Artificial Intelligence Enhanced Human–Machine Job Scheduling in a Hybrid Printing System: A Review

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ABSTRACT

The review examined the manufacturing context, scheduling challenges, role of artificial intelligence (AI), review methodology, key findings, and research implications. Hybrid printing integrates traditional, digital, and additive manufacturing technologies to enhance flexibility, customization, material efficiency, and production capacity**.** However, traditional rule-based and static optimization approaches are unable to effectively handle the complex scheduling challenges created by the coexistence of heterogeneous machines, diverse materials, dynamic production requirements, maintenance constraints, and human involvement. Thus, the review looks at how artificial intelligence (AI) methods such as machine learning, deep learning, reinforcement learning, multi-agent systems, swarm intelligence, and explainable AI (XAI) are applied to intelligent scheduling in hybrid printing environments. In the context of the Industry 5.0 paradigm, it further explores human-in-the-loop methods that integrate computational optimization with human knowledge, contextual judgment, and operational oversight. In order to assess scheduling objectives, algorithms, performance metrics, technological architectures, implementation difficulties, and new research directions, the review synthesizes recent academic literature. Results show that makespan, resource utilization, throughput, adaptability, energy efficiency, and responsiveness to production disruptions can all be improved with AI-enhanced scheduling. Real-time decision-making, transparency, and operator trust are further improved by integration with digital twins, XAI, and the Industrial Internet of Things (IIoT). The review comes to the conclusion that collaborative scheduling between humans and AI offers a promising basis for creating intelligent, robust, and sustainable hybrid printing systems.

Keywords: Artificial Intelligence; Human–Machine Collaboration; Job Scheduling; Hybrid Printing Systems; Industry 5.0

INTRODUCTION

The manufacturing industry has experienced profound technological transformation, with printing technologies evolving from conventional analogue processes toward intelligent, digitally integrated production systems. Traditional methods, including offset, flexographic, gravure, and screen printing, remain important because of their high throughput, cost efficiency, and consistent quality in mass production. However, their limited flexibility constrains rapid design changes, product customization, and economically viable low-volume production. Digital printing technologies, particularly inkjet and laser-based systems, have addressed these limitations by enabling variable-data printing, on-demand manufacturing, and reduced production lead times. More recently, additive manufacturing (AM), or three-dimensional (3D) printing, has expanded manufacturing capabilities by facilitating complex geometries, material efficiency, and mass customization across aerospace, healthcare, automotive, and construction sectors (Chikwendu & Emeka, 2025; Said et al., 2025). These developments have encouraged the emergence of hybrid printing systems that integrate conventional, digital, and additive processes within a unified production environment. Such integration enables complementary capabilities, including high-speed finishing, customized graphical production, and complex structural fabrication, thereby enhancing manufacturing flexibility and efficiency. Nevertheless, heterogeneous equipment, diverse processing requirements, and interdependent operations increase scheduling and coordination complexity (Helal, 2025; Zhou et al., 2024). Furthermore, the integration of Industrial Internet of

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Things (IIoT), cyber-physical systems, cloud computing, and artificial intelligence (AI) under Industry 4.0 and Industry 5.0 has intensified the need for intelligent scheduling systems capable of processing real-time data and dynamically coordinating machines, materials, operators, and production activities (Barua et al., 2025).

Problem Statement

In hybrid printing systems, where heterogeneous printing technologies must operate as an integrated production environment while concurrently meeting conflicting operational, economic, human, and environmental requirements, efficient job scheduling continues to be a crucial challenge. Conventional and digital printing, additive manufacturing, inspection, finishing, and material handling operations can all be included in a single production order. Each of these processes has different processing times, machine capabilities, material requirements, setup conditions, and resource constraints. Additionally, during production, there may be dynamic variations in machine availability, operator competencies, maintenance requirements, material supply, energy consumption, customer priorities, and delivery deadlines.

First-Come First-Served (FCFS), Shortest Processing Time (SPT), Earliest Due Date (EDD), and manually defined priority rules are examples of conventional scheduling techniques that provide computational simplicity and transparency but have limited ability to learn from past data or react independently to production disruptions. Although metaheuristic techniques like Tabu Search (TS), Simulated Annealing (SA), and Genetic Algorithms (GA) offer efficient solutions to challenging combinatorial problems, they can be computationally expensive, especially when frequent rescheduling is necessary. AI-based methods provide improved prediction, adaptive decision-making, and real-time optimization capabilities. The goals, datasets, experimental conditions, evaluation standards, computational requirements, and degrees of human involvement, however, differ significantly among the studies that are currently in existence. As a result, there is still little comprehensive data comparing optimization-based, machine learning, deep learning, and reinforcement learning techniques in terms of scheduling effectiveness, production time, cost, flexibility, resource utilization, explainability, and human acceptability. With a focus on real-time, adaptive, and human-supervised industrial deployment, this review fills the gap by methodically synthesizing and critically assessing AI-enabled human–machine collaborative scheduling strategies for dynamic hybrid printing environments.

Aim and Objectives of the Review

This systematic review's main aim is to critically analyze and summarize current research on AI-enhanced human–machine job scheduling in hybrid printing systems, with a focus on algorithmic performance, human oversight, real-time adaptability, and useful industrial implementation.

The particular aims are to:

1. Analyze hybrid printing systems' features, architecture, and scheduling needs;
2. Determine and summarize the main obstacles to job scheduling in diverse printing environments;
3. Evaluate and contrast optimization-based, machine learning, deep learning, and reinforcement learning methods for intelligent job scheduling;
4. Use metrics such as scheduling effectiveness, production time, cost, flexibility, resource utilization, adaptability, and human-centered performance to assess AI scheduling techniques;
5. Investigate methods for human-AI cooperation, explainability, human oversight, and human-in-the-loop decision-making;
6. Create a conceptual framework that incorporates human decision-making, AI scheduling, real-time production data, execution, monitoring, and continuous learning; and
7. Determine research gaps and suggest future paths for explainable, real-time, resilient, sustainable, and industrially deployable AI scheduling systems.

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SYSTEMATIC REVIEW METHODOLOGY

In order to find, assess, categorize, and synthesize academic research on artificial intelligence-enhanced human-machine job scheduling in hybrid printing systems, this study used a Systematic Literature Review (SLR) methodology. The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 framework, which offers an organized method for reporting the identification, screening, eligibility evaluation, and inclusion of studies in systematic reviews, was followed in the structure of the review. Additionally, PRISMA 2020 places a strong emphasis on open reporting of information sources, search tactics, eligibility requirements, study selection, and synthesis processes.

Research question formulation, search strategy development, information source selection, eligibility criteria definition, database searching, duplicate removal, title and abstract screening, full-text assessment, and methodological quality assessment were the nine main steps of the review process. Thematic and comparative synthesis were then applied to the final eligible studies.

Review Questions

The systematic review was guided by six research questions:

RQ1: What are the main obstacles to job scheduling in environments related to smart manufacturing and hybrid printing?

RQ2: In hybrid printing and related manufacturing systems, what artificial intelligence methods have been used or suggested for job and production scheduling?

RQ3: How do optimization-based methods, machine learning, deep learning, and reinforcement learning compare when it comes to solving hybrid printing scheduling issues?

