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Assessing the effects of Human–Cyber–Physical Systems on Machine Reliability: An Agent-Based Simulation Approach

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ABSTRACT

Objective: This study develops a quantitative Human–Cyber–Physical Systems (HCPS) framework to investigate how interactions among human operators, cyber systems, and physical assets influence machine reliability and maintenance performance in Industry 5.0.

Methodology: An agent-based modeling (ABM) framework was developed to simulate interactions among three agents: a physical machine, an experience-based human operator, and a rule-based cyber decision-support system. The model was calibrated using empirical production-line data from a home-appliance manufacturer and evaluated under conventional and HCPS-enabled scenarios through 80 Monte Carlo replications and sensitivity analysis.

Results: Relative to the conventional approach, the HCPS-enabled scenario was associated with lower machine downtime, fewer failures, and reduced mean time to repair (MTTR), alongside higher estimated system reliability. The observed differences were statistically significant ($p < 0.05$ for all metrics; Cohen's $d = 31.67$ for reliability), and cyber-feedback effectiveness emerged as an influential parameter in the model.

Conclusion: The proposed framework demonstrates the suitability of ABM for modeling dynamic human–cyber–physical interactions and provides a reproducible approach for quantitatively evaluating HCPS in manufacturing. The findings offer practical insights for designing human-centric maintenance systems and contribute to operationalizing Industry 5.0 through measurable performance outcomes.

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Introduction

Manufacturing systems are increasingly challenged by shorter product life cycles, growing product customization, volatile market demands, and the need to simultaneously improve productivity, flexibility, and operational reliability. These challenges have accelerated the transition toward Industry 4.0, which integrates Cyber–Physical Systems (CPS), the Internet of Things (IoT), smart sensors, cloud computing, and advanced data analytics to establish intelligent, interconnected manufacturing environments. By enabling real-time monitoring, decentralized decision-making, and data-driven operations, Industry 4.0 has significantly enhanced manufacturing performance and transformed maintenance from reactive and preventive practices toward predictive strategies. Koch et al. (2017) first demonstrated the industrial value of intelligent maintenance support, Gallo and Santolamazza (2021) highlighted the evolving role of maintenance operators in Industry 4.0 environments, while Maddikunta et al. (2022) identified predictive maintenance as one of the defining technological applications of Industry 4.0.

Despite these advances, Industry 4.0 has remained predominantly technology-driven, focusing on automation and process optimization while treating human operators mainly as supervisors of intelligent systems. However, modern manufacturing increasingly requires human expertise, contextual judgment, and adaptive decision-making to complement technological capabilities. In response, the European Commission introduced Industry 5.0, extending industrial development beyond technological excellence by emphasizing human-centricity, sustainability, and resilience. Rather than replacing human capabilities, Industry 5.0 promotes collaboration between humans and intelligent technologies to achieve more adaptive and sustainable manufacturing. Xu et al. (2021) and Wang et al. (2020) described this transition as the evolution toward human-centered intelligent manufacturing; Lu et al. (2022) identified human-centricity as its defining principle, and Ghobakhloo et al. (2022) highlighted its strategic importance for future industrial competitiveness.

This paradigm shift has led to the emergence of Human–Cyber–Physical Systems (HCPS), which extend conventional CPS by integrating human intelligence into cyber–physical manufacturing environments (Pantano et al., 2020). Within HCPS, cyber systems continuously monitor production processes and provide decision support, while human operators contribute contextual knowledge, experience, and adaptive reasoning to operational activities, reflecting the human-centric HCPS perspective proposed by Wang et al. (2021). Zhou et al. (2019) demonstrated the effectiveness of cyber-enabled decision support in improving operational intelligence, whereas Damm et al. (2024) proposed a comprehensive HCPS reference architecture for systematically integrating human, cyber, and physical entities. Among manufacturing paradigms, Reconfigurable Manufacturing Systems (RMS) provide an effective environment for implementing HCPS because their modular and scalable structures support rapid adaptation to changing production requirements

(Gräßler et al., 2021). In this context, Lu et al. (2021) emphasized the importance of anthropocentric human–machine collaboration, while Nourmohammadi et al. (2022) and Sbaragli et al. (2025) demonstrated how human-centered manufacturing architectures enhance adaptability and coordination in dynamic production systems. Although previous studies have established the conceptual foundations of Industry 5.0 and HCPS, most have concentrated on reference architectures, enabling technologies, and implementation frameworks (Lou et al., 2024; Piardi et al., 2024; Damm et al., 2024). Consequently, limited attention has been devoted to quantitatively modeling how interactions among human operators, cyber systems, and physical machines evolve over time and jointly influence manufacturing performance, despite growing interest in Human-in-the-Loop learning approaches (Kumar et al., 2024). To address this gap, this study develops an agent-based modeling (ABM) framework that explicitly represents three interacting entities—human operators, physical machines, and a rule-based cyber-support system—to simulate Human–Cyber–Physical interactions in manufacturing. Accordingly, this study makes three contributions. First, it develops a reproducible quantitative HCPS framework based on agent-based simulation. Second, it operationalizes human–cyber–physical interactions using measurable operational variables. Third, it evaluates how these interactions influence manufacturing performance through reliability, downtime, mean time to repair (MTTR), and failure frequency. The study addresses the following research questions: RQ1 examines how Human–Machine synergy within Industry 5.0 can improve machine performance indicators. RQ2 investigates the conditions under which effective collaboration between humans and cyber systems can be achieved. RQ3 explores how human expertise and system-based decision support can jointly contribute to improved operational outcomes through interaction-based learning mechanisms.

The remainder of this paper is organized as follows: Section 2 reviews the theoretical foundations of HCPS and human–machine interaction. Section 3 presents the proposed agent-based modeling methodology. Section 4 presents results. Section 5 discusses the theoretical and managerial implications of the findings. Finally, Section 6 concludes the study and outlines directions for future research.

Literature Background

Recent advances in intelligent manufacturing have highlighted the critical role of integrating human expertise with cyber intelligence to enhance system adaptability. Cui et al. (2022) demonstrated that such integration enhances system responsiveness and operational flexibility in modern production environments. The technological realization of this vision is commonly represented by Human–Cyber–Physical Systems (HCPS), which extend conventional Cyber–Physical Systems (CPS) by embedding human intelligence into cyber–physical manufacturing environments, enabling more adaptive and context-aware decision-making (Pantano et al., 2020).

Jimenez and Vanderhaegen (2019) first introduced HCPS as an architecture in which humans actively participate in cyber–physical decision-making. Damm et al. (2024) subsequently proposed a comprehensive HCPS reference architecture that systematically integrates human, cyber, and physical entities, while Bocklisch et al. (2022) and Wang et al. (2021) described HCPS as collaborative ecosystems in which human, cyber, and physical entities continuously exchange information. Huang et al. (2022) demonstrated that integrating cyber intelligence with human expertise improves production adaptability, whereas Colombathanthri et al. (2025) emphasized the role of HCPS in predictive maintenance and intelligent manufacturing. Within manufacturing environments, Gräßler et al. (2021) and Nourmohammadi et al. (2022) highlighted the suitability of human-centered manufacturing systems for implementing HCPS, while Sbaragli et al. (2025) further demonstrated how human-centered cyber–physical architectures enhance adaptability and system coordination.

As HCPS have evolved, increasing attention has been devoted to strengthening interaction between human operators and cyber systems. Mourtzis and Angelopoulos (2024), De Simone et al. (2022), and Tsutsumi et al. (2020) demonstrated that intelligent human–machine interfaces improve operator decision-making while reducing cognitive workload. Likewise, Pollini et al. (2025) showed that cyber-assisted interfaces shorten maintenance response times, whereas Ahmad et al. (2025) and Kaasinen et al. (2020) reported improvements in maintenance effectiveness through intelligent operator support. Khamaisi et al. (2025) and Rothfuß et al. (2020) further found that adaptive interfaces enhance collaboration during manufacturing operations, while Yang et al. (2024) highlighted their contribution to situational awareness. Complementing these studies, Organ et al. (2021) and Haesevoets et al. (2021) argued that integrating tacit human knowledge into cyber systems improves collaborative decision-making, an idea that was further operationalized through human modeling by Şahinel et al. (2021) and real-time intelligent control frameworks proposed by Hu et al. (2024).

