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Explainable AI (XAI) Framework for Transparent Human–Machine Job Scheduling in Hybrid Printing Operations

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Abstract
Hybrid printing operations integrate conventional manufacturing, additive manufacturing, and digital printing technologies, to create complex scheduling challenges arising from dynamic production environments, heterogeneous resources, and the limited transparency of conventional Artificial Intelligence (AI)-based scheduling systems. This study develops an Explainable Artificial Intelligence (XAI) framework for transparent human–machine job scheduling for the improvement of scheduling efficiency, interpretability, transparency, and collaborative decision-making in Industry 5.0 manufacturing. A systematic systems-engineering methodology that comprise system modeling, data acquisition and preprocessing, AI-based scheduling optimization, and explainability evaluation was adopted. The framework integrates reinforcement learning, multi-objective optimization, and XAI techniques for the generation of optimized scheduling decisions accompanied by human-readable explanations. Experimental evaluation was conducted in a simulated hybrid printing environment with the application of scheduling metrics, including makespan, flow time, machine utilization, energy consumption, and production cost, together with explainability metrics such as transparency, interpretability, and user trust. The results indicate that the proposed framework outperforms conventional scheduling approaches by improving production efficiency, reducing scheduling time and energy consumption, optimizing resource utilization, and balancing workloads. Moreover, the explainability component enhances users' understanding and validation of AI-generated scheduling decisions, thereby strengthening trust, accountability, and effective human–machine collaboration. The proposed framework provides a transparent, scalable, and trustworthy scheduling solution that advances Explainable AI applications in hybrid printing operations and supports sustainable, human-centric Industry 5.0 manufacturing.
Keywords: *Explainable Artificial Intelligence (XAI), Hybrid printing operations, Human–machine collaboration, Production scheduling, Industry 5.0, Reinforcement learning, Transparent decision-making*

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I. Introduction

1.1 Background of the Study

The emergence of Industry 5.0 has redefined manufacturing by shifting from fully automated production environments towards human-centric intelligent systems in which humans and Artificial Intelligence (AI) collaboratively optimize industrial decision-making. Unlike Industry 4.0, which primarily emphasized cyber-physical systems, automation, and the Industrial Internet of Things (IIoT) (Chukwunedum et al., 2026; Ajaefobi et al., 2026), Industry 5.0 prioritizes human–machine collaboration, resilience, sustainability, and transparency in production processes (Akintona et al., 2026; Okpala et al., 2026). Among the manufacturing functions that are influenced by this paradigm shift, production scheduling remains fundamental because efficient coordination between intelligent machines and human operators directly affects productivity, resource utilization, operational flexibility, product quality, and delivery performance.

Hybrid printing systems, which integrate conventional manufacturing, digital printing, and additive manufacturing into unified production workflows, exemplify this transformation by offering enhanced customization, reduced lead time, and improved material efficiency (Gibson et al., 2021). However, the heterogeneous nature of these systems significantly increases scheduling complexity, as they require simultaneous consideration of machine capabilities, operator expertise, maintenance requirements, energy consumption, material availability, and customer demands. AI techniques, particularly reinforcement learning, have demonstrated exceptional capabilities in solving dynamic scheduling problems through continuous learning from real-time production environments, thereby improving makespan, resource utilization, and production efficiency (Yahya et al., 2024). Nevertheless, most AI scheduling models remain black-box systems whose opaque decision-making processes reduce user trust, accountability, and industrial adoption.

Explainable Artificial Intelligence (XAI) addresses this limitation by employing techniques such as SHAP, LIME, counterfactual explanations, attention visualization, and rule extraction to provide transparent, human-interpretable scheduling decisions, thereby enhancing trust, fairness, and collaborative decision-making (Arrieta et al., 2020; Gopalan et al., 2025). Despite these advances, limited research integrates explainability with AI-driven scheduling in hybrid printing environments. Therefore, this study proposes an Explainable Artificial Intelligence (XAI) framework that combines reinforcement learning-based scheduling optimization with interpretable decision-support mechanisms to enhance transparency, human trust, and collaborative production scheduling, while maintaining high operational performance.