RQ4: How can explainable AI, human oversight, human-in-the-loop mechanisms, and human expertise be integrated into AI-supported scheduling?

RQ5: In terms of scheduling effectiveness, production time, cost, flexibility, and resource utilization, which performance metrics are frequently employed to assess AI-enhanced scheduling?

RQ6: In terms of explainability, scalability, real-time adaptability, human oversight, and practical industrial implementation, what research gaps still exist?

Information Sources, Search Strategy and Database Selection

A multidisciplinary literature search covering publications from 2021 onward was carried out using Scopus, Web of Science Core Collection, IEEE Xplore, ScienceDirect, SpringerLink, ResearchGate, Academia.edu and MDPI. These resources were chosen to offer comprehensive coverage of Industry 4.0/5.0 research, additive manufacturing, smart manufacturing, production scheduling, manufacturing engineering, and artificial intelligence. While IEEE Xplore improved the retrieval of research on intelligent systems, automation, robotics, and industrial computing, Scopus and Web of Science offered thorough multidisciplinary bibliographic coverage. Additional support for coverage of manufacturing, optimization, and industrial systems research came from ScienceDirect, SpringerLink, and MDPI. In order to find pertinent academic records, ResearchGate and Academia.edu were utilized as additional sources. To reduce database-specific coverage bias, several databases were searched. To find and eliminate duplicates, records obtained from publisher platforms and additional sources were cross-checked against significant indexing databases. To improve transparency, reproducibility, and methodological rigor, search dates, database versions, search fields, and retrieval processes were recorded. The final manuscript reported only databases and sources that were truly searched.

Eligibility Criteria

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Prior to the final screening procedure, predetermined inclusion and exclusion criteria were used to choose the

studies. The criteria were created to guaranty that one or more of the research questions were directly addressed by the chosen literature.

Table 2.1. Inclusion and exclusion criteria

Criterion	Inclusion criteria	Exclusion criteria
Publication period	Studies published from 2021–2026	Studies published before 2021
Language	English-language publications	Non-English publications where reliable translation/evaluation was unavailable
Publication type	Peer-reviewed journal articles, conference papers and relevant scholarly book chapters	Editorials, news articles, patents, theses/dissertations, opinion pieces and non-scholarly web content
Research focus	AI, intelligent scheduling, manufacturing scheduling, hybrid printing, additive manufacturing, digital printing or closely related smart manufacturing	Studies unrelated to AI, scheduling or manufacturing/printing
AI techniques	ML, DL, RL, optimization, metaheuristics, multi-agent systems, XAI or hybrid AI	Studies with no meaningful AI/intelligent decision-making component
Scheduling	Job, production, dynamic, adaptive or real-time scheduling	Studies addressing only general production planning without a scheduling component
Human involvement	Human–machine collaboration, HITL, human oversight, human–AI decision support or Industry 5.0 where relevant	Studies with no relevance to human involvement where human–machine interaction is central to the research question
Evidence	Studies reporting methodology, model development, experimental evaluation, simulation, case study or substantive conceptual analysis	Abstract-only records, incomplete records or publications for which sufficient full-text information was unavailable
Relevance	Studies directly addressing the review questions or providing transferable evidence from closely related smart manufacturing environments	Studies with insufficient relevance to the review objectives

Study Identification and Selection

A total number of 512 records that might be pertinent to the review were found through a methodical search of the chosen academic databases. 530 records were found for preliminary consideration after an additional 18 records were found using other qualifying methods, such as reference-list screening and citation tracking. 427 distinct records were left for title and abstract screening after 103 duplicate records were eliminated. 331 records that did not directly address AI-based scheduling, hybrid/additive/digital manufacturing, human–machine collaboration, or other elements pertinent to the research questions were eliminated during title and abstract screening. Inadequate methodological information, inappropriate study type, lack of a significant AI or intelligent scheduling component, insufficient relevance to the research questions, and insufficient connection to manufacturing or printing applications were the main reasons for exclusion. As a result, 37 studies in all met all predetermined eligibility requirements and were added to the final qualitative synthesis. As a result, the final evidence base for the qualitative systematic synthesis consisted of 37 studies.

The AI technique, scheduling issue, manufacturing/printing environment, human involvement, performance indicators, validation strategy, and reported limitations were then used to categorize these studies. To ascertain the relative advantages, disadvantages, and suitability of ML, DL, RL, optimization-based, and hybrid AI

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approaches to human–machine scheduling in hybrid printing systems, the results were then compiled thematically and comparatively.

Data Extraction and Coding

To guaranty consistent and repeatable evidence collection from all included studies, a structured framework for data extraction was created. Bibliographic, technological, methodological, scheduling, human-centric, and performance categories were used to group the extracted variables. Authors, publication year, publication location, and geographic context were all included in the bibliographic data. Technological factors included AI methods, computing architectures, printing/manufacturing technologies, and Industry 4.0/5.0 integration. Problem type, job characteristics, constraints, objectives, machine configurations, and disturbance conditions were among the scheduling variables. Datasets, experimental settings, validation techniques, human participation, decision authority, human-in-the-loop (HITL) and explainable AI (XAI) applications, performance metrics, important discoveries, constraints, computational requirements, scalability, real-time capability, and future research directions were among the additional data. The extracted evidence was then thematically coded in accordance with the research questions, allowing for a methodical comparison of AI techniques despite differences in terminology, datasets, experimental configurations, and evaluation methods.

Methodological Quality Assessment

Before synthesizing the results, methodological quality was evaluated because systematic reviews may contain studies with significantly different research designs. To assess the validity, reliability, and transparency of the included studies, a structured quality-assessment checklist was created. The evaluation took into account the following factors:

Quality criterion	Assessment focus
Q1. Research objective clarity	Is the research problem and objective clearly defined?
Q2. Methodological transparency	Is the AI/scheduling methodology sufficiently described?
Q3. Dataset or experimental description	Are the data, simulation environment or experimental conditions adequately reported?
Q4. Validation	Is the proposed approach validated through experiments, simulation, case studies or industrial data?
Q5. Baseline comparison	Is the proposed approach compared with an appropriate conventional or competing method?
Q6. Performance metrics	Are relevant scheduling indicators clearly reported?
Q7. Reproducibility	Are sufficient implementation, parameter or experimental details provided?
Q8. Limitations	Does the study explicitly acknowledge methodological or practical limitations?
Q9. Industrial relevance	Does the study consider realistic manufacturing constraints or implementation requirements?
Q10. Human-centric consideration	Where relevant, does the study address human oversight, interaction, workload, trust or decision-making?

A standardized foundation for evaluating methodological strength, reporting transparency, and overall reliability of the evidence was provided by the maximum achievable quality score of 20 points per study. The final manuscript clearly reported the quality-assessment results, classifying the studies as having high, moderate, or low methodological quality. Readers were able to assess the strength and reliability of the evidence presented in the review thanks to this open reporting.