Building on these technological developments, researchers have increasingly investigated how human roles should be organized within HCPS. Lou et al. (2024) and Piardi et al. (2024) proposed the Human-in-the-Loop (HitL), Human-on-the-Loop (HotL), and Human-in-the-System (HitS) paradigms to support adaptive task allocation and bidirectional learning. Ansari et al. (2018) argued that these collaborative mechanisms improve knowledge sharing during manufacturing operations, while Wang et al. (2021) demonstrated their contribution to system reliability. Yu et al. (2021) showed that adaptive collaboration improves maintenance performance, and Wei et al. (2025) further confirmed the benefits of dynamic human involvement in intelligent manufacturing. In parallel, Zhou et al. (2019) demonstrated that cyber-enabled decision support strengthens monitoring and operational intelligence, whereas Ling et al. (2020) showed that repetitive analytical tasks can be delegated to cyber systems without removing human oversight. These developments are consistent with the concepts of Operator 4.0 and Smart Human Capital 4.0

(Sivathanu & Pillai, 2018), which emphasize workforce capability rather than workforce replacement. Bousdekis et al. (2020) highlighted AI-enabled human–machine symbiosis, Teubner et al. (2020) and Lodgaard and Dransfeld (2020) emphasized operator preparedness, Goldin et al. (2022), Bitsch (2022), and Vernim et al. (2022) stressed continuous capability development, while Berger et al. (2020), Tortorella et al. (2020), and Fernandes et al. (2025) argued that organizational culture and knowledge management remain fundamental for successful Industry 5.0 implementation.

Unlike previous studies that primarily conceptualize HCPS architectures, propose reference frameworks, or evaluate isolated aspects of human–machine interaction, the present study develops a quantitatively calibrated agent-based HCPS framework that simultaneously represents human operators, cyber decision support, and physical machines within a unified simulation environment. Rather than examining these components independently, the proposed framework explicitly models their continuous interactions and quantitatively evaluates their combined effects on manufacturing reliability, downtime, mean time to repair (MTTR), and failure frequency. This interaction-oriented and reproducible modeling perspective extends the predominantly conceptual HCPS literature and provides quantitative evidence on how human–cyber–physical collaboration translates into measurable manufacturing performance. The summary of the literature review and research innovation is presented in Table 1.

Table 1. Summary of the Literature Review and Research Innovation

Level of coverage: ■ Full ◩ Partial □ Absent – Not reported

Study	Method	Human	Machine	Cyber	Quant.	Reliability Metrics
Sbaragli et al. 2025	Cyber-physical architecture	■	■	■	◩	Monitoring accuracy, reliability trend
Islam et al. 2025	Systematic review	■	◩	■	□	– NR
Li & Duan 2025	Conceptual Industry 5.0	■	□	■	□	– NR
Khamaisi et al. 2025	Adaptive HCPS design	■	■	■	◩	Flexibility index
Fernandes et al. 2025	CPS human-in-loop model	■	■	■	◩	System responsiveness
Duraimutharasan et al. 2025	AI-enhanced control	■	■	■	◩	Efficiency gain, decision quality
Hu et al. 2024	Real-time control framework	■	■	■	■	Latency, stability, throughput
Piardi et al. 2024	HCPS architecture	■	■	■	◩	System stability, robustness
Lou et al. 2024	Conceptual framework	■	□	■	□	– NR
Kumar et al. 2024	Human-in-loop learning review	■	◩	■	□	– NR
Bocklisch & Huchler 2023	Human-machine teaming analysis	■	■	■	◩	– NR
Ciccarelli et al. 2022	Ergonomics experiment	■	■	■	■	Ergonomic improvement index

Chiurco et al. 2022	Emotion detection experiment	■	■	■	■	Accuracy, interaction effectiveness
Vernim et al. 2022	Value-sensitive design	■	■	■	◩	Usability metrics
Bocklisch et al. 2022	Fuzzy cognitive model	■	◩	■	■	Model consistency
Gallo & Santolamazza 2021	Industry 4.0 maintenance role study	■	■	□	◩	Operator role adaptation
Ostheimer et al. 2021	Hybrid intelligence design	■	■	■	◩	Learning performance
Şahinel et al. 2021	Human modeling framework	■	◩	■	□	– NR
Tzouras et al. 2021	Agent-based simulation	■	□	■	■	Network impact indicators
Wang et al. 2021	HCPS framework	■	■	■	◩	System reliability (qualitative)
Atashfeshan et al. 2021	Dynamic allocation model	■	■	■	■	Task success rate
Ansari et al. 2020	Knowledge-based modeling	■	■	■	■	Performance indicators
Berger et al. 2020	Architecture design	■	■	■	□	– NR
Bousdekis et al. 2020	HCPS AI symbiosis framework	■	■	■	◩	Decision quality
Kaasinen et al. 2020	Operator 4.0 empowerment study	■	■	■	◩	Engagement metrics
Ling et al. 2020	Computer vision workstation	■	■	■	■	Detection accuracy, efficiency
Somarathna 2020	Agent-based HR simulation	■	□	■	■	System stability
Graessler & Poehler 2019	Design methodology	■	■	■	□	– NR
Zhang et al. 2019	Agent-based safety model	■	□	■	■	Safety compliance index
Zhou et al. 2019	HCPS conceptual model	■	■	■	□	– NR
Ansari et al. 2018	Conceptual model	■	□	■	□	– NR
Inan & Beydoun 2017	Agent-based modeling	■	□	■	■	Simulation validity
Macal 2016	ABM methodology	■	□	■	■	Simulation validity standards
Present Study	Agent-Based Modeling	■	■	■	■	Reliability, Average Uptime, Average Downtime, MTTR, Failure Count

To address these critical gaps, the present study proposes an ABM framework that mathematically simulates dynamic Human-Machine interactions within a unified HCPS in a real-world manufacturing environment. The framework integrates predictive maintenance strategies, adaptive HMI, and operator learning mechanisms to quantify their combined effects on key performance indicators, including reliability, average uptime, average downtime, MTTR, and Failure Count. As illustrated in Fig. 1 and Table 2, the proposed framework provides a reproducible simulation-based approach for analyzing human-cyber-physical interactions and offers a quantitative foundation for designing resilient, adaptive, and human-centric Industry 5.0 manufacturing systems.

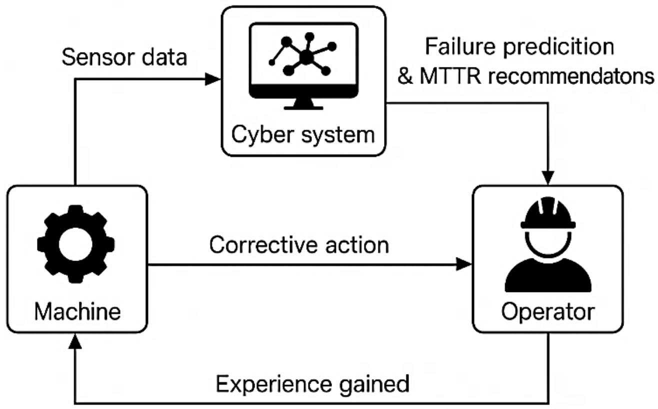

Fig. 1. Intelligent HCPS feedback loop

Fig. 1 illustrates the integration of Machine, Cyber, and Operator agents within a manufacturing environment. It comprises three primary agents operating in concert:

Machine Agent:

- **Role:** This agent represents the physical equipment or machinery on the manufacturing line, serving as the "executor" of the manufacturing process.
- **Functionality:** "Generates sensor data." Machines are equipped with various sensors that continuously collect operational data, including parameters such as temperature, pressure, vibration, speed, energy consumption, quality metrics of manufactured parts, and more. This raw information is labeled as "Real-time data" and fed into the subsequent stage of the system.

