HAS.

3.4 Behavioral Intervention Design for Human-automation Collaboration

Once tasks are allocated to operators and automation agents, manufacturing procedures begin. In the production environment, training operators to interact effectively with automation agents takes time, and it is very common for operators to deviate from standard procedures. Such deviations can reduce collaboration efficiency and production performance. To address this, this study proposes to apply behavioral interventions, or manufacturing nudges, to influence or alter operator behavior towards desired standards. Several technical issues are involved in this approach. (i) Human decision-making behavior modeling in manufacturing systems. This involves developing behavioral economic models to quantify the utility of different behaviors. Understanding how operators make decisions concerning losses and gains in the manufacturing context is essential for designing effective interventions. (ii) Nudging design for improving collaboration efficiency. This focuses on modeling the design process of manufacturing nudges, including the process of nudging and evaluation of nudges with different configurations. The goal is to develop mathematical formulations that can reflect operator perception toward nudges under different working scenarios. (iii) Nudging personalization. This aims to tailor nudge configurations to better fit individual operators who use the nudges, which further enhances the effectiveness of the nudges. Personalized nudges help accommodate operators with diverse backgrounds and preferences, thus improving team synergy. These three issues provide a comprehensive approach to designing behavioral interventions that enhance human-automation collaboration.

4. Visual Analytics and Intelligent Reasoning for Smart Defect Identification

4.1 Inspection Automation

Prevailing approaches to visual inspection include manual inspection, machine vision, and deep learning (See et al., 2017). Manual inspection relies on operators to make decisions based on their observations and judgment, with or without vision equipment like a microscope. Manual inspection requires human resources and training for operators, while inspection accuracy and efficiency are unstable and influenced by individual differences. Moreover, operators have limitations in both inspection precision and speed. To conduct a fast and reliable inspection and to improve productivity, human operators need to be assisted with vision systems that can provide visual analytics support. Thus, there are growing demands for inspection automation by using advanced vision techniques (Mallik-Goswami and Datta, 2020). Current industrial solutions to visual inspection are either machine vision or deep learning, which perform well when inspection criteria are explicitly formulated to describe defect features, and defects can be clearly distinguished with non-defective features. These solutions are usually less efficient when complex inspection criteria with ambiguity are involved, and solution development highly relies on engineering experience and knowledge.

Smart visual inspection aims for algorithm-based visual analytics and autonomous decision-making to mitigate operators' cognitive load. Therefore, a smart visual inspection process usually involves two types of tasks: image data analysis and intelligent reasoning. The first task aims to obtain information from raw vision images through visual processing or deep learning techniques. The second task is to derive knowledge with obtained information through reasoning and to apply the derived knowledge to operations. Several technical challenges exist for implementing smart visual inspection, including the trade-off between the false positive and the false negative during inspection, and intelligent reasoning for autonomous decision-making. (1) Visual inspection is expected to strike a balance between the false positive rate and the false negative rate while keeping them both at a low level. The former refers to the rate of missing identification of a defective part, while the latter is the rate of rejecting a good part. False positives are usually more important to manufacturers since they are related to product quality and can influence customer trust. Meanwhile, a high false negative rate leads to less yield and increases manufacturing costs. In real-world applications, adjusting the machine vision system to be more sensitive to defects sometimes also makes it easier to identify more acceptable features that are similar to defect features, and the trade-off between the false positive and false negative needs to be made. (2) To conduct a full cycle of inspection, sometimes intermediate decision-making needs to be made for aggregating the inspection results and making a conclusion for pass/fail or needed rework operations. To enable autonomous decision-making, apart from vision devices and algorithms that implement image data analysis, an intelligent reasoning system needs to be established to conduct the inference that operators will go through.

4.2 Two-level Visual Analytics Approach

To overcome the shortcomings of image processing or CNN for cosmetic inspection, this study proposes a two-level visual analytics approach that integrates machine vision and deep learning: the former detects and locates the objects that are potential defects with the objective of reducing the false positive rate, while the latter classifies detected objects into different categories and handles the false negative issues.