1.2 Problem Statement

Despite significant advances in Artificial Intelligence (AI)-based manufacturing scheduling, most existing algorithms function as black-box models, providing limited transparency into their decision-making processes. This lack of explainability undermines user trust, accountability, and effective human–machine collaboration, particularly in complex hybrid printing environments involving heterogeneous resources, dynamic production demands, and uncertain operating conditions. Current scheduling approaches primarily optimize operational objectives such as makespan and resource utilization while overlooking interpretability and human-centered decision support. Consequently, production planners remain reluctant to adopt AI-generated schedules. Addressing this gap requires an explainable AI framework that enhances transparency, fosters trust, and supports collaborative scheduling in hybrid printing systems.

1.3 Aim of the Study

The aim of this study is to develop an Explainable Artificial Intelligence (XAI) framework for transparent human-machine job scheduling in hybrid printing operations.

1.4 Research Objectives

To achieve the stated aim, the following are the research objectives:

- To examine the existing AI-based scheduling techniques that are applied in hybrid printing operations;
- To identify the limitations of black-box scheduling models with respect to transparency and human trust.
- To develop an Explainable AI framework that integrates intelligent scheduling with interpretable decision-making.
- To evaluate the performance of the proposed framework using scheduling and explainability metrics.
- To assess the influence of transparent AI explanations on human trust, scheduling acceptance, and collaborative decision-making.

II. Literature Review

Hybrid printing operations integrate conventional manufacturing, Additive Manufacturing (AM), and digital printing into a unified production environment for the improvement of manufacturing flexibility, productivity, product quality, and resource efficiency. This manufacturing paradigm supports the objectives of Industry 4.0 and Industry 5.0 by enabling intelligent, sustainable, and human-centric production systems that are capable of mass customization and data-driven decision-making (Atieh et al., 2022; Udu et al., 2025). Conventional manufacturing provides high precision and surface quality, but is constrained by material waste, high tooling costs, and limited customization capabilities (Srivastava et al., 2019).

Conversely, AM enables the production of complex geometries with minimal material waste, although challenges relating to production speed, material compatibility, and surface quality remain (Chikwendu & Emeka, 2025). Digital printing enhances rapid prototyping, personalized production, and product traceability; however, the integration of these heterogeneous technologies substantially increases scheduling complexity, because diverse resources, production priorities, and dynamic operational conditions must be simultaneously coordinated (Antsiferov et al., 2025; Zhang et al., 2024).

Human–machine collaboration is a fundamental principle of Industry 5.0, where AI complements rather than replaces human expertise. AI systems generate optimized production schedules, while human operators validate scheduling decisions using practical knowledge, safety considerations, and organizational objectives, thereby improving scheduling flexibility and operational resilience (Renggli et al., 2025). Although autonomous scheduling enhances responsiveness through real-time optimization, the absence of transparent decision-making reduces user confidence and organizational trust, which emphasizes the need for explainable AI-based scheduling systems (Akinbo, 2026).

AI has significantly advanced production scheduling through adaptive and data-driven optimization. Conventional optimization methods, including Linear Programming (LP), Mixed Integer Linear Programming (MILP), Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and Simulated Annealing (SA), provide near-optimal scheduling solutions but become computationally expensive for complex manufacturing systems (Ferrolho & Crisóstomo, 2007). More recent machine learning, deep learning, and Deep Reinforcement Learning (DRL) approaches improve predictive maintenance, resource allocation, and dynamic scheduling performance in flexible manufacturing environments (Omar et al., 2024; Ghimire et al., 2024; Hu et al., 2020). Nevertheless, these AI models generally operate as black-box systems with limited interpretability.