Cyber System Agent:

- **Role:** This agent constitutes the "intelligent" core of the system, responsible for processing collected data and deriving decisions. It may involve an industrial computer, server, or cloud-based system.
- **Functionality:** The cyber-system is implemented as a rule-based module that modifies failure probability and MTTR parameters. It does not use machine-learning predictions. Instead, the cyber-system applies fixed improvement coefficients (detection improvement and MTTR reduction), calibrated using historical data.

Operator Agent:

- **Role:** This agent embodies the human operator or technician tasked with controlling and maintaining machinery.

- **Functionality:** Operator performance evolves through a Markovian learning model represented by five skill states. Skill progression affects machine failure probability and MTTR.

Table 2. Agents of HCPS.

Component	Description	Role in framework
Machine agent	Generates hypothetical sensor data providing real-time operational data reflecting machine health status and sensor data for (temperature, vibration, errors, last maintenance). Machines randomly fail based on failure rates (MTBF)	Provides real-time operational status and sensor data for analysis
Cyber system agent	Provides real-time decision support through deterministic adjustment factors. It reduces failure probability and repair time based on fixed parameters derived from calibration.	Enables predictive maintenance and decision support for operators
Operator agent	Adjusts machine repair times (MTTR) based on experience and Cyber System recommendations. Operator skill evolves across five states: Novice, Advanced Beginner, Competent, Proficient, Expert.	Executes maintenance and repairs; adapts based on Cyber System insights

This feedback loop represents a fundamental iterative process in which operators' experiential insights, gained through successive interventions, are systematically reintegrated into the cyber-physical system. This ongoing feedback refines predictive models while progressively improving the system's precision, adaptability, and overall performance. Embodying a closed-loop paradigm, this approach exemplifies next-generation industrial maintenance by orchestrating the dynamic interplay of real-time data, advanced computational intelligence, and human judgment, resulting in a resilient, self-optimizing operational ecosystem.

Materials and Methods

Agent-Based Modeling (ABM) has become a prominent methodology for investigating social phenomena and modeling human capital, organizations, and communities, as it provides an explicit framework for representing the behavior and interactions of agents. This approach facilitates the identification of causal relationships among agents and enables the integration of causal processes and mechanisms within the model (Macal, 2016), thereby supporting the analysis of complex systems, particularly socio-technical systems (Somarathna, 2020; Inan & Beydoun, 2017). Within ABM, complex system dynamics are simulated through sets of rules governing the iterative and adaptive interactions between heterogeneous agents and their environments (Zhang et al., 2019; Tzouras et al., 2021). In ABM, independent agents make decisions based on their environments and interactions with other agents, which allows for the simulation of complex and dynamic contexts. Nevertheless, one major drawback is that the development of agent-based models requires substantial expertise in microscopic simulation tools and programming, which can make implementation and interpretation challenging for many researchers (Tzouras et al., 2021). More recently, ABM has also emerged as a valuable approach for simulating interactions within Human-Cyber-Physical Systems (HCPS), offering insights into how human engagement with machines influences performance metrics and operator satisfaction (Ansari et al., 2020; Prassida & Asfari, 2022). This research applies an agent-based simulation framework explicitly designed to quantify machine performance improvement under HCPS intervention. The model integrates three core agents —Machine, Operator, and Cyber— interconnected through adaptive feedback loops where machine reliability and repair efficiency dynamically evolve in response to human learning and cyber assistance. All computational modules are developed in Python 3.10 using open-source libraries to ensure reproducibility and transparency.

Model architecture

Machine agent: The machine constitutes the analytical nucleus of this simulation. Each machine operates with a baseline daily failure probability (λ) and an associated Mean Time to Repair (MTTR). Its operational state is updated each simulated day stochastically through Bernoulli sampling, generating cumulative statistics on Reliability, Average Uptime, Average Downtime, and Failure Count. Under HCPS intervention, both λ and MTTR are adaptively modified according to predefined dynamic coefficients:

- Detection Improvement Factor (δ): reduces the probability of undetected anomalies, thus lowering λ.
- MTTR Reduction Factor (ρ): accelerates recovery after failure through optimized decision support and predictive maintenance scheduling.

These parameters serve as machine-level proxies for adaptive intelligence—reflecting how system cognition translates directly into tangible performance metrics.

The framework supports varying failure modes and machine types by allowing each machine agent to be initialized with distinct baseline failure probabilities and MTTR values. These parameters can be calibrated from data or varied across simulation runs. Because failure and repair processes are encapsulated at the agent level, machines with different behaviors (e.g., high-cycle vs. low-cycle equipment, or components with different aging profiles) can be simulated concurrently without structural changes to the model.

Operator agent: The human operator's expertise is modeled as a discrete stochastic process (Markov chain) evolving over five competence levels (Novice–Expert). Transition probabilities between states depend on empirical training data or calibrated defaults and influence machine reliability indirectly by affecting response time and repair effectiveness.

Cyber agent: The cyber agent functions as a rule-based decision-support component within the HCPS architecture. Based on predefined maintenance rules and calibrated operational parameters, it evaluates machine-condition information and provides maintenance recommendations to operators. The cyber agent does not employ machine-learning algorithms or adaptive predictive models. Instead, its contribution is represented through fixed detection-improvement and repair-efficiency coefficients derived from historical maintenance records. These recommendations support operator decision-making and indirectly influence machine reliability and maintenance performance.

Justification for selecting agent-based modeling

Several simulation approaches have been applied in manufacturing-system analysis, including Discrete Event Simulation (DES), System Dynamics (SD), and Agent-Based Modeling (ABM). The selection of an appropriate modeling approach depends on the nature of the research problem and the underlying system behavior. DES is particularly effective for modeling process flows, resource utilization, queue dynamics, and production scheduling. However, DES generally represents system entities as passive objects moving through predefined process sequences and is less suitable for capturing adaptive behavioral changes, learning processes, and decentralized decision-making among interacting actors. In contrast, the objective of this study is to model Human–Cyber–Physical interactions, where machine behavior, operator learning, and cyber-assisted decision support evolve dynamically through repeated interactions. Such interactions involve heterogeneous entities with distinct behavioral rules, adaptive responses, and feedback mechanisms that cannot be adequately represented through traditional process-oriented simulation alone.

Agent-Based Modeling was therefore selected because it allows each system component—including operators, machines, and cyber-support mechanisms—to be represented as autonomous agents with individual states, decision rules, and interaction capabilities. This enables the explicit modeling of operator learning trajectories, cyber-assisted maintenance recommendations, and their combined effects on machine reliability over time. Furthermore, ABM is particularly suitable for investigating emergent system-level outcomes that arise from local interactions among heterogeneous agents. Since the primary objective of this study is to quantify how Human–Cyber–Physical interactions influence reliability-related performance indicators, ABM provides greater analytical flexibility than DES for representing the adaptive and interactive characteristics of HCPS environments. Accordingly, the use of ABM is not intended to replace traditional manufacturing-simulation approaches but rather to complement them in situations where learning dynamics, human behavior, and decentralized interactions constitute essential elements of the system under investigation. A summary comparison of these methods is presented in Table 3.

Table 3. A summary comparison of these methods.

Criterion	DES	ABM	Relevance to This Study
Process flow modeling	High	Medium	Medium
Resource scheduling	High	Medium	Low
Human learning representation	Low	High	High
Adaptive decision making	Low	High	High
Human–Machine interaction	Limited	Strong	High
Emergent behavior analysis	Limited	Strong	High
HCPS modeling capability	Moderate	High	High

Mathematical formulation

Operator learning is represented as a bounded learning process in Equation 1:

$$L\,(t+1) \;=\; L(t) \;+\; \beta F(t)\,[1 - L(t)] \tag{1}$$

where $L(t)$ denotes operator skill level at time t, β represents the learning coefficient, and $F(t)$ denotes cyber-feedback frequency.

Machine failure probability evolves according to Equation 2:

$$Pf\;(t) \;=\; \lambda\,[1 - \delta L(t)] \tag{2}$$

where λ is the baseline failure probability, and δ represents cyber-assisted detection effectiveness.