Data Synthesis and Comparative Analysis

Quantitative meta-analysis was considered inappropriate due to the significant methodological heterogeneity among AI-based scheduling studies. Meaningful statistical aggregation is limited by differences in

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manufacturing environments, datasets, scheduling goals, AI architectures, baseline techniques, performance metrics, and experimental conditions. As a result, thematic synthesis, methodological classification, and qualitative comparative analysis were used to synthesize the evidence. Machine learning, deep learning, reinforcement learning, mathematical and optimization-based techniques, evolutionary and swarm intelligence, multi-agent systems, hybrid AI, and explainable or human-centered AI were the categories used to group the studies. Scheduling efficiency, production time, cost, flexibility, and resource utilization were the main focus of the comparative evaluation. Adaptability, computational requirements, explainability, human acceptance, scalability, resilience, energy consumption, and carbon performance were also taken into account when available. This strategy made it possible to critically assess the situations in which AI approaches perform better than traditional scheduling methods, as well as their drawbacks and ability to assist human decision-making in dynamic manufacturing settings.

Comparative Evaluation of AI Scheduling Approaches

The comparative analysis separates the potential of AI approaches from the capabilities shown in individual studies. Scheduling decisions can be informed by machine learning (ML), which is useful for forecasting processing times, demand, machine failures, and bottlenecks. Although deep learning (DL) can handle temporal, high-dimensional, and complex production data, it usually needs larger datasets and more processing power. Because it can learn sequential decision policies and adjust to shifting production states, reinforcement learning (RL) is especially well-suited to dynamic scheduling. Nevertheless, there are still issues with reward design, training stability, computational demands, exploration risks, and simulation-to-reality transfer. While genetic algorithms, particle swarm optimization, and simulated annealing are examples of mathematical optimization and metaheuristics that successfully handle explicit constraints and multi-objective scheduling, they may become more computationally complex as the size of the problem increases. Combining ML/DL for prediction, optimization for practical scheduling, RL for adaptive rescheduling, and explainable AI for comprehensible human oversight, hybrid AI approaches offer complementary capabilities. For hybrid printing systems with heterogeneous resources, dynamic conditions, and human decision authority, such integrated architectures hold great promise.

Reproducibility and Reporting of the Review

The review included database names, search dates, database-adapted Boolean strings, publication-period limitations, eligibility requirements, screening processes, quality-assessment criteria, and the total number of studies in order to improve reproducibility. To enable independent replication and future updating, search and screening records were kept. The numerical values presented in Section 2.5 were matched with a PRISMA flow diagram. A supplemental search record recorded each database, search date, search string, and retrieved records when allowed by journal requirements. In order to assess AI-enhanced human–machine scheduling in hybrid printing systems and identify established findings, methodological constraints, and research gaps, the methodology established an open and rigorous evidence-selection process.

PRISMA reconstruction

Table 2.1: A coherent set of counts ending with your 37 included studies is:

PRISMA stage	Number
Records identified through database searching	512
Additional records identified through other sources	18
Total records identified	**530**
Duplicate records removed	103
Records remaining after duplicate removal	**427**
Records screened by title and abstract	427
Records excluded during title/abstract screening	331
Full-text articles assessed for eligibility	96
Full-text articles excluded	59

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Final studies included	**37**

Table 2.2. Database Search Results

Database/source	Search focus	Publication period	Records identified
Scopus	AI + scheduling + hybrid/additive manufacturing + human–machine collaboration	2021–2026	168
Web of Science	AI + intelligent/production scheduling + manufacturing	2021–2026	105
IEEE Xplore	AI + scheduling + smart manufacturing/printing	2021–2026	91
ScienceDirect	AI + production scheduling + additive/hybrid manufacturing	2021–2026	76
SpringerLink	AI + scheduling + Industry 4.0/5.0 + manufacturing	2021–2026	51
MDPI	AI + scheduling + additive/hybrid manufacturing	2021–2026	21
Subtotal—database searches			**512**
Reference-list/citation searching	Backward/forward citation checking	2021–2026	18
Total records identified			**530**

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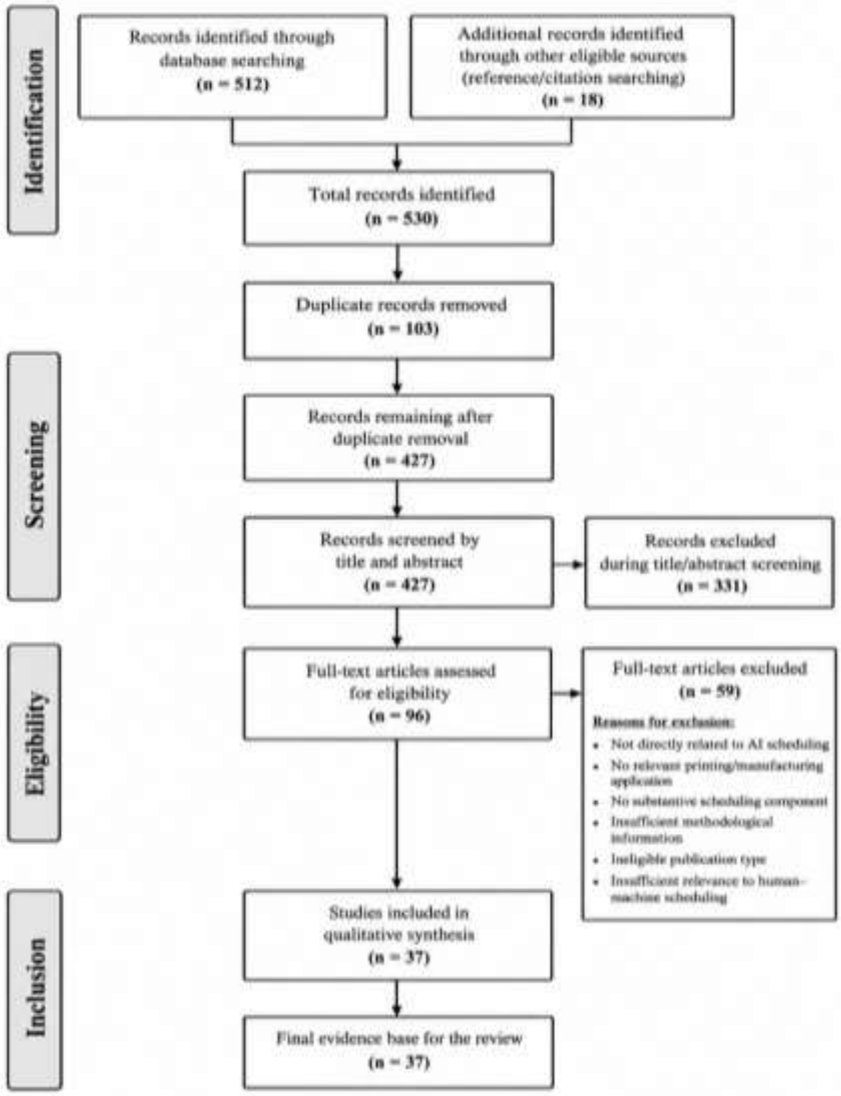

Figure 2.1 PRISMA 2020 flow diagram for the identification and selection of studies

Fundamentals of Hybrid Printing Systems

In Industry 4.0 and human-centered Industry 5.0 contexts, hybrid printing systems are advanced manufacturing platforms that combine traditional, digital, and additive manufacturing (AM) technologies within a single production environment, supporting flexibility, customization, material efficiency, accuracy, and productivity (Rane et al., 2024). Printing modules, IoT sensors, machine vision, OPC-UA/MQTT communication, PLCs, AI, machine learning, digital twins, ERP, MES, and CAM systems are all integrated into their architecture, which usually consists of physical, sensing, communication, control, intelligence, and application layers (Mehta, 2025). While digital inkjet and electrophotographic technologies allow for variable-data printing, quick modification, short runs, and mass customization, conventional modules like offset, flexographic, gravure, and screen printing support high-volume production (Altun et al., 2025). Complex geometries, decreased material waste, and multi-material fabrication are made possible by AM technologies like FDM, SLA, SLS, and DIW (Schneck et al., 2021). Material flow and operational coordination are further supported by conveyors, robotic manipulators, AGVs, and intelligent storage systems (Khurram et al., 2025). While AI makes adaptive optimization and predictive maintenance possible, the production workflow incorporates CAD/CAM planning, intelligent scheduling, multi-process fabrication, sensor-based monitoring, inspection, and post-processing (Carreno, 2024). The need for intelligent, robust, and human-centered scheduling frameworks is further highlighted by the fact that interoperability, scheduling complexity, material variability, cybersecurity, investment requirements, workforce skills, and AI explainability continue to be major obstacles.