The workflow is illustrated below. i) Potential defect detection. This step is to use different detection algorithms, such as blob detection and template matching, to identify potential defects in the image. The objective is to avoid missed detection as much as possible, which may find many non-defective objects. For the detected objects, the outputs should include the x and y position, the area, the ferret diameter, and other geometric features that can help classification. ii) Filter objects by specifications and remove duplicates. Some detected objects can be filtered out before classification based on defect specifications on defect area and shape. Meanwhile, different machine vision algorithms may have overlapped detection on the same image and identify the same object multiple times. Using the object location information to remove duplicated features can decrease the number of classifications needed. iii) Image cropping. After machine vision identifies all the objects, they need to be cropped from the image as CNN inputs. Considering defect features may have a different dimension, the size of the cropping window can be dynamically changed according to the object ferret diameter. iv) Classification. With all object images prepared, the next step is to determine if these objects are defects and their defect types. Because defect classification is a multi-classification problem, this step normally uses one multi-classification model. However, mixing the defect classification task with the classification between defects and non-defects can increase the problem complexity and decrease the overall performance, this study proposes to first conduct binary classification to identify defect objects and then classify defects with a multi-classification model.

There are several advantages of the proposed approach. Firstly, it can conduct a qualitative inspection with quantitative measurement. Geometric features like area and aspect ratio are difficult to capture in deep learning algorithms but can be precisely extracted by machine vision tools. On the other hand, pure machine vision solutions have limited functionality for classification tasks, making them improper for complex qualitative analysis. Secondly, it has better control over the false positive and false negative performance. In production, inspection specifications are set by quality engineers to guide and control the manufacturing and to guarantee final products meet the requirements. Therefore, defects are defined subjectively. Unlike classification between objects that are naturally different, the difference between defect features and non-defect features can be small. It is common that a machine vision system would need to detect a lot more non-defect features to capture some subtle defects. If the system needs to be less sensitive, it will be unable to detect subtle defects. The proposed approach solves this problem by controlling the false positive with machine vision and the false negative with deep learning. Thirdly, it allows the detection and classification of defects with a very small area compared to the field of view. Prevailing deep learning techniques have their limitations if defect and non-defect features share many similarities and when the feature size is very small. Because machine vision techniques manipulate the image at the pixel level, its detection is based on the number of pixels that a target has and is irrelevant with the raw image resolution. This enables the system to capture features that only occupy 0.001% of the image, while it is very challenging for deep learning-based solutions.

5. Cognitive Intelligent Manufacturing Defect Mitigation

5.1 Manufacturing Defect Mitigation

In the manufacturing industry, defect mitigation encompasses the methodologies and tactics aimed at minimizing, controlling, and eradicating defects in products, systems, and processes. This approach is pivotal in enhancing the efficiency and sustainability of manufacturing operations (Psarommatis et al. 2021). Advanced data-driven technologies are instrumental in this context, facilitating real-time monitoring and predictive maintenance, which are essential for effective defect mitigation. The implementation of robust data management systems is crucial as it ensures the accuracy and usability of data for defect detection and classification (Thung et al. 2012). The research underscores the importance of a strong data management system and effective information management in achieving successful defect mitigation (Woo & O'Connor 2021).

Various manufacturing processes have adopted different strategies for defect mitigation. For instance, Borish et al. (2019) highlight the significant enhancement in defect identification and mitigation in large-scale additive manufacturing through the integration of real-time data collection and analysis. Additionally, reinforcement learning-based approaches have proven effective in mitigating new defects by dynamically adjusting process parameters, thereby improving overall quality and efficiency (Chung et al.2022). In this scenario, continual G-learning is employed to adjust these parameters, integrating both offline and real-time knowledge. Meli et al. (2018) also emphasize the necessity of advanced defect detection and process improvement strategies to address stochastic defects in Extreme Ultraviolet lithography. These examples illustrate the diverse applications and methodologies of defect mitigation across different manufacturing contexts.

5.2 System Analysis

Case-based reasoning is a tool to reference historical examples for decision-making and can be used for infrequent reasoning activities that rely on human experience. The advantage over conventional rule-based reasoning is that it does not need expert knowledge to develop a knowledge base. Instead, it relies on the accumulation of solved cases and the ability to identify similar historical cases. Then the solution to the current case is the reuse or modification of the historical solution. This enables the system to evolve as new cases continuously accumulate.