Repair efficiency is modeled as Equation 3:

$$MTTR\;(t) \;=\; MTTR0\,[1 - \rho L(t)] \tag{3}$$

where ρ denotes the maintenance-support coefficient provided by the cyber system.

These equations enable dynamic interaction among operator competence, cyber support, and machine reliability throughout the simulation horizon.

The mathematical formulation is grounded in reliability engineering, organizational learning theory, and HCPS principles. The operator learning equation adopts a bounded logistic learning process in which learning progresses rapidly during early experience and gradually approaches a saturation level as operator expertise increases. This formulation reflects established learning-curve theory, whereby additional learning becomes progressively smaller as operators approach expert-level competence. Consequently, operator skill remains bounded and converges toward a stable equilibrium instead of increasing indefinitely.

The machine failure probability equation extends classical reliability modeling by incorporating the effect of operator competence through cyber-assisted decision support. The baseline failure probability λ represents the intrinsic failure likelihood of the machine under conventional operation, while operator learning proportionally reduces this probability through improved maintenance decisions and earlier anomaly detection. Likewise, the MTTR formulation assumes that greater operator competence enables faster diagnosis and repair, thereby reducing repair duration while maintaining a positive lower bound.

To ensure physical interpretability and numerical stability, all parameters are constrained within feasible intervals:

- Learning coefficient: $\beta \in [0,1]$
- Cyber detection effectiveness: $\delta \in [0,1]$
- Maintenance-support coefficient: $\rho \in [0,1]$
- Operator learning level: $L(t) \in [0,1]$
- Cyber-feedback frequency: $F(t) \in [0,1]$
- Baseline failure probability: $\lambda \in (0,1)$
- Initial repair time: $MTTR_0 > 0$

These bounds guarantee that failure probabilities remain valid probabilities, operator competence remains normalized, and repair time remains physically meaningful throughout the simulation. The asymptotic behavior of the model is also consistent with theoretical expectations. As $\beta \to 0$, operator learning becomes negligible and the system approaches conventional maintenance behavior with nearly constant operator competence. Conversely, as $\beta \to 1$, learning rapidly converges toward its upper bound, representing accelerated knowledge acquisition under intensive cyber feedback. When $\delta \to 0$, cyber support provides no improvement, and the failure probability approaches the baseline value λ. In contrast, as $\delta \to 1$ and operator competence approaches L(t)=1, the failure probability approaches zero, corresponding to nearly ideal preventive maintenance conditions. Similarly, when $\rho \to 0$, repair time remains close to the baseline $MTTR_0$, whereas $\rho \to 1$ produces the maximum achievable reduction in repair time while preserving positive repair duration. These asymptotic properties ensure that the proposed equations remain mathematically stable and operationally interpretable across the complete parameter space.

Simulation Framework

Each experimental configuration simulates 365 consecutive operational days under two distinct conditions: the HCPS scenario and the conventional scenario. To ensure statistical robustness, 80 Monte Carlo replications are executed per condition. Daily operations encapsulate sequential machine reliability checks, operator skill adjustments, and computation of HCPS-enhancement effects. Aggregate indicators are extracted as mean values across all runs, including Reliability, Uptime, Downtime, MTTR, and Failure Count, thereby isolating the incremental benefit of HCPS-enabled cognition on machine performance stability.

Computational implementation

The simulation is developed entirely in Python utilizing:

- numpy for matrix operations and stochastic sampling,
- pandas for parameter calibration and empirical data integration,
- matplotlib/seaborn for visualization, and
- scipy.stats for statistical comparison and t-tests.

Parameter sets are automatically imported from calibration files (calibrated_params_final.json) and experimental data sheets (Data.xlsx), from which transition matrices are inferred. In the absence of longitudinal data, transition probabilities are normalized across rows to preserve probabilistic consistency and system stability.

Calibration procedure

Model calibration was conducted using historical maintenance data collected from the home appliance manufacturing line to estimate the parameters governing operator learning, machine reliability, and cyber-assisted maintenance. The calibration process consisted of five sequential stages.

Step 1: Data preprocessing. Historical maintenance records were screened for missing observations and inconsistent entries. Reliability indicators, repair durations, and failure events were standardized to ensure consistent units across all simulation inputs. Transition probabilities for operator learning were derived from empirical observations and normalized so that each transition matrix satisfied probability conservation.

Step 2: Initial parameter estimation. Initial values of the learning coefficient (β), cyber detection effectiveness (δ), maintenance-support coefficient (ρ), baseline failure probability (λ), and baseline MTTR were estimated from descriptive statistics and engineering knowledge obtained from the maintenance records.

Step 3: Parameter optimization. Parameter estimation employed an iterative least-squares calibration procedure in which simulation outputs were repeatedly compared with observed reliability indicators. During each iteration, the parameter vector was updated to minimize the cumulative error between simulated and empirical values of reliability, uptime, downtime, MTTR, and failure count. Monte Carlo replications were executed for each candidate parameter set to reduce stochastic variability.

Step 4: Convergence assessment. Calibration iterations continued until the objective function stabilized and all primary performance indicators differed from their observed counterparts by less than 5%. Additional iterations produced negligible improvement, indicating convergence toward a stable parameter set.

Step 5: Validation. The calibrated parameters were subsequently validated through independent Monte Carlo simulations and sensitivity analysis. Model outputs were compared with empirical maintenance statistics using absolute percentage error and statistical hypothesis testing. Robustness was further examined by perturbing key parameters over predefined ranges to verify that the model maintained stable behavior under moderate uncertainty.

This calibration workflow improves model transparency and reproducibility by explicitly documenting parameter estimation, optimization, convergence assessment, and validation procedures.

Sensitivity analysis

Sensitivity tests are conducted to examine how machine performance varies under HCPS configuration gradients:

- Detection improvement coefficient δ ranging 0.1–0.5,
- MTTR reduction coefficient ρ ranging 0.1–0.5.

For each parameter combination, 20 Monte Carlo replications are executed. Results are visualized via multi-dimensional heatmaps and confidence intervals to reveal reliability-maintainability interactions. Finally, an integrated optimization index (Ω) aggregates normalized values of reliability, MTTR, and skill progression to identify the optimal HCPS configuration that maximizes machine stability and adaptive efficiency.

Model verification and validation

To ensure model robustness and replicability, three complementary validation steps were performed:

- Verification: The simulation logic and agent interactions were iteratively tested through unit debugging and consistency checks within Python. All parameter updates were verified to ensure accurate stochastic sampling and convergence.
- Empirical Validation: As can be seen in Table 4, results were compared against actual reliability and downtime records from the Home-appliance manufacturing line to confirm realistic performance ranges.
- Sensitivity Testing: Multi-parameter sensitivity analysis confirmed the model's internal consistency, with stable reliability outcomes ($\Delta \approx 0.003$) across parameter perturbations.

These steps collectively ensure that the model accurately represents the causal dynamics of Human-Cyber-Machine interactions in manufacturing environments. To validate the simulation model, a three-stage validation procedure was adopted.

First, verification tests were conducted to ensure logical consistency of agent interactions, parameter updates, and stochastic transitions. Second, calibration parameters were estimated using historical maintenance records obtained from the home appliance manufacturing line. Simulated outputs were iteratively compared with observed reliability indicators until convergence was achieved. Convergence was considered satisfactory when the deviation between simulated and observed values remained below 5% for all primary performance indicators. Third, robustness analysis was performed through Monte Carlo replications and parameter perturbation experiments. The resulting variation in reliability remained below 0.3%, indicating stable model behavior under moderate parameter uncertainty. These validation procedures increase confidence that the model adequately represents the causal mechanisms underlying Human–Cyber–Physical interactions in industrial environments.

Table 4. Empirical validation

Metric	Actual value	Simulated value	Absolute error	Percent error
Reliability	642.46	725.23	82.76	12.88
Uptime	107.54	4.76	102.78	95.56
Downtime	4.30	2.09	2.20	51.35
MTTR	94.24	99.57	5.32	5.64
Failure Count	82.99	96.92	13.92	16.78
Note: The high percentage error for Uptime and Downtime is a function of their small absolute baseline values, which amplifies relative differences.				