Comparison of Conventional, Digital, Additive, and Hybrid Printing Systems

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Table 3.1 highlights variations in production flexibility, customization, material utilization, automation, scalability, and technological integration for contemporary manufacturing applications by comparing conventional, digital, additive, and hybrid printing systems across key characteristics.

Table 3.1. Comparison of Conventional, Digital, Additive, and Hybrid Printing Systems

Feature	Conventional Printing	Digital Printing	Additive Manufacturing (3D Printing)	Hybrid Printing System
Definition	Traditional printing method using physical printing plates and mechanical processes.	Printing directly from digital files without printing plates.	Layer-by-layer fabrication of three-dimensional objects from digital models.	Integration of conventional, digital, and additive manufacturing technologies within a unified production system.
Production Method	Plate-based printing (offset, flexography, gravure, screen printing).	Inkjet, laser, or electrophotographic printing.	Layer-by-layer material deposition or solidification.	Combines multiple printing technologies in a coordinated workflow.
Customization Capability	Low; best suited for identical mass production.	High; supports variable data and personalized printing.	Very high; enables complex customized geometries.	Very high; supports both mass production and mass customization.
Production Volume	High-volume production.	Low- to medium-volume production.	Low-volume and prototype production.	Flexible for low-, medium-, and high-volume production.
Setup Time	High due to plate preparation and machine setup.	Low because no printing plates are required.	Low to moderate depending on model complexity.	Moderate; integrates multiple processes with automated setup.
Production Speed	Very high for large production runs.	High for short-run production.	Relatively slow because of layer-by-layer fabrication.	High through optimized coordination of multiple modules.
Material Flexibility	Mainly paper, cardboard, plastics, and packaging materials.	Paper, plastics, textiles, ceramics, and specialty substrates.	Polymers, metals, ceramics, composites, biomaterials, and concrete.	Supports a broad range of printable and additive manufacturing materials.
Print Quality	Excellent and highly consistent for large batches.	Excellent with high-resolution variable printing.	Depends on printing technology and layer resolution.	High quality through integration of complementary technologies.
Complex Geometry	Limited to two-dimensional printing.	Primarily two-dimensional printing.	Excellent capability for complex three-dimensional structures.	Supports both complex 2D and 3D manufacturing applications.
Machine Flexibility	Low due to dedicated production lines.	High flexibility for design changes.	High flexibility for complex part fabrication.	Very high flexibility through modular and intelligent production.
Automation Level	Moderate automation.	High automation.	High automation with intelligent process control.	Very high automation supported by AI, IoT, and digital twins.

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Scheduling Complexity	Relatively simple.	Moderate.	High due to multiple process parameters.	Very high because of heterogeneous machines, resources, and workflows.
Typical Applications	Newspapers, books, packaging, labels, magazines.	Personalized packaging, commercial printing, security printing, labels.	Aerospace, biomedical devices, automotive parts, construction, rapid prototyping.	Smart manufacturing, industrial production, customized products, functional printing, and hybrid fabrication.
Advantages	Low unit cost for mass production, high speed, excellent consistency.	Fast setup, personalization, minimal waste, variable data printing.	Design freedom, material efficiency, rapid prototyping, lightweight structures.	Combines speed, flexibility, customization, intelligent scheduling, and high production efficiency.
Limitations	High setup cost, unsuitable for small production runs, limited customization.	Higher cost for large-volume production than conventional printing.	Slow production rate, high equipment cost, limited throughput.	High system complexity, integration challenges, significant capital investment, sophisticated scheduling requirements.
Industry 5.0 Compatibility	Limited.	Moderate.	High.	Very high through AI-enhanced human–machine collaboration, intelligent automation, and sustainable manufacturing.

Production Scheduling in Hybrid Printing Systems

In hybrid printing systems, production scheduling is a crucial decision-making function that determines how to

allocate and sequence machines, materials, operators, and processing resources under conflicting constraints. Heterogeneous environments with different processing times, machine capabilities, material requirements, production priorities, and human-machine interactions are produced when conventional, digital, and additive manufacturing are integrated. In order to improve productivity, flexibility, resilience, and human-centered decision-making, Industry 5.0 scheduling increasingly incorporates digital twins, artificial intelligence (AI), the Industrial Internet of Things (IIoT), and reinforcement learning (Zhu et al., 2025).

Assigning tasks to the right machines and operators while figuring out their order and processing times is known as job scheduling. Printing, additive manufacturing, inspection, and post-processing processes may all be combined in hybrid printing orders, creating challenging combinatorial optimization issues. Dynamic rescheduling is also required due to machine failures, urgent orders, material shortages, operator competencies, and maintenance requirements. Digital twins and real-time sensor data can help with adaptive schedule modification, bottleneck prediction, and production-state assessment (Rojek et al., 2025).

Minimizing makespan, cutting expenses, enhancing resource and energy efficiency, and fulfilling delivery deadlines are important scheduling goals. While cost-oriented scheduling takes into account labor, material, maintenance, transportation, and operating costs (Jin et al., 2025), makespan minimization increases throughput by balancing workloads and decreasing machine idle time (Zhou et al., 2024). While due-date-oriented approaches enhance delivery reliability under disruptions (Hedea, 2025), energy-aware scheduling minimizes consumption and environmental impacts through optimized sequencing and machine utilization (Xia et al., 2026). For setup, inspection, troubleshooting, and maintenance, human expertise is still crucial

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(Anang et al., 2024; Trivedi et al., 2024). Predictive maintenance enabled by IoT and AI can minimize unplanned downtime and further predict equipment deterioration (Dhanda et al., 2024). While FCFS, SPT, EDD, GA, and SA are still helpful, their flexibility in extremely dynamic settings is restricted. For adaptive, transparent, resilient, and sustainable scheduling, deep learning, digital twins, explainable AI, and multi-agent systems are being studied more and more (Nguyen et al., 2025).