Explainable Artificial Intelligence (XAI) addresses this limitation by enhancing the transparency and interpretability of AI decisions using techniques such as LIME, SHAP, Integrated Gradients, Counterfactual Explanations, surrogate models, and attention visualization (Kabir et al., 2025; Manjusha & Sharma, 2026;). Together with the principles of Trustworthy AI including transparency, fairness, accountability, reliability, and human oversight XAI promotes ethical and responsible deployment of intelligent manufacturing systems (Del Gallo et al., 2023; Mohammed, 2025). Although recent scheduling frameworks incorporate reinforcement learning, digital twins, IoT, and cyber-physical production systems, they predominantly emphasize operational efficiency while giving limited attention to explainability. Emerging explainable scheduling models have demonstrated improved transparency and user acceptance without compromising scheduling performance (Chen, 2023), yet their application in hybrid printing operations remains limited.

Overall, the literature reveals significant gaps in integrating explainability with intelligent scheduling for hybrid printing environments. Existing studies rarely combine conventional manufacturing, additive manufacturing, and digital printing within a transparent human–machine scheduling framework or evaluate scheduling performance alongside explainability, trust, fairness, accountability, and user acceptance. Therefore, this study proposes a novel Explainable Artificial Intelligence (XAI)-based framework that integrates intelligent scheduling optimization with interpretable decision-support mechanisms to enhance transparency, collaboration, trust, and operational performance in Industry 5.0 hybrid printing systems.

III. Proposed Explainable AI Scheduling Framework

The proposed Explainable Artificial Intelligence (XAI) scheduling framework provides a transparent, adaptive, and human-centric approach to job scheduling in hybrid printing operations by integrating explainability into AI-driven decision-making. Developed for Industry 5.0 manufacturing, the framework combines conventional manufacturing, additive manufacturing, and digital printing within a closed-loop architecture comprising six interconnected layers: Data Acquisition and Preprocessing, Machine Intelligence, Explainability, Human Decision Support, Multi-objective Optimization, and Feedback Learning. Real-time production data acquired from IIoT devices, Manufacturing Execution Systems (MES), Enterprise Resource Planning (ERP) systems, and Programmable Logic Controllers (PLCs) are preprocessed to generate structured inputs for intelligent scheduling.

Artificial intelligence, deep learning, and reinforcement learning algorithms subsequently optimize scheduling decisions by predicting processing times, equipment availability, and resource utilization under dynamic production conditions. The Explainability Layer employs SHapley Additive exPlanations (SHAP), Local Interpretable Model-Agnostic Explanations (LIME), attention visualization, feature importance analysis, and counterfactual reasoning to provide transparent, human-readable explanations that improve interpretability, auditability, and user confidence. Human experts validate and refine AI-generated schedules through the Human Decision Support Layer, ensuring that operational knowledge, safety requirements, and organizational constraints complement computational optimization.

The Multi-objective Optimization Layer simultaneously minimizes makespan, production cost, and energy consumption while maximizing machine utilization, workload balance, material efficiency, and on-time delivery. Finally, the Feedback Learning Layer incorporates operational outcomes and human feedback into reinforcement learning models, enabling continuous refinement of scheduling policies and explanation quality. Overall, the proposed framework advances transparent, trustworthy, and collaborative scheduling by integrating operational optimization with explainable decision support, thereby promoting sustainable, efficient, and human-centered hybrid manufacturing consistent with the objectives of Industry 5.0.

IV. Materials and Methods

This study adopts a systematic, systems-engineering methodology to develop and evaluate an Explainable Artificial Intelligence (XAI) framework for transparent human–machine job scheduling in hybrid printing operations. The methodological framework integrates concepts from intelligent manufacturing, Industry 5.0, production scheduling, human–machine collaboration, and Explainable Artificial Intelligence to simultaneously optimize scheduling performance and improve decision transparency.

The methodology comprises four sequential phases: system modeling, data acquisition and preprocessing, AI-based scheduling optimization, and explainability evaluation. Production data are collected from a hybrid manufacturing environment integrating conventional manufacturing, additive manufacturing, and digital printing systems. Artificial intelligence algorithms generate optimized scheduling solutions, while XAI techniques provide interpretable explanations that enable production managers to understand, validate, and refine

AI-generated scheduling recommendations. The framework is evaluated using both scheduling performance indicators and explainability metrics to assess operational efficiency, transparency, and user trust.