Results

This study employs a quantitative approach to evaluate the impact of integrating a Cyber System within the HCPS of a Home-appliance manufacturing line, with a specific focus on machine performance. To comprehensively evaluate system performance, five key metrics were selected: Reliability, Average Uptime, Average Downtime, MTTR, and Failure Count. These metrics provide a holistic evaluation of the synergistic effects of Human-Machine collaboration under predictive, data-driven, and adaptive manufacturing conditions. Two scenarios, centered on the role of the machine, were compared:

- Conventional Scenario: In this scenario, machines undergo maintenance based solely on operators' experience and traditional methods. Machines rely entirely on the personal knowledge and skills of operators, without the support of real-time data or system recommendations, which may result in reduced machine efficiency, increased downtime, and prolonged MTTR.
- HCPS Scenario: Machines operate in interaction with the Cyber System, which collects real-time sensor data and provides actionable recommendations through adaptive Human-Machine Interfaces (HMIs). These recommendations enable operators to optimize maintenance actions, reduce MTTR, and enhance machine efficiency and reliability.

The following sections provide a detailed interpretation of each key metric:

Reliability. Reliability rises from 94.2% in the conventional scenario to 99.6% in the HCPS scenario, equivalent to an improvement of 5.7%. This enhancement stems from the synergistic integration of cyber intelligence and human cognition—where the human operator acts as the primary source of resilience. In the HCPS scenario, reliability is not merely a function of algorithmic consistency but emerges from contextual interpretation and real-time corrective human feedback. The observed reliability improvement is attributable to the combined effects of cyber-assisted maintenance recommendations and operator learning. The results suggest that earlier detection and response to maintenance requirements contribute to more stable operational performance. The importance of incremental improvements in reliability has been well documented in prior research. Lee et al. (2024) emphasized that even single-digit gains in reliability can yield exponential reductions in long-term maintenance costs, particularly in high-throughput manufacturing environments. Similarly, Martini et al. (2024) demonstrated that modest increases in system reliability significantly mitigate systemic risks, lowering both operational disruptions and the likelihood of costly downtime cascades. The present findings therefore corroborate the broader literature, confirming that reliability is a cornerstone metric whose incremental progress translates into disproportionately large benefits for both operational continuity and economic sustainability.

Average uptime. Average uptime increases from 642.5 hours in the conventional scenario to 725.2 hours in the HCPS scenario, marking a 12.8% improvement in effective operating time. This result highlights the human role as a dynamic performance orchestrator within the hybrid loop. In HCPS, sensor data is not passively processed by algorithms but cognitively interpreted. This mechanism forms what may be termed an adaptive maintenance capability, in which continuous operation is sustained by human reasoning synchronized with cyber control. The direct practical outcome is sustainable operability: manufacturing continuity achieved through adaptive collaboration between human intuition and machine logic. The uptime increase therefore signifies not only improved mechanical efficiency, but also more stable manufacturing cycles and heightened overall equipment effectiveness (OEE) driven by hybrid intelligence. Previous studies have reported similar outcomes: Xu et al. (2021) highlighted that predictive maintenance frameworks in discrete manufacturing lines led to a 9–12% increase in uptime, while Huang et al. (2022) demonstrated that cyber-enabled systems reduce unplanned downtime by forecasting component failures well in advance. The present findings therefore align closely with the broader literature, confirming the efficacy of predictive intelligence in ensuring operational continuity.

Average downtime. Average downtime decreases substantially from 107.5 hours in the conventional scenario to 4.8 hours in the HCPS scenario—a reduction of more than 95.5%. The reduction in downtime can be attributed to earlier fault detection and more timely maintenance interventions enabled by cyber-assisted decision support. Instead of responding after a fault, the system acts preventively: the human interprets early data deviations, adjusting the control logic before a malfunction escalates. The outcome is nearly uninterrupted machine operation, replacing reactive repair cycles with proactive stabilization. From an industrial engineering standpoint, such a steep decline redefines availability. Prior studies such as Sindhwani et al. (2022) emphasized that cyber-driven predictive analytics substantially mitigate disruptions across manufacturing processes, while Yang et al. (2024) confirmed that adaptive, cyber-enabled maintenance protocols reduce downtime variability and bolster resilience in high-volume manufacturing environments. Collectively, the results validate that downtime reduction is one of the most critical contributions of cyber-physical integration.

Mean time to repair. MTTR drops from 4.3 hours in the conventional scenario to 2.1 hours in the HCPS scenario, showing a 51.2% improvement in recovery speed. This acceleration arises from the human-in-the-loop paradigm where fault diagnosis, interpretation, and corrective action occur simultaneously. In HCPS, three coordinated sub-processes underpin this dynamic:

- Cyber Fault Analytics, identifying the root cause algorithmically.
- Human Contextual Interpretation, assessing the situational and operational relevance of the fault.
- Physical Recovery Execution, implementing the exact corrective measure in real-time.

Such overlap between analytical precision and cognitive judgment enables rapid restoration of stability, yielding genuine real-time maintainability. These findings are in line with the work of Kumar et al. (2024), and Ansari et al. (2020), who showed that cyber-physical intelligence accelerates fault detection and recovery times, and Poursoltan et al. (2021), who argued that intelligent decision-support systems improve operator effectiveness in both diagnostic and repair activities. Hence, the current study reinforces the argument that cyber-enabled maintenance strategies transform repair processes from reactive, experience-based tasks into streamlined, intelligence-driven operations.

Failure count. The total failure count decreases from 10.8 incidents in the conventional scenario to 2.3 in the HCPS scenario, representing a 78.7% reduction. Substantial decrease indicates a structural improvement in reliability and learning capability. HCPS not only prevents faults—it redefines machine stability through human-driven cognitive learning. Here, human feedback acts as an interpretive filter, complementing cyber analysis and enabling immediate concurrent correction. The present results align closely with established findings across prior studies. Ansari et al. (2020) demonstrated that implementing human-interpreted feedback loops in cyber-physical manufacturing systems reduced recurrent failure frequency by over 70%. Poursoltan et al. (2021) confirmed that machine-learning controllers reinforced by operator responses significantly stabilized reliability indices in high-complexity manufacturing environments. Lee et al. (2024). The reduction in failure frequency indicates that cyber-assisted maintenance support and operator learning contribute to more effective preventive maintenance actions. The results obtained from the data analysis are shown in Fig. 2. Based on Fig. 2, the pattern of improvement across all operational indicators demonstrates that HCPS significantly outperforms the conventional scenario. This superiority transcends numerical enhancement; it represents a structural and conceptual shift toward systems imbued with human cognition, adaptive decision-making, and proactive resilience—the essence of Industry 5.0. These results collectively reinforce the study's research questions. The quantitative improvements across machine performance metrics primarily address RQ1 by empirically demonstrating how Human-Machine synergy within an Industry 5.0 framework optimizes reliability, uptime, and maintenance efficiency. Furthermore, the cognitive integration mechanisms observed in HCPS—through predictive stabilization, adaptive coordination, and Human-Cyber synchronization—directly support RQ2 and RQ3, revealing how collaborative intelligence between humans and intelligent machines fosters mutual learning and operational resilience.

Independent sample t-tests, shown in Table 5, confirmed statistically significant differences between the conventional and HCPS scenarios across all reliability-related performance indicators ($p < 0.05$). Effect-size analysis further indicated moderate-to-large practical significance.