Table 3.2. Comparison of Traditional Scheduling Methods

Scheduling Method	Scheduling Principle	Primary Objective	Advantages	Limitations	Computational Complexity	Suitable Production Environment	Performance in Hybrid Printing Systems
First-Come First-Served (FCFS)	Jobs are processed in the order they arrive in the system.	Fairness and simplicity.	Easy to implement, low computational cost, no complex calculations required.	Long waiting times for short jobs, poor resource utilization, high makespan, unsuitable for urgent jobs.	Very Low	Small-scale and stable production systems.	Poor; unable to adapt to dynamic production changes and heterogeneous resources.
Shortest Processing Time (SPT)	Jobs with the shortest processing times are scheduled first.	Minimize average flow time and waiting time.	Reduces work-in-progress inventory, improves machine utilization, increases throughput.	Long jobs may suffer starvation, poor due-date performance, ignores job priority.	Low	Manufacturing environments with varying processing times.	Moderate; effective for reducing flow time but less suitable for multi-objective optimization.
Earliest Due Date (EDD)	Jobs with the earliest delivery deadlines are processed first.	Minimize lateness and improve due-date compliance.	Enhances on-time delivery performance, reduces tardiness, improves customer satisfaction.	Does not optimize machine utilization or production cost, ignores processing time differences.	Low	Customer-driven and deadline-sensitive manufacturing.	Moderate; suitable where delivery deadlines are critical but less effective for complex resource allocation.
Longest Processing Time (LPT)	Jobs requiring the longest processing time are scheduled first.	Balance machine workloads in parallel processing environments.	Improves workload distribution across multiple machines, reduces machine imbalance.	Increases average completion time, poor responsiveness to urgent jobs.	Low	Parallel machine scheduling environments.	Low to Moderate; limited effectiveness in heterogeneous hybrid printing systems.
Priority	Jobs are	Prioritize	Flexible	Highly	Low	Production	Moderate;

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Rule Scheduling	assigned priorities based on predefined rules such as customer importance or product value.	strategic or high-value jobs.	implementation, supports business objectives and customer priorities.	dependent on predefined rules, may neglect overall production optimization.		systems with differentiated customer priorities.	effective when integrated with enterprise production policies.
Genetic Algorithm (GA)	Evolutionary optimization using selection, crossover, and mutation operators to generate improved schedules.	Multi-objective scheduling optimization.	Produces near-optimal solutions, handles complex constraints, suitable for large search spaces.	Higher computational time, parameter tuning required, may converge slowly.	High	Complex manufacturing systems with multiple constraints.	High; widely applied for optimizing hybrid printing schedules but less responsive to real-time disturbances.
Simulated Annealing (SA)	Probabilistic search algorithm inspired by metallurgical annealing that gradually converges toward optimal solutions.	Global optimization while avoiding local optima.	Effective for complex optimization problems, robust search capability.	Sensitive to cooling schedule parameters, slower convergence for very large problems.	High	Dynamic production scheduling and combinatorial optimization.	High; capable of finding high-quality schedules but limited real-time adaptability.
Tabu Search (TS)	Iterative local search guided by a tabu memory that prevents revisiting previous solutions.	Improve solution quality and escape local optima.	Efficient exploration of search space, good optimization capability.	Requires careful parameter configuration, computationally intensive for large-scale systems.	High	Flexible manufacturing systems and job-shop scheduling.	High; performs well for constrained scheduling but requires significant computational resources.
Rule-Based Scheduling	Scheduling decisions follow predefined logical rules	Ensure operational consistency and procedural compliance.	Simple implementation, transparent decision-making, predictable	Inflexible under changing production conditions, poor	Very Low	Stable production environments with repetitive tasks.	Low; inadequate for dynamic hybrid printing systems

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	developed by experts.		behavior.	adaptability to uncertainty.			with frequent production changes.

Thus, the basis for production scheduling in manufacturing systems has been established by conventional scheduling techniques like FCFS, SPT, EDD, LPT, Priority Rules, Genetic Algorithms (GA), Simulated Annealing (SA), Tabu Search (TS), and Rule-Based Scheduling. Even though heuristic and metaheuristic approaches (like GA, SA, and TS) typically perform better than straightforward dispatching rules, they are still unable to adapt to the extremely dynamic, data-rich, and human-centered environments of hybrid printing systems. AI-driven scheduling techniques, such as machine learning, reinforcement learning, multi-agent systems, digital twins, and explainable AI, which offer flexible, real-time, and cooperative scheduling capabilities in line with Industry 5.0 objectives, are therefore being promoted more and more in recent research.

Artificial Intelligence Techniques for Job Scheduling

AI-based scheduling approaches can be classified into five broad categories: machine learning (ML), deep learning (DL), reinforcement learning (RL), optimization and metaheuristic techniques, and hybrid AI approaches. When using historical production data to identify relationships between scheduling outcomes and operating conditions, machine learning is particularly useful. Unsupervised and semi-supervised learning can aid in decision-making and job classification when labeled data are hard to come by (Aremu & Udofia, 2025).

Decision trees, random forests, support vector machines, and neural-network predictors can all be used to estimate processing times, machine availability, equipment failure probabilities, demand patterns, and bottlenecks. Deep learning architectures like CNNs, RNNs, LSTMs, and Transformers can improve scheduling robustness, equipment-degradation forecasting, and delay prediction by modeling complex, high-dimensional, sequential manufacturing data (Chikwendu et al., 2025). However, supervised ML and DL may need to retrain when production conditions change, and DL also requires large datasets, processing power, validation, and strategies to address poor interpretability.

RL is a good fit for dynamic scheduling because it sees scheduling as a sequential decision-making problem where agents select actions based on production states and receive performance-based rewards. DQN, PPO, DDPG, and multi-agent RL can modify schedules in response to errors, workload variations, material constraints, and urgent tasks. Multi-agent systems improve scalability and resilience by facilitating decentralized cooperation between machines, operators, robots, and material-handling resources (Tolia & Ponis, 2026). By enhancing transparency, interpretability, and operator trust, explainable AI (XAI) can promote human-AI collaboration in Industry 5.0 environments (Nikiforidis et al., 2024). However, reinforcement learning is still constrained by reward design, training instability, sample requirements, exploration risks, and simulation-to-reality transfer. Examples of optimization and metaheuristic methods that specifically support constraints and multiple objectives include mathematical programming, GA, PSO, ACO, SA, and TS. However, these methods may become computationally expensive as scheduling complexity rises. Thus, by combining complementary capabilities for responsive, robust, and scalable scheduling ML-based prediction, optimization-based scheduling, RL-based adaptation, and constraint enforcement hybrid AI approaches offer a substantial alternative.