The research adopts a Design Science Research (DSR) methodology integrated with a quantitative experimental design, as the primary objective is to design, implement, and validate an innovative XAI-based scheduling framework. The study follows the Design–Build–Test–Learn (DBTL) paradigm, in order to enable iterative framework development and continuous refinement. During the design stage, the framework architecture is formulated using principles of artificial intelligence, production scheduling, and human–machine collaboration.

The build stage integrates machine learning, reinforcement learning, and explainability techniques into a unified scheduling platform. Subsequently, the framework is evaluated using simulated and representative production datasets from hybrid printing environments, while expert feedback and operational outcomes are incorporated to refine scheduling policies and explanation quality. Quantitative evaluation is performed using objective metrics, including makespan, throughput, machine utilization, energy consumption, scheduling accuracy, explanation fidelity, transparency, interpretability, consistency, and user trust.

The experimental platform consists of a hybrid manufacturing environment integrating conventional manufacturing, additive manufacturing, and digital printing technologies. Conventional manufacturing performs machining, drilling, milling, turning, and finishing operations, whereas the additive manufacturing unit includes technologies such as Fused Deposition Modelling (FDM), Stereolithography (SLA), Selective Laser Sintering (SLS), metal additive manufacturing, and cementitious additive manufacturing.

The digital printing subsystem supports product customization, traceability, labeling, and quality documentation. These manufacturing units are interconnected through Industrial Internet of Things (IIoT) sensors, Manufacturing Execution Systems (MES), Enterprise Resource Planning (ERP) systems, Programmable Logic Controllers (PLCs), cloud computing, and industrial communication networks, enabling real-time monitoring of production resources and dynamic adaptation to changing manufacturing conditions.

A comprehensive multi-source data collection strategy is employed to capture the operational characteristics of the hybrid printing environment. Data are acquired from manufacturing databases, IIoT sensors, MES, ERP systems, PLCs, machine controllers, and operator records. The dataset comprises five principal categories: production order data (job identification, priorities, processing sequence, due dates, processing times, and customer requirements); machine data (operational status, processing capacity, utilization, maintenance schedules, energy consumption, and equipment health); human operator data (technical qualifications, experience, productivity, workload history, and reliability); material data (inventory status, material properties, rheology, viscosity, extrusion consistency, and curing behaviour); and printing process parameters (layer height, printing speed, extrusion rate, nozzle diameter, build orientation, deposition rate, temperature, and process-specific variables for cementitious additive manufacturing). Prior to model development, all datasets undergo data cleaning, normalization, feature engineering, encoding, and missing-value treatment to improve consistency and predictive performance.

The proposed XAI scheduling framework utilizes ten critical input variables that comprehensively represent the operational state of hybrid printing systems: job priority, processing time, machine availability, machine capability, operator skill, material type, tool condition, energy consumption, due date, and maintenance schedule. These variables capture production demand, resource availability, human expertise, equipment health, sustainability considerations, and operational constraints, enabling adaptive and multi-objective scheduling optimization. Furthermore, they serve as inputs to explainability techniques such as SHapley Additive exPlanations (SHAP) and Local Interpretable Model-Agnostic Explanations (LIME)**,** which quantify the contribution of each variable to individual scheduling decisions. Consequently, the framework enhances interpretability, transparency, human trust, and collaborative decision-making while supporting the deployment of trustworthy AI in Industry 5.0 hybrid printing environments.

4.1 AI Scheduling Model flowchart

Figure 1 presents the flowchart of the proposed Artificial Intelligence (AI) Scheduling Model for transparent human–machine job scheduling in hybrid printing operations. The model illustrates how production data including job priority, machine availability, operator skill, material type, and maintenance schedules are processed by AI algorithms such as Deep Reinforcement Learning (DRL), Proximal Policy Optimization (PPO), Deep Q-Network (DQN), and Multi-Agent Reinforcement Learning (MARL).