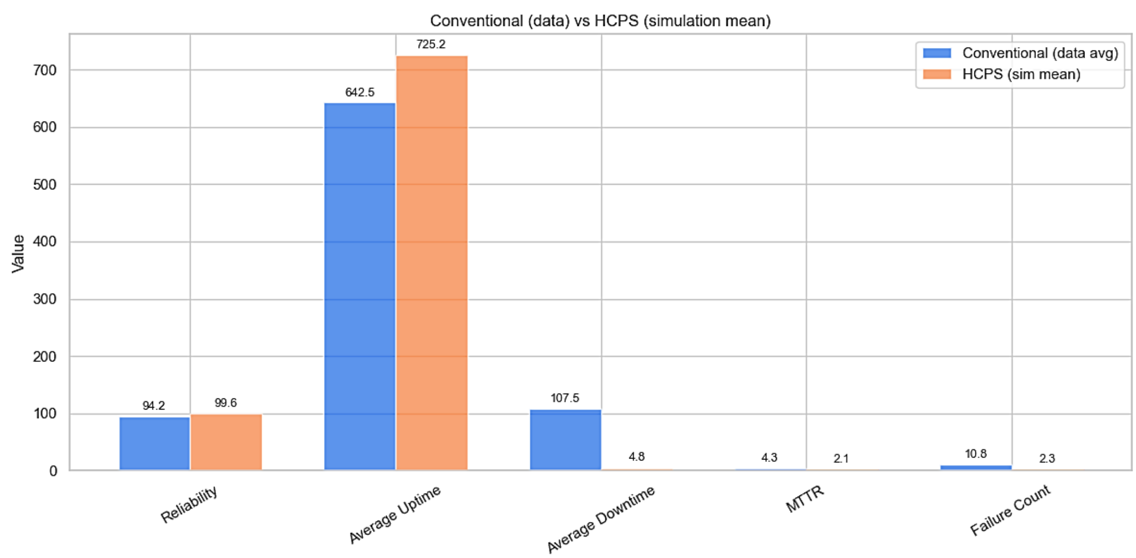

Fig. 2. Performance comparison chart

Table 5. Statistical validation

Metric	Mean	SD	95% CI Lower	95% CI Upper	t-statistic	p-value	Cohen's d
Average uptime	725.23	1.53	724.89	725.57	482.58	0.00	53.95
Average downtime	4.76	1.53	4.423	5.10	-599.27	0.00	-67.00
MTTR	2.09	0.10	2.06	2.11	-187.37	0.00	-20.94
Reliability	99.57	0.16	99.53	99.60	283.33	0.00	31.67
Operator Efficiency	96.92	7.70	95.20	98.63	16.16	0.00	1.80
Failure count	2.26	0.69	2.11	2.42	-109.43	0.00	-12.23

Sensitivity analysis

Sensitivity analysis was conducted to examine the effects of two HCPS parameters—Detection Improvement (δ) and MTTR Reduction (ρ)—on machine-performance indicators. The objective was to evaluate the robustness of the proposed framework and identify parameter regions associated with improved operational performance. Figure 3 presents the reliability response surface under different combinations of detection improvement and MTTR reduction. Reliability values remained within a relatively narrow range (98.41%–98.70%), indicating that the proposed HCPS architecture maintains stable performance under moderate parameter variations. The highest reliability values were observed when detection improvement ranged approximately between 0.2 and 0.3 and MTTR reduction remained within the low-to-medium range. This finding suggests that balanced improvements in detection capability and repair efficiency contribute more effectively to reliability enhancement than aggressive optimization of a single parameter.

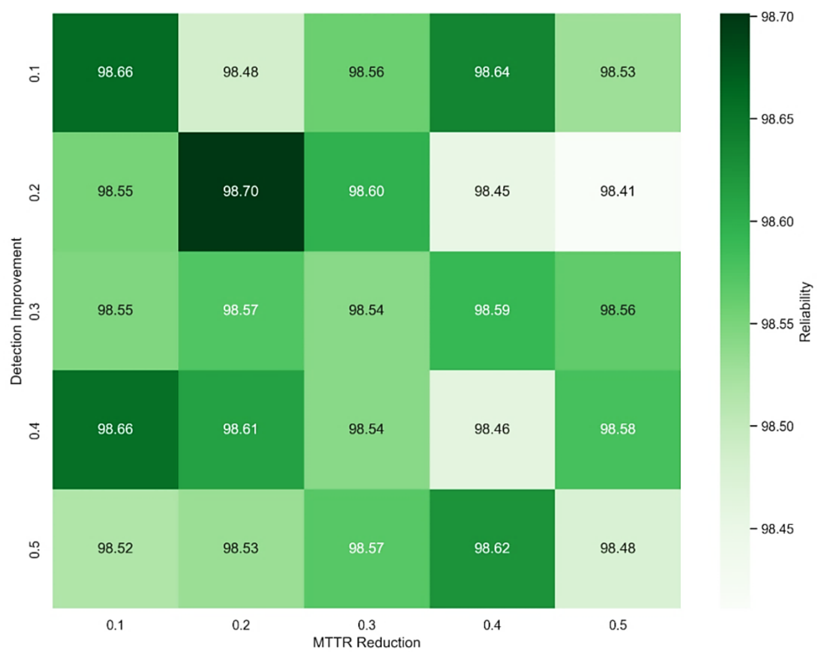

Fig. 3. Sensitivity analysis: reliability

Figure 4 illustrates the sensitivity of MTTR. The results show only limited variation across the parameter space, with MTTR values ranging from approximately 2.00 to 2.03 hours. The lowest MTTR values were obtained under moderate detection improvement and MTTR reduction levels, indicating that coordinated cyber-assisted maintenance support can improve recovery efficiency without requiring extreme parameter settings.

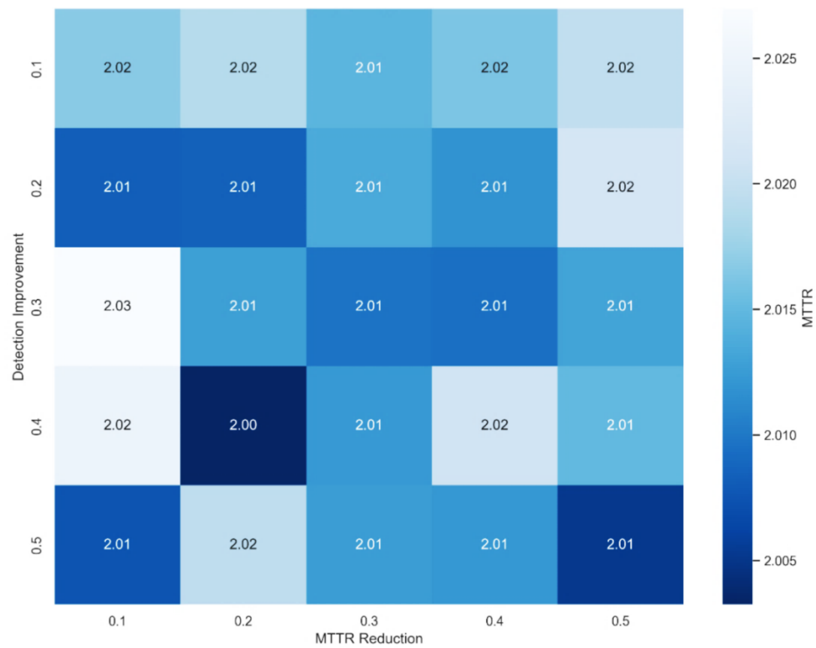

Fig. 4. Sensitivity analysis: MTTR

Figure 5 provides an integrated view of machine-performance indicators. The reliability and MTTR heatmaps reveal relatively smooth response surfaces, confirming the robustness of the model. In contrast, failure count exhibits greater variability across parameter combinations. The lowest failure frequencies occur when detection improvement is approximately 0.4 and MTTR reduction is approximately 0.2, suggesting that early fault detection has a stronger influence on failure prevention than further reductions in repair duration. The comparative sensitivity results indicate that reliability and MTTR are relatively insensitive to moderate parameter fluctuations, whereas failure count responds more noticeably to changes in HCPS configuration. This pattern suggests that improvements in fault detection mechanisms may generate greater operational benefits than equivalent investments aimed solely at accelerating repair processes. Figure 6 summarizes the relative sensitivity of each performance indicator. Failure count exhibits the largest relative variation ($\Delta \approx 0.168$), identifying it as the most responsive performance metric. In comparison, reliability ($\Delta \approx 0.003$) and MTTR ($\Delta \approx 0.012$) display substantially lower variation, indicating stable system behavior across the investigated parameter ranges.

Overall, the sensitivity analysis demonstrates that the proposed HCPS framework is robust to moderate parameter uncertainty while highlighting fault prevention as the most influential mechanism for improving machine performance. These findings support the practical value of cyber-assisted maintenance strategies in enhancing operational reliability within manufacturing environments.