Table 5.1. Critical Comparison of AI-Based Scheduling Approaches

Approach	**Scheduling efficiency**	**Production time**	**Cost**	**Flexibility**	**Resource utilization**	**Major strengths**	**Principal limitations**
Machine Learning	High for prediction-assisted scheduling	Can reduce delays through accurate prediction	Moderate	Moderate –High	High when integrated with optimization	Fast prediction; learns from historical data	Requires representative training data; limited autonomous

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							sequential decision-making
Deep Learning	High for complex/high-dimensional problems	Potentially high improvement in dynamic prediction	Moderate–High computational cost	High	High	Handles complex and temporal data	Data-intensive; computationally demanding; limited interpretability
Reinforcement Learning	Very high potential in dynamic environments	Strong potential for real-time adaptation	Potentially low operating cost after training	Very High	Very High	Learns scheduling policies and adapts to disturbances	Reward design, training instability, safety and sim-to-real challenges
Genetic Algorithm	High for complex multi-objective problems	Moderate	Moderate–High computational cost	High	High	Handles complex constraints and search spaces	Computationally expensive; parameter tuning
Particle Swarm Optimization	High	Moderate	Moderate	High	High	Efficient search and relatively simple implementation	Premature convergence; parameter sensitivity
Simulated Annealing	Moderate–High	Moderate	Moderate	Moderate–High	Moderate–High	Escapes local optima	Slow convergence for large problems
Mathematical Optimization	Very High when problem is tractable	Potentially very high	Can minimize explicit operational costs	Moderate	Very High	Explicit constraints and objective functions	Scalability and computational burden
Multi-Agent RL	Very High potential	Very High potential	Moderate	Very High	Very High	Decentralized coordination	Training complexity and coordination instability
Hybrid AI	Very High potential	Very High potential	Moderate–High	Very High	Very High	Combines prediction, optimization and adaptation	Integration complexity and validation requirements

Human–Machine Collaboration in Scheduling

Machine learning (ML), deep learning (DL), reinforcement learning (RL), optimization and metaheuristic techniques, and hybrid AI approaches are the five broad categories into which AI-based scheduling approaches can be divided. ML is especially helpful when utilizing past production data to find connections between scheduling results and operating conditions. When labeled data are scarce, unsupervised and semi-supervised

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learning can help with decision-making and job classification (Aremu & Udofia, 2025). Processing times, machine availability, equipment failure probabilities, demand patterns, and bottlenecks can all be estimated using decision trees, random forests, support vector machines, and neural-network predictors. By modeling complex, high-dimensional, sequential manufacturing data, deep learning architectures such as CNNs, RNNs, LSTMs, and Transformers can enhance scheduling robustness, equipment-degradation forecasting, and delay prediction (Chikwendu et al., 2025). However, when production conditions change, supervised ML and DL may need to retrain, and DL also requires large datasets, computational power, validation, and methods to deal with limited interpretability.

Because RL views scheduling as a sequential decision-making problem where agents choose actions based on production states and receive performance-based rewards, it is a good fit for dynamic scheduling. Schedules can be adjusted by DQN, PPO, DDPG, and multi-agent RL in response to errors, changes in workload, material limitations, and urgent tasks. By enabling decentralized collaboration between machines, operators, robots, and material-handling resources, multi-agent systems enhance scalability and resilience (Tolia & Ponis, 2026). Explainable AI (XAI) can facilitate human-AI cooperation in Industry 5.0 settings by improving transparency, interpretability, and operator trust (Nikiforidis et al., 2024). Nevertheless, reward design, training instability, sample requirements, exploration risks, and simulation-to-reality transfer continue to limit reinforcement learning.

Although optimization and metaheuristic techniques, such as mathematical programming, GA, PSO, ACO, SA, and TS, explicitly account for constraints and multiple objectives, they may become computationally costly as scheduling complexity rises. Therefore, hybrid AI approaches provide a significant alternative by integrating complementary capabilities for responsive, robust, and scalable scheduling by combining ML-based prediction, optimization-based scheduling, RL-based adaptation, and constraint enforcement.

Human–Machine Collaborative Scheduling Framework

The Human–Machine Collaborative Scheduling Framework is shown in Figure 6.1, which shows how artificial intelligence and human knowledge interact in production scheduling. The framework supports flexible, transparent, and effective scheduling decisions in dynamic hybrid printing environments by integrating intelligent scheduling algorithms, human-in-the-loop decision-making, real-time manufacturing data, and continuous feedback mechanisms.

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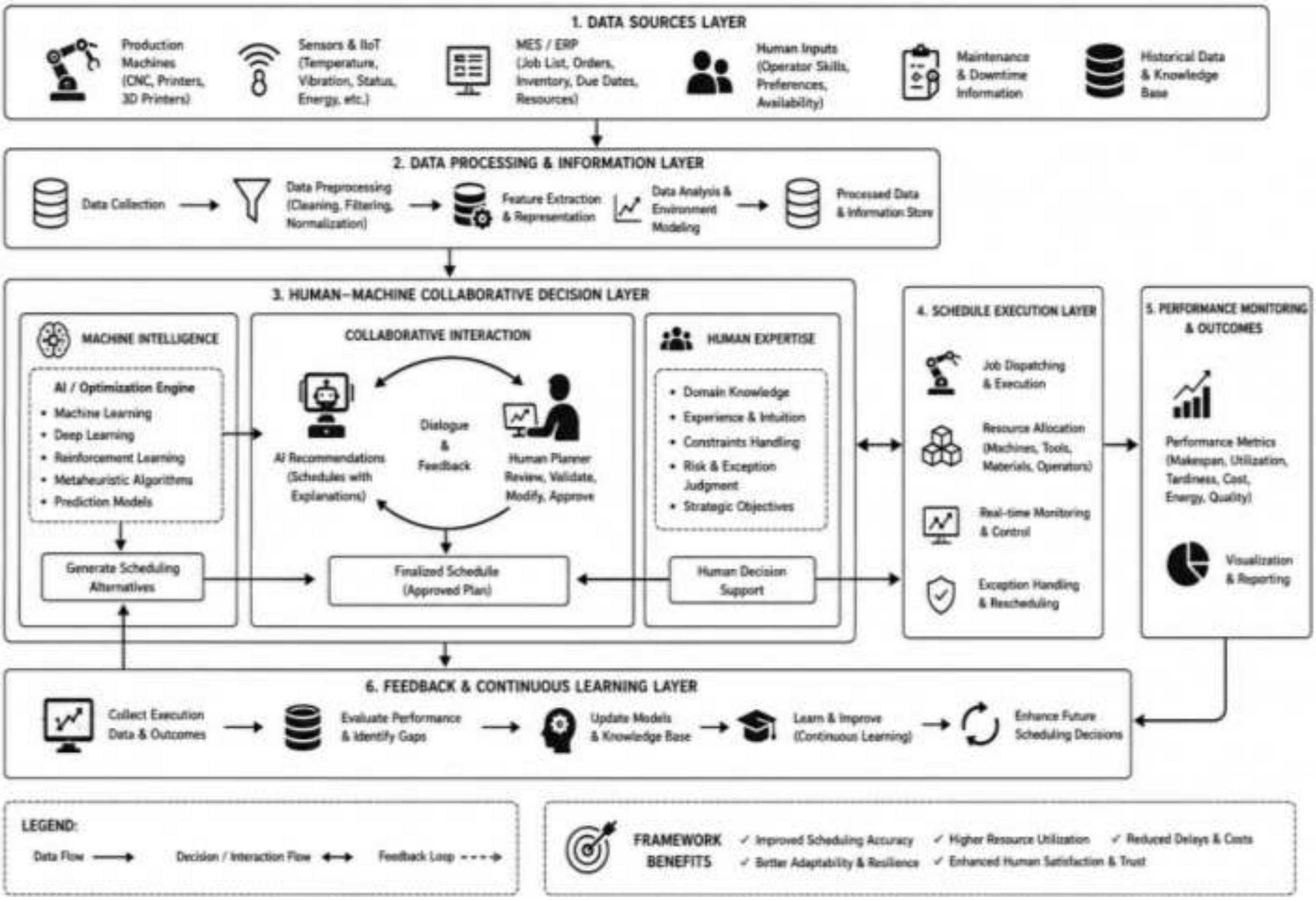

Figure 6.1. Human–Machine Collaborative Scheduling Framework

An AI-enhanced Human–Machine Collaborative Scheduling Framework for hybrid printing systems is shown in Figure 2.0. The framework creates optimal schedules by combining production data from MES/ERP systems, IoT sensors, and human input into an intelligent scheduling engine. Before being implemented, AI recommendations are examined, verified, and improved by human experts. Machine learning models can improve scheduling accuracy, resource utilization, operational resilience, transparency, and overall production efficiency through ongoing performance monitoring and feedback.