This study identifies several key steps for defect mitigation based on the procedures of case-based reasoning, ranging from the development of a case base using generative AI to inference with knowledge graphs. Firstly, domain experts will determine case representation based on historical mitigation documents, identifying the attributes that describe a mitigation case. Secondly, a case base in the form of knowledge graphs is developed using generative AI. Through effective prompt engineering, generative AI can automate the knowledge acquisition process, outputting data in the form of “entity-relation-entity”. Knowledge graphs are an effective method for knowledge modeling, enabling efficient management of the case base (Wang et al.2024). These graphs consist of nodes and edges, representing entities and relations separately. Thirdly, defect analysis can be conducted based on inspection results to create a new case for the corresponding defect features. The new case is also described using the entity-relation format. Fourthly, using the attributes of the new case and historical cases, a knowledge base can be created, and an embedding model can be trained to represent entities and relations in an embedding space. Fifthly, with the embeddings from the previous step, case retrieval can be performed by identifying the closest matching cases to the new case, allowing the selection of the mitigation strategy based on the solutions of these cases. Sixthly, after selecting the optimal strategy, specific process configurations are determined based on defect features and the chosen strategy. These configurations are then applied to the production operations. Finally, the mitigation results will be restored in the new case, which is then retained in the case base for future reference.

5.3 GPT-Powered Domain Knowledge Modeling and Reasoning

LLMs rely heavily on generative algorithms to produce data based on the knowledge they have acquired. The quality of the database from which these models learn directly impacts the relevance and accuracy of their responses. Thus, creating a high-quality knowledge database is crucial. As discussed in the previous section, the Neo4j database is a suitable tool for creating a domain knowledge-based database. Its ability to illustrate relationships between domain nodes is vital for analyzing and constructing embeddings, which are necessary for representing connections between different knowledge areas. Furthermore, Neo4j's capability to integrate with various LLMs simplifies the management and building of functions within the database for efficient retrieval and representation. The built-in functions provided by Neo4j also facilitate the modification and application of algorithms, such as embeddings and retrieval, enhancing their ease of use.

The basic process of building a domain knowledge database is depicted in Figure 2. The initial data is generated from the input of domain knowledge experts with specific expertise in an industrial domain. This information is organized as nodes (representing knowledge regions) and lines (representing the connections between these nodes). The graph database serves two primary functions: visualizing the nodes and lines of the domain knowledge and embedding all the necessary information (such as vectors or Cypher queries) for these nodes and lines using embedding algorithms. Generative algorithms can then access this data to train models for future predictions or to generate query responses to questions posed by users. Therefore, the graph database is crucial for domain experts, users, and generative algorithm agents. The agents not only retrieve data from the database but also update it with newly generated data based on expert inquiries. This step ensures that the database continuously evolves and becomes more specialized, maintaining its relevance and accuracy over time.

To enable case-based reasoning for defect mitigation, this study proposes a knowledge graph embedding approach for case representation and retrieval in the selection of mitigation strategies (Wang et al. 2023). The proposed approach offers several advantages compared to conventional symbolic case representation (Ali et al.2018). (i) Efficient knowledge base development. Generative AI facilitates automatic knowledge acquisition, eliminating the need for manual extraction from historical documents.

This allows for the efficient creation of a comprehensive knowledge base through automatic reasoning. (ii) Enhanced scalability. Traditional case representation requires adding new attributes for each new case feature. In contrast, knowledge graphs achieve this by simply introducing new types of relations, streamlining the management of the case library. (iii) Semantic feature descriptions and calculations. Knowledge graphs allow natural semantic descriptions, making case retrieval more straightforward. Semantic descriptions are initialized as entity nodes and embedded in the embedding space, facilitating difference calculations. (iv) Visualization of case similarities. Knowledge graphs can express relations between case features, visualizing case similarities. Unlike traditional case-based reasoning which relies on manually designed similarity measures, this approach minimizes the loss function during triple training to determine similarities. (v) Flexible case adaptation. Integrating the knowledge base with a LLM enhances the flexibility of case adaptation. Production rules can be modeled within the knowledge base, enabling the RAG application to apply knowledge more dynamically and respond to operator inquiries based on actual scenarios.