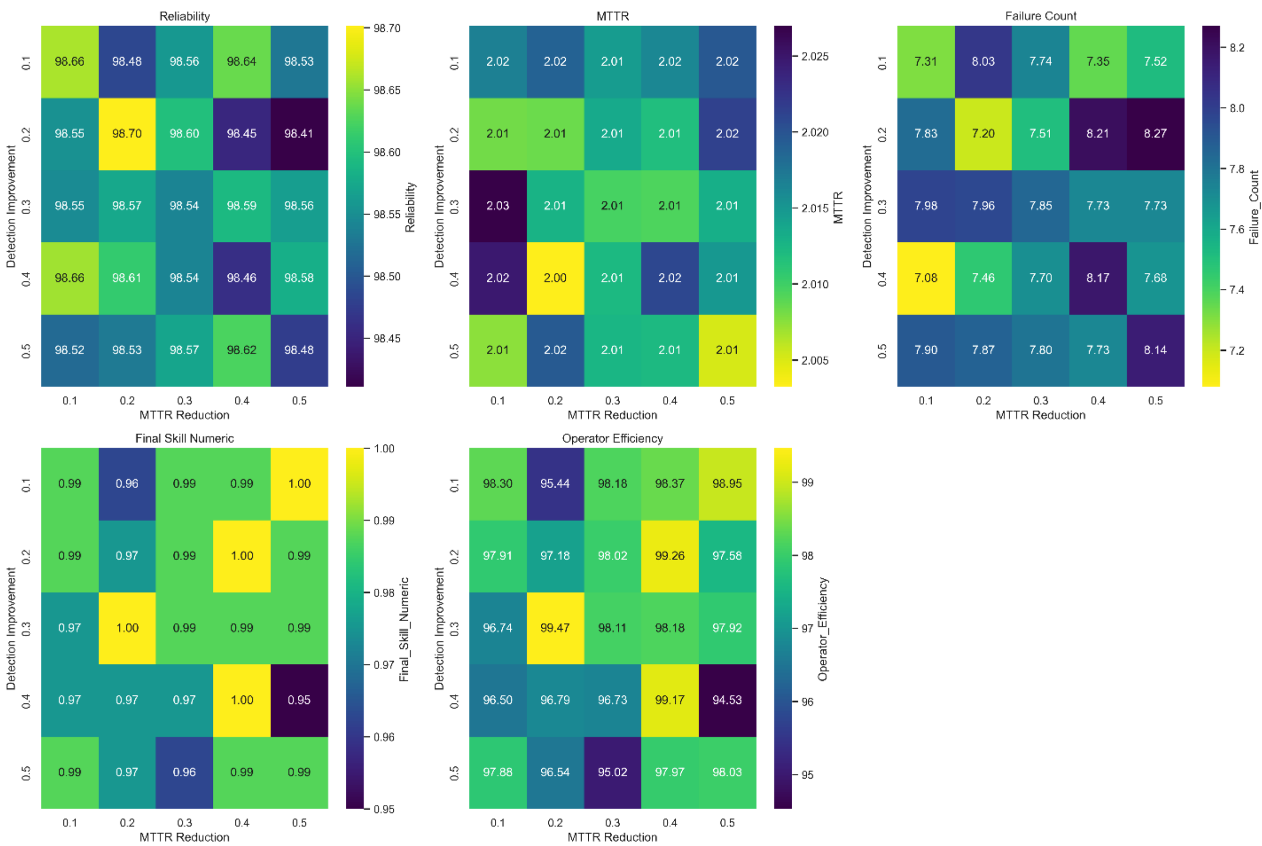

Fig. 5. The integrated analysis across operator and machine dimensions.

Discussion

A fundamental objective of Human–Cyber–Physical Systems (HCPS) is to enable effective collaboration among human operators, cyber intelligence, and physical assets to improve manufacturing performance. The findings of this study demonstrate that the proposed HCPS framework successfully achieved this objective. Compared with the conventional maintenance scenario, machine downtime, failure frequency, and Mean Time to Repair (MTTR) were substantially reduced, while overall system reliability increased. These results provide quantitative evidence that integrating human expertise with cyber-assisted decision support can generate measurable operational benefits beyond conventional experience-based maintenance.

The observed improvements can be explained by the complementary interaction between operator learning and cyber-assisted decision support. Within the proposed framework, the cyber agent continuously provides maintenance recommendations based on predefined operational rules, while operators progressively refine their maintenance decisions through repeated system feedback. This interaction enables earlier fault detection, more effective maintenance interventions, and faster recovery following failures. These findings reinforce the human-centric vision of Industry 5.0 proposed by Xu et al. (2021) and extend previous HCPS research, which has largely emphasized conceptual architectures and collaboration frameworks (Lou et al., 2024; Piardi et al., 2024), by quantitatively demonstrating how human–cyber–physical interactions translate into measurable improvements in maintenance performance. Although system reliability increased by approximately 5%, this improvement is operationally meaningful because reliability is inherently bounded near its upper limit. Consequently, even relatively small reliability gains can substantially reduce production interruptions, maintenance costs, and equipment unavailability. The considerably larger reductions observed in downtime, failure frequency, and MTTR therefore represent substantial improvements in overall manufacturing effectiveness.

The sensitivity analysis further showed that failure frequency was considerably more sensitive to cyber-support parameters than reliability or MTTR. This finding suggests that improving fault detection is more influential than further reducing repair duration after failures occur. Moreover, diminishing performance returns were observed beyond moderate levels of cyber support, indicating that balanced human–cyber collaboration is more effective than maximizing automation alone. This observation is consistent with the Industry 5.0 philosophy, in which intelligent technologies are intended to augment rather than replace human expertise. From a practical perspective, the results suggest that organizations implementing Industry 5.0 should combine cyber-assisted maintenance with systematic operator training to maximize the benefits of human–cyber collaboration. Investment in technologies that strengthen early fault detection is also likely to provide greater operational benefits than focusing exclusively on reducing repair time. Furthermore, transparent rule-based decision-support systems can enhance maintenance performance while preserving human oversight, making the proposed framework particularly suitable for organizations pursuing incremental digital transformation.

Several limitations should be acknowledged. The proposed framework was calibrated using maintenance data from a single home-appliance manufacturing line, and the reported performance improvements may therefore vary across different industrial contexts. Moreover, the cyber agent employs predefined rules rather than adaptive machine-learning algorithms, limiting its responsiveness to previously unseen operating conditions. Finally, behavioral factors such as operator fatigue, cognitive workload, and organizational influences were not explicitly represented. Future research should validate the proposed framework across multiple manufacturing sectors while incorporating adaptive cyber intelligence and richer human behavioral models to improve model realism and generalizability.

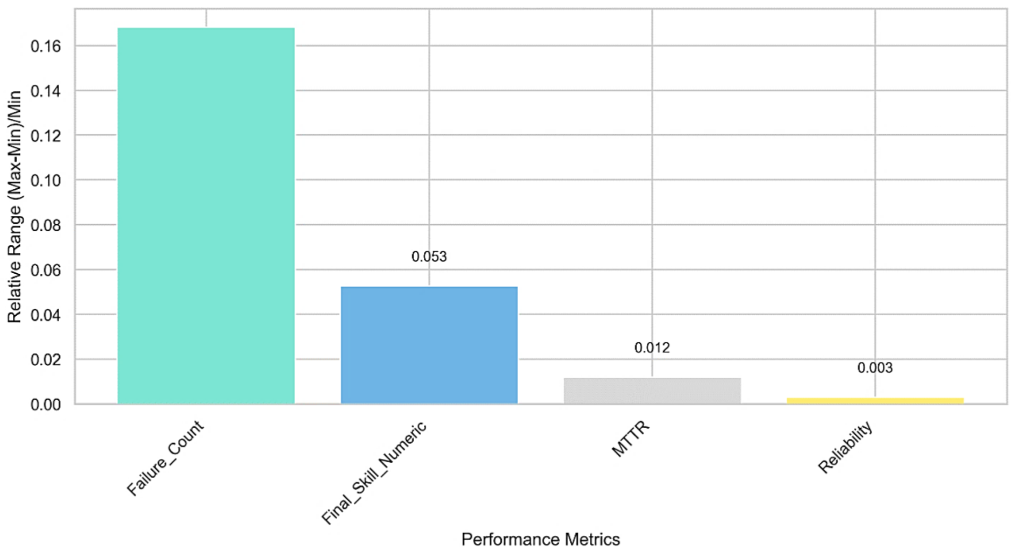

Fig. 6. Parameter sensitivity analysis (relative range of outcomes).