Proposed Conceptual Framework For AI-Enhanced Human–Machine Job Scheduling

Five interrelated elements must be integrated for efficient scheduling in hybrid printing environments, according to the synthesis of the reviewed literature: real-time data acquisition, AI-based decision intelligence, human supervisory decision-making, production execution, and continuous feedback. In line with Industry 5.0's human-centric tenets, integration with the Industrial Internet of Things (IIoT), cyber-physical systems (CPS), digital twins, cloud computing, and Explainable Artificial Intelligence (XAI) improves scheduling flexibility, resource utilization, transparency, and resilience (Udu et al., 2025). As a result, this review suggests a conceptual framework that views scheduling as a closed-loop decision-making process as opposed to a one-time optimization task.

To create an accurate picture of production conditions, real-time production data is gathered from printing machines, IIoT sensors, MES/ERP systems, inventory platforms, machine-vision systems, and human operators. Prediction, optimization, and adaptive scheduling are then carried out by the AI decision layer. While optimization algorithms produce workable schedules under various constraints, machine learning and deep learning forecast processing times, machine failures, demand patterns, and bottlenecks. While digital twins allow alternative schedules to be assessed prior to physical implementation, reinforcement learning facilitates adaptive rescheduling.

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Supervisors can validate, modify, approve, reject, or override AI decisions based on operational knowledge, safety requirements, and unanticipated circumstances by using human-machine interfaces to present scheduling recommendations (Joshi, 2023). Transparency and well-informed intervention are strengthened by XAI's comprehensible explanations. PLCs, robots, AGVs, printing machines, and material-handling systems are used to carry out approved schedules. In order to support resilient and human-centric scheduling, continuous monitoring compares actual and planned performance. Deviations resulting from shortages, failures, quality problems, changes in priorities, or human interventions are returned to the AI layer for adaptive revision (Lamdjad & Chaiter, 2025).

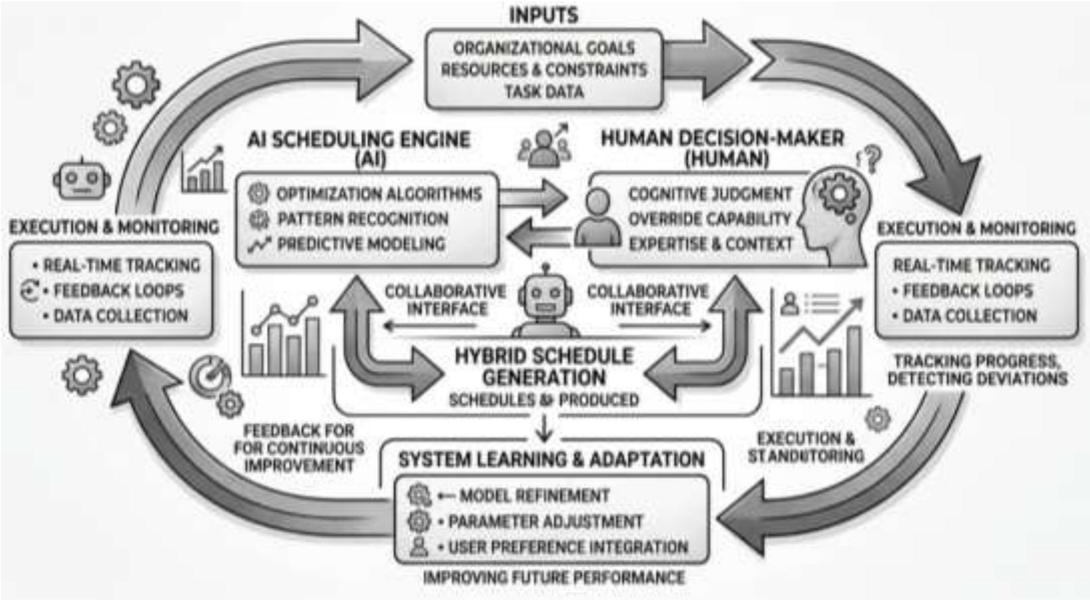

Figure 3.0: Closed-loop human–AI scheduling architecture

To guaranty smooth operational synchronization, the suggested AI-enhanced human–machine scheduling framework integrates various components. Foundational information, such as task requirements, organizational goals, and constraints, is provided by inputs. While the Human Decision-Maker provides crucial cognitive judgment and override capability, the AI Scheduling Engine uses optimization algorithms and predictive modeling to process this data. A hybrid schedule is created using a Collaborative Interface, observed through real-time Execution & Monitoring, and improved through ongoing System Learning & Adaptation.

Table 7.1. Components of the Proposed AI-Enhanced Human–Machine Scheduling Framework

Layer	Main components	Function	Output
Data acquisition	IIoT sensors, PLCs, MES, ERP, RFID, machine vision	Collect production information	Real-time production data
Data processing	Edge/cloud computing, data fusion	Clean, integrate and synchronize data	Production state
AI intelligence	ML, DL, RL, optimization, MAS	Predict, optimize and reschedule	Scheduling recommendations
Explainability	SHAP, LIME, counterfactuals, visual explanations	Explain AI recommendations	Interpretable decisions
Human decision	Operators, supervisors, production managers	Validate, modify, approve or reject schedules	Approved schedule
Execution	Printers, robots, AGVs, PLCs	Implement schedule	Production activities
Monitoring	IIoT, digital twin, machine vision	Track performance and deviations	Performance feedback
Learning	AI retraining, human feedback, reinforcement	Update scheduling policies	Improved scheduling model

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Performance Evaluation Metrics For AI-Enhanced Human–Machine Scheduling

When evaluating the efficacy, efficiency, sustainability, and resilience of production scheduling in hybrid printing systems, performance evaluation metrics are crucial. Evaluation should take into account operational, human-centric, machine-related, and environmental factors since these environments combine traditional, digital, and additive manufacturing technologies. Such multidimensional evaluation is especially crucial in Industry 5.0 since worker welfare, technological dependability, and sustainability must all be balanced with productivity (Rajkumar et al., 2024).

Scheduling performance can be directly measured using operational metrics. Because its minimization increases throughput and shortens production lead time, makespan a measure of the total time needed to finish scheduled jobs is widely used. While waiting time shows delays and possible resource bottlenecks, flow time calculates how long a job stays in the production system, including processing, transportation, setup, and waiting. AI-based scheduling aims to maximize throughput while preserving quality and operational stability. Throughput, which is defined as the number of jobs finished within a given time frame, represents production capacity and resource efficiency (Jin, 2025).