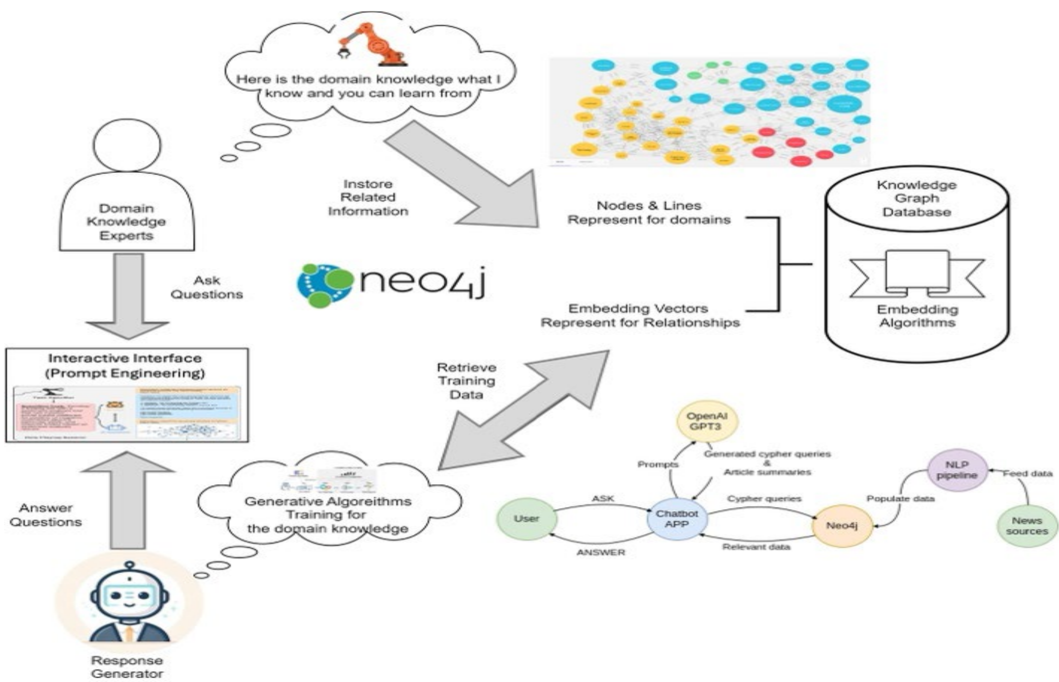

Figure 2. A basic procedure of GPT-powered knowledge base creation

6. Cognitive Intelligent Task Allocation

Task allocation aims to assign manufacturing tasks to human operators and automation agents to optimize human-automation collaboration. Unlike conventional approaches that focus solely on production performance, this study identifies cognitive intelligence as a crucial aspect of human-automation task allocation. This involves modeling human cognition, which is characterized by cognitive states and human trust, to evaluate team cognitive performance. Cognitive states represent the operator's cognitive load and attention, while human trust indicates the operator's confidence in different levels of automation. To balance the optimization of production performance and team cognitive performance, the task allocation problem is formulated as a non-cooperative game – the Stackelberg game, where the leader optimizes production performance, and the follower optimizes team cognitive performance. The non-cooperative game implies how symbiosis is achieved in a human-automation team through optimizing different team performance measures. This formulation is essentially a bi-level optimization problem. To solve it, a Multi-Environment Genetic Algorithm (MEGA) is proposed.

In a human automation team, task allocation is commonly formulated as an optimization problem, where the objective function is the evaluation of team performance, and the decision variables are the details of task assignment. Unlike conventional task allocation where the objective is to optimize cost and time, the context of HAS requires dynamic allocation considering the human cognition to enable human-automation mutual adaptation in a dynamic, team-based and distributed manufacturing operational environment (Salas et al. 2007). To include human cognition in task allocation, it is imperative to understand and measure cognition at the team level to assess team performance (Mohammed et al. 2000; Lipshitz et al.2021).

In the HAI studies, several concepts about cognition can be confusing, including team cognition, augmented cognition, and collaborative cognition. Augmented cognition refers to bolstering human cognition using technologies through human-automation interactions in complex manufacturing environments. Collaborative cognition focuses on the interaction between individuals to achieve better decision-making and performance in complex tasks. Team cognition can be characterized as an explanation of the shared understanding of tasks and teammates, which include both human-human and human-automation teams (Fiore et al.2005). team cognitive performance is therefore identified as a key component to achieving HAS in a dynamic and team-based manufacturing environment.