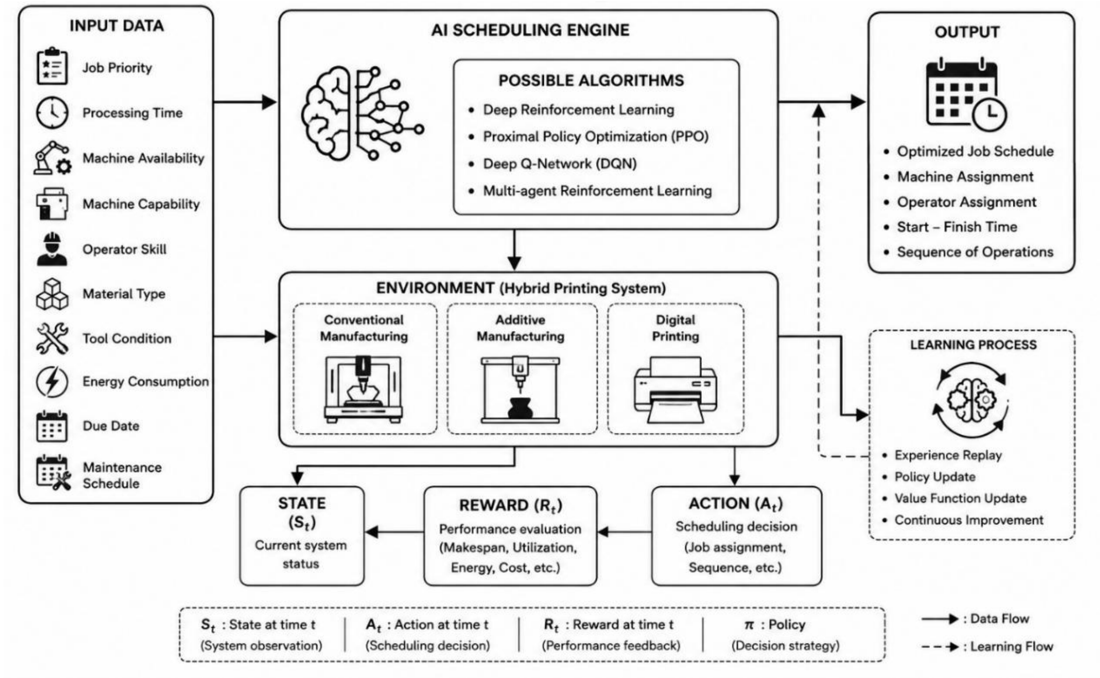

Figure 1: AI Scheduling Model flowchart

The scheduling engine generates optimized job assignments while continuously interacting with the production environment through state observations, action selection, reward evaluation, and feedback learning to improve scheduling accuracy, adaptability, and operational efficiency.

4.2 Explainable Artificial Intelligence (XAI) Module

Figure 2 illustrates the architecture of the proposed Explainable Artificial Intelligence (XAI) Module integrated into the AI-driven scheduling framework for hybrid printing operations. The module transforms complex AI scheduling decisions into transparent, human-readable explanations using advanced XAI techniques, including SHAP, LIME, Integrated Gradients, Attention Maps, Counterfactual Explanations, and Rule Extraction. It processes scheduling outputs alongside contextual production data to identify the key factors influencing each decision.