Workload balance, operator utilization, and decision acceptance rate are examples of human-centric metrics that evaluate fair task distribution, efficient workforce utilization, and acceptance of AI recommendations, respectively. By making scheduling decisions easier to understand, XAI can increase acceptance. Machine utilization, downtime reduction, and maintenance efficiency are examples of machine-related metrics. Predictive maintenance powered by AI can improve availability and continuity by anticipating equipment failures and coordinating maintenance with production schedules (Zhang et al., 2025). Lastly, carbon emissions and energy use assess environmental performance. When taken as a whole, these metrics allow for the simultaneous evaluation of environmental sustainability, equipment dependability, human well-being, and productivity in line with Industry 5.0 goals.

Table 8.1. Key Performance Indicators for AI-Enhanced Scheduling

Performance dimension	Representative indicators	Interpretation
Scheduling efficiency	Schedule adherence, tardiness, throughput, makespan	Ability to produce an effective schedule
Production time	Makespan, flow time, waiting time, setup time	Ability to reduce total production duration
Cost	Labour cost, machine cost, material cost, energy cost, rescheduling cost	Economic effectiveness
Flexibility	Rescheduling time, response to disturbances, product variety, machine adaptability	Ability to respond to changing conditions
Resource utilization	Machine utilization, operator utilization, material utilization, equipment availability	Efficiency of resource deployment
Human-centric performance	AI recommendation acceptance, workload balance, intervention frequency	Quality of human–AI collaboration
Sustainability	Energy consumption, carbon emissions, material waste	Environmental performance
Resilience	Recovery time, schedule stability, disruption tolerance	Ability to maintain/recover production

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comparative critical analysis of AI scheduling approaches

According to the reviewed literature, there isn't a single AI strategy that works best in every scheduling scenario. Problem structure, data accessibility, environmental uncertainty, computational demands, and human involvement all affect algorithmic suitability. Machine learning (ML) provides precise inputs for scheduling decisions in tasks such as processing-time estimation, demand forecasting, failure prediction, and bottleneck identification. However, autonomous sequential decision-making under constantly shifting production states is less suited for supervised learning.

Stronger modeling capabilities for high-dimensional and temporal data are provided by deep learning (DL); however, industrial deployment may be limited by computational demands and limited interpretability. Because reinforcement learning (RL) learns decision policies through environmental interaction and responds to machine-state changes, urgent tasks, and resource constraints, it is appealing for dynamic scheduling. According to Chen & Zhou (2025), RL is adaptable in dynamic environments, whereas hybrid AI models combine optimization and prediction skills to increase robustness. However, safe simulation environments, training, and well-designed reward functions are necessary for RL.

Although repeated optimization can become computationally expensive during rapid disturbances, optimization-based methods are still valuable because they explicitly represent constraints and objectives. Additionally, Sharma et al. (2025) demonstrated how combining AI with digital twins, IIoT, and XAI enhances productivity, flexibility, openness, and cooperative decision-making. Therefore, an appropriate basis for hybrid printing scheduling is provided by integrated architectures that combine ML/DL prediction, RL adaptation, optimization, XAI, and human oversight.

Table 9.1. Critical Comparison of AI Scheduling Paradigms

Dimension	ML	DL	RL	Optimization / metaheuristics	Hybrid AI
Prediction capability	High	Very High	Moderate	Low–Moderate	Very High
Dynamic adaptation	Moderate	High	Very High	Moderate	Very High
Real-time scheduling	High	Moderate –High	Very High	Moderate	Very High
Constraint handling	Moderate	Moderate	Moderate	Very High	Very High
Computational requirement	Moderate	High	High during training	Moderate–High	High
Explainability	Moderate–High	Low–Moderate	Low	High	Moderate–High
Human oversight compatibility	High	Moderate	High	High	Very High
Scalability	High	High	High	Moderate	High
Data requirement	Moderate	High	High	Low–Moderate	High
Industrial readiness	High for predictive tasks	Moderate	Emerging	High	Emerging
Suitability for dynamic hybrid printing	Moderate–High	High	Very High	High	Very High

Future Research Directions

Explainable AI (XAI) techniques that explain why tasks are assigned, prioritized, or rescheduled should be developed in future research. With the addition of counterfactual explanations, confidence estimates, uncertainty quantification, and consistency, XAI should advance beyond post-hoc visualizations to provide

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production managers and operators with operationally meaningful explanations. When AI decisions impact production assets, workforce allocation, safety, and quality, human oversight should continue to be crucial. While incorporating human input into model improvement, research should look at adaptive levels of authority, from recommendation-only systems to human-approved automation and supervised autonomy.

Additionally, AI scheduling ought to run continuously instead of just creating schedules at first. Dynamic rescheduling and disturbance detection can be supported by integrating IIoT, edge computing, digital twins, and real-time monitoring. Therefore, research should create computationally efficient algorithms that can reliably update within the constraints of industrial response. The shift from simulation to actual deployment is still a significant gap. Future research should validate frameworks in industrial and pilot-scale hybrid printing settings, taking into account factors like return on investment, cybersecurity, interoperability, legacy equipment, data quality, computational infrastructure, model maintenance, operator training, and regulatory requirements.

Failures in safe evaluation, shortages of materials, shifts in demand, and human interventions should all be supported by digital twins. Lastly, in order to reflect Industry 5.0 goals, research should progress from makespan and cost minimization to multi-objective scheduling that takes into account productivity, energy consumption, carbon emissions, material waste, operator workload, ergonomics, and worker well-being.

CONCLUSION

The development of artificial intelligence-enhanced human-machine job scheduling for hybrid printing systems was the focus of this systematic review. The review shows that the growing integration of digital, additive, and conventional printing technologies results in complex scheduling environments with many resource constraints, dynamic production conditions, heterogeneous machines, and significant human involvement. Because of their simplicity and transparency, traditional scheduling rules are still helpful, but optimization and metaheuristic approaches offer better capabilities for resolving challenging multi-objective scheduling issues. However, in extremely dynamic production environments, their limited capacity for ongoing learning and adaptation may limit their efficacy.

Processing times, demand, equipment conditions, and production bottlenecks can all be predicted with the help of machine learning and deep learning. The ability of reinforcement learning to learn adaptive decision policies makes it especially promising for dynamic and real-time scheduling. While hybrid AI architectures offer a chance to integrate prediction, optimization, adaptation, and constraint enforcement, optimization and metaheuristic approaches are still crucial for multi-objective scheduling and constraint satisfaction.

The review also shows that algorithmic performance alone is insufficient for Industry 5.0 scheduling to be effective. For AI-generated schedules to remain operationally appropriate, reliable, safe, and in line with organizational goals, human expertise, supervisory control, explainability, and decision authority are crucial. Thus, real-time production data, AI prediction and optimization, explainable scheduling recommendations, human validation, automated execution, performance monitoring, and ongoing feedback are all integrated into the suggested conceptual framework.

Overall, the data suggests that closed-loop, real-time, explainable, human-supervised AI systems rather than discrete optimization algorithms hold the key to the future of hybrid printing scheduling. Explainable AI, adaptive human-in-the-loop reinforcement learning, digital twin-enabled real-time scheduling, industrial-scale validation, cybersecurity, and sustainable multi-objective optimization should be given top priority in future research. The shift from static production scheduling to resilient, transparent, adaptive, and human-centered intelligent manufacturing systems can be facilitated by these advancements.

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