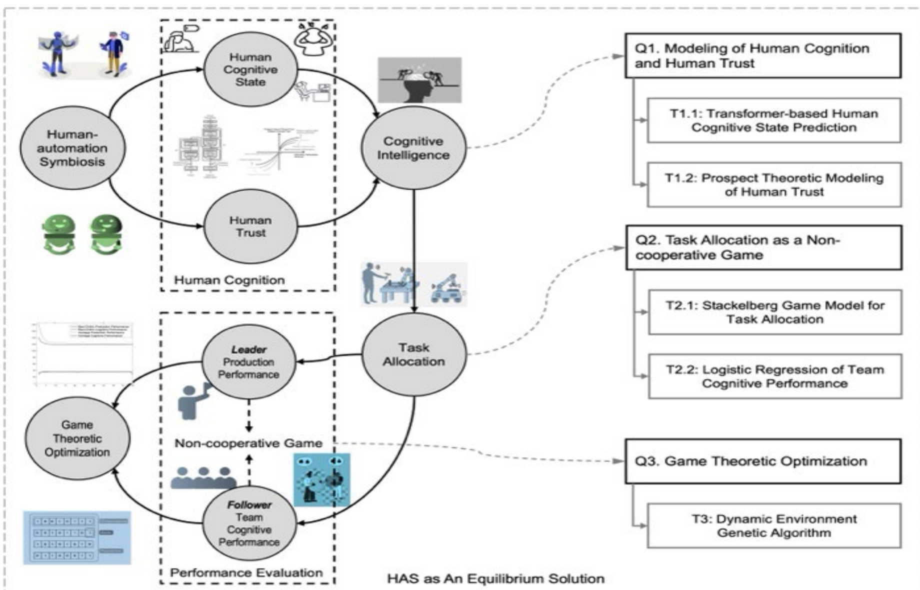

Figure 3. Roadmap of cognitive intelligent task allocation for HAS

In this context, team cognitive performance, which can be defined as the shared understanding of the tasks and teammate status, can enhance the cognitive capabilities of human workers, maximizing task performance, efficiency, and intuitiveness of the interaction (Jiao et al.2020). This further requires identifying key factors that influence human-automation interaction and their relationship with team cognitive performance. Additionally, one characteristic of Industry 5.0 manufacturing is that a single task may be fulfilled through the collaboration of a human operator and an automation agent, requiring not only agent-task assignment but also determining the level of automation for the automation agent.

In this regard, this study targets to enable cognitive intelligence during task allocation to achieve HAS, with the research roadmap displayed in Figure 3. With the objective of achieving a symbiotic relationship in a human-automation team, cognitive intelligence is envisioned to be the crucial enabler, which introduces the human cognition into the cyber-physical system. To achieve the effects of cognitive intelligence for task allocation, this study further identifies human cognitive states and human trust as two important perspectives of human cognition. There are several considerations. Firstly, cognitive intelligent task allocation implies workload and attention management, which requires evaluating human cognitive states in real time. Secondly, human trust reflects the confidence level of operators toward automation agents, and it is essential during task allocation to determine the level of automation for proper automation uses. Thirdly, evaluating cognitive performance at the team level requires team members to possess a shared understanding of their equipment and their coworkers (Salas et al., 2007), which can be represented by human cognitive states and human trust.

7. Human Behavioral Economics Modeling for Smart Manufacturing Nudging Design

The implementation of HAS implies the transformation of a CPS into a HCPS, which requires introducing the human dimension into the system. To achieve this objective, human cognitive performance is modeled during human-automation task allocation in the previous section. Meanwhile, in the production environment, many human-technology interactions involve human decision-making, such as choosing the level of automation usage. Different from task allocation where tasks are directly assigned to operators, they can make decisions independently during HAI. It is imperative to model human decision-making behaviors to add the human dimension to these scenarios.

7.1 Conjoint Prospect Theory for Human Behavioral Economics Modeling

To model the behavioral patterns in regard to decisions with conflicting goals, a microeconomic model is developed based on prospect theory. Unlike expected utility theory, which assumes people are completely objective, prospect theory characterizes human irrationality during decision-making. The prospect value function, which serves the same role as the utility function in expected utility theory, exhibits an S-shaped graph with losses and gains relative to a reference point. As the value deviates from the reference point along the graph, the curve initially starts steep and then levels out. This reflects that people are more sensitive to changes around their expected values. Meanwhile, the slope on the loss side is steeper than on the gain side, indicating that individuals weigh losses more heavily than gains.