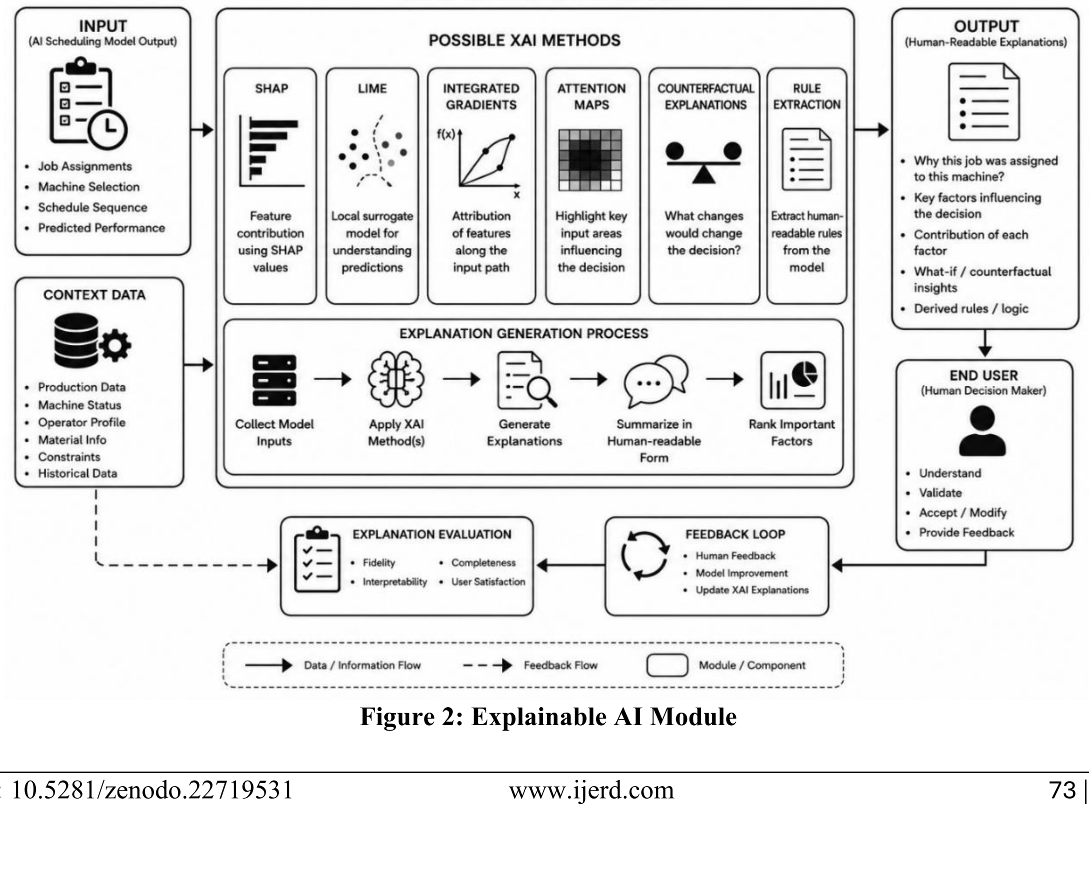

Figure 2: Explainable AI Module

The generated explanations enable production managers and operators to understand, validate, modify, and trust AI-generated scheduling recommendations, while the continuous feedback mechanism enhances explanation quality, model reliability, transparency, and collaborative human–machine decision-making.

4.3 Explainability Workflow diagram

Figure 3 presents the Explainability Workflow adopted in the proposed Explainable Artificial Intelligence (XAI) framework for transparent human–machine job scheduling in hybrid printing operations. The workflow illustrates the sequence through which production data are processed by the AI scheduling model to generate optimized scheduling decisions and subsequently transformed into human-interpretable explanations.