Managerial implications

The results of this study provide several practical implications for manufacturing organizations seeking to improve machine reliability through Human–Cyber–Physical integration. First, the findings suggest that cyber-assisted maintenance support can improve reliability-related performance indicators when operators remain actively involved in maintenance decision-making. Rather than replacing human expertise, the cyber layer functions as a decision-support mechanism that enhances situational awareness and maintenance responsiveness. Second, the results indicate that operator learning plays an important role in achieving sustained reliability improvements. Organizations should therefore invest in operator training programs that strengthen the ability to interpret cyber-generated maintenance recommendations and translate them into effective maintenance actions. Third, the sensitivity analysis suggests that moderate levels of cyber-support produce more stable outcomes than excessive automation. Managers should therefore view HCPS implementation as a collaborative human–technology strategy rather than a purely automation-driven initiative. Finally, the findings highlight the importance of combining real-time monitoring capabilities with structured maintenance processes. Such integration can support reductions in downtime and failure frequency while improving maintenance efficiency and operational continuity.

Although the proposed HCPS framework demonstrates significant improvements in machine reliability within the studied manufacturing environment, its practical implementation is subject to several contextual and operational constraints, particularly in developing economies. First, the deployment of cyber-assisted maintenance systems requires a minimum level of digital infrastructure maturity, including reliable sensor networks, real-time data acquisition systems, and stable communication protocols. In many developing industrial settings, these prerequisites may not be fully established, which can limit the immediate applicability of the proposed framework. Second, the effectiveness of the HCPS architecture depends on the availability of trained operators capable of interpreting and acting upon cyber-generated recommendations. In environments where workforce digital literacy is limited, the benefits of operator learning and cyber-assisted decision support may emerge more slowly. Third, organizational resistance to technological change may also affect implementation outcomes. The transition from conventional maintenance practices to integrated Human–Cyber–Physical workflows often requires cultural adaptation, process redesign, and management-level commitment. Finally, the rule-based nature of the cyber layer in the present study implies that its performance is bounded by predefined diagnostic rules and calibration parameters. While this ensures transparency and interpretability, it may limit adaptability in highly dynamic or previously unseen failure conditions. Despite these limitations, the results suggest that even in constrained environments, incremental adoption of cyber-assisted maintenance systems can still yield measurable improvements in reliability-related performance indicators when combined with operator training and gradual digital transformation strategies.

Conclusion

This study developed a data-informed Agent-Based Human–Cyber–Physical System (HCPS) framework to examine how cyber-assisted operator interaction influences machine reliability performance in a home-appliance manufacturing environment. The proposed model integrates machine behavior, operator learning, and cyber-assisted maintenance support within a unified simulation framework calibrated using operational manufacturing data. The results indicate improvements in reliability, uptime, downtime, MTTR, and failure frequency under the modeled HCPS scenario. The study contributes to the Industry 5.0 literature by providing a quantitative and reproducible modeling framework that operationalizes Human–Cyber–Physical interactions and links them to measurable reliability-related outcomes. The findings suggest that maintaining operators within the decision loop while providing cyber-assisted maintenance support can improve operational performance more effectively than relying solely on conventional maintenance approaches. The findings should be interpreted within the scope of the investigated case study. Future research may extend the framework through multi-site validation, integration of additional human factors, and adaptive machine-learning-based cyber systems capable of dynamically updating maintenance recommendations.

Limitations and future recommendations

While this study establishes a rigorous quantitative framework for analyzing machine performance and mechanical cognition within HCPS, several methodological limitations remain that define the agenda for future exploration. The empirical validation conducted exclusively in the Home-appliance manufacturing line constrains external generalizability, as differences in technological maturity and manufacturing complexity across other sectors could yield non-linear behavioral patterns. Furthermore, the agent-based simulation model, despite its analytical transparency, inevitably abstracts real-world micro-dynamics such as tacit operator knowledge, machine behavioral heterogeneity, and temporal learning decay. The short to medium-term assessment horizon also prevents evaluation of long-term cognitive sustainability, including skill retention and reliability saturation beyond the 0.95 boundary. Additionally, psychological and human-in-loop variables (trust, adaptation, cognitive load) were not captured, leaving an incomplete depiction of socio-technical feedback influencing machine autonomy.

Based on these constraints, the following research trajectories are recommended to strengthen scientific and industrial understanding of machine intelligence evolution (Table 6):

Table 6. Summary of limitations, potential impacts, and future research directions

Limitation / research gap	Potential impact	Future research direction
Single manufacturing case (Home-appliance industry)	Limited external validity and restricted generalizability across industries with different technological maturity and operational complexity	Conduct cross-sector comparative studies in aerospace, robotics, automotive, and process manufacturing to validate findings under heterogeneous operational conditions
Agent-based model abstraction of tacit knowledge, machine heterogeneity, and learning decay	Potential reduction in construct validity and incomplete representation of real-world dynamics	Develop hybrid modeling frameworks integrating ABM, System Dynamics, and Deep Neural Networks (DNNs) to capture nonlinear learning and organizational feedback processes.
Static rule-based cyber agent	Reduced adaptability and inability to dynamically optimize operational decisions	Incorporate machine-learning algorithms into the cyber layer to enable adaptive failure prediction, dynamic maintenance scheduling, and personalized operator support.
No machine-learning component	Limited dynamic optimization and self-learning capability	Implement reinforcement learning, edge learning, and real-time adaptive control mechanisms driven by operational feedback
Short- to medium-term evaluation horizon	Inability to assess long-term cognitive sustainability, reliability saturation, and skill retention	Conduct longitudinal studies using econometric and autoregressive models to evaluate long-term performance stability and

		validate the Cognitive Saturation Threshold (0.95)
No cognitive load variable	Simplified representation of human behavior and decision-making processes	Integrate cognitive load assessment and human-performance metrics into HCPS simulations
No operator stress modeling	Exclusion of behavioral uncertainty and human affective influences	Incorporate psychological variables such as stress, fatigue, trust, and adaptation into future human-in-the-loop models
Limited representation of socio-technical interactions	Incomplete understanding of human-machine feedback mechanisms affecting machine autonomy	Employ mixed-methods approaches combining ABM outputs with psychometric and behavioral measurements.
Absence of real-time cognitive adaptation mechanisms	Reduced responsiveness to changing operational environments	Integrate edge computing, sensor fusion, and real-time cognitive modeling capabilities
Lack of advanced cognitive technologies integration	Limited transparency and decision-support functionality	Investigate interoperability with Digital Twins, Augmented Reality (AR), and Explainable Artificial Intelligence (XAI) to enhance adaptive human-machine interfaces and predictive decision support

Future research may integrate machine-learning algorithms into the cyber layer to dynamically update model parameters based on operational feedback. Unlike the current rule-based cyber agent, machine-learning-enabled HCPS architectures could continuously adapt failure prediction thresholds, optimize maintenance schedules, and personalize operator support according to observed performance patterns. Such integration would further enhance the adaptability and realism of the proposed framework.

Ethical considerations

This study did not involve human subjects, personal data, or experiments requiring ethics approval.

Data Availability Statement

The Python simulation code, calibration parameters, and representative datasets used in this study are provided as supplementary materials. Due to industrial confidentiality restrictions, raw operational data cannot be publicly released.

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Declaration of AI-assisted technologies in the writing process

During the preparation of this work the author(s) used ChatGPT in order to visualization. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

Conflict of interest

The authors declare no conflict of interest.

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