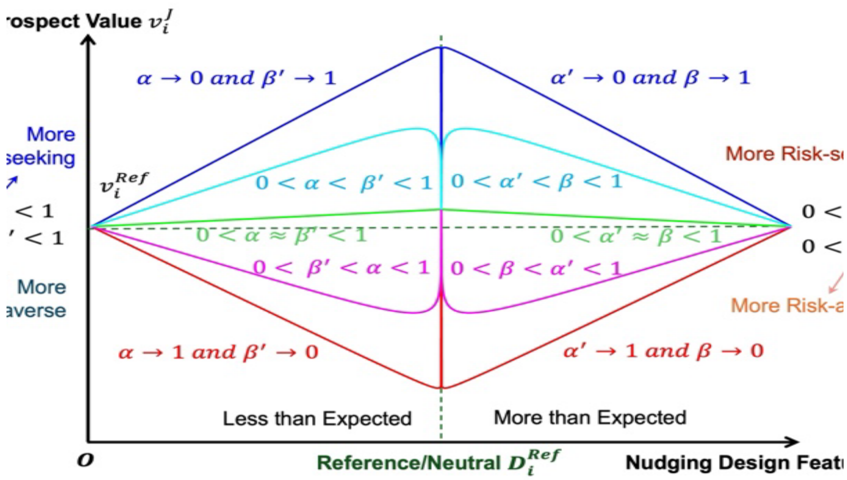

Figure 4. Varying shapes of conjoint prospect value function for different nudge effects

This study further extends the existing prospect theory with a conjoint view to accommodate and aggregate two inherently conflicting perceptions from producers and customers. The formulation of the model is presented below:

$$v^J(x) = v^P(x) + v^C(x) \tag{1}$$

$$v^P(x) = \begin{cases} v^{Ref} + (x - x^{Ref})^{\alpha'}, x \geq x^{Ref} \\ v^{Ref} - \lambda(x^{Ref} - x)^{\beta'}, x < x^{Ref} \end{cases} \tag{2}$$

$$v^C(x) = \begin{cases} v^{Ref} + \tau(x^{Ref} - x)^{\alpha}, x < x^{Ref} \\ v^{Ref} - \theta(x - x^{Ref})^{\beta}, x \geq x^{Ref} \end{cases} \tag{3}$$

where Equation (2) and Equation (3) are the producer prospect value function v^P and the customer prospect value function v^C, which are from two conflicting perspectives and formulated based on the prospect theory, and Equation (1) suggests the conjoint prospect value function v^J is derived by additive representation of v^P and v^C. Meanwhile, x is the outcome of the choice, x^{Ref} is the reference or neutral point of the outcome and used to frame different decisions (into loss and gains). v^{Ref} is the prospect value when the outcome is at the reference point. The proposed conjoint prospect-theoretic model involves three types of parameters, including (a) affective-cognition shaping parameters, α and β ($0 \leq \alpha, \beta \leq 1$) and α' and β' ($0 \leq \alpha', \beta' \leq 1$), (b) producer loss aversion parameter λ ($\lambda > 0$), and (c) customer negative experience aversion parameter θ ($\theta > 0$) and customer positive experience coefficient τ ($\tau > 0$), which are affected by their emotions during operations. In the neutral state, $\gamma = 1, \theta = \lambda$. After aggregating the two prospect value functions, the conjoint prospect value function can be studied separately to guide the application of behavioral economics modeling. Figure 4 shows potential shapes of the conjoint prospect value function with various value combinations of model parameters $\alpha, \beta, \alpha', \beta'$.

7.2 Smart Manufacturing Nudging Design and Personalization

Manufacturing nudging aims to alter or influence people's behavior by presenting certain information at the proper time. To study it from the engineering design perspective, the conceptual design of manufacturing nudges can refer to the four essential elements of axiomatic design, including customer needs, functional requirements, design parameters, and process variables (Suh, 1998). Customer needs and functional requirements of manufacturing nudges depict the key scenarios where operators mistakenly interact with automation systems and how their behavior should be guided or altered in those scenarios. Given these inputs, nudging designers further identify design parameters by describing manufacturing nudges from different dimensions (e.g. information density and visibility) and enumerate different options (e.g. low, medium, high density of information presented to operators) to explore the design space.