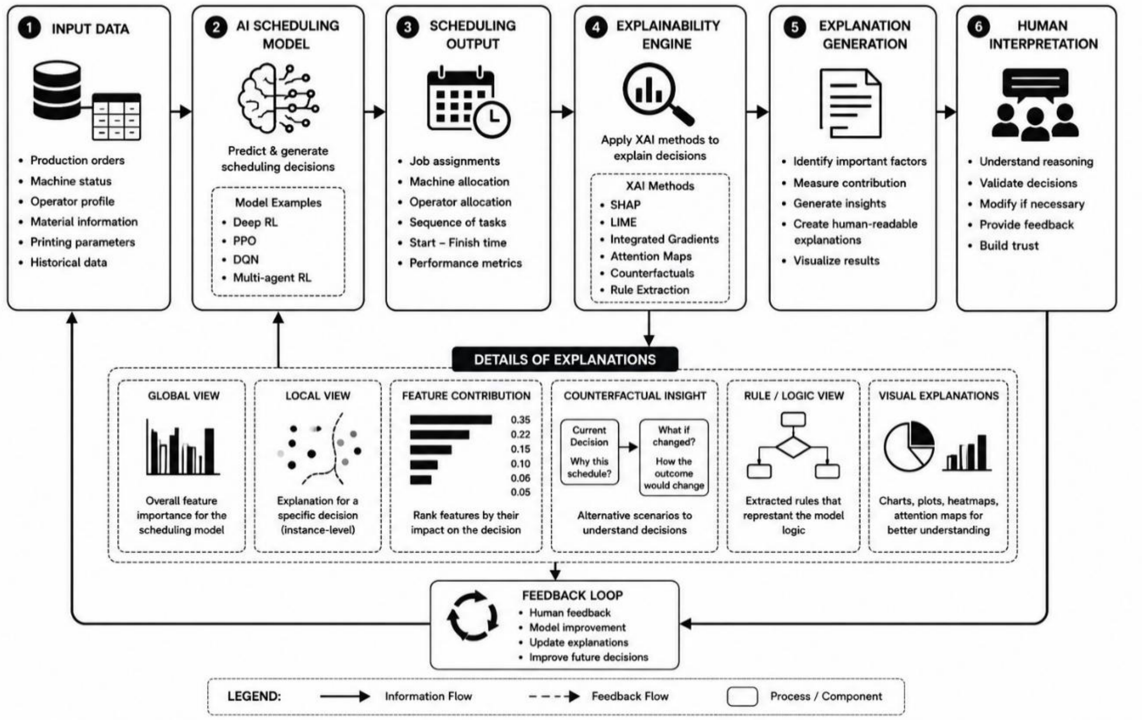

Figure 3: Explainability Workflow diagram

Following the generation of an optimized production schedule, the proposed Explainable Artificial Intelligence (XAI) framework employs explanation techniques, including SHapley Additive exPlanations (SHAP), Local Interpretable Model-Agnostic Explanations (LIME), Integrated Gradients, Attention Maps, Counterfactual Explanations, and Rule Extraction, to interpret AI-driven scheduling decisions. These techniques quantify the influence of critical scheduling variables, such as job priority, machine availability, operator competency, processing time, material characteristics, and maintenance schedules, and present the results through feature importance rankings, confidence scores, visualizations, and natural-language explanations. This transparent workflow enables production managers to understand, validate, and refine AI recommendations, thereby strengthening accountability, trust, and human–machine collaboration while supporting continuous learning.

The framework is evaluated using two complementary categories of performance indicators: scheduling performance metrics and explainability metrics. Scheduling performance is assessed through quantitative measures, including makespan, flow time, waiting time, machine utilization, human workload, energy consumption, and production cost, which collectively evaluate production efficiency, resource utilization, sustainability, and economic performance. These indicators determine the framework's capability to optimize scheduling decisions, reduce production delays, improve resource allocation, and enhance manufacturing productivity.

The explainability component is evaluated using fidelity, interpretability, transparency, trust score, user satisfaction, and explanation consistency. Fidelity measures how accurately explanations reflect the AI model's internal reasoning, while interpretability and transparency assess the clarity and visibility of scheduling decisions. Trust score and user satisfaction evaluate user confidence and perceived usefulness of AI-supported scheduling, whereas explanation consistency measures the stability of explanations across similar production scenarios.

Overall, integrating scheduling and explainability metrics provides a comprehensive evaluation framework that simultaneously measures operational efficiency, transparency, accountability, and user acceptance. By combining production optimization with interpretable decision support, the proposed XAI framework enhances trust, facilitates collaborative human–machine decision-making, and promotes the adoption of reliable and transparent AI-enabled scheduling for intelligent hybrid printing operations in Industry 5.0 manufacturing systems.