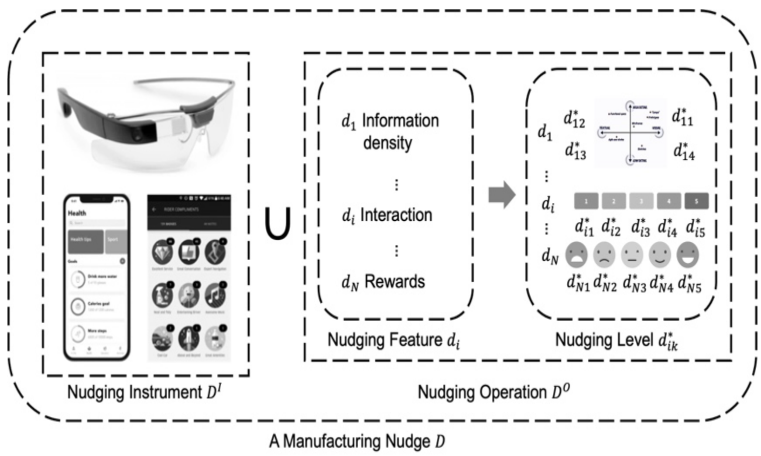

Figure 5. Modeling of a manufacturing nudge

To incorporate manufacturing nudging design and personalization problems into the above context, a manufacturing nudge can be modeled, which is illustrated in Figure 5. It is posited that manufacturing nudges D are realized through two coupled aspects, which are nudging instruments D^I and nudging operations D^O, where $D = D^I \cup D^O$. A nudging instrument can be understood as a platform to implement and execute nudges. In the manufacturing context, based on the form of the nudge (i.e. visual or auditory nudges, etc.), there can be different options for nudging instruments, such as smart glasses, smart wristbands, or earphones.

The instrument can be virtual, too, such as an application that records operator behavior details and advocates certain code of conduct by rewarding certain behaviors, which is normally seen in service systems. Meanwhile, nudging operations are the contents of a nudge. They can be characterized by a set of nudging features d_i and enabled with the instantiation of these features d_{ik}^*. Let d_i be one nudging feature, $D^O = \{d_i, i = 1,2, \dots, I\}$ where I is the total number of nudging features. A nudging feature d_i (can be referred to as design parameters) has various levels of nudging d_{ik}^* (can be referred to as process variables), which can be represented as $d_i = \{d_{ik}^*, k = 1,2, \dots, K\}$, where k corresponds to the k-th level of the nudging feature d_i, and K is the total number of levels for the nudging feature d_i. For instance, one nudging feature d_i is the nudging information density for an assembly operation using augmented reality smart glasses, and a high-level feature instance and a low-level one may differ in the number and label of highlighted assembly subparts presented to the operator.

With the above formulation, manufacturing nudging design can be treated as a multi-criteria design evaluation problem: given a manufacturing nudge $D^O = \{d^*_{1k_1}, d^*_{2k_2}, \dots, d^*_{Ik_I}\}$, how to develop a mathematical approach to evaluate its utility. Meanwhile, nudging personalization can be seen as an optimal configuration problem, which targets at a group of operators in one production line and aims to assign nudges according to the uniqueness of each individual, so the optimality can be achieved between HAS and manufacturing system performance.

8. Conclusions

In this paper, smart in-process inspection with human-automation symbiosis in Industry 5.0 is proposed as an emergent research paradigm. This research has significant influence on design and operations of Industry 5.0 manufacturing systems, which aims to improve product quality with self-optimization and self-configuration process control and achieve a symbiotic relationship between human operators and automation agents. The research emerges from three disciplines, including advanced manufacturing systems, cognitive engineering, and human-automation interaction. This research has two primary objectives, which are smart in-process inspection and human-automation symbiosis.

To achieve the two objectives, this paper contributes by proposing a holistic framework of s-IPI with HAS, where four fundamental issues are identified by examining the three levels of the manufacturing system architecture, including: In-process inspection at the workstation level; Defect mitigation planning for real-time process control at the process level; Dynamic and adaptive task allocation at the system level; Behavioral intervention design for human-automation collaboration at the system level. These four fundamental issues aim to explore the integration of s-IPI into advanced manufacturing systems as well as the implementation of HAS from the task planning and execution perspectives in I5MS. To address these fundamental issues, several research tasks are then formulated and studied in this work, including: smart defect detection and judgement; cognitive intelligent defect mitigation; cognitive intelligent task allocation; modeling of human behavioral economics; and smart manufacturing nudging design and personalization.

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