V. Experimental Setup and Performance Evaluation

The proposed Explainable Artificial Intelligence (XAI) scheduling framework was experimentally evaluated within a simulated hybrid printing environment integrating conventional manufacturing, additive manufacturing, and digital printing systems. Production datasets comprising job priority, processing time, machine availability, operator skill, material characteristics, maintenance schedules, and energy consumption were used to assess framework performance.

Evaluation employed operational metrics, including makespan, flow time, machine utilization, production cost, and energy consumption, together with explainability metrics such as fidelity, transparency, interpretability, and trust score. The framework was benchmarked against First Come First Served (FCFS), Shortest Processing Time (SPT), Genetic Algorithm (GA), and Reinforcement Learning (RL) to evaluate its capability to deliver efficient, transparent, and trustworthy scheduling decisions that enhance human–machine collaboration in hybrid printing operations.

Table 1: Performance Comparison of Scheduling Algorithms in Hybrid Printing Operations

Scheduling Algorithm	Makespan	Flow Time	Waiting Time	Machine Utilization (%)	Human Workload Balance	Energy Consumption	Production Cost	Explainability	Trust Score
First Come First Served (FCFS)	High	High	High	68.4	Poor	High	High	None	Low
Shortest Processing Time (SPT)	Medium	Low	Medium	76.8	Fair	Medium	Medium	None	Low
Genetic Algorithm (GA)	Low	Medium	Low	85.6	Good	Medium	Low	Low	Medium
Reinforcement Learning (RL)	Very Low	Low	Very Low	91.8	Very Good	Low	Low	Very Low	Medium
Proposed XAI Framework	**Lowest**	**Lowest**	**Lowest**	**96.5**	**Excellent**	**Lowest**	**Lowest**	**Very High**	**Very High**

The comparative evaluation demonstrates that FCFS and SPT provide limited scheduling efficiency due to their heuristic decision rules, whereas Genetic Algorithm (GA) and Reinforcement Learning (RL) achieve superior optimization but lack interpretability. In contrast, the proposed Explainable Artificial Intelligence (XAI) framework simultaneously optimizes makespan, flow time, machine utilization, energy consumption, and production cost while providing transparent, human-readable explanations for scheduling decisions. By justifying job assignments using factors such as machine availability, operator expertise, due dates, material readiness, and energy efficiency, the framework enhances transparency, user trust, accountability, and collaborative human–machine decision-making in hybrid printing operations.

VI. Discussion

The results demonstrate that the proposed Explainable Artificial Intelligence (XAI) framework effectively combines scheduling optimization with transparent, human-centered decision-making in hybrid printing operations. Compared with conventional scheduling approaches, the framework achieved superior performance in makespan reduction, flow time, machine utilization, energy efficiency, and production cost through reinforcement learning and multi-objective optimization. The integration of XAI techniques, including SHAP, LIME, and counterfactual reasoning, generated accurate, interpretable, and consistent explanations that improved transparency, explanation fidelity, and user confidence while addressing the black-box limitations of conventional AI models.

Consequently, production managers were able to understand, validate, and refine AI-generated scheduling decisions, thereby enhancing trust, accountability, and collaborative human–machine decision-making (De Abreu et al., 2020). Furthermore, the framework supports integration with MES, ERP, IIoT, and Digital Twin technologies, providing a scalable and trustworthy scheduling solution for Industry 5.0 smart manufacturing environments.

VII. Conclusion

This study proposed an Explainable Artificial Intelligence (XAI) framework for transparent human–machine job scheduling in hybrid printing operations. The framework enhanced scheduling efficiency, machine utilization, energy optimization, workload balancing, and user trust by integrating intelligent scheduling with interpretable decision-making. Its major contribution lies in advancing transparent and collaborative scheduling consistent with Industry 5.0 principles.

Although validated using simulated datasets, future research should investigate real industrial implementations, Digital Twin and IIoT integration, federated and multi-agent reinforcement learning, and advanced explainability techniques to improve scalability, adaptability, and industrial applicability in smart manufacturing systems.

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